BUSINESS SCHOOL

The role of intelligent systems in financial auditing and financial fraud.

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Abstract

Intelligent systems have become increasingly prominent in the current competitive and changing corporate atmosphere. Although people in firms still handle many jobs, intelligent systems will become more prominent in the short/medium future and will execute everyday jobs presently executed by people considerably more effectively. Businesses must adapt and consider how human and intelligent systems skills might be combined. This study focuses on the financial auditing profession since these individuals devote a lot of time doing repetitive tasks that intelligent technologies can straightforwardly and swiftly execute. This study investigates the influence of Artificial Intelligence, Big Data, and the Internet of Things on this profession. As per the survey, financial auditors understand that intelligent systems are the way to go as a tool to help them perform their jobs, but they are still concerned to change. Employing these systems in daily financial auditing tasks is seen as having a lot of benefits by these professionals and intelligent systems professionals, but there are still some barriers to overcome. Regardless of the circumstances, intelligent systems will significantly influence financial audits.

Key Words: Financial Auditing, Artificial Intelligence, Big Data, Internet of things

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1. Introduction

1.1. Framework and Research Problem

Several developments have occurred in the technology industry over the previous few decades, with the sector becoming extremely complex and advanced. Technology is transforming society and posing new challenges to how we live, engage, and operate. We now live in a world where intelligent systems can perform tasks that people previously could not. Companies must adapt and adjust to satisfy demand in an era of rising digitalisation of services, as well as incorporate new emerging technologies into their structure and research their influence across the firm. Companies are beginning to recognise the relevance of new technologies for their success due to the fierce competition they face and the struggle of being distinct and competitive in today's market.

Artificial Intelligence (AI), Big Data, and the Internet of Things (IoT) are three intelligent technologies becoming increasingly popular among businesses. Embedding these systems into organisational structures will significantly influence how people work, interact with information, and soon infiltrate the commercial world. The influence and relevance of financial auditing will be examined in this study.

The influence of such three intelligent systems on management accounting is essential to investigate since the function of financial auditing entails processing large volumes of data and conveying it to executives. Auditors then utilise accounting data to make critical choices. As a result, researching methods to make financial auditors' everyday jobs easier will significantly influence the speed and quality of their judgments, allowing for the creation and application of good managing decisions. Perhaps, the findings of this study will give valuable insight into the future development of intelligent systems and their benefits to the financial auditing industry.

1.2. Objectives and Research Questions

The primary focus of this research is to analyse and explore the influence of Big Data, AI, and IoT on financial auditing and respond to the three research questions listed below. Several studies focused on the influence of intelligent systems on businesses. Nevertheless, few investigations have been performed to determine the true impact of these intelligent systems on financial auditing and if these professionals can use these technologies to increase their quality and performance. This study aims to fully comprehend and describe the benefits of integrating intelligent systems into management accounting.

The following are the precise objectives and research topics, which will be discussed in more detail later:

Objective I: Understanding and analysing the potential role/value of intelligent systems in auditing

Research Question 1: Possibility of implementing intelligent systems in financial auditing?

Objective II: Analysing the limitations of intelligent systems in auditing

Research Question 2: Do IS-related boundaries positively impact the possibility of implementing intelligent systems in financial auditing?

Objective III: Understanding the role of intelligent systems in the detection of fraud detection

Research Question 3: Do the CAs (in terms of fraud detection) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?

1.3. Dissertation Structure

The following is the structure of this dissertation: The foundation for this study and the research topic from which it arose are presented in section 1, the introduction. Each subject covered in the research is presented in section 2, the literature review. This detailed study of extant literature covers topics such as Intelligent Systems and Business Intelligence (Artificial Intelligence, Internet Of Things, Big Data), as well as Auditing (the Importance Of Auditing, the Impact Of Intelligent Systems On Auditing) and financial fraud, that aims to explain how each topic works and how the link between them is conceivable.

Succeeding section 3, the theoretical approach, covers the preceding chapter's aims, research questions, and hypotheses. The process used to collect the required answers, such as a quantitative analysis based on the development of a questionnaire, is all addressed in section 4, methodology. The description of the sample for the survey is also included in the methodology section.

The findings from the statistical analysis of the online surveys and the confirmation of the previously formulated hypotheses are addressed in section 5, result presentation and discussion.

Here, the study questions are confirmed, and an integrated result conversation is held to understand better how the previously discussed subjects link and impact one another. In section 6, the study's results are presented, in section 7, a discussion of the study's limitations is presented, and recommendations for future research are presented in section 8.

2. Literature Review

2.1. Intelligent Systems and Business Intelligence

The word intelligence has been increasingly popular in recent years, and it is currently used in a variety of sectors ranging from data technology to business modelling (Nedelcu, 2013). All companies have a variety of information systems that help them run smoothly daily. Whether it is a client management system, a sales system, a payment system, or a human resources system, all of them are designed to handle everyday process transactions (Nedelcu, 2013).

The idea of an intelligent agent has been used to describe intelligent systems in the AI field, and numerous writers have defined the word. Intelligent agents, according to Maes (1995), are computerised systems that live in a complex and dynamic context, detect and act independently in that environment, and thereby achieve a set of objectives or tasks for which they were created. Intelligent agents, according to Norvig & J. Russell (2009), function independently, sense their surroundings, survive through time, adapt to change, and develop and pursue objectives. An intelligent system, according to Molina (2020), is a system that performs in a complex world with scarce resources. It has basic intellectual capabilities such as perception, action control, logic, or linguistic use and displays complex, intelligent behaviour endorsed by abilities such as rational thought, learning ability to adapt, or the ability to discuss the use of its expertise through self-analysis.

This concept provides an adequate degree of abstraction that helps to identify general properties. These definitions highlight that the system works in an environment with a set of capabilities and makes decisions about how to act. The description of an intelligent system used is part of the earlier agent-based definitions. For instance, identifying a distinct complex dynamic ecosphere is significant to give an acceptable working framework at a specific grade of abstraction (Molina, 2020).

A decision-making approach aided by integrating and analysing an organisation's information systems is characterised as business intelligence (BI). BI is becoming increasingly important in various industries since information has been recognised as a company's most valuable asset, and it is a crucial resource for its growth (Romero et al., 2021). Business intelligence refers to a set of tools and techniques for gathering, storing, analysing, and distributing data to improve the quality of business process modelling (Hancock & Toren, 2006).

BI has become a concern for information technology as well as a highly critical management issue since data has become a new kind of economic value (Djerdjouri, 2020). Its significance has been highlighted in software and computer systems for creating analytics-based decision-making skills (Łabedzka, 2018). The extremely volatile corporate climate, as well as the possibilities that arise within the economy, necessitate quick and effective decision-making. It is challenging to keep track of these dynamic changes within and outside of businesses while sustaining long-term goals. However, this can be made feasible by the various new concepts and techniques accessible, such as Business Intelligence (Odważny et al., 2019).

This section briefly introduces intelligent systems and business intelligence. We will now look at how these systems may work, developing further regarding three central systems: Artificial Intelligence, the internet of things, and big data.

2.1.1. Artificial Intelligence

Artificial Intelligence (AI) is becoming more widely used in accounting and auditing, and organisations are looking for new workers who have embraced this technology (Damerji & Salimi, 2021).

The beginnings of AI may be traced back to the 1940s, when Alan Turing created a machine capable of deciphering an Enigma code used during World War II, demonstrating the possibility of intelligence beyond the human brain (Haenlein & Kaplan, 2019). Although the term, artificial intelligence, was only introduced in 1956 during the Dartmouth Summer Research Project on Artificial Intelligence, which was chaired by John McCarthy and Marvin Minsky. Until now, there have been many different interpretations of the concept. John McCarthy himself described it as the science and engineering of creating intelligent machines, particularly intelligent computer programs (Bolander, 2019). Norvig & Russell (2010) divide artificial intelligence into four categories: systems that think or behave like people and systems that think or behave logically. Nadikattu (2019) thinks of it as the capability that machines can have to complete complex tasks that usually require human knowledge. He describes it as an electronic form of technology that does not require human power. According to Nadikattu (2019), AI is the capacity of computers to accomplish sophisticated activities that would generally need human understanding, and it is an electronic type of technology that does not require human power.

AI differs from previous generations of information technology to where it can learn from different types of data, patterns, experiences, tendencies, and procedures of human behaviour and bring up-to-date thoughts or actions. This ability is what makes the authors consider a machine to be intelligent enough to carry out processes with higher accuracy and in a shorter period than any human could (Floridi, 2019; Huang et al., 2019; Nadikattu, 2019).

Several concepts exist around the issue of artificial intelligence, with machine learning and deep learning being particularly relevant methodologies (Jakhar & Kaur, 2020; Lewis & Denning, 2018). Machine Learning is a branch of Artificial Intelligence that involves computers learning how to make accurate predictions based on previously collected data using algorithms. An algorithm is a collection of explicit instructions that computers and machines may follow to learn from the qualities of data through inferring knowledge from it. Computers and machines utilise processed data to discover patterns and create assumptions and decisions. It is a method of putting AI to work by employing algorithms to reduce mistakes by identifying the most significant characteristics of each piece of data and increasing efficiency in forecasts, and allowing the forecasts to become more thorough and precise over time (Bolander, 2019; (Bolander, 2019; Jakhar & Kaur, 2020; Khan & Al-Habsi, 2020).

Additionally, Deep Learning is a branch of Machine Learning that combines computational models and algorithms working in the same way that human neural cells do, resulting in the term Artificial Neural Networks (ANN). When this ANN receives new data, it rapidly compares it to previously collected data to spot patterns in data and speed up the outputs and improve decision-making (Bolander, 2019; Comaniciu, 2020; Jakhar & Kaur, 2020).

Artificial intelligence (AI) applications hold much promise for the future. It may make combing through hundreds of pages and compiling reports less painful. A large portion of the data obtained during audits and tax preparation is unstructured and susceptible to human error. AI-enabled technology that has been trained on this unstructured data is improving its ability to spot errors and streamline operations. Many of these skills are already being used by the auditors through various tools of the worldwide auditing firms, Deloitte, EY, KPMG, and PwC, known as the Big Four. Argus, Deloitte's first cognitive audit tool, uses powerful machine learning algorithms and natural language processing to automatically detect and extract critical accounting information from any type of electronic document. Document review using cognitive technology may now be completed in a fraction of the time it previously took. Auditors may evaluate and analyse more extensive samples of documents using artificial intelligence, even up to 100% of the papers (Davenport, 2021; Nan et al., 2020). According to EY, document intelligence solutions might very well assist companies in reducing document review and processing time by 90%, lower expenses by 80%, and reduce risk by 20% on average. They can improve processing efficiency by 25% and reliability by 50%, all simultaneously (EY Global, 2019).

This tops the section on the characteristics of Artificial Intelligence on how this system operates. The goal of this part was to perhaps give insight into how Artificial Intelligence may impact auditing and how it can aid in the detection of financial fraud. We will now look at how the internet of things may work.

2.1.2. Internet Of Things

According to Ashton (2009), the phrase "Internet of Things" (IoT) was presumably invented in 1999 as the title of his presentation to Procter & Gamble. Since then, the term "internet of things" has been defined in various ways, although, according to Wortmann & Flüchter (2015), no universal definition or concept of the Internet of Things exists.

Even though there is no universal definition for the Internet of Things, it has been described and explained countless times in the literature (Ben-Daya et al., 2019; Gigli & Koo, 2011; Lund et al., 2014; Ornes, 2016). Regardless of differences in concept, the goal of IoT is identical in a broad context. In general, the Internet of Things (IoT) is a collection of internet-based networks of uniquely identifiable endpoints or devices that collect and generate data capable of providing analytical insights and enabling new processes.

Nord et al. (2019) affirm that the global Internet of Things (IoT) market is vast and rapidly expanding. The growth and influence of IoT-enabled devices have lately been noticed by many in the expanding digital world. The Internet of Things has opened up several new possibilities in the technology world. IoT is a disruptive technology that enables ubiquitous and pervasive computer applications due to smooth interactions between vast numbers of heterogeneous objects (Mohanta et al., 2020).

A review of the IoT infrastructure is mandatory to gain a better understanding of the IoT. According to Nord et al. (2019), IoT communication architectures allow IoT devices to link to the internet's communication via an infrastructure-based wireless network paradigm, as well as communicate with one another independently (Goyal et al., 2021) add that the infrastructure of the Internet of Things is composed through three layers: sensing, network, and application. In real-time, the sensing layer function collects data from multiple sources. With the support of an efficient wireless network, the network layer transports the data acquired from the sensing layer to the data processing centre. The network layer acts as a link between databases, operating systems, and applications, and it includes on-demand storage as well as a variety of other computing and data processing capabilities. It leverages big data analytics and is cloud-based. Finally, after data is uploaded to the cloud, it may be processed by a variety of tools and programs, and the application layer can apply this knowledge to several choices and tasks in daily life.

IoT is considered a component of the future of almost every industry, including financial services in which auditing is included. However, as the widespread use increases, concerns regarding privacy, security, and trust are becoming increasingly widespread (Nord et al., 2019). According to Rose et al. (2015), users of the Internet of Things must have confidence that the data is safe while it drifts across networked devices, much like the feeling that browsing the internet is harmless and that the uses user's data is private and anonymous. By facilitating connections with and among intelligent devices, the Internet of Things will radically alter how we live in various ways (Goyal et al., 2021).

AI and IoT are reshaping the audit world and setting new standards for effective control measures in processes worldwide. Since auditors should try to embrace such strategies in response to the often-changing digital complex environment, these two factors, from internal controls to risk management, are enabling the processing of data and big data is increasingly available and necessary than it has ever been. Organisations all around the world are using these technologies to achieve the efficiency improvements required to compete in the global economy. Inventory control, risk planning, consulting, assurance, and many more may be improved by combining AI and IoT. These systems would gather all relevant information and afterwards process it using an AI system that understands the outcomes similarly to an auditor (Griffin, 2017).

This section regards the features of the Internet of Things and how it works. The purpose of this section was to provide some insight into how the Internet of Things may affect auditing. We will now take a look at how Big Data may function.

2.1.3. Big Data

Big Data is a notion that is gaining in importance and relevance, owing to the previously stated advancements in the Internet of Things and its smart gadgets, as well as the ever-increasing generation of data offered by social networks and online transactions. Although the term big data is now widely used. There is no one unifying definition due to a common genesis amongst academics, industry, and the media, and numerous stakeholders produce diverse and frequently contradicting meanings. The lack of a unified definition creates ambiguity and stifles discussion around big data (Ward & Barker, 2013).

According to anecdotal evidence, Ward and Barker (2013) highlight that the term big data is commonly connected with two concepts: data storage and data analysis. Despite the recent surge in interest in big data, these ideas are not new and have a long history. As a result, it is essential to understand how big data differs from traditional data processing methodologies. Oussous et al. (2018) add that big data refers to enormous, expanding data collections in which data is presented in various formats, including structured, unstructured, and semi-structured data. Dinov (2016) withstands that Francis Diebold created the phrase "big data" in 2000 to describe a predicted burst in the quantity of accessible and possibly relevant data. While in 2001, Doug Laney defined the core qualities of Big Data, known as the 3Vs—volume, velocity, and variety (Félix & Thomas, 2004; Gandomi & Haider, 2015).

Volume, the magnitude of data, is referred to as volume. As the term indicates, large volumes of data are being transmitted between devices, and it could be petabytes, exabytes, or zettabytes, necessitating the creation of a framework to analyse and store this data. Velocity regards the pace at which data is created, as the speed at which it must be analysed and acted upon and transported across multiple systems and devices is referred to as velocity as real-time insight may be derived from massive amounts of data using Big Data analytics. Variety refers to the variability of data sets. The many formats, forms and sorts in which data is provided may be studied more efficiently with Big Data analytics than with traditional statistical and small data analytical methods to get desired information (Félix & Thomas, 2004; Gandomi & Haider, 2015; Younas, 2019).

Since Laney's original work, other concepts have been added, the main ones being veracity and value. Gandomi and Haider (2015) also include variability. Veracity, the quality of data, such as accuracy, coherence, trust, security, and dependability, is referred to as veracity, a reference to the inaccuracy of some data sources. Value refers to the many forms of advantages that may be generated from handling and analysing large amounts of data, implying that the data received has a low value in contrast to its volume (Gandomi & Haider, 2015; Younas, 2019). Variability refers to changes in data flow rates (Gandomi & Haider, 2015).

George et al. (2014) categorise familiar sources of the high volume of "big data" into five categories, public data, private data, data exhaust, community data, and self-quantification data. The techniques for analysing data are just as important as the data sources. These techniques can be used in various specialised ways, but most organisations utilise one of three computational models to cope with enormous data sets: data mining, artificial neural networks, and machine learning (Grable & Lyons, 2018). AI algorithms are used in ANN and machine learning to examine massive amounts of data rapidly. Machine learning and statistics are commonly used to create data mining models (Choi et al., 2018). Data mining uses current data and analytics to look for hidden or developing patterns in data that may be used to explain an occurrence or anticipate future trends(Grable & Lyons, 2018). Deep learning is also highly useful for evaluating massive data; it is feasible to separate hidden patterns and obtain answers without over-fitting the data using deep learning (Richins et al., 2017). Big Data analytics is quickly gaining traction as a technology that can not only identify trends but also anticipate the possibility of an occurrence (Choi et al., 2018).

The vast amounts of data currently available both inside and outside of organisations, as well as the capability of emerging data analytics technology, are fundamentally altering the auditing process. They employ a data analysis strategy for auditing, allowing everyone to deliver higher-quality, more in-depth insights and more client-relevant audits while maintaining a higher degree of professional scepticism. EY Helix is a critical component of their audits since it was built to expand to satisfy the expectations of all EY customers. It is indeed their global big data and analytics platform, which contains a set of significant data acquisition and analytics tools that vastly improve the scope and depth of data acquired, as well as the relevance of insights produced from that too. The EY Helix collection of analyses helps with the audit process from risk assessment to execution, covering the whole business cycle. For instance, auditors can utilise the data and analytics to examine sales invoicing activities over the course of the year, the effect of credit memos, and also how invoicing is eventually landed (Delarue et al., 2020; EY Assurance, 2019).

The wave of data and analytics (D&A), very much in today's corporate world, focuses all-around indispensable the use of technologies, and just as vital is the capacity to link and correctly use all data. According to KPMG's D&A work in practice during an audit, a corporation's financial data can be thought of as being structured in tiers. The very first tier is the 'general ledger,' which would be an organisation's principal bookkeeping process. More specialised tiers or sub-ledgers exist below the general ledger, such as those relating to sales, transactions, inventories, and so on. Auditors can begin by reviewing the general ledger and comparing all of the journal entries in the general ledger to accounting and audit rules and principles to determine whether or not the content of the ledger is all in line with expectations. In addition to reviewing a company's financial data, analytical tools can be helpful to in evaluating the forward-looking hypotheses that are used to arrive at a few of the figures. As we have seen, D&A has a lot of auditing potential, and it is being utilised in a growing amount of audits, especially the more prominent and most sophisticated (O'Donnell, 2017).

This last portion concludes the topic "Intelligent Systems and Business Intelligence". The topic discusses the characteristics of Big Data and how it operates. The goal of this part was to give some insight into how big data can impact auditing. We will take a look in the next chapter at what auditing is, how it may work, and several other characteristics.

2.2. Auditing

Iuliana (2012) traces the origins of auditing back to ancient times. The ancient Egyptians and Babylonians were reported to have had auditing systems to verify the in and outflow of storehouses by around 400 BC," leading to the name "auditor" (derived from the Latin word "audire," which means "to hear").

According to Lee (1994), the early historical evolution of auditing is not recorded. Ancient civilisations such as China, Egypt, and Greece used auditing in the form of ancient checking activities (Boyd, 1905). Ancient Greek checking efforts, about 350 BC, appear to be the most similar to modern-day auditing. Similar kinds of checking activities were also found in the ancient Exchequer of England around 1100-1135. Afterwards, in response to socio-economic developments in the United Kingdom between the 1840s and the 1920s, the Joint Stock Companies Act was established in 1844, allowing for the nomination of auditors to examine the company's accounts.

Nevertheless, the Companies Act 1862 only made the yearly disclosure of the balance sheet statement to the shareholders and the demand for a statutory audit mandatory in 1900 (Leung et al., 2007). The rise of the US economy from the 1920s to the 1960s resulted in a change in auditing progress from the United Kingdom to the United States. Following the 1929 Wall Street Crash and subsequent depression, it was necessary to persuade financial market participants that the company's financial statement gave a truthful and fair representation of the appropriate company's financial situation and performance (Porter et al., 2003).

In the 1970s, auditors played a critical role in strengthening the trustworthiness of financial data and advancing the operations of a functioning capital market (Porter et al., 2003). The auditing profession has witnessed substantial and rapid change since the 1990s. According to Porter et al. (2003), present-day auditing has developed into new processes that build on the business risk perspective of their clients. The business risk approach is based on the idea that the audit should cover a broad spectrum of the client's business risks.

Internal and external audits are the two types of audits that companies conduct daily. Typically, these are interrelated and complementary, with the end goal of making the overall audit more successful and the reports produced completely defensible and useful. Internal audit plays a critical role in improving the efficacy of internal control in both private and public companies. Internal audit is in charge of advising the institution's management of any shortcomings or weaknesses in the internal control system (Mehmeti, 2018).

Although there are two forms of auditing, internal and external, we will only discuss external auditing in the remainder of this article, and anytime we discuss auditing, we will be referring to external auditing. In the simplest terms, external auditors are the first line of defence for a company's leadership. They play a crucial role in ensuring that the financial information supplied to shareholders is accurate. External auditors examine the organisations' financial statements and provide an independent judgment on the financial statements on whether they reflect a candid and fair picture of the organisation's annual financial reporting review (Goodson et al., 2012; Knechel et al., 2020; Mehmeti, 2018). In addition to the financial statement opinion, auditors look into the accuracy of specific financial data, compliance with essential procedures and rules, and asset safeguarding (Goodson et al., 2012).

The literature distinguishes between an auditor, a fraud auditor, and a forensic accountant. The audit performed by a fraud auditor plays an important preventive role in identifying potential frauds. However, its capabilities are limited because auditors are not responsible for planning and carrying out audits to detect mistakes that are not of material significance for presenting financial statements (Knežević et al., 2019).

Concluding, the goal of an audit should be to ensure that financial statements that are prepared by business management to reflect a "true and fair representation" of the assets, liabilities, financial position, and profit or loss of the company or group (Companies Act 2006, section 393).

This closes the introduction to the features of auditing. We will go through why auditing is necessary, how intelligent systems affect auditing, and what the future of auditing looks like. The purpose of these sections is to help understand auditing and potentially offer some insight into how intelligent systems might affect auditing and how they might help expose financial fraud.

2.2.1. The Importance Of Auditing

The domains of auditing and assurance, as well as financial reporting and analysis, are two of the most closely connected disciplines of accounting. Both of these large areas of accounting face comparable concerns of rising risk and widespread ambiguity. Furthermore, in these current days of scandals, controversies and failures, a lawsuit is always a concern (Baldwin et al., 2006).

The fundamental idea is that the clients and auditors have informational advantages that must be exploited to conduct a good audit, with the client's advantage being primarily internal and the auditor's advantage being largely external. Because informational asymmetries exist in both directions, a potentially strong argument for the "co-creation of value" emerges through the audit process, the need to collaborate in the audit process. This bi-directional information flow contrasts sharply with the more common agency-driven concept of the auditor as being at a disadvantage in terms of information compared to the client (Knechel et al., 2020). Auditors keep a close eye on the effectiveness of management's internal control structure to spot and eliminate the conditions that encourage corruption. In many parts of the world, auditors are also responsible for detecting and deterring corruption charges in the organisations of the sector they serve. Detection is used to find out about improper, inefficient, unlawful, fraudulent, or abusive behaviour that has already occurred and to gather evidence to support judgments about criminal charges, disciplinary procedures, or other remedies. This deterrence aims to identify and eliminate the conditions that allow for corruption (Goodson et al., 2012).

Banks will not lend, shareholders will not invest, workers will not commit their labour, suppliers will not engage, and customers will not buy if there are no rigorous audits (Leaver et al., 2020). Auditors have a particularly essential role that is critical for enhancing credibility, equity, and acceptable behaviour while lowering the risk of corruption. As a result, audit activities must be appropriately organised and given a broad mandate to meet these goals. Although the specific means by which auditors achieve these aims differ, the audit activity must be enabled to act with integrity and offer dependable services (Goodson et al., 2012). An audit provides assurance, which is an intangible and unobservable kind of risk reduction (Knechel et al., 2020). Several corporate scandals and frauds sparked a significant social debate over the auditor's profession's responsibility and position. There is a distinction between what an auditor does and what the public expects of them. Auditing provides reasonable assurance, not absolute assurance, that financial statements are free of materially significant errors (Knežević et al., 2019).

Several explanations can highlight the value of auditing, some of them are the activity monitoring explanation, the evidence explanation, the management regulator explanation, the corporate governance explanation, the hypothesis confirmation explanation, and many more explanations.

Shareholders are aware that managers may behave in their own best interests and may provide false information as a consequence of the activity monitoring explanation. When one party assigns power, particularly control over resources, to another, this is known as an agency relationship (W. Wallace, 1980). As a result of value protection, audits are carried out. Because certain managers in specific contexts may have an incentive to deliver inaccurate information, shareholders (or other stakeholders) may underestimate the data they get and consequently aim to pay a lower price for shares than the financial reality suggests (Jensen & Meckling, 1976; Pincus et al., 1989). Previous studies support the surveillance, bonding, and other contractual theories by demonstrating that auditing or equivalent assurance services are required when administrative costs would otherwise be high, as indicated by bigger size, more debt leverage, or less management ownership.

In terms of the evidence explanation, one option for managers to address this data discrepancy is to hire an auditor to verify their statements. The appointment of an auditor signal to investors that the company's financial statements may be trusted. Where auditing is required, managers may, nevertheless, send a message of more outstanding quality by hiring a high-quality auditor – possibly a major worldwide company or one that specialises in the client's business. This might be a way for insiders to communicate excellent performance and lower imprecisions (Wallace, 2004).

Concerning the explanation provided by the management regulator, another reason for auditing is to help the organisation's internal management, which is particularly true in smaller businesses that may be family-owned or have less sophisticated financial arrangements. Some company owners invest in optional audits as part of their internal control system. Auditing, according to Abdel-Khalik (1993) and his findings, aids top management in controlling complex companies as a compensating control technique for hierarchical organisations' loss of control because there are substantial connections between audit fees and the number of levels of hierarchy.

Concerning the explanation of corporate governance, Corporate governance and auditing are inextricably linked. The process by which firms are planned and managed is characterised as corporate governance. It is made up of a company's management or its equivalent, as well as additional procedures such as an internal auditor, supplementary board committees, and external auditors. Corporate governance components differ from country to country. Banks, for example, play a role in various economies (La Porta et al., 2000). It has been defined as a diversity of contacts between auditors and other players, including administration and the external auditor (Cohen et al., 2008). As a result, it is helpful to think of auditing as a supplement to the other aspects of corporate governance. As a result, it is an essential part of a company's risk management strategy. Auditing is an excellent technique to mitigate the risks that stakeholder experiences, mainly if the stakeholders are at higher risk (Knechel & Willekens, 2006). Internal audits, audit committees, and independent directors are all utilised as complementary techniques to manage risk.

Regarding the hypothesis confirmation explanation, previous financial performance and positioning declarations are still essential since they corroborate prior unaudited statements. Audited financial reporting and voluntary disclosure of confidential managerial communications are supplementary processes for interacting with shareholders, not substitutes, according to Ball et al. (2012), and executives are urged to be more honest and straightforward even before they know their statements of sensitive data will then be revealed later.

Because auditing is so heavily controlled throughout most circumstances, empirical evidence for or against these arguments for the benefit of auditing is challenging to come by. Nonetheless, the usefulness of auditing has been investigated in various methods. Although when auditing is required, businesses have the option of hiring whatever auditors they like. There are several reasons that larger audit companies, particularly the Big Four worldwide auditing firms, are of superior quality (Deloitte, EY, KPMG, and PwC). These companies have a greater motivation to preserve excellent quality to safeguard their brand image, as well as a more significant stake in failing an investigation. They also request higher costs, implying that their audits are evaluated significantly greater. They seem to be less liable to be sued in the past (Palmrose, 1988). Other research has looked at whether audit companies that specialise in a specific area deliver relatively decent audits (Audousset-Coulier et al., 2016; Craswell et al., 1995; Francis et al., 2005; Lawrence et al., 2011). The research on whether expertise affects audit quality or costs is still inconclusive.

This brings the discussion of the necessity of auditing to a close. The goal of this part was to help understand why auditing is so important. We will go on to the next topic, which is how intelligent systems affect auditing, and we will see if we can get some insight into how intelligent systems affect auditing and how they might assist detect financial fraud.

2.2.2. The Impact of Intelligent Systems On Auditing

In the 1980s, researchers began to expand their study into intelligent systems and other AI applications for accounting duties. In auditing, these applications have been proposed, explored, and developed (Abdolmohammadi, 1987; Baldwin et al., 2006). Artificial Intelligence (AI) is a prominent topic right now. Countries are paying attention to it, and for the best of reasons. In the subject of accounting and auditing, AI leads the path to a more favourable and supportive environment. AI advancements can undoubtedly be of considerable assistance to human labour. In an area where the workload is massive and includes an ocean of data, AI usage should be encouraged, and attempts to expand its potential can accomplish wonders (Gusai, 2019). Digitalisation makes the use of technology more beneficial in today's changing environment. The concept of the Fourth Industrial Revolution is constantly scrutinised and debated. It creates a platform on which enterprises may be entirely digitalised, robots implemented, and artificial intelligence applied to auditing. Audit companies must use integrated and sustainable Ai learning for their client's risk aversion and cost reduction strategies. This new development is known as AI-assisted auditing. It has shifted accounting from a paper-based to a computerised approach (Gusai, 2019).

The decisive aspect of intelligent systems in the field of accounting and auditing is their potential of handling massive amounts of data faster, reducing the time spent by accountants and auditors in analysing financial data, as artificial intelligence systems will indeed be capable of completing most accounting steps, and even outperforming human capabilities, identifying incorrect statements, and generating risk reports, and aiding the preparation of reports that fulfil the auditing industry (Gusai, 2019; Rashwan & Alhelou, 2020)

Artificial intelligence, according to Noor and Mansor (2019) and Rashwan and Alhelou (2020), aid and enhances auditing by allowing auditors intellectual, ground-breaking, and productive effort in parallel with the increase in the intelligence of machines and tools, as it improves both humans and machines effective interaction. The authors claim that AI aids all parties in the auditing process in communicating more effectively. The reliance on intelligent systems that join in knowledge and helps solve complex problems has distinct characteristics, the most important of which are speed, accuracy, and time reduction, this being the foundation for the development of these systems for the auditing profession (Rashwan & Alhelou, 2020).

Many researchers have expressed concern about the lack of intelligent systems in auditing (Brown-Liburd et al., 2015; Cao et al., 2015; Earley, 2015). Remarkably, the auditing profession has been reluctant to incorporate intelligent systems tools, given the well-developed literature on financial crisis, financial fraud modelling, and stock market prediction (Gepp et al., 2018).

Brown-Liburd et al. (2015) investigate the behavioural consequences of intelligent systems on auditor judgment, including information overload, significance, pattern recognition, and uncertainty. They concluded that incorporating intelligent systems approaches into the auditing toolkit would be beneficial. They also emphasise the need of using the approach and data collection that are most relevant for each situation, indicating the need for future research in this area.

Anecdotal information from partners at several of the country's top audit firms suggests they ha\ve begun to employ intelligent systems, but the exact degree of its usage in practice is unknown, and additional study would be beneficial (Gepp et al., 2018). Earley (2015) recognises that intelligent systems might be a game-changer in auditing, predicting that data analytics would drastically alter the way auditors operate. Intelligent systems, according to Cao et al. (2015), can help with financial statement audits. Furthermore, highlight the sluggish adoption of big data as the field's most significant danger, and advocate for its increased usage in practice, teaching, and research.

The intelligent systems approach provides significant potential for the auditing profession. However, unlike in other sectors, this possibility has not yet been fully exploited. As previously stated, employing current big data models to anticipate financial hardship and detect financial fraud will enhance auditing. Updated standards may be able to assist the auditing profession to overcome its apparent aversion to intelligent systems approaches. Without a doubt, having access to regularly updated large data sets that include non-traditional data would be extremely beneficial to the audit function. Traditional technologies are insufficient for assessing big data since it is so large, comes so quickly, and its variability or significance varies substantially over time (Hay & Cordery, 2021).

Ultimately, Smith (2015) argues that accountants and auditors should possess intelligent systems, not just because it gives superior information but also because they will help elevate the profession up the value chain, from primary service provider to real business partner.

The debate on the future of auditing comes to a halt at this point. This section's purpose was to understand what the future of auditing holds and why it is so vital. In the following chapter, we will look at what financial fraud is, how it works, and a few other features.

2.3. Financial Fraud

Fraud, corruption, and bribery are not new problems across the world. They may be found in any sort of business, although the severity varies (Gepp et al., 2018; Sow et al., 2018). According to the Association of Certified Fraud Examiners (2016), the average company loses 5% of its income each year to fraud. The financial consequences of fraudulent acts committed throughout the world during the last two decades are projected to be worth over five thousand trillion dollars, with losses growing by 56% in the last ten years (Gee & Button, 2019). These figures have spurred experts to investigate how intelligent systems may be used to identify, predict, and prevent fraud. Even though regulators are investigating many cases, fraud is clearly on the increase and one of the most significant business issues that attract more exposure in the media (Hashim et al., 2020).

Different definitions of fraud have emerged from various industries and authors. Khanh Nguyen (1995) defined fraud as the material errors or false representation resulting from a deliberate failure to report financial information in line with uniform accounting standards. In 2008, the Institute of Internal Auditors, in partnership with the American Institute of Certified Public Accountants and the Association of Certified Fraud Examiners, defined fraud as an act in which the victim suffers loss and/or the perpetrator gains profit via a deliberate act of exclusion intended to deceive others.

There are many types of fraud, and the manner fraud is perpetrated evolves as technology becomes more sophisticated (Ozili, 2020). Due to the controversies surrounding financial statement fraud, it continues to stalk the business sector. The expression "cooking the books" derives from financial statement fraud. Financial fraud statements are primarily performed through various methods, including inappropriate asset capitalisation, accounting record manipulation, and purposeful manipulation of financial balances by declaring false costs and revenues. Managers may alter financial statements to meet a particular accounting goal or improve the financial look of their business (Fung, 2015).

The difficulty is that risk management solutions for identifying and preventing fraud are limited among company finance managers and auditors. The auditor's job is to look for irregularities in financial statements (Dyck et al., 2010). Detecting indications of fraud, despite established norms, can be difficult. External auditors must get reasonable certainty regarding whether the financial statements are free of material misrepresentation, whether due to fraud or error, according to Section 200 of Statement on Auditing Standards No. 122/123 (American Institute of Certified Public Accountants, 2011). Despite the ongoing controversy about the exact meaning of "reasonable certainty," auditors might give this assurance by using modern big data models (Hogan et al., 2008). According to Free & Murphy (2015), the social aspect of fraud may aid in detecting distinguishing characteristics. In order to increase the accuracy of fraud models, these features might be added. Using big data financial fraud models that extend traditional models, auditors can improve their fraud risk assessments (Dechow et al., 2011) as the data from previous scams are used to create these financial fraud intelligent systems models. They provide crucial information to auditors since auditors frequently have limited real-world fraud experience (Humpherys et al., 2011).

Financial statement fraud may be disastrous. Shapiro (2014) described and deconstructed a paradigm for internal fraud risk control, and he emphasised the need for auditors to have a better awareness of five internal control components. The five main components are environment control, communication and information, risk evaluation, control operations, and surveillance.

Song et al. (2014) advanced on past literature by presenting a hybrid machine learning strategy for determining the risk of financial statement fraud. The authors collected data from Chinese companies to identify risk indicators and create the model. The effectiveness of the proposed strategy to enhance fraud prediction findings was investigated as part of the study. The authors looked at risk variables, evaluation methods, and preventative strategies in the field. A machine learning model with fraud risk criteria was used in the risk assessment technique provided. The authors used quantitative regression to test the model. The strategy appears to assist in estimating the likelihood of financial statement fraud, according to the findings of the experiments. Overall, the suggested technique is beneficial to auditors since the variables and regulations are simple to comprehend.

Several authors focused on previous fraud instances. The desire to cross into fraudulent behaviour was the topic of Free & Murphy (2015). The goal of the study is to understand criminal behaviour via the social dimension of other financial crimes to explain why people choose to commit fraud. The evidence is seen through the lens of an organisational and social framework by the writers. Interviews with 37 persons convicted resulted in the development of three archetypes of social relationships that lead to fraudulent behaviour. Individual interests, organisational interests, and affective are indeed the three patterns. The study focuses on the individual's motivations and rationalisations. The study has the advantage of expanding fraud research to include the social element of crime and emphasising the need of considering company culture while committing fraud.

With a study of the reputational penalties associated with financial fraud and the following reputational consequences of companies linked with the guilty firms, Kang (2008) added yet another perspective to the fraud research. He considered director interlock, which occurs when a person connected to one business serves on the board of the other. The data suggested that the related firm's reputation damage had increased. One of the adverse repercussions is a decrease in market price. To explain the link to affiliated companies, the author used signalling and imputation theory. From 1998 to 2002, a total of 244 connected companies and 30 convicted firms were studied. Investor confidence is also affected by more significant uncertainty, according to the data. A robust governance system boosted investor trust. The outcomes of the study show that governance change is required.

Some academics looked at what drives people to commit fraud. Hollow (2014), for instance, investigated why financial institutions' managers and staff commit fraud. A mixed-methods, exploratory investigation was used in this study. To have a better understanding of the motivations for committing fraud, the author used 64 examples from the UK financial industry. The study is aimed at accountants and regulators to help them better examine and enhance prevention and detection methods. The author discussed the factors that drive people to commit fraud, as well as the fraud triangle as a risk assessment tool. Personal, work-related, or external motivators may all be used, and the author discovered that occupational position has an impact on motivation. The study included qualitative data from the sample to support the findings, as well as advanced knowledge to have a better grasp of the incentive elements. (Hollow, 2014) conducted a quantitative interpretation of the data as well as a discussion of the findings. The research revealed that bank managers and workers have motives that are comparable to those of managers and staff in other industries.

Hollow (2014) also discovered that the motivational elements differed significantly depending on the employment level. Staff at lower levels, for example, respond to personal demands, whereas those at higher levels respond to work-related or external pressures. This study is beneficial for learning about motivational factors, the impact of occupational level, and qualitative techniques.

Influence is another part of fraud motivation. Albrecht et al. (2015) investigated the impact of power and influence on financial fraud involvement using a case. They presented a power classification centred on the French and Raven systems. The study looked at how higher management recruits fraud actors. According to recent studies, financial statement fraud may be the result of collaboration. The importance of understanding the links between offenders and conspirators was underlined by Albrecht et al. (2015). The study presented in this article extends the fraud triangle also to include leverage upon co-workers' attitudes.

At this point, the discussion on financial fraud comes to a standstill. The goal of this segment was to learn about financial fraud and why it is so important. The purpose is to look at how Intelligent systems can help to audit, preventing early detection of financial fraud. The next chapter of the dissertation covers the study's research design and rationale and the theoretical approach.

3. Theoretical Approach

3.1. Possibility of implementing intelligent systems in auditing

Succeeding the Literature Review, several exciting topics emerge. As a result, and based on the vast quantity of data accessible, three hypotheses emerge to respond to my first research question. My main goal we will strive to figure out if Intelligent Systems can provide value to auditing. We also want to know if there is any benefit in implementing intelligent systems.

RQ1: Possibility of implementing intelligent systems in financial auditing?

Regarding my main goal, determining the potential role/value of intelligent systems in auditing, auditors are increasingly employing intelligent systems in their engagements. These aid as decision support systems and knowledge-based expert systems are gaining traction for use in auditing. The capacity of improving the effectiveness and presumably efficacy of audit decision making is what makes them so appealing (Abdolmohammadi, 1987). Data is said to be the new trend. Data is long-lasting, reusable, easily transportable, duplicable, and infinitely transferable. IS is widely known for learning from the data it is and improving its findings over time (Floridi, 2019). Although auditing is holdup behind the other areas in terms of the usage of valuable big data approaches (Abdel-Khalik, 1993; Gepp et al., 2018a). This clears the way for the first hypothesis.

H1: Do IS-related motivations positively impact the possibility of implementing intelligent systems in financial auditing?

Besides, we can see that intelligent systems are critical in the development of more substantial and more efficient auditing. The main focus on these types of systems will be on how intelligence systems can be integrated into auditing, demonstrating that they can handle massive amounts of data faster, reducing the time spent by accountants and auditors in analysing financial data. Artificial intelligence systems will be capable of completing most accounting steps, and even achieving great results on the early detection of financial fraud (Gusai, 2019; Rashwan & Alhelou, 2020). We additionally strive to comprehend how technologies like Intelligent systems may aid the financial auditing industry, as described in the Literature Review section.

According to Rashwan & Alhelou (2020), IS has a significant influence on improving and developing the quality of accountants' and auditors' professional performance, increasing the ability to complete complex auditing work, and improving and developing the efficiency of auditing systems. Digitalisation makes the use of technology more beneficial in today's changing environment. It creates a platform on which enterprises may be entirely digitalised, robots implemented, and artificial intelligence applied to accounting and auditing. As a result, Richins et al. (2017) believe that big data analytics complements rather than replaces accountants' skills and expertise. This brings us to the second hypothesis:

H2: Do the characteristics of IS positively impact the possibility of implementing intelligent systems in financial auditing?

Additionally, we also discuss the importance of auditing and how it may impact if there are no thorough audits, banks will not lend, shareholders will not invest, workers will not devote their labour, suppliers will not participate, and customers will not purchase (Leaver et al., 2020). Since these new Intelligent Systems provide almost limitless opportunities for forward-thinking businesses to profit from shifting behaviour (Gee & Button, 2019). Baldwin et al. (2006) and Cao et al. (2015) have numerous concerns to investigate both the positive and negative impacts of this implementation. This brings us to the fourth hypothesis:

H3: Do the CAs (in terms of standards and efficiency) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?

Table 1 – Theoretical Approach

Objective	Hypotheses	Analysis method	Literature Review
I. Understanding and analysing the potential role/value of intelligent systems in auditing	RQ1: Possibility of implementing intelligent systems in financial auditing?	Smart-PLS	
	H1: Do IS-related motivations positively impact the possibility of implementing intelligent systems in financial auditing.		Abdel-Khalik (1993), Abdolmohammadi (1987), Floridi (2019), Gepp *et al.* (2018)
	H2: Do the characteristics of IS positively impact the possibility of implementing intelligent systems in financial auditing.		Rashwan & Alhelou (2020), Richins *et al.* (2017)
	H3: Do the CAs (in terms of standards and efficiency) of the IS positively impact the possibility of implementing intelligent systems in financial auditing.		Baldwin *et al.* (2006), Cao *et al.* (2015), Gee & Button (2019), Leaver *et al.* (2020)

Author´s Elaboration

3.2. Analysing the limitations of intelligent systems in auditing

Following the initial research question, a slew of intriguing possibilities arises. As a result of this, and in light of a large amount of data available, a new research question develops. We will try to figure out the limitations of Intelligent Systems in auditing.

Furthermore, although there are some arguments that we could lose something as a result of Intelligent systems automation is because, despite the objective of simulating features of human cognition, machine intelligence is fundamentally different. The advantages and disadvantages of human intelligence and intelligent systems are pretty different. Some things that humans seem simple have proven to be quite difficult for these systems and vice versa (Bolander, 2019). This brings us to the third hypothesis:

RQ2: Do IS-related boundaries positively impact the possibility of implementing intelligent systems in financial auditing?

3.3. Understanding the role of intelligent systems in the detection of fraud detection

Following the second research question, there comes a third research question. We will try to figure out whether there is an advantage and if intelligent systems may help with early financial fraud identification.

Despite projections of both the scope and value of fraud that remains complicated by unreported and monitoring difficulties, it is commonly acknowledged that fraud has a significant financial impact on businesses as in the community. Despite its general prevalence and devastating consequences, it has been widely ignored fraud and fraud risk until recently (Free & Murphy, 2015). Albrecht et al. (2015), Hashim et al. (2020), Hollow (2014), Knežević et al. (2019) have analysed the benefit and if implementing intelligent systems can aid the early detection of financial fraud. We will attempt to comprehend if these systems could help identify and combat inaccurate financial reporting in a corporate context, as well as the standpoint of auditors in detecting financial fraud. Finally, this brings us to our last hypothesis:

RQ3: Do the CAs (in terms of fraud detection) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?

Table 2 – Theoretical Approach

Objective	Research Questions	Analysis method	Literature Review
II. Analysing the boundaries of intelligent systems in auditing	RQ2: Do IS-related boundaries positively impact the possibility of implementing intelligent systems in financial auditing?	Descriptive Statistics	Bolander (2019)
III. Understanding the role of intelligent systems in the detection of fraud detection	RQ3: Do the CAs (in terms of fraud detection) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?		Albrecht *et al.* (2015), Hashim *et al.* (2020), Free & Murphy (2015), Hollow (2014), Knežević *et al.* (2019)

Author´s Elaboration

4. Methodology

4.1. Research Model

In terms of the study's methods, the study depended on the use of a quantitative methodology as the primary source, which consisted of an online survey to answer each of the research questions. This technique is a research instrument covering a wide range of topics and focuses on the systematic collecting of answers, according to Bhattacherjee (2012). This is the most appropriate approach when the study's analytic unit is a person, according to Vilelas (2020), the most utilised in the management area and the one that provides the most benefits in terms of cost, data processing, and error reduction.

Many hypotheses were developed for Research Question 1 after reviewing the literature for this dissertation. The survey results were analysed using a Structural Equations Model (SEM), which is a technique that allows us to construct correlations between dependent and independent variables using multiple regression analyses of different parts (Ullman & Bentler, 2012). This approach allows us to measure relationships without measurement error since it estimates and removes measurement error. The usage of SEM models in behavioural and social science research has expanded considerably in recent years, according to (Raykov & Marcoulides, 2000), and they serve to meet the demand to explain and forecast individual, group, and organisational behaviour, according to Tarka (2018). According to Tarka (2018), SEM is particularly useful in studies that need some prior knowledge of themes since it aids the model's estimate procedures. SEM models enable us to conduct a comprehensive and sophisticated analysis of empirical data that takes into consideration theoretical frameworks, as well as elements of the investigated reality or even abstract conceptions.

According to Ringle *et al.* (2015), SEM was used to assess the conceptual model, which was previously mentioned, by using the Least Parcial Square (LPS), which is a technique for modelling structural equations based on the variation. Consequently, the program SmartPLS3 was selected to analyse the survey data. Smart PLS 3 analyses data using a Partial Least Squares (PLS) route modelling approach, which is a variance-based structural equation modelling technique that is particularly helpful when situations such as limited sample sizes exist (Henseler et al., 2015). There were two stages to the analysis and interpretation of the results. The model of measurement's reliability and validity were first assessed, and then the structural model was examined. Researchers looked at individual indicators of reliability, convergent validity, internal consistency reliability, and discriminant validity to assess the model's quality, all of which were done following Hair Jr et al. (2017) assertions for this type of study. The following part contains the Conceptual Model of the Research Topic, as well as the hypothesis offered to every question.

RQ1: Possibility of implementing intelligent systems in financial auditing?

Table 3 – RQ1 Dependent Variable

	Indicator	Questionnaire Question
Dependent Variable	Implementing intelligent systems in auditing	Possibility of implementing intelligent systems in auditing.
		Is there any value in implementing intelligent systems in auditing?

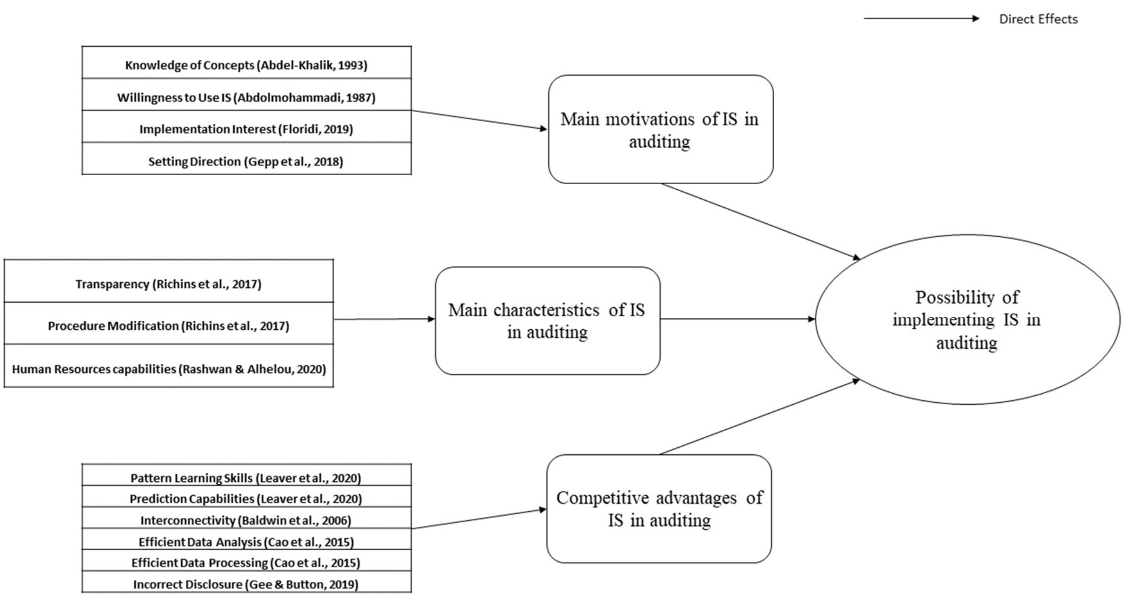
Author´s Elaboration

H1: Do IS-related motivations positively impact the possibility of implementing intelligent systems in financial auditing?

H2: Do the characteristics of IS positively impact the possibility of implementing intelligent systems in financial auditing?

H3: Do the CAs (in terms of standards and efficiency) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?

Figure 1 – RQ1 Conceptual Model

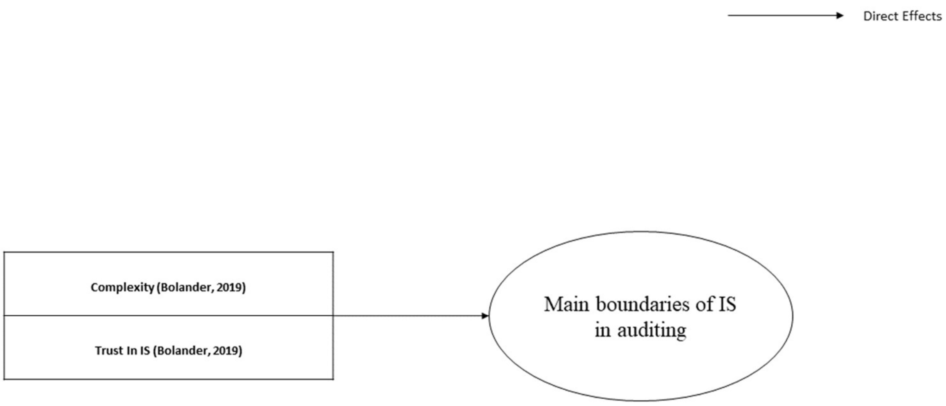


Author´s Elaboration

In terms of quantitative analysis, for research question 2 and research question 3, even though it could have been considered a statistical analytic technique for assisting in inferring results from tests of conformity, homogeneity, and independence based on parametric and nonparametric tests, the technique that I found most appropriate for data analysis was a statistical analytic technique. The display of results was obtained using tables with a set of techniques and guidelines that summarised the information gathered from the questionnaire's questions into a dispersion of data in the form of the Mean, Median, Mode, Standard Deviation, Minimum and Maximum.

RQ2: Do IS-related boundaries positively impact the possibility of implementing intelligent systems in financial auditing?

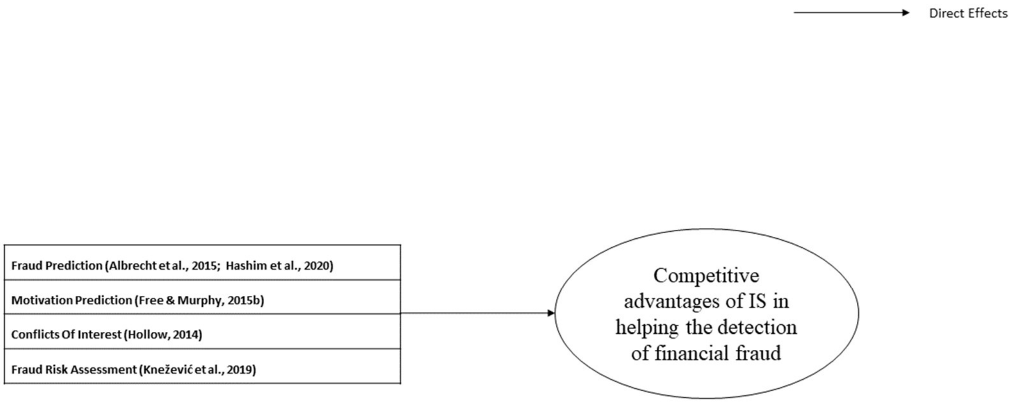
Figure 2 – RQ2 Conceptual Model



Author´s Elaboration

RQ3: Do the CAs (in terms of fraud detection) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?

Figure 3 – RQ3 Conceptual Model



Author´s Elaboration

Table 4 – RQ1 Independent Variables, Indicators and Questions

Independent Variable	Indicator	Questionnaire Questions
Main motivations of IS in auditing	Knowledge of Concepts (Abdel-Khalik, 1993)	Do you understand what Intelligent Systems are?
		Are you familiar with the ideas and applications of Intelligent Systems?
	Willingness to Use IS (Abdolmohammadi, 1987)	Would you be willing to give Intelligent systems the knowledge of a firm, decreasing the human need considerable in making audit judgments?
	Implementation Interest (Floridi, 2019)	With its promises and achievements, Intelligent Systems has dominated recent headlines. Do you think it has hopes for the near future of auditing?
	Setting Direction (Gepp *et al.*, 2018)	The adoption of beneficial intelligent systems approaches in auditing is behind. According to some evidence, some companies have begun to put big data strategies into practice. Do you agree?
Main characteristics of IS in auditing	Transparency (Richins *et al.*, 2017)	Do you have the technical knowledge required to supervise Intelligent systems activities?
	Procedure Modification (Richins *et al.*, 2017)	With continuous advancements in Intelligent systems along with an increasing ability to analyse faster and with less error margin vast amounts of data, do you believe the process will get much more automated in the future?
	Human Resources capabilities (Rashwan & Alhelou, 2020)	Do you think Intelligent Systems have positive effects on enhancing and developing the quality of an auditor's professional performance?
Competitive advantages of IS in auditing	Pattern Learning Skills (Leaver *et al.*, 2020)	Did you know that Intelligent System learns from the facts it is given and seeks the best solutions to complicated problems?
	Prediction Capabilities (Leaver *et al.*, 2020)	An Intelligent System can predict future trends by learning from the data it is supplied.
	Interconnectivity (Baldwin *et al.*,	Do you think intelligent systems among themselves may complete highly complex tasks?

	2006)	
	Efficient Data Analysis (Cao *et al.*, 2015)	Do you agree that an intelligent system can analyse large volumes of data and generate reports with the most effective uses for each user?
	Efficient Data Processing (Cao *et al.*, 2015)	Do you agree that Intelligent Systems may pre-process data and provide simplified information to auditors?
	Incorrect Disclosure (Gee & Button, 2019)	Do you believe that Intelligent Systems can prevent financial statement false disclosure?

Author´s Elaboration

Table 5 – Research Question 2 & 3, Indicators and Questions

Research Questions	Indicator	Questionnaire Questions
Main boundaries of IS in auditing	Complexity (Bolander, 2019)	Do you have concerns about technical issues raised when humans are replaced by Intelligent Systems in decision making in general?
	Trust In IS (Bolander, 2019)	Do you believe some human tasks can be performed by Intelligent systems and are capable of being beneficial by saving human resources and resulting in better solutions and conclusions?
Competitive advantages of IS in helping the detection of financial fraud	Fraud Prediction (Albrecht *et al.*, 2015; Hashim *et al.*, 2020)	Do you believe Intelligent Systems are a crucial element of fraud prevention and prediction?
	Motivation Prediction (Free & Murphy, 2015b)	Do you think anyone in the organisation could have the motivation to commit fraud, and could IS aid in the detection of fraud?
	Conflicts Of Interest (Hollow, 2014)	Do you think financial pressures play a hugely significant role in motivating employees and managers to commit fraudulent offences at work?
		Do you think the nature of these financial pressures appears to differ significantly depending on what role the offender occupies?
	Fraud Risk Assessment (Knežević *et al.*, 2019)	To what extent has the company you work for created a continuous procedure for identifying serious fraud threats that it faces regularly?

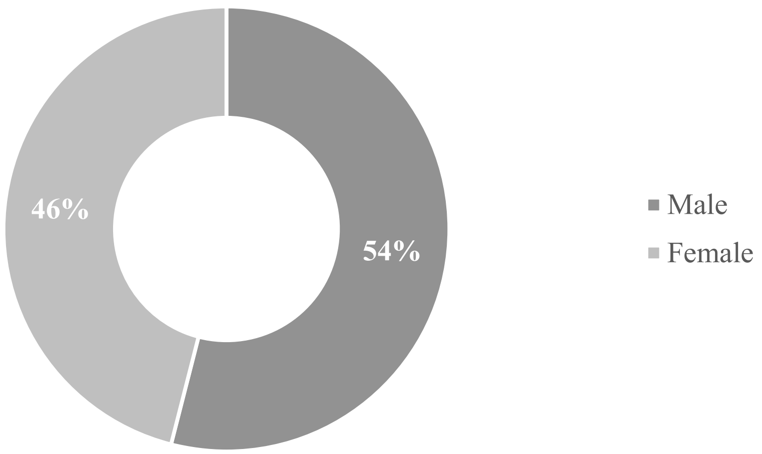
Author´s Elaboration

4.2. Sample Characterisation

Personal information of every respondent was asked at the end of each questionnaire, regarding Gender, Age, Education, Work Background and years of experience in work. The surveys are fully anonymous, and this information is helpful to understand if the samples are sufficiently heterogeneous for the results to be valid.

The presented sample includes 105 persons. Regarding the gender distribution, 54% were male, and 46% were female. No respondent chose the option "Other". The following figure shows the gender distribution:

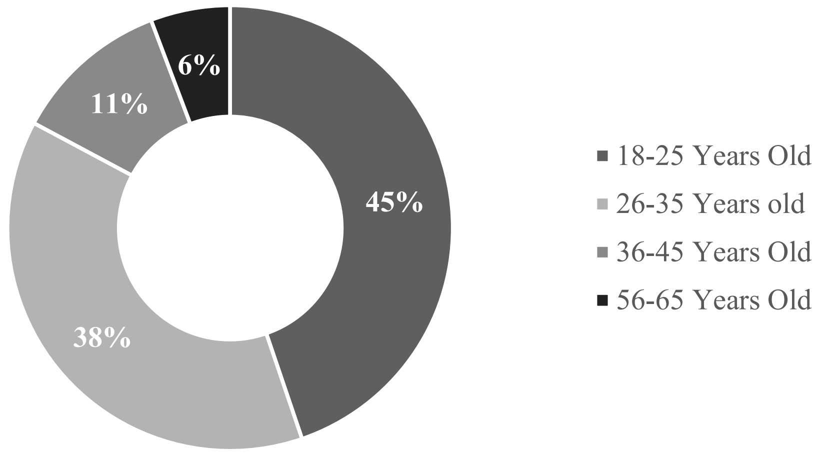
Figure 4 – Survey Gender Distribution



Author´s Elaboration

Regarding the respondent's age, 45% were "Between 18 and 25", 38% were "Between 26 and 35", 11% were "Between 36 and 45", and 6% were "Between 56 and 65". The following figure shows the age distribution:

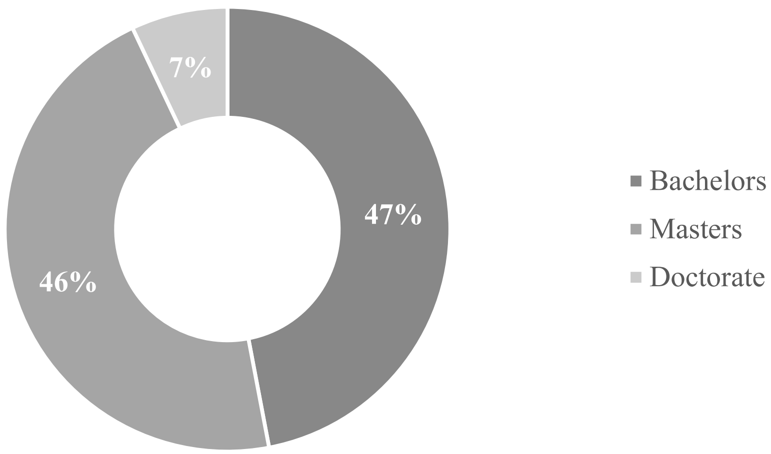
Figure 5 – Survey Age Distribution



Author´s Elaboration

Regarding education, 47% had a Bachelor´s Degree, 46% had a Master's Degree, and 7% had a PhD. The following figure shows the educational distribution:

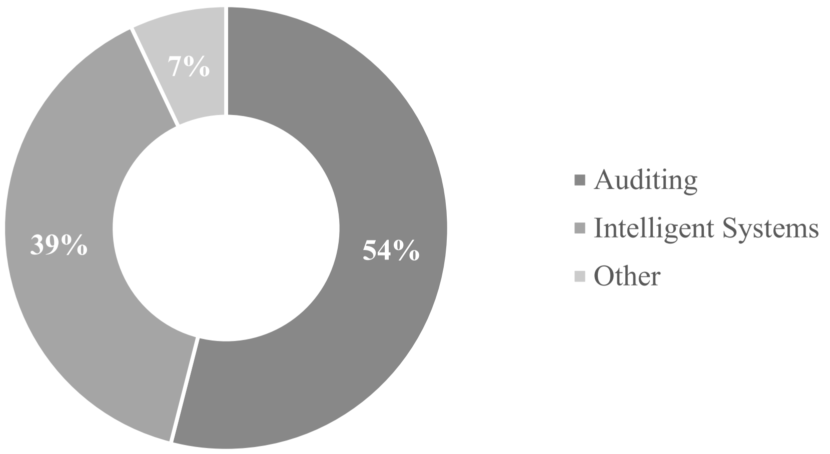
Figure 6 – Survey Educational Distribution



Author´s Elaboration

Regarding the previous work experience, 54% had a background in Auditing, 39% had experience in Intelligent Systems and 7% have other backgrounds. The following figure shows the work background:

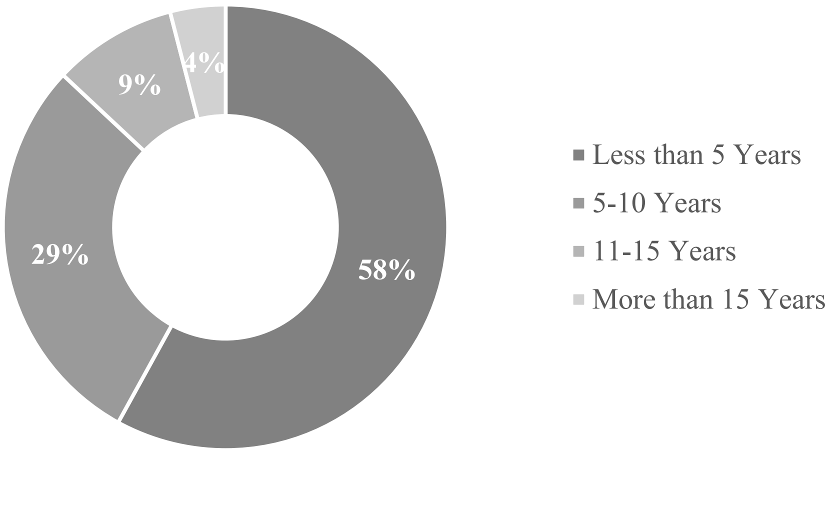
Figure 7 – Survey Work Experience Distribution



Author´s Elaboration

Regarding the previous work experience, we also questioned their years of experience. 54% had a background in auditing, 39% had experience in Intelligent Systems, and 7% had other backgrounds. The following figure shows the years of experience:

Figure 8 – Survey Work Years of Experience Distribution



Author´s Elaboration

5. Result Presentation & Discussion

5.1. RQ1: Possibility of implementing intelligent systems in financial auditing?

5.1.1. Result Presentation

For the online survey, a 7-point Likert Scale was used. We used structural equation modelling (SEM) to test our conceptual model. More specifically, we used partial least squares (PLS), which is a variance-based structural equation modelling technique, using SmartPLS 3 software (Ringle et al., 2015). The analyses and interpretation of the results followed a two-stage approach. We first evaluated the reliability and validity of the measurement model and then assessed the structural model. To assess the quality of the measurement model, we examined the individual indicators of reliability, convergent validity, internal consistency reliability, and discriminant validity (Hair et al., 2017). The results showed that the standardised factor loadings of all items were above 0.6 and were all significant at $p < 0.05$, which provided evidence for the individual indicator reliability (Hair et al., 2017). Internal consistency reliability was confirmed because all the constructs Cronbach alphas and composite reliability (CR) values surpassed the cut-off of 0.7 (Hair et al., 2017).

For three crucial reasons, convergent validity was also proven. To begin, all elements loaded favourably and significantly on their respective structures, as previously stated. Second, the CR values for all constructions were more than 0.70. Third, the extracted average variance (AVE) for all constructs surpassed the 0.50 criterion (Bagozzi & Yi, 1988). Two methods were used to test discriminant validity. We started with the Fornell and Larcker criteria. This criterion demands that a construct's square root of AVE (given in bold in Table 6) be more significant than its most considerable correlation with any other construct (Fornell & Larcker, 1981). This requirement is also met for all constructions, as shown in the table. Second, the heterotrait-monotrait ratio (HTMT) criteria were applied (Hair et al., 2017; Henseler et al., 2015). All HTMT ratios are below the more conservative threshold value of 0.85 (Hair et al., 2017; Henseler et al., 2015), as shown in Table 6.

Table 6 – Composite Reliability, Average Variance Extracted, Correlations, and Discriminant Validity Checks

	α	CR	AVE	1	2	3	4
Competitive advantages of IS in auditing	0.898	0.925	0.712	**0.844**	0.8	0.66	0.64
Implementing intelligent systems in auditing	1	1	1	0.804	**1**	0.67	0.65
Main characteristics of IS in auditing	1	1	1	0.656	0.67	**1**	0.55
Main motivations of IS in auditing	0.852	0.893	0.626	0.641	0.65	0.55	**0.791**

Note: a-Cronbach Alpha; CR-Composite Reliability; AVE-Average Variance Extracted; Blue-Square roots of AVE; Below diagonal elements-correlations between the constructs; Above diagonal elements-HTMT ratios.

Author´s Elaboration

They contribute to the evidence that discriminant validity exists. The sign, magnitude, and significance of the structural path coefficients were used to evaluate the structural model, as well as the magnitude of R2 values for each endogenous variable as a measure of the model's predictive accuracy and the Stone Stone-Q2 Geisser's values as a measure of the model's predictive relevance (Hair et al., 2017). Before analysing the structural model, we examined for collinearity (Hair et al., 2017). The VIF values varied from 1 to 1.15, falling short of the suggested critical value of 5. (Hair et al., 2017). There was no collinearity based on these results. The endogenous variable of deploying intelligent systems in auditing has an R2 coefficient of determination of 67.7%. This number exceeded the ten per cent barrier (Falk & Miller, 1992). The endogenous variable's Q2 value was 0.36, which was above zero, indicating that the model was predictively relevant. To assess the significance of the parameter estimations, we utilised bootstrapping with 5,000 subsamples (Hair et al., 2017).

Table 7 – Structural Model Assessment

	Path Coefficient	Standard Errors	T Statistics	P Values
Main characteristics of IS in auditing -> Implementing intelligent systems in auditing	0.208	0.103	2.019	0.044
Main motivations of IS in auditing -> Implementing intelligent systems in auditing	0.178	0.084	2.124	0.034
Competitive advantages of IS in auditing -> Implementing intelligent systems in auditing	0.553	0.115	4.821	00

Author´s Elaboration

The results from the table show that the main characteristics of IS in auditing IS have a significant positive effect on implementing intelligent systems in auditing ($\beta=0.208$, $p<0.044$), supporting hypothesis H1. The results also show that the main motivations of IS in auditing have a significant positive effect on implementing intelligent systems in auditing (β=0.178, p<0.034), supporting hypothesis H2. Finally, results show that the competitive advantages of IS in auditing have a significant positive effect on implementing intelligent systems in auditing (β=0.553, p<00), supporting hypotheses H3 – Table 7.

5.1.2. Result Discussion

In this section, the results of the empirical data regarding research question 1 are critically compared with the findings explored throughout the Literature Review Chapter. The conceptual model presented in this section is intended to understand the impact intelligent systems can have on auditing. As so, both auditors and intelligent systems professionals have been enquired, ultimately aiming to understand their perception regarding the impact of three main categories which were based on the Literature Review conducted for the dissertation: Main characteristics (Rashwan & Alhelou, 2020; Richins et al., 2017), main motivations (Abdel-Khalik, 1993; Abdolmohammadi, 1987; Floridi, 2019; Gepp et al., 2018) and competitive advantages (Baldwin et al., 2006; Cao et al., 2015; Gee & Button, 2019; Leaver et al., 2020). These categories were latent variables in our model and were tested using SmartPLS 3 (Ringle et al., 2015). The validity of the model is shown in the previous section.

Several indicators were used for each variable. Regarding main motivations, the indicators were Knowledge of Concepts (Abdel-Khalik, 1993), Willingness to Use IS (Abdolmohammadi, 1987), Implementation Interest (Floridi, 2019) and Setting Direction (Gepp et al., 2018). Concerning main characteristics, the indicators were Transparency (Richins et al., 2017), Procedure Modification (Richins et al., 2017) and Human Resources capabilities (Rashwan & Alhelou, 2020). About competitive advantages, the indicators were Pattern Learning Skills (Leaver et al., 2020), Prediction Capabilities (Leaver et al., 2020), Interconnectivity (Baldwin et al., 2006), Efficient Data Analysis (Cao et al., 2015), Efficient Data Processing (Cao et al., 2015) and Incorrect Disclosure (Gee & Button, 2019).

Although having created the model with its variables and indicators, two other variables were added alongside the model and asked in the survey. These variables were the main boundaries of IS in auditing and the competitive advantages of IS in helping the detection of financial fraud. Regarding main boundaries, the indicators were Complexity (Bolander, 2019) and Trust In IS (Bolander, 2019). Regarding competitive advantages of IS in helping the detection of financial fraud, the indicators were Fraud Prediction (Albrecht et al., 2015; Hashim et al., 2020), Motivation Prediction (Free & Murphy, 2015), Conflicts Of Interest (Hollow, 2014) and Fraud Risk Assessment (Knežević et al., 2019). These additional questions allowed us to understand the boundaries better impact the possibility of implementing intelligent systems in financial auditing and competitive advantages in terms of fraud detection impact.

After identifying the main factors that may contribute to the increased value of intelligent systems implementation in auditing, the previously formed hypotheses were tested. The results supported all of the direct effects presented in our model.

We start by showing that the Main characteristics of IS in auditing positively influence the implementation of intelligent systems in auditing, thus confirming hypothesis H1. This is in line with our literature, which showed that the characteristics are essential in its development and acceptance (Rashwan & Alhelou, 2020; Richins et al., 2017).

Following, we can see that the main motivations of IS in auditing positively influence the implementation of intelligent systems in auditing, therefore confirming hypothesis H2. This is in line with our literature, which displayed that the characteristics are imperative in its progress (Abdel-Khalik, 1993; Abdolmohammadi, 1987; Floridi, 2019; Gepp et al., 2018).

Succeeding, we can get that the competitive advantages of IS in auditing positively impact the implementation of intelligent systems in auditing, consequently confirming hypothesis H3. This is in line with our literature, which exhibited that appearances are vital in its development (Abdel-Khalik, 1993; Abdolmohammadi, 1987; Floridi, 2019; Gepp et al., 2018).

5.2. RQ2: Do IS-related boundaries positively impact the possibility of implementing intelligent systems in financial auditing?

5.2.1. Result Presentation

Equally to the previous research question analysis, we also used a 7-point Likert Scale on the online survey. To analyse the two indicators, complexity and trust in intelligent systems, for the research question, "Do IS-related boundaries positively impact the possibility of implementing intelligent systems in financial auditing?" I used Microsoft Excel for Microsoft 365 MSO (16.0.14326.20850) software.

Table 8 – RQ2 Descriptive Statistics Results

	Complexity			Trust In IS		
	Auditing	Intelligent Systems	Sum	Auditing	Intelligent Systems	Sum
Mean	4.86	3.50	4.29	5.83	6.33	6.04
Median	5	3.50	4	6	7	6
Mode	5	1	3	6	7	6
Standart Deviation	1.46	2.22	1.78	0.88	1.11	0.98
Minimum	2	1	1	4	4	4
Maximum	7	6	7	7	7	7

Author´s Elaboration

The data from the survey and regarding the above indicators were evaluated on a scale from 1 (Totally disagree) to 7 (Totally agree). The results show that regarding the complexity, there are still some concerns about technical issues raised when humans are replaced by Intelligent Systems in decision making. The results also show that the trust in intelligent systems and the belief that some human tasks can be performed by Intelligent systems and are capable of being beneficial is much higher.

5.2.2. Result Discussion

The results of the empirical data for research question 2 are critically contrasted with the findings discussed in the Literature Review Chapter in this section. The goal of this section's study topic was to see if the boundaries had a favourable influence on the ability to adopt intelligent systems in financial auditing. As a result, both auditors and intelligent systems specialists were questioned to learn about their perspectives on the influence of two key indicators: complexity (Bolander, 2019) and trust in IS (Bolander, 2019).

These additional questions let us better understand how the boundaries affect the feasibility of adopting intelligent systems in financial audits, as well as competitive advantages in terms of fraud detection.

We begin by demonstrating that there are still specific technical challenges that arise when people are replaced by Intelligent Systems in decision-making processes in general. We can observe from the data that auditors ($\overline{x} = 4.86$; $s = 1.46$) have far more worries than intelligent systems professionals ($\overline{x}$ = 3.50; s = 2.22), which may be explained by scepticism. This somehow contradicts what we have in our literature, which showed that people and organisations might be lured to automate specific critical components of decision-making before even addressing their limits and flaws (Bolander, 2019).

Following is an example of faith in intelligent systems, which demonstrates that intelligent systems can handle some human duties and may be beneficial by saving human resources and resulting in better answers and conclusions. Despite the fact that both industries have high expectations, intelligent systems experts ($\overline{x}$ = 6.33; s = 1.11) have a greater level of confidence than auditors ($\overline{x}$ = 5.83; s = 0.88). This is consistent with our research, which has shown that intelligent systems are better at solving particular tasks and are more efficient at doing so (Bolander, 2019).

5.3. RQ3: Do the CAs (in terms of fraud detection) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?

5.3.1. Result Presentation

We employed a 7-point Likert Scale on the online survey, just like we did with the preliminary research question analysis. I utilised the Microsoft Excel for Microsoft 365 MSO (16.0.14326.20850) program to analyse the four indicators, fraud prediction, motivation prediction, conflicts of interest and fraud risk assessment in intelligent systems, for the study question, "Do the CAs (in terms of fraud detection) of the IS positively impact the possibility of implementing intelligent systems in financial auditing?". – Table 9

Table 9 – RQ3 Descriptive Statistics Results

	Fraud Prediction			**Motivation Prediction**			**Conflicts Of Interest**						**Fraud Risk Assessment**		
	Auditing	Intelligent Systems	Sum	Auditing	Intelligent Systems	Sum	Auditing	Intelligent Systems	Sum	Auditing	Intelligent Systems	Sum	Auditing	Intelligent Systems	Sum
Mean	5.4	6.33	5.79	4.77	6.33	5.42	5.49	6.17	5.77	5.34	5.67	5.47	5.34	4.5	4.98
Median	6	6.5	6	5	6.5	6	6	6	6	6	6	6	6	4	5.16
Mode	6	7	6	5	7	6	6	6	6	6	6	6	6	4	5.16
Standart Deviation	1.46	0.75	1.16	1.61	0.75	1.24	1.18	0.69	0.97	1.22	1.25	1.23	1.33	1.26	1.30
Minimum	2	5	2	2	5	2	2	5	2	2	3	2	1	3	1
Maximum	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7

Author´s Elaboration

The data from the survey and regarding the above indicators were evaluated on a scale from 1 (Totally disagree) to 7 (Totally agree). The results show that regarding fraud prediction, the professionals that were interviewed highly believe that the Intelligent system aid in fraud prediction and prevention. The results also show that regarding the motivation to commit fraud that anyone could have the motivation to commit fraud and that it also suggests that intelligent systems could support the detection of fraud. Regarding the topic of conflicts of interests, two questions were asked. The first one revealed that experts in the field think financial pressures play a hugely significant role in motivating employees and managers to commit fraudulent offences. The second question confirmed that these financial pressures appear to differ significantly depending on what role the offender occupies. Regarding the last question, we can confirm that most of the companies the professionals work for have created a continuous procedure for identifying serious fraud threats that it faces regularly.

5.3.2. Result Discussion

The empirical data for research question 3 is compared and contrasted with the findings reported in this section's Literature Review Chapter. The purpose of this section's research was to examine if intelligent systems competitive advantages in fraud detection had a beneficial influence on the potential of deploying intelligent systems in financial auditing. As a result, auditors and intelligent systems experts were questioned about their perspectives on the influence of four key indicators: fraud prediction (Albrecht et al., 2015; Hashim et al., 2020), motivation prediction (Free & Murphy, 2015), conflicts of interest (Hollow, 2014), and fraud risk assessment (Kneevi et al., 2019).

The additional questions help us understand how the impact the viability of using intelligent technologies in financial audits, as well as competitive advantages in fraud detection.

We start by proving that both auditors and intelligent systems specialists agree that intelligent systems are an important part of financial auditing fraud prevention and prediction. We can see from the statistics that auditors ($\overline{x} = 5.4$; $s = 1.46$) are less confident than intelligent systems specialists ($\overline{x} = 6.33$; $s = 0.75$), despite the fact that both believe it is a critical component. This is in line with our findings, which suggest that intelligent systems can aid in the detection and prevention of fraud (Albrecht et al., 2015; Hashim et al., 2020).

Following this, we may deduce from the findings that anybody in the organisation could be motivated to commit fraud, and while auditors ($\overline{x} = 4.77$; $s = 1.61$) are sceptical, intelligent systems specialists ($\overline{x} = 6.33$; $s = 0.75$) are sure that intelligent systems can help identify fraud.

This is consistent with our research, which shows that management and audit firms have a new challenge in sharpening their fraud risk diagnostic tools (Free & Murphy, 2015).

Financial pressures, according to auditors ($\overline{x} = 5.49$; $s = 1.18$) and intelligent systems experts ($\overline{x} = 6.17$; $s = 0.69$), play a key role in driving employees and management to perpetrate workplace fraud. This is consistent with our findings, which show that financial pressures play a significant role in motivating employees and managers to commit fraud at work, as with other types of white-collar crimes. However, the literature goes on to say that those in lower positions are motivated by personal pressures in general, whereas more senior management offenders are motivated by professional financial considerations (Hollow, 2014).

We may infer that the nature of these financial demands appears to fluctuate greatly depending on what function the offender performs, according to auditors ($\overline{x} = 5.34$; $s = 1.22$) and intelligent systems professionals ($\overline{x} = 5.67$; $s = 1.25$). This is congruent with our research, which shows that the nature of these financial demands tends to vary greatly depending on the offender's job (Hollow, 2014).

In addition, to gain a better understanding of the current state of Portugal's procedure for identifying serious fraud threats that it faces regularly, we asked professionals how far their companies have created a continuous procedure for identifying serious fraud threats that it faces regularly, and we found that auditing firms ($\overline{x} = 5.34$; $s = 1.33$) have far more procedures in place than firms that work with intelligent systems ($\overline{x} = 4.5$; $s = 1.26$).

6. Conclusion, Limitations and Suggestions

6.1. Conclusion

In today's digital world, more and more intelligent technologies are being introduced to assist and enhance a variety of jobs. The primary goal of this dissertation was to learn how intelligent systems and financial auditing are linked and how the first may be utilised to enhance the second. Because financial auditing is a profession that requires a lot of repeated duties and standardised procedures, intelligent systems might readily optimise it. Following the examination of the literature review and the responses to the research questions, some final considerations were made that, in some ways, allowing for a deeper investigation of the suggested subject. Based on the results of the survey conducted, it is clear that intelligent systems will have a significant influence on financial auditing. Financial auditing auditors can benefit from intelligent systems in a variety of jobs and processes that they do regularly.

In the studied sample that consists of employees that work for Portuguese companies or companies based in Portugal, there is still a long way to go in implementing intelligent systems to aid the work and to improve their continuous procedures to identify serious fraud threats.

Most auditors and specialists in IS agree that Artificial Intelligence, the Internet of Things and Big Data can bring value to financial auditors' procedures after analysing the results of the study, and that goes along with the findings of Richins et al. (2017). However, they are still some challenges, technical challenges that emerge when intelligent systems replace individuals in decision-making processes in general (Bolander, 2019).

When questioned about the essential benefits, the experts indicated that the increased efficiency and productivity resulting from automation is a significant benefit. Additionally, cost and time optimisation are also considered essential benefits. These benefits are mutually beneficial since increased workplace efficiency and productivity lead to improved time management and cost reduction in the long run.

Given the advantages, the large percentage of respondents to the questionnaire say they are willing to delegate tasks to intelligent systems increasingly but will not fully delegate all tasks to intelligent systems because of the lack of confidence in the systems as these systems are might still be a little shadowy, and it is critical to be able to justify the decision made. The path that the author believes will better suit initially will be a collaborative effort between humans and these systems.

By analysing the findings, it is also feasible to conclude that these technologies will revolutionise the auditing profession; these findings are consistent with Brown-Liburd et al.

(2015), Cao et al. (2015) and Earley (2015). Most of the auditing and some intelligent systems experts believe it is critical to begin including artificial intelligence, internet of things and big data expertise as new required skills for this career right now. These experts will be able to adapt and become more beneficial to the firm if they update their present abilities since they will have all of the essential talents to deal with the developing technologies of the future.

Additionally, as stated previously, all and every employee might be a potential threat, although the motives might differ, of committing financial fraud, the intelligent systems could be an asset in supporting the prevention and prediction of the finances.

Moreover, keep in mind that intelligent systems are still in their early stages of research. Not only are these technologies projected to develop in the following years, but it is also likely to become even more widely utilised, which will influence auditors' perceptions of their capabilities. As a result, intelligent systems will continue to significantly influence the field, resulting in new research and opportunities.

6.2. Study limitations

Furthermore, despite the sample size (n=105) in the initial survey, the study has a disadvantage in that it utilised a convenience sample, which limits the capacity to generalise results because the sample is neither representative of a community nor randomly selected (Sampieri, 2014). As a result, results cannot be generalised in terms of external validity since they are not typical of a larger population. It is also worth noting that this is exploratory research that cannot be generalised or representative owing to the study's sample characteristics. Furthermore, this study focused on Portugal's specific environment, which restricts the ability to generalise perception to a larger population.

6.3. Suggestions for future research

I think it would be fascinating to expand the study to other nations to provide a research recommendation. In this approach, it would be feasible to determine if people's attitudes on the themes under discussion are consistent across nations and cultures. Research including interviews of both experts, IS professionals, and auditing professionals would be beneficial to go more into this topic. It could also be interesting to investigate the feasibility of applying AI in auditing using alternative, independent variables than those employed in this study to determine which factors have the most impact on the likelihood of successful implementation. Furthermore, based on the findings of this study, it is clear that big data, artificial intelligence and the internet of things will have an impact on several auditing processes, so it will be exciting to see how these technologies affect these procedures in practice in the medium/long term by applying these technologies to the auditing area in a company or studying a company that has already implemented them.

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