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Master of Science Thesis

The role of artificial intelligence in internal audit procedures

A research paper on the relation between internal control weaknesses and the use of artificial intelligence in internal audit procedures for US-listed companies.

Supervisor:

Mert Erinc

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Abstract

This thesis examines the relationship between the use of artificial intelligence (AI) and the success of internal control over financial reporting for US-listed companies. Based on the existing theory, we see AI as an advanced tool that can contribute to detecting internal control weaknesses (ICW) in internal audit procedures. Theory shows that there has been quite a lot of research on internal control and ICW. However, little to no research exists on how AI can impact internal audit procedures and ICW. This is why we wanted to investigate and aim to answer the following research question: *Is it less likely for a firm to have internal control weaknesses when artificial intelligence is integrated into the internal audit procedures of the company?* We predicted a significant relationship between the use of AI and ICW. We use archival data to conduct a univariate and multivariate test consisting of both logistic and ordinary least squares regression models. Our findings provide some empirical evidence that there is a weak significant relationship between the use of AI and the number of weaknesses, meaning that the use of AI is associated with a lower number of weaknesses.

1.0 Introduction

Artificial intelligence (AI) is continuously developed and adopted in modern businesses and professions' technical and managerial operations, including auditing (Kroll, 2021). We are currently experiencing the importance of technologies with the availability of platforms such as Chat GPT. Previous research has shown that AI and machine learning have a remarkable potential to help decision-making, as humans alone cannot analyse the amount of data available. Technologies such as AI can contribute to ruling out intentional and unintentional human errors (Omoteso, 2012). Since internal auditors are under increased pressure to become more efficient and add value to their company, the field is a prime target for automation (Seethamraju & Hecimovic, 2022). It is anticipated that as much as 30% of financial audits will be performed using AI by 2025 (World Economic Forum (WEF), 2015, as cited in Seethamraju & Hecimovic, 2022). It is, therefore, essential to understand how big of an impact AI has on detecting internal control weaknesses (ICW) when used in internal audits.

Artificial intelligence can be defined as "The science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable" (McCarthy, 2007). By recognising patterns, elucidating, and learning by using reasoning, AI enables us to solve complex business problems (Zhang et al., 2023). There have been identified some possible drawbacks of adopting AI-based systems, such as the considerable cost of building, updating, and maintaining systems (Pieptea & Anderson, 1987); the inhibition of developing professional judgement skills (Dillard & Yuthas, 2001); and the risk of the tools being transferred to competitors. Additionally, the possibility of the tools being used against the auditor in a court of law for having over-relied on the evidence of decision aids (Omoteso, 2012; Abdolmohammadi & Usoff, 2001). With the rapid accessibility of AI ethical dilemmas arise. However, the ethical impact of using AI may only be observed long-term (Granlund & Malmi, 2002, as cited in Zhang et al., 2023).

The internal audit department's role includes providing an objective source of information regarding risk, control environment, operational effectiveness, and compliance to the organisation's governing bodies (Clarke, 2022). The goal is to identify weaknesses within these four administrative areas so that they can be improved to prevent any harm to the organisation or its stakeholders (Clarke, 2022). This is done by reviewing internal systems and processes with an unbiased and independent view (Clarke, 2022). Internal audits play a critical role as it is required by the Sarbanes-Oxley Act of 2002 that a public company's internal controls need to be documented and reviewed as a part of its external audit (Tuovila, 2022b). Technologies such as AI will affect all stages of auditing, such as audit planning, performing client risk assessment, performing internal control, testing, or gathering evidence (Appelbaum et al., 2017a, pp. 3-4, as cited in Agustí & Orta-Pérez, 2022). Therefore, AI and expert systems may be inevitable in the present-day audit (Dalal, 1999, p.1, as cited in Omoteso, 2012).

In accordance with the COSO original framework, effective internal control is expected to have a positive effect on environmental, social and governance ratings. These are all indicators of corporate sustainability, as it ensures improvements in efficiency and effectiveness in operations and reliable reports. Thus, helping entities achieve essential objectives and are compliant with applicable laws and regulations (COSO, 2013). Internal control should also increase the reliability of reports that firms produce and disclose, helping their stakeholders evaluate and monitor their sustainability more accurately (Koo & Ki, 2020). A *material weakness* in internal control is defined as "a significant deficiency, or combination of significant deficiencies, that results in more than a remote likelihood that a material misstatement of the annual or interim financial statements will not be prevented or detected" (PCAOB, 2004, as cited by Doyle et al., 2007). ICW are more common in firms experiencing financial distress as they may be unable to devote adequate resources to control systems (Albring et al., 2018). Several studies have also found that ICW are associated with higher financing costs and other changes in financing agreements (e.g. Ashbaugh-Skaife et al., 2019; Castello & Wittenberg-Moerman, 2011; Dhaliwal et al., 2011; Kim et al., 2011, as cited in Albring et al., 2018). Although disclosures of material weaknesses are effectively mandatory, and the management must disclose the identified material weakness, individual firms or auditors may apply different materiality standards in deciding what to disclose (Doyle et al., 2007). Donelson et al. (2017) find a strong association between material weaknesses and future fraud revelation. They theorise that this link could be attributable to weak controls, giving managers a greater opportunity to commit fraud or signalling a management characteristic that does not emphasise reporting quality and integrity.

This thesis studies the relationship between ICW and the use of AI in internal audit procedures for US-listed companies. In addition, the paper will address relevant issues associated with the two topics. We conduct the research by collecting necessary data and running regression analyses to examine whether the use of AI in internal audit procedures contributes to fewer ICW. Based on existing theory, we predicted a significant relationship between the use of AI and ICW.

The research paper is organised as follows: The section “Theoretical foundations” provides a sufficient theory on the status of research in the area as of June 2023. It covers relevant definitions and presents existing literature on the topic. “Research question and hypothesis” will further elaborate on the research question and describe the motivation behind the hypothesis. The “Methodology” section describes our chosen methodology for the research. Under “Results”, we present our findings before we discuss them further under the “Discussion” section. In addition to discussing this paper's contributions and limitations. Finally, we summarise and conclude this thesis in the “Conclusion” section.

2.0 Theoretical foundations

In the following chapter, existing research, and theory relevant to this study will be introduced. First, we will briefly introduce the literature on AI and machine learning. Further, research on AI in connection with internal audit procedures and ICW will be presented. Finally, a summary of key findings in recent literature will provide context for our research.

2.1 Artificial intelligence and machine learning

Artificial intelligence can be defined as "The science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable" (McCarthy, 2007). According to Hilb (2020), AI is technology in the making, as it is becoming rapidly more advanced, sophisticated, and accessible (ICAEW IT Faculty, 2018). AI is not a new concept. However, rather than imposing a top-down set of rules, more recent successes in AI use a bottom-up approach and learn rules based on observation of what has happened (ICAEW IT Faculty, 2018). By recognising patterns, elucidating, and learning by using reasoning, AI enables us to solve complex business problems (Zhang et al., 2023). Thus, AI can identify rules and models from historical data and improve the efficiency by analysing complex data under various decision-making scenarios (Sutton et al., 2018, as cited in Zhang et al., 2023). Therefore, AI is a tool that can help reduce automotive tasks, increase quality, produce reliable financial information, and simplify accounting and auditing cases (Brown et al., 1995).

A part of AI and computer science focuses on algorithms and the use of data to imitate how humans learn and gradually improve their accuracy (IBM, N.d. b). *Machine learning* can process large amounts of unstructured and structured data, highlighting weaker and more complex patterns than humans can. It is also highly adaptive and can learn from errors or new cases. Thus, providing a more substantial basis for learning (ICAEW IT Faculty, 2018). Algorithms are trained to make classifications or predictions and uncover critical insights in data mining projects using statistical methods (IBM, n.d. b). On the one hand, not having human biases, machine learning can be far more consistent in its decision-making (ICAEW IT Faculty, 2018). On the other hand, it is critical to maintain professional judgement when using AI to reduce the impact of expert bias on decision-making (Hilb, 2020; Zhang et al., 2023). AI and machine learning are brilliant tools for organisations that aim to take advantage of the increasing amount of available data, as humans alone cannot analyse and extract insight from the volumes of data created today (ICAEW IT Faculty, 2018).

Since AI is becoming rapidly more accessible, ethical dilemmas arise, and it is relevant to ask if AI can be trusted. However, the ethical impact of using AI may only be observed long-term (Granlund & Malmi, 2002, as cited in Zhang et al., 2023). This is due to implementation, the complexity of the design, and the use of AI in managerial accounting systems (Lee et al., 2014). The complexity and subjectivity of management accounting, control and decision-making usually result in many human interventions and interactions with AI. This can lead to ethical issues on competence, accountability, and power over the user (Zhang et al., 2023). Organisations also need to consider all stakeholders' interests and preferences, both explicit and implicit (Rodgers & Gago, 2003, as cited in Zhang et al., 2023). Ethical concerns like how to balance various interests of stakeholders, data security, privacy, misuse of data, accountability, accessibility, benefits and challenges, transparency, and trust in AI are among the most common ethical risks in the development and use of AI in managerial accounting (Zhang et al., 2023).

Humans apply their knowledge to specific situations to make reasoned, quick, and intuitive decisions based on experience in their field. However, our thought process is imperfect and subject to many biases and inconsistencies (ICAEW IT Faculty, 2018; Omoteso, 2012; Hilb, 2020). Human judgement is often just a substitute for a lack of data. However, AI with access to new data sources may replace the need for human judgement in some cases (ICAEW IT Faculty, 2018). Furthermore, accountants who use and control AI in their work could have their behaviours influenced (Guaragai et al., 2017, as cited in Zhang et al., 2023). Their behaviour could increase ethical risks by using AI and should be under control to mitigate bias, unfairness, harm to user autonomy and independence; and poor decisions (Kleindofer et al., 1993; Munoko et al., 2020, as cited in Zhang et al., 2023). At the same time, decisions are based on predictions of possible outcomes. *Prediction* is defined as "The process of filling in the missing information. Prediction takes the information you have, often called "data", and uses it to generate information you do not have" (Agrawal et al. 2018, as cited in Hilb, 2020). Predictions can influence the reliability of financial information. Reliability represents the extent to which the information is unbiased, error-free, and representationally faithful (FASB, 1978). Data quality and -quantity are fundamental for valid predictions (Hilb, 2020). Since data often reflects existing bias and prejudice in society, AI must learn from errors and be controlled by an auditor. While models can potentially eliminate human biases, they can also anchor societal biases (ICAEW IT Faculty, 2018).

These systems aim to assist auditors in making better decisions by handling potential biases and omissions that could have ordinarily occurred in purely manual decision-making processes (Omoteso, 2012). Nevertheless, there have been identified some possible drawbacks of adopting AI-based systems, such as the considerable cost of building, updating and maintaining systems (Pieptea & Anderson, 1987), the inhibition of developing professional judgement skills (Dillard & Yuthas, 2001), and the risk of the tools being transferred to competitors and the possibility of their being used against the auditor in a court of law for having over-relied on the evidence of decision aids (Omoteso, 2012; Abdolmohammadi & Usoff, 2001). In addition, AI may bring extra workload and new challenges to both managerial accountants and managers. Therefore, companies should provide training to help managerial accountants fully understand AI, improve their professional judgement, and strengthen ethics to achieve trustable results (Zhang et al., 2023). Less experienced accountants are likely to over-rely on results from AI, which may impair their professional judgement. They will need help from senior accounting personnel and receive sufficient training (Zhang et al., 2023). Another aspect is accountability, who is liable for the information the AI provides. Who is liable if an error in an algorithm leads to wrong decisions? The user of the algorithm, its developer, or its vendor? What happens if a company develops the algorithm internally? Will there be insurance to cover the risks? (Armour and Eidenmueller, 2019, as cited in Hilb, 2020). These are all questions that need to be addressed in the near future.

There is a natural competition between the human mind and the machine for the efficiency of intelligence; however, they are highly complementary (Hilb, 2020). Executives believe that using AI and other related technologies creates value for their companies (Elbashir et al., 2013, as cited in Zhang et al., 2023). Thus, accounting professionals have increasingly applied AI to identify potential business risks, estimate accounting values, and detect financial errors and fraud (Amani & Fadlalla, 2017; Dai, 2017; Dai & Vasarhelyi, 2020; Ding et al., 2020 as cited in Zhang et al., 2023). As big data continues to expand and grow, the market demand for data scientists will increase (IBM, n.d. b).

Traditionally, auditing is a late adopter of new technology; however, its labour-intensive nature, compliance burden and competitive pressures make it a prime target for automation (Issa et al., 2016, as cited in Seethamraju & Hecimovic, 2022). By using AI, management accountants can employ sophisticated analyses to improve corporate performance measurements (Appelbaum et al., 2017), establish effective management control systems (Warren et al., 2015) and improve the quality of managerial accounting (Chen et al., 2021; Rodgers, 2020, as cited in Zhang et al., 2023).

2.2 Internal audit procedure

An *internal audit* evaluates the company's internal controls, identifies problems, and corrects them before they are discovered in an external audit (Tuovila, 2022b). The company hires an internal auditor and works on behalf of its management teams. Internal audits may occur daily, weekly, monthly, or annually (Tuovila, 2022b). An internal audit department's role includes providing an organisation's governing bodies with an objective source of information regarding risk, control environment, operational effectiveness, and compliance (Clarke, 2022). The goal is to identify weaknesses within these four administrative areas to improve them to prevent any harm to the organisation or its stakeholders (Clarke, 2022). This is done by reviewing internal systems and processes with an unbiased and independent view (Clarke, 2022).

On July 30, 2002, President Bush signed into law the Sarbanes-Oxley Act of 2002, P.L. 107-204, mainly to hold managers legally responsible for the accuracy of their company's financial statements after the WorldCom scandal and the declared bankruptcy of the Enron Corporation (Tuovila, 2022b; CRS, 2002). In this context, internal audits play a critical role as it is required that a public company's internal controls need to be documented and reviewed as a part of its external audit (Tuovila, 2022b). “Section 404 requires the Commission to prescribe rules requiring each annual report to contain an internal control report which shall state the responsibility of management for establishing and maintaining an adequate internal control structure and procedures for financial reporting and an assessment of the effectiveness of the internal control structure and procedures of the issuer for financial reporting” (CRS, 2002). Some have criticised these requirements as it is often expensive to establish and maintain the necessary internal controls for publicly traded companies (Kenton, 2022a).

AI is continuously developed and adopted in the technical and managerial operations of modern businesses and professions, including auditing (Kroll, 2021). New technologies such as AI will affect all stages of auditing, such as audit planning, performing client risk assessment, performing internal control, testing, or gathering evidence (Appelbaum et al., 2017a, pp. 3-4, as cited in Agustí & Orta-Pérez, 2022). AI could help auditors determine where to focus and test, which is not always an easy challenge given the volume of operational and financial information flowing through most organisations (Kroll, 2021). It could also help auditors pinpoint unusual transactions to take a nuanced look at them and provide actionable information that internal auditors can use to mitigate risk (Kroll, 2021). For example, AI can contribute to revealing where unusual sales reversals are occurring within one location’s accounts receivable ledgers at quarter-end so that auditors would know to focus there (Kroll, 2021). As internal auditors are increasingly pressured to boost their value to the company, AI can be a tool to reach this goal. AI can help internal auditors more efficiently identify areas of risk by leveraging algorithms to understand patterns and anomalies within datasets (Kroll, 2021).

As the use of AI becomes increasingly popular within the auditing field, success in their application will require different skills than those taught in business schools. Therefore, it is necessary to update the accounting curriculum (Al-Htaybat et al., 2018; Qasim & Kharbat, 2020, as cited in Agustí & Orta-Pérez, 2022). It will also require professionals to expand their skill set, particularly regarding their competence and understanding of technologies such as AI and machine learning (Moll & Yigitbasioglu, 2019, as cited in Agustí & Orta-Pérez, 2022). AI significantly impacts managerial accounting and provides control and previously unavailable information (Brown et al., 1995). Furthermore, due to an increase in population and the complexity of the nature of transactions, applying audit procedures will increasingly depend on software (Dalal, 1999, p.1, as cited in Omoteso, 2012). Seethamraju & Hecimovic (2022) states that while AI has the potential to improve audit quality and deliver value-adding services to audit clients. Their study concludes that AI adoption requires a review of audit practice considering the perceived lack of control in AI black-box, potentially rendering audit practice even more hidden from view and exposed to increased scrutiny over audit quality. Therefore, AI and expert systems may be inevitable in the present-day audit (Dalal, 1999, p.1, as cited in Omoteso, 2012). However, the influence of AI and machine learning in auditing has not yet been uncovered and works analysing it is still scarce (Agustí & Orta-Pérez, 2022).

2.3 Internal control and internal control weaknesses

The Committee of Sponsoring Organizations of the Treadway Commission (COSO) defines *internal control* as "a process, effected by an entity's board of directors, management, and other personnel, designed to provide reasonable assurance regarding the achievement of objectives relating to operations, reporting, and compliance." The COSO original framework was released in 1992 and is recognised as a leading framework for designing, implementing, and conducting internal control and assessing the effectiveness of internal control (COSO, 2013).

Internal control over financial reporting has been acknowledged as an essential feature of a company for a long time (Kinney et al., 1990; Kinney, 2000, 2001, as cited in Doyle et al., 2007). First, effective internal control is expected to have a positive effect on environmental, social and governance ratings. These are all indicators of corporate sustainability, as they ensure improvements in efficiency and effectiveness in operations, and reliable reports. Thus, helping entities achieve essential objectives and are compliant with applicable laws and regulations

(COSO, 2013). Second internal control increases the reliability of reports that firms produce and disclose, helping their stakeholders evaluate and monitor their sustainability more accurately (Koo & Ki, 2020). However, Doyle et al. (2007) state that a satisfactory internal control requires both financial resources and management time, which may be a low priority for firms concerned about simply staying in business. Therefore, ICW are more likely for firms in financial distress as they may be unable to devote adequate resources to control systems (Albring et al., 2018). Greater use and dependence on technology demand any system of internal control to be agile in adapting to changes in business, operating and regulatory environments (COSO, 2013). Gao et al. (2020) report that internal control influences corporate financing decisions. However, internal control cannot prevent bad judgement, decisions or external events that can cause an organisation to fail to achieve its operational goals. Thus, even an effective internal control system can experience failure (COSO, 2013).

A *material weakness* in internal control is defined as "a significant deficiency, or combination of significant deficiencies, that results in more than a remote likelihood that a material misstatement of the annual or interim financial statements will not be prevented or detected" (PCAOB, 2004, as cited by Doyle et al., 2007). Section 404(a) of the Sarbanes-Oxley Act of 2002 (SOX) requires all publicly traded firms to declare the effectiveness of their internal control over financial reporting. Accelerated filers must also have an audit firm express an opinion on the effectiveness of internal control over financial reporting under Section 404(b) (Albring et al., 2018). Although disclosures of material weaknesses are effectively mandatory, and the management must disclose the identified material weakness, individual firms or auditors may apply different materiality standards in deciding what to disclose (Doyle et al., 2007). Donelson et al. (2017) find a strong association between material weaknesses and future fraud revelation. They theorise that this link could be attributable to weak controls, giving managers a greater opportunity to commit fraud or signalling a management characteristic that does not emphasise reporting quality and integrity. Even the Public Company Accounting Oversight Board, AT Section 501, section 14, describes some limitations to internal control and states that “controls can be circumvented by the collusion of two or more people or management override of internal control”. Furthermore, Askary et al. (2018) argue that a primary reason for ICW is poor corporate governance, where cost-benefit constraints may impact the development, design, implementation, and maintenance of an effective internal control system. Ashbaugh-Skaife et al. (2007) argue that growth is likely to be positively associated with ICW as accounting and information systems may not keep pace with the demands placed on the system. They also find that firms disclosing significant deficiencies typically have more complex operations, recent changes in organisational structure, more accounting risk exposure, and fewer resources to invest in internal control. Doyle et al. (2007) also finds that firms with more serious entity-wide control problems are smaller, younger, and weaker financially. Contrary to the firms with less severe account-specific problems are healthy financially, but have complex, diversified, and rapidly changing operations.

Predicting material weaknesses may be helpful to investors and other financial statement users because these disclosures have adverse economic impacts on disclosing firms (Albring et al., 2018). Hoitash et al. (2008) find that audit fees are higher for firms disclosing material weaknesses in internal control. Cheng et al. (2013) find that firms underinvest/overinvest when they are financially constrained/unconstrained prior to material weakness disclosures. Skaife, Veenman and Wangerin (2013) find that insider trading is more profitable in firms that disclose material weaknesses. Hammersley et al. (2008) find a significantly negative stock price response when disclosing ICW. They also report that the negative stock price response becomes stronger when the ICW are profound, difficult to detect through external audits and ambiguous (Koo & Ki, 2020). Several studies have also found that ICW are associated with higher financing costs and other changes in financing agreements (e.g., Ashbaugh-Skaife et al., 2019; Castello & Wittenberg-Moerman, 2011; Dhaliwal et al., 2011; Kim et al., 2011, as cited in Albring et al., 2018). Cheng et al. (2019) find that a firm is less likely to disclose ICW if one of its audit committee members has been on the board of an internal control weakness firm within the previous three years. This implies that the directors' prior experience with adverse disclosure outside the firm influences the disclosure of ICW (Koo & Ki, 2020). ICW also affects the shareholders' reputation and the top manager. Ye et al. (2013) find a positive association between material weaknesses and the withholding of shareholder votes, implying a reputation penalty to certain directors. Firms with CFOs that lack expertise are more likely to report ICW and are also likely to replace the CFO after reporting the weakness (Chen et al., 2017; Li et al., 2020, as cited in Koo and Ki, 2020).

There has been a lot of research on internal control, the impact of ICW, how the weaknesses impact the company and how they may occur. However, we cannot find research on how significant AI can help uncover ICW.

2.4 Summary

In summary, AI is constantly developing and becoming more accessible. AI is, however, nothing new. In 1995, Brown et al. stated that AI significantly impacts accounting, provides a level of control and previously unavailable information. Previous research has shown that AI and machine learning have a remarkable potential to help decision-making since humans alone cannot analyse the amount of data available. Although AI can help structure more historical data and contribute to a more objective view, it also needs to be able to learn from errors to avoid biases. A key takeaway from the literature is the need for high data quality and availability to get reliable and relevant accounting information. This is crucial for several stakeholders; however, this heavily depends on the internal control system.

To our knowledge, there has been quite a lot of research on internal control and ICW. ICW not only affect a firm's reputation and integrity, but have several economic effects (e.g., Albring et al., 2018; Hoitash et al., 2008; Skaife et al., 2013; Cheng et al., 2013; Hammersley et al., 2008; Koo & Ki, 2020). Since internal auditors are under increased pressure to become more efficient and add value to their company, it is a prime target for automation (Seethamraju & Hecimovic, 2022). Auditors may be liable for not adequately using a modern decision aid, just as they may be liable for basing their judgement exclusively on an expert system to make an incorrect judgement (Ashton, 1990; Sutton et al., 1994, as cited in Omoteso, 2012). It is, therefore, essential to understand how big of an impact AI has on detecting ICW when used in internal audits. However, we cannot find any research on how AI impacts ICW when a firm uses AI as a part of its internal audit procedure.

3.0 Research question and hypothesis

This chapter will further clarify and elaborate on our research question and present our hypothesis. In addition, we will introduce some predictions based on our knowledge of the theory presented in chapter two. This will be the foundation of our research and create an understanding of the goal and motivation behind the thesis.

3.1 Research question

This thesis studies the relationship between ICW and the use of AI in internal audit procedures for US-listed companies. More specifically, we will examine whether using AI in internal audit procedures contributes to fewer ICW. The research question is therefore derived as follows:

Is it less likely for a firm to have internal control weaknesses when artificial intelligence is integrated into the internal audit procedures of the company?

Our motivation and goal for this thesis is to explore the possible relation as little to no research exists on the effects of AI on internal audit and the combination of both AI and ICW. Although the topic is a novel one, we believe our data is sufficient to establish a relationship between use of AI and ICW. We focus solely on ICW as it is an organisational topic requiring more research, especially in combination with use of technology. Many companies experience ICW in the internal or external audit procedures, which is a ubiquitous issue. As technologies such as AI and machine learning are becoming permanent fixtures in more companies, it is intriguing to see whether AI contributes positively to reducing ICW by being a part of the internal audit procedures.

3.2 Hypothesis

Either AI in the internal audit procedure will contribute to fewer ICW, or it will not have an impact. We predict a significant relationship between the use of AI and ICW. Based on the existing theory, we see AI as an advanced tool that can contribute to detecting ICW in the internal audit. Since AI should provide a more objective view of the data, we should find evidence that companies using AI are less likely to experience ICW. We also anticipate discovering that use of AI has increased over the last few years and that most observations will lie within the last few years.

Formally, we pose the following hypothesis in the alternative form:

H_1: Companies with artificial intelligence integrated into the internal audit procedure are less likely to experience internal control weaknesses.

4.0 Methodology

This chapter will describe our methodological approach and how this will be used to answer our research question. This chapter includes our research design, data collection, sample, and an explanation of the different variables used in our regression models.

4.1 Research design

In our research paper, we have used an empirical research design based on secondary data analysis. We collected and used archival data to conduct both a univariate and multivariate test consisting of a logistic regression model and ordinary least squares regressions made in the statistical program STATA. We limited the geographical region of the research paper to the United States as there are substantial geographical differences in technological development and regulations within our topic, and it would be hard to compare different regions. Data gathering was restricted to publication dates between 01.01.2014 and 31.12.2021. This restriction was set as we thought it would be irrelevant including earlier years than 2014 since AI, as we know it, has become more advanced in the last decade. We also wanted to go as far back as 2014 to see the development of AI and get enough variation in our data. We have collected a large number of observations in order to increase the power of our tests.

4.2 Data collection

4.2.1 Dataset 1 - Wharton Research Data Services (WRDS)

We used the Compustat and Audit Analytics section of the Research Data Services by Wharton for our data collection. We chose this specific database for our data collection as we have access through BI, and it is a comprehensive database where we could create a wide range of reliable data models. The data collected from Wharton were collected at the beginning of February.

From Audit Analytics, we extracted the dataset “SOX 404 Internal Controls” from the year 2014 to year 2021. The dataset contains cases of US-listed companies with or without ICW and the specifics of the weakness. The dataset contains information about the year, auditor, range of auditors, company key, name and financial information among other things. We only kept one observation in each firm per year as we did not want duplicate cases.

4.2.3 Dataset 2 - Annual report review

After the data gathering of ICW from Audit Analytics, we needed information on the use of AI in the internal audit procedures of each company. We went systematically through each case from Dataset 1. We used the EDGAR Company Database provided by the U.S. Securities and Exchange Commission to search and find the company name. We were then able to find the annual report for the respective fiscal year for each company. It was necessary to go through each fiscal year to see if the company went from not mentioning AI to mentioning it. We decided it was enough if the words “artificial intelligence” or “AI” were included in the Management Discussion and Analysis (MD&A) section of the annual report to assume that the company in some way uses AI in their internal audit procedures. We made this decision due to time constraints of the thesis. In addition, we identified that information about AI was adequately reported in the annual reports. We figured that as long as the dataset contained enough cases, there would be a visible connection in some way. We created a dataset in Excel where we plotted whether or not each company mentioned “artificial intelligence” or “AI” in their annual report during the respective fiscal year for each case.

4.3 Sample

After we had collected all the data, we merged Dataset 1 and Dataset 2 in STATA. We ended up with a sample of 30 370 cases. A minimum sample size of 500 is necessary for observational studies with a large population that involves logistic regression (Bujang et al., 2018). A larger sample is a better representative of the population and will provide more accurate results, however, to a certain point (Andrade, 2020). Since we included every case where “artificial intelligence” or “AI” was mentioned in the annual reports, the dataset will most likely contain more noise than if we only included the internal control weakness cases where we knew with certainty that the company involved used AI. However, we will elaborate on this further in the discussion section of this paper.

4.4 Variables

4.4.1 Dependent and independent variables

The following variables are used as dependent and independent depending on our tests. In the univariate test, the variable “AI” is the dependent variable, while the variables “icw” and “count_weak” are independent. In the multivariate test, both “icw” and “count_weak” are dependent variables, while “AI” is independent.

The variable “internal control weaknesses (ICW)” is a binary variable that takes on the value one if the internal control is ineffective and ICW exists. The value is zero if the internal control is effective and there is no ICW.

The variable “artificial intelligence (AI)” is a binary variable that takes on the value one if the words “artificial intelligence” or “AI” was mentioned in the annual report of the company and the value zero if the words were not mentioned.

The variable “count weaknesses (count_weak)” has the value of the number of weaknesses the different cases have.

4.4.2 Control variables

We generated some performance- and control variables to establish a causal relationship between the variables of interest, to avoid research bias and to identify common patterns where detailed data may not be much different between various scenarios (Sheikh, 2013). The control variables are also independent and are included in the logistic regression as any other independent variable (Bhandari, 2021).

The control variables and how they are calculated are described below:

- Liquidity

Good internal controls require financial resources, which a company's liquidity can be a good indicator of. This may not be a priority for firms concerned about simply staying in business. (Doyle et al., 2007) Therefore we generated liquidity as a control variable by dividing Total current assets by Total current liabilities:

Liquidity = total current assets / total current liabilities

- Size

The size of a company can be an indicator of whether it can afford AI and the resources available to use AI effectively. Doyle et al. (2007) finds that firms with more serious entity-wide control problems are smaller, younger, and weaker financially, while firms with less severe, account-specific problems are healthy financially but have complex, diversified, and rapidly changing operations. Therefore, we took the natural logarithm of total assets to generate size:

Size = ln (total assets)

- Leverage

Leverage measures the company's level of debt relative to its equity and is a solid indication of whether a business can make good on its financial obligations (Fuchs, 2023). A high leverage ratio means that a company mainly uses debt to finance its assets and operations, and a low ratio will tell us that a company is financially responsible with a steady revenue stream (Fuchs, 2023). Companies with high debt can have invested in costly technologies such as AI or may not afford it. In contrast, companies with a low leverage ratio could potentially have the money to invest in it or already have invested in it because of steady revenue. Leverage was calculated as followed:

Leverage = (total long-term debt + total debt in current liabilities) / total common equity

- Return on assets (ROA)

The return on assets ratio indicates a company's profitability in relation to its total assets (Hargrave, 2022a). It measures how management uses its assets or resources to generate more income (Hargrave, 2022a). AI can be considered a digital, intangible asset under both IFRS and GAAP (IFRS Institute, 2022). Therefore, AI can contribute to generating more income, or it can be used inefficiently and be costly for the company. ROA was calculated as followed:

ROA = income before extraordinary items / total assets

- Operating cash flow (OCF)

Operating cash flow tells us about the cash generated from a company's normal business operations. It indicates whether a company is able to generate sufficient positive cash flow to maintain and grow its operations. A company experiencing insufficient operating cash flow, may require external financing for capital expansion (Tuovila, 2022a). A poor operating cash flow can be a reason for not owning technologies such as AI because the company cannot afford it. Vice versa, it can indicate that a company with a solid operating cash flow can afford such technologies. Operating cash flow is calculated by dividing the net cash flow of operating activities by total assets:

OCF = net cash flow of operating activities / total assets

- Book to market (BM)

The book-to-market ratio identifies undervalued or overvalued securities by taking the book value and dividing it by the market value, which can be used to determine the value of a company (Kenton, 2022b). The book-to-market ratio should be around 1, as a lower ratio would imply that a company can be bought for less than the value of its assets, and a higher ratio would imply that one could overpay (GoCardless, 2020). The book-to-market ratio was calculated as followed:

*BM = total common equity / the absolute value of x (annual price close * common shares outstanding)*

- Foreign

The foreign variable was generated by taking every value of pretax income that is not empty. Pretax income is part of the income subject to taxation and is calculated by taking a company’s total operating expenses and subtracting them from its total revenue (Papaya Global, n.d.).

We then proceeded with a winsorisation of the control variables at a 1/99 percentage. We winsorise the control variables to limit the influence of outliers and abnormal extreme values in the dataset (Hargrave, 2022b).

5.0 Results

In this chapter of our thesis, we will present the empirical findings of the research and highlight essential results before discussing the outcome in Chapter 6. We present statistical observations before analysing the outcome of the different regression models.

5.1 Artificial intelligence

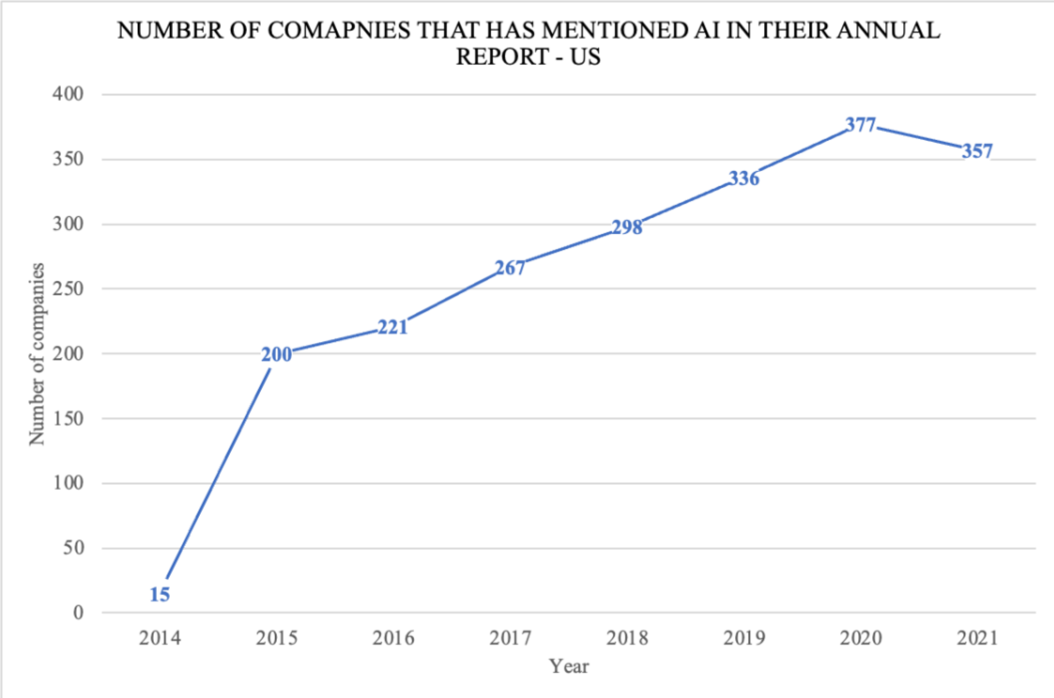
Table 1 shows how many cases among the 29 239 annual reports that mention “artificial intelligence” or “AI”. The table shows that only 7,08% of all the annual reports mention the binary independent variable AI.

Table 1: Companies that have mentioned AI in their annual report from 2014-2021

AI	**Freq.**	**Percent**	**Cum.**
No	27 168	92,92 %	92,92
Yes	2 071	7,08 %	100,00
Total	29 239	100,00 %	

Figure 1 shows the respective companies’ distribution of AI over the fiscal years. From 2014 to 2015, there was a difference of 185 cases. The diagram also shows an increase in companies mentioning AI from 2014 to 2020. However, there is a slight decrease from 2020 to 2021, from 377 to 357 cases. It is also interesting to discover that over 50% of the observations are from the last three years in the year range.

Figure 1: Illustration of US-listed companies that have mentioned AI in their annual report from 2014-2021.



5.2 Internal control weakness (ICW)

Table 2 shows how many cases among the 29 239 in the dataset containing ICW. The table shows that only 3,26% of all cases have ICW.

Table 2: Companies that have reported ICW from 2014-2021.

ICW	Freq.	Percent	Cum.
No	28 285	96,74 %	96,74
Yes	954	3,26 %	100,00
Total	29 239	100,00 %	

Figure 2 shows the distribution of reported cases of ICW over the fiscal years for the respective companies. From 2014 to 2015, there was a difference of 122 cases, with 2014 only having 11 cases of ICW. It is also worth mentioning that the number of reported ICW decreased in 2017 and 2020.

Figure 2: Illustration of US-listed companies that have reported ICW 2014-2021.

5.3 Count weakness

Table 3 illustrates the number of weaknesses the different cases have. The majority of the dataset, 93,62%, has no weaknesses. Approximately 6,2% have between 1 and 8 weaknesses. However, there are some outliers where a couple of firms have reported 33 weaknesses.

Table 3: The frequency of count weaknesses.

Count weakness	**Frequency**	**Percent**
0	13 944	93,62 %
1	425	2,85 %
2	209	1,40 %
3	115	0,77 %
4	72	0,48 %
5	47	0,32 %
6	27	0,18 %
7	19	0,13 %
8	10	0,07 %
9	2	0,01 %
10	4	0,03 %
11	3	0,02 %
12	2	0,01 %
13	5	0,03 %
14	3	0,02 %
15	2	0,01 %
16	1	0,01 %
19	1	0,01 %
20	1	0,01 %
33	2	0,01 %
Total	**14 894**	**100 %**

5.4 Univariate Test

Table 4 shows the univariate test of the mean from the different variables, with AI as the dependent variable. The test shows that all the variables are significant on different levels. Size, Liquidity, Foreign (business), and Book-to-market is significant on a 1% level, count weaknesses and return on assets are significant on a 5% level, and ICW and leverage are significant on a 10% level. From the test, the number of count weaknesses is reduced when the company mentions AI in their annual report, which aligns with hypothesis 1. The binary variable internal control weakness (ICW) shows the opposite. AI in the annual report does not reduce the number of cases; the numbers slightly increase.

Table 4: The univariate test of mean with AI as the dependent variable

	AI			
	No	**Yes**	**Difference**	**p-value**
ICW	0,03	0,04	0,0074978	0,0641*
Count Weaknesses	0,17	0,11	-0,0566498	0,0308**
Size	5,70	6,62	0,9210235	0,0000***
Leverage	0,56	0,68	0,1165786	0,0522*
Liquidity	3,60	2,56	-1,042923	0,0000***
ROA	-0,58	-0,40	0,17357	0,0170**
Foreign	0,39	0,59	0,2001114	0,0000***
BM	0,43	0,32	-0,1133217	0,0003***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.5 Multivariate Tests

Table 5 presents the three separate regressions conducted in this research, consisting of a logit test with ICW as the dependent variable and two Ordinary Least Squares (OLS) regressions, one with ICW as the dependent variable and the other with count weaknesses as the dependent variable.

Table 5: Multivariate tests, three regression models.

VARIABLES	LOGIT icw	OLS icw	OLS count_weak
AI	0.166	0.003	-0.049*
	(0.304)	(0.735)	(0.076)
Size	0.174***	0.015***	0.057**
	(0.000)	(0.000)	(0.041)
Leverage	0.008	0.000	-0.004
	(0.585)	(0.967)	(0.364)
Liquidity	-0.036***	-0.001**	-0.007**
	(0.003)	(0.017)	(0.043)
ROA	0.015	-0.001***	-0.140**
	(0.682)	(0.000)	(0.020)
Foreign	0.577***	0.015	-0.061
	(0.000)	(0.122)	(0.382)
BM	0.032	0.001	-0.009
	(0.393)	(0.444)	(0.499)
Constant	-6.694***	-0.057***	-0.222
	(0.000)	(0.000)	(0.324)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	30 370	29 239	14 543
R-squared	-	0.352	0.576
LR-Test	0,000	-	-

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The regression analysis provides some interesting findings. The OLS regression with count_weak as the dependent variable has shown that AI is significant on a 10% level. However, the regression does not show that AI is as significant as found in the univariate test, where it was significant on a 5% level. This test does illustrate that AI has a weak negative effect on the count weaknesses. The sample size has also decreased from 30 370 and 29 239 observations the half, only 14 543 observations. All three regressions find that the company's size is significant, where the logit regression and the OLS regression with ICW as the dependent variable have a significance of 1%, and 5% on the OLS regression with count weaknesses as the dependent variable. Thus, this research supports (Ashbaugh-Skaife et al., 2007; Doyle et al., 2007) research that size impacts ICW. We cannot state that the leverage of the company has an impact on ICW or the number of weaknesses in a company. As mentioned in section 4.4. Variables, leverage do have an influence/impact on what a company can invest in or borrow to invest in technology to reduce ICW, this research finds no relationship. However, we find that a company's liquidity has a weak significant impact on ICW on a 1% level in the logit regression and has significance on a 5% level for OLS regressions. Thus, liquidity will decrease a company's ICW and the reported weaknesses. The return on assets (ROA) is only significant in the OLS regressions, with a significance level of 1% for the ICW model and 5% for the count weaknesses model. The tests show that return on assets has a negative effect on ICW. The logit regression is the only regression which shows that a company with foreign business has a positive significance on a 1% level with ICW. However, the OLS regressions do not find this significant. None of the regressions finds that the book-to-marked has a significance on the ICW or the number of weaknesses.

The R-squared of the OLS regressions are respectively 0.352 and 0.576. The OLS model with ICW as the dependent variable has 35,2% of the variance in the outcome explained by the independent variables. For the OLS regression, with the count weaknesses as the dependent variable, 57,6% of the variance in the outcome is explained by the independent variables. For reference, a perfect R-squared of 1.00 means that the independent variables explain 100% of the variance in the outcome.

5.6 Summary of results

The univariate and multivariate tests find that AI is significant at 5% and 10%. The univariate test shows that the amount of weaknesses is decreasing with AI as the dependent variable, and the univariate test shows that AI has a weak negative effect on the number of weaknesses reported. Although the number of weaknesses is significantly related to the mention of AI in the annual reports, our study cannot find that AI will influence whether the company has ICW; this will be further addressed in the discussion.

6.0 Discussion

The following chapter will discuss and elaborate on our findings from this research. We will connect and compare the results with existing and previous theories and research and discuss the theoretical contribution of this research. Further, we will discuss the limitations and finally propose ideas and suggestions for future research.

6.1 Results

To test our research question, we hypothesise H_1, which states that companies with AI integrated into the internal audit procedure are less likely to experience ICW.

The results reveal some interesting implications, as both the univariate and multivariate tests show that the mention of AI in the annual reports will decrease the number of weaknesses reported. Although the logit regression and the OLS regression with ICW as the dependent variable do not imply this, the results from the univariate test and the OLS regression with count weakness support hypothesis 1. Although we cannot find evidence that AI in the internal audit procedures is significant for fewer companies reporting on ICW. The results show that AI, size, liabilities and return on assets is significant for the number of weaknesses reported for each firm. Supporting the literature that AI can contribute to management accountants to improve reliability and effectiveness in analyses to improve corporate performance measurement (Appelbaum et al., 2017), establish effective management control systems (Warren et al., 2015), and improve the quality of managerial accounting (Chen et al., 2021; Rodgers, 2020, as cited in Zhang et al., 2023). Thus, AI should help companies reveal and reduce their ICW. This research has provided several interesting findings. Further, we will elaborate on three major factors we believe to have great importance as to why we got the result.

First, as AI is rapidly growing, so is its popularity. In this study, every company that mentioned AI in its annual report was included. Therefore, the data is most likely influenced by companies that use, sell, or deliver services which include AI.

This can include using AI in other areas of the company than in the internal audit. It can also imply that some companies have planned to invest in AI. However, these companies did not reveal which department would implement AI or when. Another assumption is that with the increasing popularity of AI, companies may also use the term as a buzzword as it is trendy, and which may influence potential stakeholders. Still, with such a big sample size, the data reveals a trend and aligns with the literature on how AI can contribute to the audit process. When reading the annual reports, several companies disclosed that they had invested in more software. However, they did not disclose what kind of software they had invested in and were therefore not included. Since only the companies that did mention AI in their annual report were included, we also believe that when a company using AI or selling AI solutions also uses AI in their internal audits. Even though the results are encouraging, the data quality in this research is likely to consist of noise from companies not using artificial intelligence in their internal audits.

Second, there are no other limitations to which companies were included. Therefore, there is a significant variance in the economy, size, and age of the different companies, not to mention the industries they operate in. This research supports Doyle et al. (2007) and Ashbaugh-Skaife et al. (2007) as it found that size, liquidity and return on assets are significant on the count weaknesses. Furthermore, there is significant variance in how advanced the AI technology in each company is and works. As described in theory, newer and more advanced AI should be able to learn from errors, although it needs access to excellent and reliable data (ICAEW IT Faculty, 2018). Younger and smaller companies are limited in the available historical data. This would affect the machine learning aspect of AI, which requires data input. Therefore, these companies could originally be subject to a more primitive and ineffective AI. Hence, a smaller contribution to the internal audit and less reliable uncovering of ICW would be expected.

The third and final factor is that individual firms or auditors may apply different materiality standards in deciding what to disclose (Doyle et al., 2007). Companies with good internal audit procedures where advanced AI is implemented will also deal with the weaknesses when they occur more continuously. However, those companies that do not invest or have the knowledge and skills to put into a system like that will need to address the ICW more periodically. Therefore, companies with AI in the internal audit procedure may not feel the need to disclose every weakness in their annual report if the issue is already dealt with. However, companies that deal with ICW on a more periodic basis may need to deal with more, and perhaps more severe, weaknesses as they “build up” over time without being dealt with. These companies will most likely feel the need to disclose ICW in the annual report.

Even though, to our knowledge, there has not been any research on how significant AI’s role is. This study shows how complex the research topic is and that finding good available data for quantitative research is challenging. The following chapters will present the theoretical contribution, elaborate on the study’s limitations, and present suggestions and ideas for future studies.

6.2 Theoretical contribution

The overall theoretical contribution of this thesis is the study of both AI and ICW. As mentioned, the combination of the two is an unexplored topic, leaving us to be some of the first to try to find a connection between the use of AI in internal audits to reduce the number of ICW.

This paper used a quantitative analysis containing a logistic regression based on two datasets. Although the method chosen has limitations, it can contribute to further research by showing what did and did not work. We used the annual reports for each case of ICW, and searching for AI in the reports was probably not good enough, and the data probably had some noise. Therefore, the methodology used in this paper contributes as the results reveal that AI impacts count weaknesses leading to fewer ICW. We found an increase in the term AI, which can indicate that the term is more popular to include in the annual reports. However, companies might sell or use AI in some way, but they may still need to implement AI in their internal audit procedures. Therefore, this paper also illustrates and contributes to highlighting the importance of data quality and suggesting ideas for future research (as discussed in section 6.4).

This paper has also gathered and summarised several theories and articles discussing both AI, some of its limitations, and benefits but also ethical concerns. We have also addressed how AI can affect internal audit procedures. Based on the theory, we expected to find that AI does help reduce ICW. Hypothesis H_1 sought to find out if it is less likely to experience ICW if AI is a part of the internal audit procedures of a company. Our findings presented in the results section supports our hypothesis. Even though we did not find evidence of whether AI impacts whether a company has ICW or not, it impacts the number of weaknesses reported. Implying that AI helps reduce the number of weaknesses.

We found that size, liquidity and return on assets are significantly related to the amount of weaknesses. Therefore, this research supports Doyle et al. (2007) and Ashbaugh-Skaife (2007) and their research on the size, growth, and resources to invest in internal control systems. However, there needs to be more research on the effects of AI, and more specifically its effects on ICW. On this matter our paper can serve as a starting point for further research.

This research has found some captivating findings, as we found evidence that AI is connected to fewer ICW. Thus, the thesis has highlighted the importance of diving into this theoretical area and that the topic's relevance will only increase by the year. Finally, this paper contributes to the existing literature on AI, internal audit procedures and ICW (e.g., Doyle et al., 2007; Seethamraju & Hecimovic, 2022; Zhang et al., 2023; Askary et al., 2018; Koo & Ki, 2020; Omoteso, 2012; Donelson et al., 2017).

6.3 Limitations

Even though this thesis contributes to the existing literature by illustrating the relationship between AI and internal audit procedures concerning ICW, the study has several limitations. The first limitation of the research is the reliability of dataset 2. To gather information about the use of AI in internal audit procedures of the companies, we searched for the words “artificial intelligence” and “AI” in all the annual reports. If the reports contained the words, it was enough to state that the company had AI in their internal audit procedures. This can give inaccurate data as this might not be true for some companies. Even though the annual report contained the words “artificial intelligence” or “AI”, it could mean that the company is using such technologies in other ways than in the internal audit, or it can be used in an irrelevant sentence. This allows for errors in the data, making it a significant limitation of the research. We made this decision due to time constraints of the thesis. In addition, we identified that information about AI was adequately reported in the annual reports. However, we believe that a sample size of 30 370 cases provides good enough indications that AI would contribute to the internal audit procedures leaving the companies with fewer cases of ICW. Furthermore, several annual reports mentioned the “use of software” or the “investment in new software”. However, they did not disclose what kind of software they had invested in. Thus, the word “software” was not good enough for this research, which could have led us to exclude some relevant cases. However, this paper focuses on AI and not software.

Another limitation is the year range for the study. We chose to look at the years between 2014-2021. Even though AI precedes this, major improvements have been made which makes it more suitable for the task at hand. It would be irrelevant to include earlier years than 2014 since AI as we know it has become more advanced in the last decade. However, we wanted to go as far back as 2014 to see the development of AI over the last decade. Several research articles have also focused on ICW before the financial crisis in 2007-2008 (e.g., Abdolmohammadi & Usoff, 2001; Dillard & Yuthas, 2001; Sutton et al., 1994). It was, therefore, interesting to research the years after the financial crisis. A more extensive range could have given us more observations and more variation in the answers. However, there would also have been more variation in AI's development, effectiveness, and reliability.

Furthermore, we limited the data to be from US-listed companies, as they are more alike as they have the same access to technology and the economy. However, if we had included companies from different countries and continents, there would have been a larger span in technological advancement which would affect the results. If we had included countries with significant economic differences, they would be more likely not to have the resources to invest in AI. There would also have been different laws and regulations for what the companies needed to disclose in their annual reports.

Finally, this study has not considered how advanced variations of AI some companies have implemented. As previous research has shown that although AI can help in decision-making as it should work as an objective part, only focusing on the data and information accessible, if the AI is not as advanced that it can learn from previous errors, the system might be prone for biases based on previous data.

Although this research has several limitations, it provides ideas and inspiration for future research.

6.4 Future research

Given this study's results, several future study proposals are presented. Future research is necessary to comprehend the importance and influence AI has on internal audit procedures and its value in uncovering ICW. Since AI is becoming more and more accessible, it is crucial to understand its benefits and limitations to make accounting procedures more effective.

Several aspects of AI, internal audit and ICW are yet to be investigated. Doyle et al. (2007) stated that there had been a marked increase in the disclosure of material weaknesses following the passage of Sarbanes-Oxley, which opens doors for new studies in the area. It is interesting to ask why there has been an increase in the disclosure of material weaknesses when we find that more and more companies use the term AI in their annual report. Doyle et al. (2007) found that the type of internal control problem is an essential factor when examining determinants and thus should be considered by future research on internal control. ICW vary widely concerning the severity and underlying reason. Therefore, future research should explore whether AI works better at uncovering some ICW than others based on the type of weakness. Seethamraju & Hecimovic (2022) argue that further in-depth case studies and empirical survey studies to understand the extent of AI adoption and its impact on the audit profession are necessary. Zhang et al. (2023) underline the importance of future research conducting interviews on a larger sample size that includes clients of multiple AI vendors in multiple countries. Second, since AI is still rapidly developing, they argue that more ethical issues and challenges could emerge later as new algorithms and approaches are introduced, which is also an area which needs further research. Askary et al.

(2018) found that despite several research articles on the importance of AI in business decision-making, no research shows how AI can improve the quality of accounting information by strengthening the internal control system. Omoteso (2012) found a vacuum in the previous research and recommended, among other things, further research on the benefits of adopting intelligent systems with their costs, assessing the impact of AI on internal control systems design and monitoring, as well as audit committee effectiveness, and implications of using such systems for small and medium audit firms. Further, research on how the audit committee understands and challenges auditors' judgements when artificial intelligent systems underpin such judgements is also necessary. Koo & Ki (2020) argue that the knowledge and skills of the internal control personnel are relevant. However, Koo & Ki suggests that future studies provide more direct evidence concerning the effect of internal control personnel's career experience on the reliability of sustainability management reports. Lastly, Donelson et al. (2017) suggest future research to examine whether auditor expertise or other characteristics mitigate the relation between material weaknesses and the future revelation of financial reporting fraud.

Our study also has some limitations, opening up future research opportunities. This research did find evidence that AI is significant for uncovering ICW. Still, better data collection could provide better results. Therefore, we recommend doing similar research as we have done to improve the quality of the research area. A qualitative research approach will also be necessary to close any gap in this research and see how a few companies have benefited from using AI in their internal audit procedure. It would benefit the research area to understand how different companies use AI and why they might not use it. However, it may be challenging to find companies willing to reveal if and how they have benefited from AI or if it has led to the disclosure of more internal weaknesses. Finally, there is also room to limit the research to different industries to have a smaller sample size and more similar firms in the data selection.

To summarise, several aspects of AI, internal audit and ICW still need further research. Since AI is becoming more accessible and ICW has been shown to not only have economic effects on the company, it is highly relevant to do further research on this topic.

7.0 Conclusion

This study has investigated the relationship between AI and ICW and contributes to the literature on AI in combination with internal audit procedures and ICW (e.g. Doyle et al., 2007; Seethamraju & Hecimovic, 2022; Zhang et al., 2023; Askary et al., 2018; Koo & Ki, 2020; Omoteso, 2012; Donelson et al., 2017). The theory revealed that AI has several benefits and can contribute to a more effective internal audit and thus increase the effectiveness of internal control. Previous research has shown that AI and machine learning have a remarkable potential to help decision-making since humans alone cannot analyse the amount of data available. Although AI can help structure more historical data and contribute to a more objective view, it also needs to be able to learn from errors to avoid biases. Since internal auditors are under increased pressure to become more efficient and add value to their company, it is a prime target for automation (Seethamraju & Hecimovic, 2022). However, the need for high data quality and availability to get reliable and relevant accounting information is essential for AI to be sufficient. This thesis has therefore aimed to answer the research question:

Is it less likely for a firm to have internal control weaknesses when artificial intelligence is integrated into the internal audit procedures of the company?

The data consists of 30 370 cases of reported ICW in US-listed companies between 2014 and 2021. We have consistently reviewed every case and included every company mentioning AI in their annual report. In the results, we start by presenting some general statistics from the dataset, and as suspected, AI has become increasingly popular to include in the annual reports. Further, the study consists of a univariate and multivariate test. We used AI as the dependent variable for the univariate test and found the count of weaknesses to be significant on a 5% level. The binary variable ICW was, in contrast, not significant. Further, we present the multivariate test consisting of one logit regression with ICW as the dependent variable and two OLS regressions with ICW and count weakness as the dependent variables. The last OLS regression, with count weakness as the dependent variable, shows that AI is significant on a 10% level. The univariate test shows that the amount of weaknesses is decreasing with AI as the dependent variable, and the univariate test shows that AI has a weak negative effect on the number of weaknesses reported. Thus, two of the models support hypothesis 1, companies with AI integrated into the internal audit procedure are less likely to experience ICW. The number of weaknesses reported is significantly related to the mention of AI in the annual reports. Still, our study cannot find that AI will influence whether the company has ICW. Furthermore, we have presented several ideas for further research and addressed the limitations of this research. It is necessary to conduct a similar study as this one to increase the quality in the research area, where we recommend increasing the quality of the dataset, as this dataset consists of noise which can have influenced our results.

This research supports Ashbaugh-Skaife et al. (2007) and Doyle et al. (2007) as we also found that size, liquidity and return on assets are significant for the count weaknesses. There is still a considerable amount to investigate concerning AI in combination with internal audit and ICW. Therefore, this study illustrates the importance of data quality, and that data accessibility might be challenging. We have addressed three factors which can have influenced the results. Firstly, the term AI could be a trend, and a buzzword companies use in their annual report to impress potential stakeholders. Second, this study has not considered the different companies or industries. However, we set a geographical limitation. This is necessary as the companies have to report on the effectiveness of their internal control. Still, the companies in this study are very different; they operate in different industries and differ in economy, age, and size. The development, advancement and contribution of the artificial systems implemented vary among companies. Finally, if the AI systems are effective and positively contribute to the internal audit procedures. The ICW could be dealt with as they occur, making it less likely for a company to need to disclose the weaknesses in its annual report. Thus, fewer count weaknesses were reported, as we found. Conclusively, there is a weak significant negative relationship between AI and the number of weaknesses, meaning that AI reduces the number of weaknesses.

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9.0 Appendix - Preliminary Thesis Report

Study programme:

Master in Business with Major in Accounting and Business Control

Title:

How artificial intelligence can contribute to detecting accounting fraud

Name of supervisor:

Mert Erinc

Table of Contents

Executive Summary

This paper is a Preliminary Master Thesis Report for Masters in Business with a Major in Accounting and Business Control at BI Norwegian Business School in Oslo, Norway. The preliminary thesis report is a proposal of research and an introduction to the topic of how Artificial Intelligence can contribute to detect accounting fraud. Financial crime is a wide topic. However, focusing on accounting fraud and business control will help us delineate our topic and make it highly relevant for our major. We have also planned to research whether it is more likely for a firm to get involved in accounting fraud when artificial intelligence is integrated into the internal audit procedures of the company.

First, we cover the introduction to our topic and why we have chosen our preliminary research question:

If and how artificial intelligence can be used to detect accounting fraud, and if it is more likely for a firm to get involved in accounting fraud when artificial intelligence is integrated into the internal audit procedures of the company.

This is followed by a presentation of six articles where we briefly discuss their relevance. The articles cover some of the newest articles on artificial intelligence, auditing, and fraud. Our paper also covers our choice of research design and methodology, where we have chosen an empirical research design with a secondary data analysis. Finally, we have structured a plan for data collection, analysis, and delivery of the final master thesis.

1. Introduction

Despite several efforts to eradicate financial fraud, its persistence adversely affects the economy and society as very large amounts of money are lost to fraud every day (Ryman-Tubb et al., 2018). The continuous development and advancement in technology is becoming greater, and brings both new opportunities in efficiating our demands, while also bringing some challenges. Over the last years there has been a rapid development of Artificial Intelligence technology and AI has already replaced and will continue to replace human labor. Which raises both technical and ethical questions. In the fields of accounting and auditing, Big Data (BD) and Artificial Intelligence (AI), plays an important role in the attempt to prevent and detect accounting fraud. However, the research on the influence of how such technologies can help detect and uncover accounting fraud are still scarce (Agustí & Orta-Pérez, 2022).

1.1 Research question

The preliminary research question for the master thesis is:

If and how artificial intelligence can be used to detect accounting fraud, and if it is more likely for a firm to get involved in accounting fraud when artificial intelligence is integrated into the internal audit procedures of the company.

Our motivation and goal for the master thesis is to identify when AI is used and how AI can be used in order to detect more financial fraud in the accounting industry. In addition, if the data allows, we will inspect if it is more likely for a firm to get involved in accounting fraud when artificial intelligence is integrated into the internal audit procedures. Technology is rapidly changing the world, therefore it will be interesting to use our major to see if and how we can benefit from AI in the fight against accounting fraud.

2. Description of the problem area

2.1 Economic Crime

Economic crime refers to illegal acts committed by an individual or a group of individuals to obtain a financial or professional advantage. The motive is economic gain (Europol, 2022). In a world constantly evolving, are sufficient controls in place for the various new digital technologies? Are enterprises managing risks related to a sustained hybrid work environment? Have organisations implemented the appropriate policies and incentives as they emerge from the pandemic into an uncertain economy? What, exactly, is the fraud risk that companies face today? The low risk and high profits associated with economic crime make it a very attractive activity for organised crime groups. The likelihood that fraud will be detected and prosecuted is low because of the complexity of the investigations required.

2.2 Accounting Fraud

Accounting fraud is the intentional manipulation of financial records or statements (Nickolas & Brock, 2022). It can be done by for example hiding profits or losses by overstating revenue, tax evasion, failing to record expenses and misstating assets and liabilities (Nickolas & Brock, 2022). False financial records will make it impossible to determine the actual stability of a company. Which again can lead to investors paying too much for their investments and gaining less value for their money than believed. In worst cases, fraud can lead to company layoffs or a total collapse of the business. Accounting fraud is a reoccurring problem in society and most companies wish to prevent it from happening to avoid the costly losses it entails. A way of prevention is to implement internal auditing controls to create an anti-fraud work environment. A team of certified internal auditors will be able to detect eventual fraud and to keep financial records accurate. An ERP system could also be a way to enforce segregation of duties, so that no single employee has authorization over all financial data (Beaver, 2022). (Best Accounting Schools, n.d.)

Over the last years, artificial intelligence has emerged as a relatively new and efficient tool for detecting financial fraud (Anand, 2021). With the implementation of more technology to detect accounting fraud such as artificial intelligence, questions arise such as: Is artificial intelligence a more reliable way to prevent accounting fraud than internal auditing controls? Is the use of artificial intelligence in fraud detection suited for specifically accounting fraud? Or, is artificial intelligence too costly for businesses?

2.3 About Artificial Intelligence

"It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable." (McCarthy, 2007).

Chatting with a chatbot in the bank, talking to SIRI and Alexa, spam filters, song recommendations on Spotify are all examples of how we use and interact with AI on a daily basis. These are all examples of "narrow" or "weak" AI, which provide solutions towards a specific area or developed with one specific task in mind. Although these machines may seem highly intelligent, they have far greater limitations than simple human intelligence (PWC Norge, n.d.). However, AI is becoming rapidly more advanced and sophisticated with programs that can write texts and answer all kinds of questions based on very little input. It is therefore relevant to ask if AI can be trusted? In a moral sense, experts emphasize that AI itself is neither good nor bad, but how it is used can lead to both positive and negative outcomes (Caltech Science Exchange, n.d.). Both humans and companies, even industries are eager to increase their use of AI technology to increase efficiency and save time and money. For humans it is natural to resonate, look at the whole picture, recognize sounds and images, solve problems, deal with uncertainty, use knowledge in different settings, use common sense, learn from mistakes and communicate in an understandable way. AI similar to human intelligence, known as artificial general intelligence (AGI), is yet to be achieved (PWC Norge, n.d.). "General" or "strong" AI is so far only seen in movies, such as Interstellar and the Terminator.

3. Literature review

In this preliminary thesis paper we have looked at some articles we believe will be relevant for our final master thesis. We have looked at six papers to start with and we agree that they lay a foundation for understanding the topic and the research on the area. Throughout the researching process we used the "snowballing" method and continuously looked at the number of citations and what kind of journals the papers were published in. Two of the papers are literature reviews to help us get an overview over what has been researched before, their findings and suggestions for further research. All of the papers have either discussed artificial intelligence, accounting and/or financial fraud. Moving forward, we need to be even more specific, and look into regions. However, it will be easier to delineate relevant papers after we have looked at the data. The papers are all published between 2012 and 2023 and it is interesting that the papers we found most relevant have been published in 2022. One of the papers is a bibliometric analysis of fraud in accounting between 1926 and 2019 and represents a large timeframe which helped us get an overview.

The Impact of Artificial Intelligence on Accounting by Zehong Li and Li Zheng.

The article focuses on how to use artificial intelligence to avoid accounting fraud and to generate a positive impact on accounting information quality. The article analyses how artificial intelligence will affect the accounting personnel in the future stating that the basic accounting practitioners are one of the groups that will be affected by artificial intelligence. Traditional accounting personnel will leave a few more complicated tasks to the accounting software to complete, which will greatly improve the working efficiency, reduce the working error, improve the competitiveness of the enterprises, the accounting industry, this will also be conducive to promote the transformation of the accounting industry (Li & Zheng, 2018). With the continuous development of science and technology, artificial intelligence is gradually replacing some parts of the accounting personnel, in this case, the enterprises will gradually reduce the demand for accounting personnel in the accounting department. This article does not however discuss the impact of economic crime due to transitioning to more artificial intelligence in accounting. However, this article sums up some other challenges accountants face due to more artificial intelligence in the accounting industry.

The application of artificial intelligence in auditing: Looking back to the future by Kamil Omoteso.
In this article Omoteso discusses the advancement in computer technology, where most of the large accounting firms have introduced the use of artificial intelligence in making audit judgements as part of their integrated audit systems. The author states that as earlier predicted by Abdolmohammadi (1987) and Bell, Knechel, Payne, and Willingham (1998), ICT devices such as Electronic Data Interchange (EDI), Electronic File Transfer (EFT) and image processing are gradually replacing traditional audit trails thus changing the entire audit process. The article discusses the sustained effort in the development of highly complex artificial intelligence-based systems to assist auditors in making judgements (Abdolmohammadi & Usoff, 2001). The objective of these systems is to assist auditors to make better decisions by taking care of potential biases and omissions that could have ordinarily occurred in purely manual decision making processes (Omoteso, 2012). Nevertheless, there have been identified some possible drawbacks of adopting artificial intelligence-based systems, such as the huge cost of building, updating and maintaining systems (Pieptea & Anderson, 1987), the inhibition of developing professional judgement skills (Yuthas & Dillard, 1996), and the risk of the tools being transferred to competitors and the possibility of their being used against the auditor in a court of law for having over-relied on the evidence of decision aids (Abdolmohammadi & Usoff, 2001).

Financial Fraud Detection Based on Machine Learning: A Systematic Literature Review by Abdulalem Ali, Shukor Abd Razak, Siti Hajar Othman, Taiseer Abdalla Elfadil Eisa, Arafat Al-Dhaqm, Maged Nasser, Tusneem Elhassan, Hashim Elshafie and Abdu Saif.
This literature review has addressed 93 articles, and summarises the most popular machine learning techniques used for detecting financial fraud and the most common types of financial fraud. The article states that support vector machine (SVM) and artificial neural network (ANN) are popular machine learning algorithms used for fraud detection, and credit card fraud is the most popular fraud type addressed using machine learning techniques (Ali et al., 2022). In this paper the auditors have categorised fraudulent activities and discussed credit card fraud, financial statement fraud, insurance fraud, financial cyber fraud and other

financial fraudulent types. Despite that the article addresses several aspects of fraud and machine learning, it does not address fraud directed to auditing. This article is therefore only relevant for understanding how machine learning can help detect different types of financial fraud.

Fraud in accounting and audit research (1926-2019) – a bibliometric analysis by Nicole V. S. Ratzinger-Sakel and Thorben Tiedemann.
The research paper studies the evolution and trends of fraud-related research within the accounting and audit field from 1926 to 2019. They use bibliometrics to explore 260 cases of fraud articles published in leading accounting and auditing journals. The study reveals shifts in theories, frameworks, and research topics that shaped the research field. One of the big findings is that the evolution of fraud research within the accounting and audit discipline is closely linked to developments in the regulatory environment. They also found that over time research began to focus more on financial statement fraud rather than on asset misappropriation. The authors state that the fraud cases studied emphasize that gaining a deeper understanding of fraud remains a crucial part in order to effectively detect and prevent fraud. Unlike most literature, their study provides a large timeframe, but it also has some weaknesses. A bibliometric analysis cannot comprehensively represent why a certain author cites another publication but can provide insight into which publications are cited by others. Also, a time lag exists between the publication of an article and its subsequent citation by others, because research needs sufficient time from development to establishment. Last, their study is limited to the leading, most influential accounting and auditing journals, excluding a lot of research. The authors suggest several promising future research avenues. They suggest that changes in the regulatory framework and their effects on fraud prevention and detection, should be investigated further. They also state that research on emerging markets, including China, has been gaining importance in recent years and that one could try to identify success factors for detecting and preventing fraud in these diverse corporate governance and enforcement regimes. Last, they propose that the field of digitalization and big data could need further research. This is because business processes and the possibilities for fraud are becoming increasingly digital and that tools and capabilities to detect fraud are continuously developing. (Ratzinger-Sakel & Tiedemann, 2022).

Big data and artificial intelligence in the fields of accounting and auditing: a bibliometric analysis by María A. Agustí and Manuel Orta-Pérez.

The research article contains a bibliometric analysis of a sample of 247 articles, with the motive to identify the different research fronts within the emerging topic "Big Data and Artificial Intelligence in the fields of accounting and auditing". The authors see the importance of Big Data and Artificial Intelligence in the fields of accounting and auditing and the lack of research around the influence of these technologies. They use co-word and bibliographic coupling techniques, to expand and extend the knowledge on this research line and to describe the evolution of publications. The paper investigates three main questions: 1. What is the current state of research on AI and BD in the domain of the auditing and accounting fields? 2. What research contexts and topics have been explored in the literature to date? 3. What research lines or themes can future research address? They find that there is a growing interest in the research topic over the last years and that there are publications in different journals. Their analysis shows that the research line is opening up towards a perspective with a greater focus on stakeholders, both internally and externally. In addition, the authors claim new fronts are emerging, such as blockchain. In this sense they state that to be successful in the application of new technologies in accounting and auditing, people will require different skills than those taught in business school. Furthermore, they say that it is necessary to change the way an accountant or auditor is seen. The research contains some limitations. One major limitation on the research front is the predominance of studies with limited practitioner orientation. One other is difficulty in delimiting the research domain which may have led to exclusion of some relevant papers. The authors see promising future research avenues such as the use of machine learning to detect possible frauds, or how Big Data will affect accounting disclosures. (Agustí & Orta-Pérez, 2022)

Fintech in financial reporting and audit for fraud prevention and safeguarding equity investments by Paulina Roszkowska.

The research paper explores cases of audit-related financial fraud and advice on how emerging technologies (such as Artificial Intelligence) can provide solutions. More specifically they look into financial statement fraud and Fintech as a solution. They use a case study of a specific financial scandal/company to document the evidence of audit-related issues in historical financial scandals. They then proceed with a comprehensive literature review to propose technology advancements that can solve identified problems in accounting and auditing. The research shows several emerging technologies such as artificial intelligence solutions effectively can solve various financial reporting and audit-related problems. Jointly, they have a strong potential to enhance the reliability of the information in financial statements and generally change how companies operate. The study findings also provide insights into how the role of an external auditor might evolve in the future (Roszkowska, 2020).

4. Methodology

In our research paper we will use an empirical research design with a secondary data analysis. For parts of the paper, we wish to collect and use derived/compiled data to get quantitative results through a propensity score matching. This applies especially to the part where we want to test if it is more likely for a firm to get involved in accounting fraud when AI is integrated in the internal audit procedures of the company. We aim to collect a fair amount of observations so that the results will be as reliable as possible, while keeping the paper feasible. We will try to limit the data to a certain geographical region (hopefully Norway) if possible as there are huge geographical differences in technological development and regulations within our topic.

In addition, we will also try to conduct a semi-structured interview with a big Norwegian company to gain more of an overall understanding of the topic "Accounting fraud". This applies only if the geographical region gets limited to Norway.

5. Plan of data collection and analysis

After handing in this preliminary thesis report, we will start writing the introduction and the theory part of the thesis. We aim to finish the data collection by February in order to analyse the data as soon as possible. We have asked our supervisor for access to a database we believe we would use for this master thesis. In March and April, we will mostly be writing and would like to get feedback from our supervisor, both orally and in writing. The overall goal of the master thesis is to finish and deliver by May 14th, 2023. This timeline will give us two weeks to finalise the master thesis after receiving the last feedback from our supervisor. This plan is open for change as the final deadline for the master thesis is July 3rd, 2023.

Month	Activity	Start	End
January	Preliminary Thesis Report	01.01.2023	16.01.2023
January	Writing introduction, read and collect relevant articles	16.01.2023	31.01.2023
February	Collecting data and analysing / writing	01.02.2023	28.02.2023
February	Talking to supervisor about the data and our progression, sharing thoughts about the thesis	Week 9	Week 9
March	Writing the main part of the thesis, writing about our findings etc.	01.03.2023	31.03.2023
March	Sending 70% to supervisor		31.03.2023
April	Meeting with supervisor, getting feedback on 70% and addressing further work	Week 15	Week 15
April	Results and conclusions	10.04.2023	30.04.2023
April	Sending 98% to supervisor and getting written feedback.		30.04.2023
May	Finalising and delivery of Master Thesis	01.05.2023	14.05.2023

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