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The Importance of Learning in the Age of Artificial Intelligence: The Evolution of the Role of the Auditor

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1. INTRODUCTION

This dissertation is about the audit profession in Quebec and artificial intelligence. The audit profession is of great economic significance. The Big Four auditing firms have a combined annual global revenue of more than $148 billion in 2018 (RAPOPORT, 2018). This amount is greater than the GDP of the sixtieth-richest country in the world. Millions of people, pension funds, investment firms, etc, are relying on high-quality audits to help allocate their savings, their pensions and their livelihoods, so it is critical that the auditor's job is of the greatest quality. There are three important reasons users of financial statements demand for audited financial statements. First, complexity. A company's transactions can be complicated and very difficult for readers to understand. Second, remoteness. Users of financial statements are usually separated from a company's accounting records by distance and time, as well as by lack of expertise. Lastly, consequences. Financial decisions are important to the state of investors' and other users' wealth. Decisions can involve large dollar amounts and massive efforts. The consequences are so important that reliable information, obtained through financial reports, and audited by auditors, is an absolute necessity.

Audits cannot be effective unless they are performed ethically. The essence of information risk is the possibility the reporting will be done unethically (for example, to conceal fraud or provide a deceptive and misleading impression of the financial performance and condition of a company). The essential role and responsibility of an auditor is to establish and communicate assurance to users that financial statements are fairly presented, implying that unethical reporting has not occurred.

The audit environment in Canada (and worldwide) has undergone profound changes as a result of corporate failures such as Enron and WorldCom, starting in 2001. After Enron's bankruptcy, questions were raised about the effectiveness of its auditors, Arthur Andersen, since there was no official indication of serious problems at Enron until mid-October 2001, when it had to restate previously reported earnings. One may expect that the audit profession would have learned and improved over time. Unfortunately, history repeated itself again. In July 2020, the FINANCIAL REPORTING COUNCIL in the UK released its latest audit inspection results at the seven largest UK accounting firms. The FRC's Audit Quality Review (AQR) reviewed 88 audits conducted by KPMG, Deloitte, PwC, EY, Grant Thornton, BDO and Mazars and concluded only two thirds of the audits were of a good standard or required limited improvement (FINANCIAL REPORTING COUNCIL, 2020).

1.1. Problem Statement

Technology lies at the core of the changes that the audit profession is currently facing. Artificial intelligence (or what is called in the computer science field – intelligent agent) is one of the technologies that will impact the audit profession. As artificial intelligence (AI) will gradually be integrated in the audit profession, this will impact how an audit is performed, the knowledge required to practice the audit profession and the learning requirement. A reasonable assumption is that, as auditors leverage increasingly intelligent agents to conduct their financial audit work, it should increase the quality of an audit.

The question of whether human-based activity can be executed by an intelligent agent has primarily been addressed using the distinction between routine and non-routine tasks. The effects of automation or computerization of jobs have been studied intensively in economics since the publication of the seminal paper by AUTOR, LEVY & MUNDANE in 2003 (ALM). Since the ALM study, a large and growing strain of literature on task automation has been published. Many of these studies, however, tend to simplify the feasibility of the automation of a task. There are many reasons for this, but two important ones are worth mentioning. First, the methodology used by the authors of these highly cited studies take a high-level view. Second, there is a lack of a common understanding of the term artificial intelligence (AI). An improved task model to assess the potential contribution of intelligent agents in the audit profession is a research gap.

The most fundamental question when conducting research work in the field of artificial intelligence is defining the word intelligence. Intelligence is a concept that we use in our daily lives that seems to have a concrete meaning. We say that our child who received 99% on his calculus test is very intelligent. Although this intuitive notion of intelligence presents us with no difficulties, scientists have not been able to come up with a generally accepted definition of intelligence. “For hundreds of years we have tried to understand and define intelligence and still, we have no agreement on what intelligence is” (TEGMARK, 2017, p. 49). Since there is no generally accepted definition of intelligence, there are many competing ones, including the capacity of logic, understanding, planning, emotional, knowledge, self-awareness, creativity and problem solving. In the context of AI research, LEGG & HUTTER (2007, p. 12) summarized no fewer than 70 definitions on intelligence from the literature into a single statement: “Intelligence measures an agent’s ability to achieve goals in a wide range of environments.” The lack of a satisfying definition of intelligence is a testament to the immaturity of the research field in AI. If the only success of AI so far has been in developing narrow, task-specific intelligent agents, it is perhaps because only within a very narrow and grounded context have scientists been able to define the goal to be sufficiently precise, and to measure progress in an actionable way. Leveraging on prior work and research, the concept of intelligence will be further in analyzed in the context of the audit task execution.

To practise auditing in Quebec, professional auditors must comply with practice standards, which cover the know-what, know-how, know-why, and know-that type of knowledge. Practice standards are general guides for the quality of professional work. Practice standards can be grouped in two broad families: the fitness to practise (know-how) and the technical standards (know-what, know-why, know-that). These standards are part of what we call Canadian Auditing Standards (CAS). Practice standards require that auditors have relevant and sufficient evidence to reach a conclusion on the financial statements prepared by a firm's management. Relevant and sufficient evidence imply that auditors must understand and document appropriately the outcome or recommendations of an intelligent agent. Explainability (known as explainable AI) can refrain or slow down the adoption of intelligent agents to perform audit tasks.

After reviewing the literature, a research gap was identified in the four key topics of this dissertation: the audit profession in Quebec, artificial intelligence, knowledge and learning. In today's digital world, it is obvious that the effectiveness of an audit critically depends on the ability to process the enormous amount of information that is constantly arriving digitally. Auditors need to be well informed about their clients not just at the time to start an audit, but on a continuous basis. The rate of arrival of new information far outstrip the capacity of audit firms and their staff to process such information. With such a diversity and speed of incoming new information, the audit profession in Quebec has to research how it can leverage intelligent agents. To the best of my knowledge, at present, there is a lack of comprehensive conceptual frameworks to assess the feasibility to leverage intelligent agents to accomplish a specific audit task. The results of this study are expected to give new insights to the audit profession in Quebec.

1.2. Significance of the Study

The purpose of this research is to assess the contribution of intelligent agents to execute a specific audit task: the identification of fraud risk factors. The focus of most audit academic technology-related research has been on point solutions and fairly rudimentary use of technology such as email and Microsoft Office, and on specific aspects of the audit function, such as checklist by account and scheduling (JANVRIN et al., 2008). The primary purpose of most commercial software has been to assist in audit management, and not in automating specific audit tasks. Today, financial audits are still largely a manual endeavor. With the advances in business process automation and big data, there is an opportunity to leverage on intelligent agents to accomplish specific audit tasks.

The significance of this study is the contribution to the existing literature on task automation or task computerization. Considering the absence of a comprehensive conceptual framework to assess the feasibility to rely on intelligent agents to perform an audit task, this research offers a Task Formula Framework. The Framework was inspired by my audit practical expertise, my professional work in cognitive computing with IBM and my research work during my PhD studies.

In 1971, the American Accounting Association Committee on Basic Auditing Concepts prepared a comprehensive definition on auditing as follows: "Auditing is a systematic process of objectively obtaining and evaluating evidence regarding assertions about economic actions and events to ascertain the degree of correspondence between the assertions and established or suitable criteria and communicating the results to interested users" (AMERICAN ACCOUNTING ASSOCIATION, COMMITTEE ON BASIC AUDITING CONCEPTS, 1973). The definition contains important concepts that this study will apply specifically to financial audit (I refer to financial audit because there are other types of audit). An audit is a systematic process. Auditors execute action that is purposeful, logical, and based on the discipline of a structured approach to decision-making. The audit process involves obtaining evidence, which this study will label as data. Based on computer science terminology, auditors will have access to either structured data (numbers) or unstructured data (mainly text and images). Another important concept in this definition is to ascertain which require the auditor to use their judgment. Finally, due to the volume of transactions in a company, auditors cannot audit every single transaction. Statistical sampling is used, which involved extrapolation and prediction to make inference. Based on the aforementioned definition, I submit the following Audit Task Formula for this dissertation:

$$\text{Auditor's job} = f\ (\text{tasks})$$

$$\text{Task} = f\ (\text{data} + \text{prediction} + \text{judgment} + \text{action})$$

In addition to the Audit Task Formula, I developed the Audit Task Complexity Framework which will contribute to assess the feasibility and the complexity to leverage intelligent agents to accomplish a specific audit task. The ability for an auditor to leverage intelligent agents to perform a specific audit task is complexified by the fact that the auditor has to understand and document properly the outcome of an intelligent agent's work to comply with the Canadian Auditing Standards. Explainability of the outcome of an intelligent agent can refrain the audit profession to leverage intelligent agents. While the field of explainable machine learning expanded in recent years, much of this work does not take real-world needs into account. A majority of proposed methods use benchmark machine learning problems with generic explainability goals without clear use-case or intended to the end-users or the recipient's community of the explanation. Leveraging on prior work, I developed two important conceptual frameworks in the field of explainable AI for the audit profession in Quebec: The Framework to Reach Artificial Intelligence Explainability (XAI) and the Artificial Intelligence Explainability Recipients' Framework.

To assess the potential contribution of artificial intelligence in the audit profession in Quebec, we must consider the current state of artificial intelligence. This research will focus on machine learning. Technically, machine learning is a subfield of artificial intelligence. At its core and for the purpose of this dissertation, machine learning is about prediction. Prediction is the process of filling missing information. Prediction takes information you have, often called data, and uses it to generate information you don't have. Better data, models, and computers are at the core of progress in prediction.

This research is exploratory and descriptive in nature as it examines the potential impacts of artificial intelligence to practice the audit profession in Quebec. Findings of this study along with previous literature available in the area explored in this research is expected to give insights to the audit profession regulatory body in Quebec, computer scientists, audit professionals and universities.

1.3. Objectives of the Study

1. To conceptualize and test four conceptual frameworks to assess the contribution of intelligent agents on the identification of fraud risk factors.
2. To assess the impacts of intelligent agents on the audit profession.
3. To figure out the complexity surrounding explainable artificial intelligence.

1.4. Research Questions and Hypotheses

The emergence of intelligent agents poses a new set of opportunities for the audit profession in Quebec, as well as new challenges. The tasks that can be done by intelligent agents are much broader in scope than previous generations of technology have made possible. The expended scope will change the value employers place on tasks, and the types of skills most in demand. As a result of that, the research questions and the hypotheses hereafter are based on my literature review of previous AI research. Three questions will be addressed:

1. What is the main ethical consideration CPA Quebec should analyze and understand as artificial intelligence will penetrate the audit profession in Quebec?
2. What are, or could be, the impacts of artificial intelligence on both the content of the curriculum to access the chartered professional accountant profession in Quebec and the reskilling requirements?
3. What could be the role of the CPA Quebec ecosystem (government, professional order, universities and firms) in learning in the age of artificial intelligence?

Based upon the stated research questions and objectives, the hypotheses are:

1. Intelligent agents are not a substitute for the audit profession in Quebec and cannot result in a massive employment loss.
2. Intelligent agents cannot assume creative cognitive tasks.
3. The regional audit ecosystem is playing a key role in collective learning and developing ethical and moral regulations for the future of the audit profession in Quebec.

2. MATERIALS AND METHODS

This chapter gives a summary of the material and methods used to conduct this research. The chapter begins with the empirical evidence: the audit profession in Quebec. Next, an important discussion on the automation debate and how previous research led me to develop the Task Complexity Framework. Then, I perform a critical analysis of definitions of artificial intelligence and propose a practical definition of artificial intelligence. Such discussion is critical to assess the type of intelligent agents that can contribute to the audit profession in Quebec.

2.1. Overview of the Auditing Profession in Quebec

Since auditing is a critical function in the economy, it is extensively regulated to ensure it remains effective. In Canada, the regulation of professional auditors is currently a provincial responsibility, varying somewhat depending on the legislation in different provinces. There are fourteen provincial CPA Orders in Canada. All provincial Orders fall under the umbrella of a national organization called Chartered Professional Accountant (CPA) Canada. CPA Canada is authorized by legislation to set all auditing standards for Canada, and it also sets the education and examination requirements for students interested in obtaining the CPA designation. The provincial Orders deliver the CPA Canada educational content and define the specific content requirement that universities are expected to teach to the students enrolled in the CPA designation process. The provincial Orders also set the code of ethical conduct that members must follow. They are responsible for the admission of members, as well as inspection of auditors' practices and disciplinary actions to enforce the professional ethics code.

2.2. Quebec CPA Order

The Quebec CPA Order has 40,000 members and 5,000 future CPAs. The CPA Order is a professional order as defined by the Professional Code, that is, a body whose primary mission is to protect the public. It is also an order whose members practice an exclusive profession, such that only individuals who hold the CPA auditor designation may practice public accountancy (perform audit or review engagements, and issue special reports).

The CPA Order must carry out specific functions related to issuing practice permits to candidates for the profession, keeping the roll of the Order current, supervising the practice of the audit profession and detecting illegal practice. It must also comply with a set of operating rules imposed by the Professional Code. To practice auditing in Quebec, professional auditors must comply with practice standards, which cover the know-what, know-how, know-why, and know-that type of knowledge. Practice standards are general guides for the quality of professional work. Practice standards can be grouped into two broad families: the fitness to practice (know-how) and the technical standards (know-what, know-why, know-that). These standards are part of what we call Canadian Auditing Standards (CAS).

2.3. Auditing Process in Quebec: An Overview

The preliminary stage of determining if an audit engagement can be accepted by an audit firm involves several important tasks. Based on the Canadian Auditing Standards (CAS), I decomposed the auditor's job into 32 high level tasks. This study will focus on assessing the contribution of intelligent agents in performing one specific audit task: the identification of fraud risk factors. To perform this assessment, I decomposed the identification of fraud risk factors task into 160 sub-tasks.

2.4. Brief Overview of the Mainstream Automation Debate

Since the publication of the seminal paper by AUTOR, LEVY & MUNDANE LM in 2003, a large and growing strain of literature on task automation has been published. Many of these studies, however, tend to simplify the feasibility of the automation of a task. There are many reasons for this, but two important ones are worth mentioning. First, the methodology used by the authors of these highly cited studies take a high-level view. Second, there is a lack of a common understanding of the term artificial intelligence. Table 1 summarizes the findings of these key reports.

Table 1. Summary of Key Reports on Job Automation

Frey et Osbourne (Oxford University)	OECD	PwC
▪ "The Future of employment" ▪ 2013 ▪ "Occupation-based study" ▪ 47% of jobs in the United States can be automated	▪ "The risk of automation for jobs in OECD countries" ▪ 2016 ▪ "Task-based study" ▪ 9% of jobs can be automated	▪ "Will robots really steal our jobs?" ▪ 2017 ▪ "Task-based study" ▪ 38% of jobs in the United States have a high risk of being automated
McKinsey Global Institute	**Bain and Company**	
▪ "What the future of work will mean for jobs, skills, and wages" ▪ 2017 ▪ "Task-based approach" ▪ 50% of tasks at the international level can be automated	▪ "Labor 2030: The collision of demographics, automation and inequality" ▪ 2018 ▪ Macro approach ▪ By 2030, employers will require 20% to 25% less employees	**How to interpret these studies?**

Source: Author's compilation

2.4.1. Task Complexity Framework

A research gap was identified in the task automation debate. Consequently, I developed a new conceptual framework: The Task Complexity Framework. The framework can contribute to assessing the potential contribution of intelligent agents for a specific audit task. The framework contributes to performing a more precise assessment than the methodologies used by the authors of the studies summarized in Table 1. There is little consensus among researchers concerning the properties that make a task complex. My position is that complexity is rooted in the task and not the task-doer. To develop the Task Complexity Framework, I will start with the Task Formula. A task has four components:

$$\text{Task} = f\ (\text{data} + \text{prediction} + \text{judgment} + \text{action})$$

Data have a direct impact on the complexity of a task. STEINMANN (1976) equates complexity with the amount of information (data) involved in a task, the internal consistency of this information, and the variability and diversity of the information itself. SCHRODER et al. (1967) identified three primary properties of a complex task: the number of dimensions of information (data) requiring attention (information load); the number of alternatives associated with each dimension (information diversity); the rate of information change (the degree of uncertainty involved). Researchers on multiple-cue probability learning argued that complexity is built upon six sources: the number of information (data) sources; cue inter-correlations; reliabilities; validities; function forms (linear, etc.) and the principle underlying the integration of the information (STEINMANN, 1976).

The more judgment that is involved in executing a task, the more complex the task. Judgment is significantly involved when accessibility to data is a challenge. Judgment plays a key role when a task has multiple performance dimensions, including non-quantitative ones (LATHMAN & YUKL, 1975) and when a task has several interrelated and conflicting elements to satisfy (CAMPBELL, 1984).

Task execution (action) impacts complexity. Complex tasks are characterized by "unknown or uncertain alternatives to reach an outcome" (MARCH & SIMON, 1958, p. 139-141) and by inexact or unknown means-end connections. Complex tasks are characterized by "the existence of a number of sub-tasks, which may or may not be easily factored into nearly independent parts" (MARCH & SIMON, 1958, p. 151-152). Complex tasks have path-goal multiplicity – i.e., the existence of several ways for accomplishing the task (TERBORG & MILLER, 1978).

Based on the aforementioned analysis, I developed the following Task Complexity Framework to assess the capability of an intelligent agent to accomplish an auditor's task:

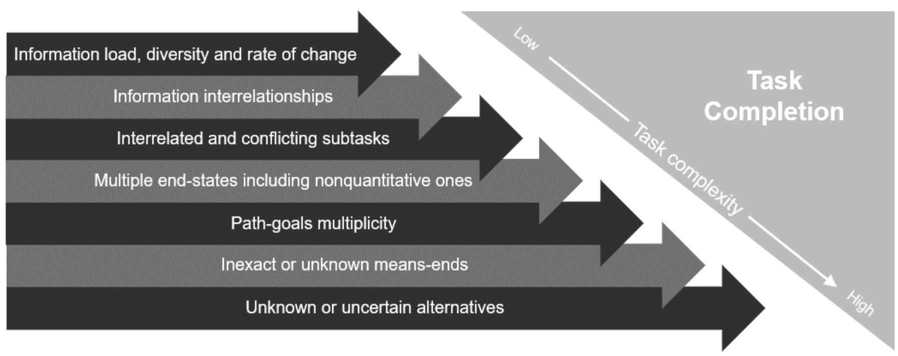

Figure 1. Task Complexity Framework

Source: Author's framework

2.4.2. Artificial Intelligence

The emergence of intelligent agents poses a new set of opportunities – and challenges – for the audit profession. The tasks that can be done by intelligent agents are much broader in scope than previous generations of technology have made possible. The expanded scope will change the value employers place on tasks, and the types of skills most in demand.

The first challenge in artificial intelligence is that there is no common definition of the term intelligence. "For hundreds of years we have tried to understand and define intelligence and still, we have no agreement on what intelligence is" (TEGMARK, 2017, p. 49). Since there is no generally accepted definition of intelligence, there are many competing ones, including the capacity of logic, understanding, planning, emotional, knowledge, self-awareness, creativity and problem solving.

In the context of AI research, LEGG & HUTTER (2007, p. 12) summarized no fewer than 70 definitions on intelligence from the literature into a single statement: "Intelligence measures an agent's ability to achieve goals in a wide range of environments." This is closely related to Professor TEGMARK's definition of intelligence: "the ability to accomplish complex goals, including learning" (TEGMARK, 2017, p. 49). The reason TEGMARK opted for a broader definition is to "capture all other conflicting definitions of intelligence since they are all complex goals" (TEGMARK, 2017, p. 49). This points to two characterizations, which are nearly universally – but often separately – found in definitions of intelligence: one with an emphasis on task-specific skills (achieving goals), and one focused on generality and adaptation (in a wide range of environments).

The lack of a satisfying definition of intelligence is a testament to the immaturity of the research field in AI. If the only successes of AI so far have been in developing narrow, task-specific systems, it is perhaps because only within a very narrow and grounded context have scientists been able to define the goal sufficiently precisely, and to measure progress in an actionable way.

2.4.3. Toward a Practical Definition of AI

The resurgence of machine learning in the 1980s has led to an interest in formally defining, measuring, and maximizing generalization. Generalization is a concept that predates machine learning, originally developed to characterize how well a statistical model performs on inputs that were not part of its training data. In recent years, the success of Deep Learning (LECUN et al., 2015), as well as increasingly frequent run-ins with its limitations (MARCUS, 2019), have triggered renewed interest in generalization theory in the context of machine learning (see for example NEYSHABUR et al., 2017). The notion of generalization can be formally defined in various contexts but statistical learning theory (VAPNIK, 1999) provides a widely-used formal definition that is relevant for machine learning. We can informally define generalization or generalization power for any AI system to broadly mean the ability to handle tasks that differ from previously encountered situations. The notion of "previously encountered situations" can be broken down as follows:

- System-centric generalization: this is the ability of a learning system to handle situations it has not itself encountered before; and
- Developer-aware generalization: this is the ability of a system, either learning or static, to handle situations that neither the system nor the developer of the system have encountered.

It is also useful to qualitatively define the degree of generalization for information processing systems (CHOLLET, 2019):

- Local generalization, or robustness: This is the ability of a system to handle new points from a known distribution for a single task or a well-scoped set of known tasks, given a sufficiently dense sampling of examples from the distribution (e.g., tolerance to anticipated perturbations within a fixed context). One could characterize it as an adaptation to known unknowns within a single task or well-defined set of tasks. This is the form of generalization that machine learning has been concerned with from the 1950s up to this day.
- Broad generalization, or flexibility: This is the ability of a system to handle a broad category of tasks and environments without further human intervention. This includes the ability to handle situations that could not have been foreseen by the creators of the system. This could be considered to reflect human-level ability in a single broad activity domain (e.g., driving in the real world), and could be characterized as an adaptation to unknown unknowns across a broad category of related tasks. Arguably, even the most advanced AI systems today do not belong in this category, although there is increasing research interest in achieving this level.
- Extreme generalization: This describes open-ended systems with the ability to handle entirely new tasks that only share abstract commonalities with previously encountered situations, applicable to any task and domain within a wide scope. This could be characterized as adaptation to unknown unknowns across an unknown range of tasks and domains. Biological forms of intelligence (humans and possibly other intelligent species) are the only example of such a system at this time.

The intelligent agents that will be analyzed in the next section belongs to the local generalization category. Leveraging on the theoretical concepts analyzed in this section and the Task Formula, intelligence can be defined as a measure of skill-acquisition efficiency over a specific task, with respect to prior knowledge, experience, and local generalization ability. As a result, I submit that artificial intelligence is a non-biological intelligence.

Many possible definitions of intelligence may be valid, across many different contexts, and this study does not pretend that the definition above represents the single version of truth. Nor is that definition meant to achieve broad consensus. Rather, the purpose of this definition is to be actionable for the purpose of detecting fraud risk factors and to serve as a useful perspective to assess the ability of an intelligent agent to contribute to identify fraud risk factors. This definition captures an important concept: if you consider two systems that start from a similar set of prior knowledge, and that go through a similar amount of experience (e.g., practice time) with respect to a set of tasks not known in advance, the system with higher intelligence is the one that ends up with greater skills (i.e., the one that has turned its prior knowledge and experience into skill more efficiently). This definition of intelligence encompasses meta-learning prior knowledge, memory, and fluid intelligence (CHOLLET, 2019).

2.5. Research Methodology: CPA Quebec Case Study

Qualitative research focuses on understanding how people interpret their experiences, how they construct their world, and the meaning they attribute to their experiences. There are many definitions of qualitative research. A Google search reveals more than 132,000,000 definitions. MAANEN offers one of the most comprehensive definitions of qualitative research: "An umbrella term covering an array of interpretive techniques which seek to describe, decode, translate, and otherwise come to terms with the meaning, not the frequency, of certain more or less naturally occurring phenomena in the social world" (MAANEN, 1979, p. 520).

While researching how intelligent agents can contribute to detect fraud risk factors in artificial intelligence and audit journals, I could not find a case study that encompasses the hypothesis and the three research questions in this dissertation for the audit profession in Quebec. Because of the subjective nature of the research questions, I decided to rely on qualitative research, which focuses on understanding the contribution of intelligent agents in the identification of fraud risk factors and the consequences on the learning requirement for the audit profession in Quebec. Because of the exploratory goal, I decided to focus on a case study.

Case study is a significant qualitative strategy, along with critical narrative analysis, phenomenology, ethnography, and grounded theory (MERIAM, 2009). However, case study differs from other research strategies in that it conducts an in-depth analysis of a bounded system. The case in this context is a unit, with defined boundaries, and the bounded system in my research is a business entity. In *Case study research: Design and methods,* YIN (2009) compares case study methods with other forms of research: experimental, survey, archival, analytic, and historical. The author explains that case study research focuses on answering questions that ask how or why, and where the researcher has little control of events that are happening at present, and when the focus is on contemporary occurrence within some real-life environment. This study meets YIN's criteria. First, based on the Task Formula presented in this dissertation, I want to explore how intelligent agents can improve fraud detection. Second, I want to understand why auditors should leverage intelligent agents to perform their audit work. Third, I do not have control on whether or not an audit firm will decide to leverage intelligent agents to execute audit tasks. Finally, intelligent agents start to impact some tasks of other professions such as doctors and lawyers.

2.6. Unit of Analysis: Algorithms Selection

Based on the research questions, I selected the units of analysis, which is the type of algorithms. When choosing the algorithms, it was important to scope them properly since artificial intelligence is a broad field of research. The current research in artificial intelligence goes well beyond what this study will cover. There is so much active research in all areas of artificial intelligence. There have been and continue to be impressive advances in planning, learning, perception, predictive, natural language understanding, robotics, and other subareas of artificial intelligence. The decomposition of artificial intelligence in subarea is not surprising. The design space is too big to explore all at once. Once a researcher has decided to handle, say, predictive analytics or relational domain and reasoning about the existence of objects, it is difficult to specialize in other areas.

The problem domain will affect the kind of algorithm needed. Based on the Task Formula, the problem domain in this dissertation is the ability to predict. The focus in this dissertation is on predictive learning agents.

3. RESULTS AND DISCUSSION

3.1. Empirical Analysis

This section addresses the first two hypotheses presented in the Introduction:

1. Intelligent agents are not a substitute for the audit profession in Quebec and cannot result in a massive employment loss.
2. Intelligent agents cannot assume creative cognitive tasks.

Two tribes of algorithms will be put to work: symbolists (rule-based learners) and connectionists (machine learning algorithms). I was given access to nine algorithms developed by MindBridge Ai. For intellectual property reasons, some information cannot be disclosed about these algorithms.

3.1.1. Connectionists: Machine Learning Algorithms

The three machine learning algorithms analyzed are all based on supervised learning. In supervised learning, the agent observes some example input-output pairs and learns a function that maps from input to output. More specifically, in supervised learning, there is a set of examples, and a set of features, partitioned into input features and target features. The aim is to predict the values of the target features from input features.

The first learning algorithm analyzed is a Rare Flow Control Point. A rare flow is an assessment of how common a flow between different accounts are. Rare flow does not analyze the amount of money between accounts in the general ledger. It examines the frequency of occurrence of the flow relative to all the other flows in a set of data from the general ledger. The rarity of the flow is calculated as follows: each flow or the direction money is moving, is analyzed, grouped and scored based on their rarity in comparison to all other flows. If the money flowing from one account to another account is unusual within a ledger, then flows between these accounts are given a higher score. In contrast, if money flowing from an account to another account is common within a ledger, then the flows between these accounts are given a low score. This analysis is performed in a company general ledger (online data) – all transactions for a specific fiscal year end. Offline data for this algorithm comes from the designer of the algorithm – called account ontology. What is the value of the Rare Flow Control Point during an audit? By analyzing transactions for rare flows, auditors can quickly analyze the uncommon flows which could be caused by fraudulent behaviour or could violate internal controls. Rare flows can indicate unique insights which could require additional investigation or inclusion into the audit.

The second learning algorithm analyzed is looking for outlier anomaly – the Outlier Anomaly Control Point. It uses a combination of nearest-neighbour and stochastic outlier selection (SOS) to create "neighborhoods" (clusters) for flows within a general ledger and then identifies outliers that aren't grouped within a neighborhood. If a flow cannot be classified in a neighborhood, it is flagged as anomalous and triggers the outlier anomaly control point. The following inputs are used to determine neighborhoods and outliers:

- Dollar amount of the monetary flow;
- Source and destination accounts of the monetary flow;
- Number of flows that occur alongside this flow in this flow's transaction; and
- The proximity of this flow's transaction to the end of the month (time).

In general terms, the nearest-neighbour and SOS techniques find the anomalous points in data sets by asking what points are the closest neighbours to this point? Then they ask, would this point's neighbours consider it to be a neighbour as well? If the answer to the second question is no, then the point is anomalous. SOS also considered many details of the transaction which can be easily overlooked by a human auditor. The algorithm can find something superficially "like" other transactions but which differ in some detail that sets that transaction apart and makes it unusual. What is the value of the Outlier Anomaly Control Point in an audit? The outlier anomaly provides a powerful lens for identifying flows that contain a combination of uncommon monetary value, flows, frequencies and timing within a month. This control can help pinpoint flows that fall outside of the normal course of a company's operations or accounting controls. The Outlier Anomaly Control Point in combination with:

- Cash expenditures can indicate an uncommon flow, amount or frequency in which a cash account is being credited. This is important because the way in which the cash is being distributed is uncommon within the general ledger; and
- Manual entry indicates an outlier flow that was also entered manually and was not included in a batch transaction. The origin of the transaction was from an employee and the result was an

outlier. If user information is also present in the general ledger data, the transaction information can be compared to other employees to indicate anomalous behaviour.

The third learning algorithm analyzed is looking for unusual amounts. The Unusual Amounts Control Point looks at all entries associated to an account code and determines which amounts are anomalous based on their proximity to neighbouring amounts. The analysis begins at the lowest level of the account structure and is then examined at other levels of the account structure. The assessment of unusual amounts is scoped to the accounts involved in the journal entries. Because of this, the Unusual Amounts Control Point will find amounts that do not normally occur in specific account interactions. This is important because different business processes can cause vastly different amounts in each account so the account focus is essential. Each entry receives a continuous 0-100% anomaly score at each account level, then the maximum score is used in the overall calculation of risk. What is the value during an audit? The value of the Unusual Amounts Control Point is in determining how uncommon entries are within a ledger and increasing the risk associated with the transactions to increase the likelihood of being sampled. Although an anomalous amount is not suspicious on its own, examining the combination of the unusual amounts control point with the Rare Flow Control Points identify entries that are both anomalous and part of a monetary flow that is uncommon. This ensemble insight is valuable because it identifies both the amount and the flow as being uncommon.

3.1.2. Symbolists: Rule-Based Learners

Six rule-based algorithms have also been analyzed. For these types of algorithms, the developer manually encoded the knowledge required to accomplish a task.

The first algorithm analyzed, the Unbalanced Debits and Credits Control Point, is a transaction level analysis which sums the debits and credits associated with the transaction and identifies differences between the sums. The control point quickly identifies which transactions are unbalanced for further review. Reviewing any unbalanced transactions are an important step in the data validation process as well. Let's have an example. A company uses an ERP system that has limited controls and allows users to enter unbalanced transactions. The unbalanced transactions have caused an issue during previous audits in which determining both sides of a general ledger entry has been difficult. Using the Unbalanced Debits and Credits Control Points can help identify the erroneous transactions and, in the event that the general ledger file balances, can be used to help match the unbalanced transactions to create complete transactions. What is the value during the audit? The Unbalanced Debits and Credits Control Point is critical to understanding if a general ledger is unbalanced and which transactions may be unbalanced. Unbalanced transactions can either be generated by mistake as part of the entry into the ERP system, or could be entered deliberately to hide a portion of a transaction. It is also possible that unbalanced transactions could be caused through the creation of transaction IDs during the MindBridge import process. In either case, unbalanced transactions should be examined and the cause determined. Examining the combination of the Unbalanced Debits and Credits Control Points with end of a period or year-end accounting entries could indicate a deliberate effort to conceal a portion of a transaction which could have a material impact on financial statements.

The second algorithm analyzed is the Zero-Entry Control Point. This algorithm triggers on entries with $0 listed in its debit and credit and can be particularly helpful in identifying the source of unbalanced transactions and determining the quality of the ERP export being used for analysis in the AI Auditor. Zero entries can indicate an accidental or deliberate exclusion from a transaction, but could also be caused during the export or conversion of financial data. If zero entries are included as part of the general ledger data, the entries should be reviewed with the audit company to determine if the cause was within the ERP system. Some ERPs allow rules which can cause additional empty entries; for example, tax as part of a sales journal where no tax was applicable. What is the value during the audit? Zero entry can provide feedback on the quality of the data being analyzed and quickly identifies entries that may have been entered incompletely or by accident. Additional value is present when the Zero-Entry Control Point is triggered with the Unbalanced Debits and Credits Control Points as the zero entry could be the cause of the unbalanced transaction.

The third algorithm analyzed is the Weekend Post Control Point. This algorithm triggers based on the posted date associated with entries occurring during a weekend. The control point is of particular value for organizations that have stricter controls over when transactions can be entered into the general ledger. What is the value during an audit? The weekend posting can identify transactions which are being entered at potentially abnormal times. Although an abnormal posting time does not mean the transaction is suspicious by itself, for organizations with stronger controls or regular business hours, the Weekend Post Control Point can be an important insight when identifying higher risk transactions. Examining the combination of the Weekend Post Control Point with cash expenditures flag transactions where cash or cash equivalents have been credited during a weekend. The timing of these transactions should be considered within the context of the company's normal operations to determine their inclusion in the audit plan.

The fourth algorithm analyzed is statistical by nature: the Benford's Law. Benford's Law was discovered by Frank Benford during the 1930s when examining a book of logarithmic tables. Benford noticed the wear on each page within the book wasn't evenly distributed and that pages beginning with the digit 1 were more worn than pages beginning with digits 2-9. After analyzing the distribution of numbers across a great number of subjects including atomic weights, baseball statistics and the areas of river, he published the article on Benford's Law. Benford's Law has a distribution that includes the following distribution of leading digits: 1 = 30.1%, 2 = 17.6%, 3 = 12.5%, 4= 9.7%, 5 = 7.9%, 6 = 6.7%, 7 = 5.8%, 8 = 5.1%, 9 = 4.6%. The frequency of each first and two digit combination is then counted and mapped against the Benford distribution. How is Benford's Law applied for an audit? Given the complexity of general ledger data, all entries are analyzed within a two-digit distribution of Benford's Law. The observed counts of the first two digits in the general ledger are computed against the expected counts of the first two digits using the Benford probability. If the difference between the observed and expected counts is found to be significant, the Benford's control point is triggered. Although the full analysis of the general ledger will provide a greater likelihood of returning false positives, the application of Benford's Law, in conjunction with the ensemble of other control points, still provides a meaningful analysis and risk profile. What is the value of Benford's Law during an audit? Benford's Law can provide insight into anomalous patterns of entry and transaction data, which can represent falsification of accounting data.

The fifth algorithm analyzed is the cash to bad debt conversion. The Cash to Bad Debt Conversion Control Point flags matching dollar amounts from credited cash and cash-equivalent accounts to debits in the bad expense account. This control point does not look at transactions or flows: it looks at the dollar value of specific entries. If a bookkeeper or an accountant is committing fraud, they may disguise the movement of a monetary asset through multiple transactions as a single transaction from a cash equivalent to a bad debt. The Cash to Bad Debt Conversion Control Point triggers when multiple transactions or a single transaction is used, provided the dollar values are matching. Will this return false positives? In general, a direct conversion from cash to bad debt is a problem requiring review. As this control point is performing number matches, false positives are possible. Potential relationships between triggered entries may not be immediately obvious, which is another important reason to consider the examination of these entries. What is the value of the Cash to Bad Debt Conversion Control Point in an audit? The value is that auditors can quickly identify entries that could be involved in a fraudulent chain of transactions. Although false positives will be present, examining the triggered entries should be considered as part of an audit.

The last algorithm analyzed is the Complex Instrument Control Point. This algorithm flags transactions that appear to be complex in nature by examining the memo field for specific keywords. The default configuration of the Complex Structure Control Point is configured to look for transactions that are complex in nature including forward contracts and options. The default keywords include: fair value, guarantee, embedded derivative, net settlement, fix for fix, forward contracts, swap, option, taps, callers, hedge, hedging, commodities, host contracts, forward options, re-commission, extinguishment, modifications and transaction cost. What is the value during an audit? The combination of the complex instrument with two other algorithms can provide higher value insights:

- The combination of the complex instrument and Rare Flow Control Points indicate an uncommon monetary flow within the transaction that could be unique or significant based on the complex instrument keywords entered; and
- The combination of the complex instrument and high monetary value will quickly identify transactions that are within the top two percentile of the general ledger but also include specified keywords requiring further analysis. The combination ensures the transactions being viewed are material.

3.1.3. Analysis

The nine intelligent agents analyzed can contribute to 10 out of the 160 sub-tasks related to the identification of fraud risk factors.

For the specific tasks they are built for, the nine intelligent agents analyzed provide useful insight to the auditor. The quality of the task is considered as satisficing, meaning it is not optimal, but it provides direction to the auditors about what to pay attention to. They cannot make a comprehensive assessment (generalization) like an auditor can do. To do so, the auditor must address the other 150 sub-tasks. There are many reasons why a person decides to commit a fraud and case like Enron demonstrated that this type of crime is carefully planned and difficult to discover. Discovering a fraud involves going through many of the seven steps in the Task Complexity Framework.

As an example, no algorithm can evaluate the values and integrity of an executive in relation to his title and function in a company and assess if these values increase the risk of fraud. To do so, you need a broad range of information (steps 1 and 2 in the Task Complexity Framework), conduct interviews and understand the state of mind of the executive (step 4 in the Task Complexity Framework), then figuring out if, for example, the three components of the fraud triangle – opportunity, justification, pressure – (step 5 and 6 in the Task Complexity Framework) are present and can lead to an increase in the risk of fraud. Based on all the evidence collected, the auditor will have to assess the risk of fraud. The auditor's judgment can direct him to further investigate if some risks exist. Abstraction and generalization play an essential role in the auditor cognitive process. A lot of what we know is fairly abstract. The representations that underlie both cognitive models and common sense are all built on a foundation of a rich collection of such abstract relations combined in complex structure. Humans can abstract just about anything: time, features, theories, space and so forth and use them in a sentence, an explanation, a comparison, stripping hugely complex situations down to their essentials and giving the mind enormous leverage in reasoning broadly about the world.

Machine learning thus far has struggled with open-ended inference. Auditors, as they read texts and read numbers, frequently derive wide-ranging inferences that are both novel and only implicitly licensed. At present, there is no machine learning system that can draw open-ended inferences based on real-world knowledge with anything like human-level accuracy. Basically, they cannot ask the question who, what, why, when, where and how. What is missing in machine learning is common sense reasoning.

The analysis of the nine intelligent agents demonstrates that they are not a substitute for the audit profession in Quebec and they cannot result in a massive employment loss because of the complexity of the audit work. They also cannot assume creative cognitive tasks. Interestingly, intelligent agents don't have to work like humans. Based on the Task Formula:

$$\text{Task} = f\ (\text{data} + \text{prediction} + \text{judgment} + \text{action})$$

intelligent agents working with auditors can improve the quality of an audit. The nine algorithms analyzed are faster and better at finding inference (predict) in structured data – accounts in the general ledger – and auditors are better at contextualizing the outcome. All the time an auditor would have spent on doing the work of the nine algorithms analyzed previously can be reallocated to value-added work (the other 150 sub-tasks) and, therefore, increase the quality of the audit.

There is an important limit that auditors must understand to properly rely on intelligent agents: bias. The key challenge for auditors is to understand the nature of biases that can be built in connectionist machine learning algorithms. Connectionist learning agents rely heavily on data generated by humans (user-generated content) or collected via systems created by humans. Therefore, whatever biases exist in humans enter in the system and, even worse, they can be amplified depending on the complexity of the model and the sources of data. If the data or the decisions taken on it are biased and the machine uses them as an example, then the machine is going to incorporate this bias into the model. It learns the bias from the examples given to it. Generally speaking, data is biased if the sampling distribution (the data which we use for training the model) is different from the population distribution (referring to the true situation in the real world). Putting it another way, to avoid bias we have to make sure that the data sample that we use for training the model resembles as closely as possible the true distribution of the features and the decisions taken on them. I have identified seven important biases that auditors must be aware of: covariate shift bias, sample selection bias, imbalance bias, measurement bias, aggregation bias, evaluation bias, and deployment bias. Accounting for bias not only requires understanding of the different sources – i.e., data, knowledge-base and algorithms – but more importantly, it demands the interpretation and description of the meaning, potential side effects, provenance, and context of bias. This is one of the reasons that explainability is critical.

3.2. The Social and Moral Dimension of AI: Ethical Challenge

This section addresses the first question of this research: What is the main ethical consideration CPA Quebec should analyze and understand as artificial intelligence will penetrate the audit profession in Quebec?

To practice the audit profession in Quebec, auditors must comply with the Code of Professional Ethics. The ethical dilemma created by learning agents relates to professional competence and due care of the Code. Professional competence and due care require auditors to comply with the Canadian Auditing

Standards (CAS). CAS require auditors to obtain sufficient appropriate evidence as the basis for an audit opinion on financial statements. Appropriateness of evidence relates to its qualitative aspects: is it relevant and reliable? Sufficiency considers how much appropriate evidence is enough. The real test of sufficiency is whether the body of evidence you have gathered allows someone else to reach the same conclusions you reached. If an auditor has not been able to obtain sufficient appropriate audit evidence, the auditor cannot reach a conclusion.

The first three algorithms analyzed (Connectionists) create a challenge for an auditor with respect to appropriateness, relevance and sufficiency. Auditors face fundamental limits on their ability to trace the inductive reasoning of a complex intelligent system, specifically machine learning. The most significant limitation of the first three algorithms analyzed is the opaqueness or the lack of explainability, which inherently characterizes them as black box machine learning models. This means that these models' internal logic and inner workings are hidden to the auditors, which is a serious disadvantage as it prevents an auditor from being able to verify, interpret, and understand the reasoning of the system and how particular decisions are made. This is where explainable AI can play a significant role because as long as high-performing models remain opaque, it seems rational to withhold how trustworthy AI really is when conducting an audit, especially in high-risk areas like fraud detection.

3.2.1. Explainable Artificial Intelligence

To address this challenge, Explainable Artificial Intelligence (XAI) emerged the past few years as a field of study which focuses research on machine learning interpretability and aims to make a shift towards a more transparent AI. Since XAI is a relatively new research field, there is no consensus over what is meant by "explainable" and "interpretable" (LIPTON, 2016). At its core, explainability is about the translation of technical concepts and decision outputs into intelligible, comprehensible formats suitable for evaluation. Technically, there are no standards and generally accepted definitions of explainable AI and we may never have such a generally accepted definition because explainable AI, I submit, should focus on the recipient of the explanation. Only few papers focus on such an approach and none related to the audit profession in Quebec. Recipients of an explanation in the CPA ecosystem have different beliefs and goals depending on their roles in relation to the machine learning system. The two frameworks I developed will guide the analysis of what their relevant beliefs and goals might be for specifying suitable measures of explainability.

3.2.2. Proposed Framework to Reach Explainability

Based on cognitive science research, I developed the following framework to reach explainability for the audit profession in Quebec:

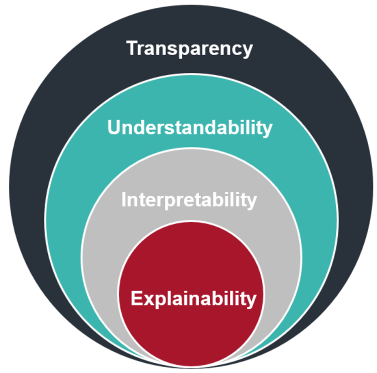

Figure 2. Framework to Reach Explainability

Source: Author's framework

- Transparency: the level to which a system provides information about its internal workings or structure, and the data it has been trained with (LIPTON, 2016). A model is considered to be transparent if, by itself, it is understandable. If a model is transparent, it can be understood. Transparency does not necessarily mean that the underlying information is easily comprehensible by everybody.
- Understandability: denotes the characteristic of a model to make a human understand its function (MONTAVON, SAMEK, & MÜLLER, 2018). If we can understand a model, it is possible to interpret the outcome.
- Interpretability: the level to which a recipient gains and can make use of the information embedded in a machine learning system.
- Explainability: I submit that if a model is transparent, understandable and interpretable, it can be explained. An explanation is a product (answering the why-question) and a process (a cognitive process and knowledge transfer process); this is why it is an active characteristic between an intelligent agent and a human. This is consistent with LIPTON's (2016) definition of explainability – the level to which a system can provide clarification for the cause of its outputs.

An explanation can be classified by the timing of its requirement: pre-model, in-model or post-model. Transparency, understandability and interpretability are three conditions required for pre-model and in-model. Explainability is related to a post-machine learning model.

Based on the explored literature and the professional responsibility of the auditor in Quebec, I have defined five different recipients of an explanation of a machine learning system output in the audit ecosystem in Quebec. The roles are not mutually exclusive: a single recipient could occupy any combination of roles and some combinations are more likely than others.

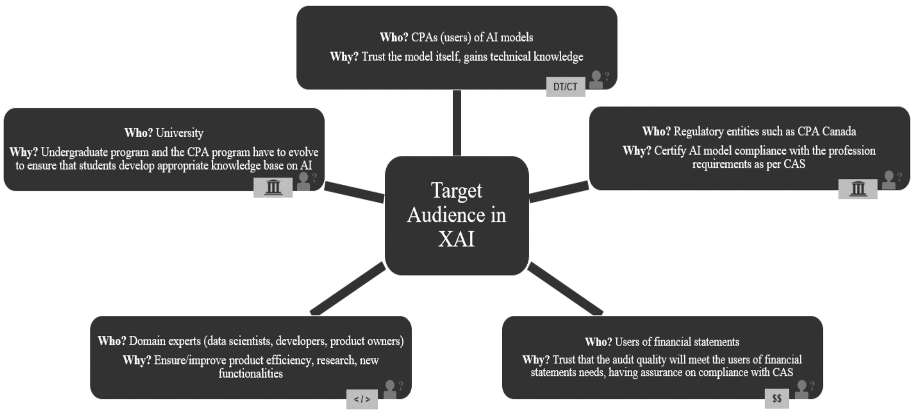

Figure 3. XAI Recipients’ Framework

Source: Author’s framework

The recipients of an explanation have different beliefs and goals depending on their roles in relation to the machine learning system. LEAKE (1995) demonstrated that goal-directed explanations in abductive reasoning explicitly aim at reducing knowledge gaps (information asymmetry), specifically, to explain why an observed event is reasonable. This is important because the more a recipient will learn from an intelligent agent, the less ambiguity will be in his mind and the more trustworthy an intelligent agent should become over time.

Domain experts are concerned with building intelligent systems. Members of this community are in the industry (business world); some could be academics or researchers creating systems. Their primary motive in XAI is the quality of the product, i.e., system devolvement, testing, robustness, evaluation. Universities (theorists) are concerned with understanding properly AI to teach it to students in the CPA program and advancing theories. Some will also be active CPA practitioners/users. It is a group that will advance the state-of-the-art technology by bridging CPAs’ needs/requirements and current

AI applications. Regulator is a broad category that includes CPA Canada, CPA Quebec, lawyers, scientists, and the government (since it regulates the CPA profession in Quebec). They have many motives for XAI: accountability, verifiability of the quality of an audit, compliance with CAS, unbiased behaviour and transparency. Users are the CPAs using the intelligent system. Members of that community need explanations to help them decide whether/how to act given the outputs of the system, and/or to help justify and document their audit work.

3.3. Professional Competence

This section addresses two research questions and one hypothesis.

- What are or could be the impacts of artificial intelligence on both the content of the curriculum to access the chartered professional accountant profession in Quebec and the reskilling requirements?
- What could be the role of the CPA Quebec ecosystem (government, professional order, universities and firms) in learning in the age of artificial intelligence?
- The regional audit ecosystem is playing a key role in collective learning and developing ethical and moral regulations for the future of the audit profession in Quebec.

3.3.1. CPA Quebec Competency Map

To practice the audit profession in Quebec, students must meet the requirements of The CPA Competency Map. The CPA program in Quebec is designed to meet the needs of public accounting, industry, and government by ensuring that all CPAs have a strong foundation of ethics, knowledge and skill to succeed and lead in any professional accounting role or position. The Competency Map describes the competencies for all the elements of the CPA program in Quebec. Based on the Task Formula, the CPA Competency Map in Quebec is missing two critical components: first, developing students' professional judgment and second, developing the skill requirements associated with artificial intelligence.

3.3.2. The Role of the Ecosystem and the Audit Profession of the Future

As artificial intelligence penetrates the audit profession in Quebec, an effective audit labour market profession will be critical. Different skills will be required to perform the audit profession in Quebec.

Based on the Task Formula, we can observe that as intelligent agents become better at predicting, developing the professional judgment of the students in the CPA program will be important. Better critical thinking should contribute to increase the quality of an audit and, more specifically, the ability to identify fraud risk factors.

In this evolution of the audit profession in Quebec, policies with the aim of promoting and regulating intelligent agents and setting the stage for the audit profession of tomorrow will become essential. Since in Canada the audit profession is regulated at the provincial level, the government of Quebec (the State) will play a critical role to craft the future of the profession by working in collaboration with the audit profession ecosystem. The government of Quebec can leverage four types of policies to craft the future of the profession: push policies, pull policies, grow policies, and strengthen policies.

3.4. Discussion of the Findings

The study examined the potential contribution of intelligent agents on the identification of fraud risk factors. Three research questions were formulated and three hypotheses were tested.

All hypotheses were proven. This study demonstrates that these learning agents have a limited but valuable contribution to identify fraud risk factors: the prediction variable. If an auditor leverages properly on the outcome of the work of these learning agents to identify fraud risk factors, it gives them more insight and more time to leverage on their judgment. This can only contribute to increase the quality of the audit. The intelligent agents analyzed in this dissertation cannot make a comprehensive assessment (generalization) like an auditor can do, they cannot contextualize and have no common-sense reasoning like an auditor has. As a result, intelligent agents are not a substitute of the audit profession in Quebec (as well as other countries) and cannot result in a massive employment loss. To rely on these learning agents and ensure that an audit will comply with the Canadian Auditing Standards, the auditor must understand the limits of these learning agents and the type of biases they might be subject to. As companies enter the digital world, the audit profession ecosystem in Quebec (and other countries as well) will play an important role to reshape the future of the profession.

With respect to the research questions, findings can be summarised as follows.

First Question: Professional competence and due care require auditors to comply with Canadian Auditing Standards, which require obtaining sufficient appropriate evidence as the basis for an audit opinion on the financial statements. The most significant ethical challenges created by machine learning for the audit profession in Quebec (and other countries as well) is explainability. Auditors face fundamental limits on their ability to trace inductive reasoning of complex intelligent agents and, as a result, rely blindly on their outcome which will not allow the auditors to comply with CAS. Explainable AI is important for the audit profession in Quebec (and other countries as well) since it will allow the auditors to comply with the Code of Professional Ethics. There is a large consensus on the need for machine learning to be interpretable/explainable.

Second Question: There are six technical competencies in the CPA curriculum in Quebec: financial reporting, strategy and governance, management accounting, audit and assurance, finance and taxation. The CPA enabling competencies provide the essential skills for ethical behaviour, leadership, teamwork, decision-making, problem-solving, and communication as a professional accountant. However, the CPA curriculum focuses on the technical competencies or specialization. In the undergraduate studies, there are no specific classes on the topic of creative thinking (professional judgment). Since the audit profession operates in a wicked environment the contribution of intelligent agents is limited – they cannot contextualize and generalize. Creative thinking allows humans to do it. Creative thinking can use abstraction, is portable from one situation to another, is flexible, is interleaving and more. Studies show that economists are better prepared in that regard and the audit profession may learn from them on how to improve the CPA curriculum in Quebec.

Third Question: To improve the quality of the audit work, the profession should leverage on artificial intelligence. The audit profession ecosystem can contribute to improve the quality of an audit at three levels: improving the ability of students in the CPA program to develop their creative thinking, developing the appropriate skill requirements associated with artificial intelligence for an auditor and developing intelligent agents that can contribute in the execution of specific audit tasks.

3.5. New Scientific Results

Based on the results and discussion, the new scientific results from this research are as follows:

1. The study reveals that the Task Formula provides a useful starting point to assess the contribution of intelligent agents to execute a task.
2. Another distinctive result observed from this study is the Task Complexity Framework. The framework can contribute to assess the potential contribution of intelligent agents for a specific

audit task. The framework contributes to a more precise assessment than the methodologies used by the authors of the studies summarized in Table 3.

3. One of the novel results brought forth by this study is the five recipients' conceptual framework for the audit ecosystem in Quebec to reach explainability in AI. Auditors face fundamental limits on their ability to trace the inductive reasoning of complex intelligent agents. This is where explainable artificial intelligence can play a significant role because as long as high-performing models remain opaque, it will impact the ability of the audit profession in Quebec to leverage intelligent agents and comply with CAS.
4. Another distinctive result observed from this study is the need to better prepare the students in the CPA certification program to develop their creative thinking. As intelligent agents will contribute more and more to find risk fraud factors in structured data, auditors with better creative thinking that leverage on the contribution of intelligent agents will provide added value by increasing their ability to detect fraud.

4. CONCLUSION AND RECOMMENDATIONS

4.1. Conclusion

The fundamental aim of this research was to assess the contribution of intelligent agents to the audit profession in Quebec. This research is exploratory and descriptive in nature and it is novel for the audit profession in Quebec since there is no research that I am aware of that encompasses the four topics analyzed in this dissertation: the audit profession in Quebec, artificial intelligence, knowledge and learning.

The dream of creating an intelligent machine – one that is as smart as or smarter than humans – is centuries old but became part of modern science with the rise of the digital computer. Since its earliest days however, artificial intelligence has been long on promise, short on delivery. General-purpose artificial intelligence with the flexibility of human intelligence is not a small achievement to reach. An important challenge starts with the meaning of intelligence. Voltaire once said "define your terms…. or we shall never understand one another." This study presented different dimensions of human intelligence. There is no one way the human brain works because the brain is not one thing. Instead, the brain has parts, and the different parts of the brain operate in different ways. Interestingly, intelligent agents don't have to work the same way as humans. There is no need for them to make the same cognitive errors that impair human thought, such as confirmation bias, or the many limitations of the human mind, such as the difficulty that human beings have in reciting the alphabet in reverse order in less than 10 seconds. Defining intelligence as a measure of skill-acquisition efficiency over a specific task, with respect to prior knowledge, experience, and local generalization ability is a good starting point to assess the contribution of intelligent agents on the audit profession in Quebec.

Predicting the scale of impacts of intelligent agents on jobs and tasks has become a cottage industry for economists and consulting firms. Depending on which model one uses, estimates range from terrifying to totally not a problem. While I respect the expertise of economists and scientists who pieced together the studies presented in this dissertation, I also respectfully disagree with their methodology and estimates. Based on the Task Formula and the Task Complexity Framework, the results indicate that intelligent agents can contribute to improve the quality of an audit but cannot replace the auditor. There are a number of reasons that can explain such an outcome. The key one is trustworthiness. The narrow intelligent agents analyzed in this study work on what they are programmed for, but they cannot be trusted with anything that hasn't been precisely anticipated by their programmer. Intelligent agents need to be able to deal not only with specific situations for which there is an enormous amount of data, but also for tasks that are novel, and variations that have not been seen before. The phrase "barrier of meaning" perfectly captures the limitations of intelligent agents. Auditors, in some deep and essential way, understand the business situations they encounter, whereas no intelligent agents yet possess such understanding. While the state-of-the-art AI systems have nearly equaled, and in some cases surpassed, humans on certain narrowly defined tasks, the nine intelligent agents analyzed in this study lack a grasp of the rich meaning that auditors bring to bear in language, reading, perception and reasoning. This lack of understanding is revealed by the limited number of sub-tasks they can accomplish to identify fraud risk factors; their difficulties with abstracting and transferring what they have learned; and by their lack of commonsense knowledge.

4.2. Recommendations

Based on the findings of this research, an important recommendation is provided for further research. Technological innovation is changing the nature of many jobs, and the qualifications that employers seek in their workers and the audit profession in Quebec is not exempt from such situations. As intelligent agents penetrate the audit profession in Quebec, the knowledge required to practice the profession will have to evolve. In future research, it is strongly recommended that an Essential AI Audit Skills Framework be defined and developed for tomorrow's CPAs. Today, the capacity of Quebec's university ecosystem to respond to the skill evolution requirements for the audit profession is limited. The audit profession regulatory body is also struggling the understand and define the profile of tomorrow's CPAs.

4.3. Research Limitations and Future Research Directions

Limitations of this research must be recognized. First, this is an exploratory research. No such research has been conducted to assess the impact of artificial intelligence on the audit profession in Quebec. The novelty of this research is to assess the impact of intelligent agents on a specific audit task, but it carries a second limitation – only nine algorithms will be analyzed. Over time, many more algorithms can be analyzed. The third limitation is that I did not have access to the source code, neither the training or testing data, because of privacy regulation in Canada. Finally, ethics is an important challenge in the field of artificial intelligence. There is much research on the topic, and it is subject to hundreds of PhD dissertations every year. Based on my research, I carefully selected a limited number of challenges I wanted to analyze in the field of ethics and artificial intelligence.

To prepare for tomorrow's business landscape, the profession must evolve and provide more value added. The expectation gap that exist between the profession in Quebec and the stakeholder's community must be reduced. As a result, the following research can provide valuable insights to CPA Quebec:

- Leveraging on the Task Formula, research can be undertaken to assess the readiness of audit firms to re-skill the audit workforce that have limited knowledge of intelligent agents.
- Further research can be undertaken to assess how CPA Quebec can improve the CPA Competency Map to better develop artificial intelligence technical knowledge to CPA candidates and CPA professionals.
- Assessing the contribution of natural language processing technology (NLP intelligent agents) to execute the audit task 6 (understanding the auditee's business, environment, risk, management and strategy) in Table 1. NLP intelligent agents may provide a concise and precise summary in that regard, helping auditors get a better understanding of a company.
- Further research on XAI can be undertaken and, more specifically, on post-hoc intelligent systems to assess if auditors can understand explanations provided by these systems.
- Other intelligent agents can be evaluated to assess their ability to contribute to other audit tasks.

5. SUMMARY

This dissertation takes a step in understanding how intelligent agents can impact the audit profession in Quebec. This research should assist the audit profession ecosystem in Quebec (and other countries as well) to prepare the next generation of auditors and ensure that the CPA continuing education program for auditors in Quebec reflects the progressive impacts of intelligent agents on the audit profession.

Findings from this research can be characterized as follows: intelligent agents can contribute to some sub-tasks related to the identification of fraud risk factors. This should allow an auditor to reallocate his time to more complex sub-tasks related to the identification of fraud risk factors. The combination of human and machine should increase the quality of an audit. Intelligent agents suffer two main obstacles: they have no ability to generalize and contextualize as an auditor can do. AI biases and explainability could slow down the integration of intelligent agents by the audit profession in Quebec (and other countries). Explainability can generate an ethical challenge for the audit profession in Quebec (and other countries). As intelligent agents will contribute more to accomplish certain audit tasks, auditors will have more time to leverage on their professional judgment to address more complex audit issues. However, The CPA Quebec Competency Map focuses mainly on six technical competencies. The CPA Competency Map does not address the development of creative thinking (professional judgment) of the students in the CPA designation program. The audit profession ecosystem can contribute to improve the quality of an audit at three levels: improving the ability of students in the CPA program to develop their creative thinking, developing the appropriate skill requirements associated with artificial intelligence for an auditor and developing intelligent agents that can contribute in the execution of specific audit tasks.

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