The Role of Data Analytics in Audit Risk Assessment

Hanna Kuusinen & Veera Miettinen
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Supervisor: Professor Thomas Carrington
Faculty of Social Sciences, Business and Economics, and Law
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Writers: Hanna Kuusinen & Veera Miettinen	
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Abstract:

The changing business environment and technical advancements have presented new challenges for the audit industry. Audit clients have adopted data analytics to understand their business and consequently enhance their decision-making. The audit industry is usually a follower when it comes to new techniques on the market, and data analytics is not an exception. Analytical procedures are included in the traditional audit methods, but these procedures differ from the tools that data analytics provides. In the new business environment, data is generated at an accelerating pace in increasingly complex IT systems. Thus, auditors face the problem of verifying this information in a reliable way. Furthermore, this can lead to issues in audit effectivity and quality in the long run. Audit data analytics (ADA) has presented promising characteristics to aid auditors in the new era. ADA provides increased data processing capabilities, effective risk identification, possibilities to test complete populations, and support for auditors' judgments.

The aim of this study is to discover the role of data analytics in audit risk assessment with semi-structured interviews conducted with industry experts from Big Four accounting firms. The focus of the thesis is on how audit data analytics is used in risk assessment and how the use affects the audit process. Parts of grounded theory were used to analyze the empirical material. Thereafter, the results were analyzed through a conceptual framework which was derived from previous research in the field. Thereby, this study contributes to the existing literature with new findings.

This study made findings regarding the practical implementations of ADA and the use of ADA in risk assessment. It was discovered that, for example, general ledger analysis, process mining, and other standardized data analytical tools are used by auditors in the planning phase of an audit. An improved overall understanding of the entity is formed as increased amount of data is processed, and the ADA applications guide auditors in finding the areas of financial statement including the most risk. Consequently, more precise and targeted audit measures are possible, and unnecessary substantive procedures are avoided. Additionally, the advancements in control and process identification were discovered. The effective data analytical assessment of controls and processes is possible for only certain systems, but the importance of effective controls for ADA usage is noted by the interviewed experts. The results agree to some degree with previous research but particularly findings regarding auditing standards contradict the previous research. The thesis contributes to previous research with new practical knowledge within the field.

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Abbreviations

ADA - Audit data analytics. Further discussed in chapter 2.4.

AICPA - Association of International Certified Professional Accountants

Big Four - With Big Four it is referred to the four largest companies providing accounting and professional services. At the moment these are Deloitte, EY, PwC, and KPMG. A large number of public companies are audited by the Big Four accounting firms.

IAASB - International Auditing and Assurance Standards Board. Issues International Standards on Auditing.

ISA - International Standards on Auditing (Issued by IAASB)

PCAOB - Public Company Accounting Oversight Board

1 Introduction

The audit industry is part of the service industry, although it operates under strict conditions enforced by local and international laws, and auditing standards. Even if an audit often takes the form of mandatory procedures, this does not mean that the audit industry can remain unchanged because the demand for the services is constant. Auditors must respond more effectively to the needs arising from the clients' changing business environment to fulfill the requirements defined by regulators and stakeholders. However, the main requirement for auditors is to accumulate reasonable assurance that the audited financial statement is free from material misstatements (Appelbaum, 2016). The business environment in which organizations operate has been changing at an accelerating pace due to technological advancements. These advancements are attractive for organizations since they include several benefits for business processes. Due to the advancements, it is possible to capture and analyze more useful data, automate processes, and make better decisions. At the same time, there is still a high number of auditing clients who are not effectively using the newest technologies to capture the information produced. Additionally, the size of an organization has an impact on the amount of data produced. This creates a demand for different types of knowledge and the application of different tools.

According to Huang, No, Vasarhelyi, and Yan (2022), we live in an age of information explosion, even though it is happening at a different pace within organizations. Appelbaum, Kogan, and Vasarhelyi (2017) recognize the possibilities that big data and complex analytical procedures used by clients provide but emphasize the urgency for the adoption of advanced analytics in auditing. When data and information are discussed, the use of analytics comes into play. Austin, Carpenter, Christ, and Nielson (2021) are of the opinion that data analytics will have a significant effect on the financial reporting environment. Various types of analytics are being developed and implemented in the field of auditing. For auditors, it is critical to understand where organizations stand in the market and the factors affecting their operations. Different industries have specialized needs for auditors, which must be considered when developing new audit procedures. Analytics could provide the means for auditors to succeed better in the new era of big data.

1.1 Problem discussion

The fact that auditors' methods, tools, and procedures have not been updated at the same pace as clients' technological advancements poses a risk to the reliability of the audit. Consequently, the audit risk increases. If clients' financial and non-financial information is not effectively assessed, several concerns will arise. In the past, auditors have been familiar with structured financial information, but the nature of the data provided by clients has been transformed. Audits provide assurance for users of the information, and any deficiencies severely impact the trust placed on this information. Jacky and Sulaiman (2022) highlight how the demands presented by stakeholders have risen with the new technologies. Salijeni, Samsonova-Taddei, and Turley (2018) discovered in their interviews how stakeholders want to learn more about unstructured data, as the tools used by clients are becoming more sophisticated. According to them, the appropriateness of the audit is being questioned as clients implement tools that can handle big data.

The audit industry is highly regulated, which poses additional challenges in adopting new methods. Both laws and standards dictate auditors' work, and how organizations have to provide information. On the one hand, Appelbaum et al. (2017) argue that the lack of discussion regarding the appropriate analytical methods within the current standards hinders the effective use of analytics in auditing. On the other hand, standards require auditors to undertake analytical procedures, but they should do this relying on their own judgment (Appelbaum, Kogan & Vasarhelyi, 2018). Jacky and Sulaiman (2022) discuss the possibility of guidance gathered by the regulators that could be used while the auditing standards are revised. Another cause for the low utilization of data analytics might be the need for legitimacy (De Santis & D'Onza, 2021). By this, De Santis and D'Onza (2021) mean that audit firms should build legitimacy around new methodologies that are implemented. Consequently, the environment is not flexible enough for agile changes and is unable to respond to the transformed needs.

The use of data analytics in auditing leads to additional challenges. The reliability of analytical tools is a relevant concern for clients and auditors. Earley (2015) discusses further challenges with the implementation of data analytics in the field of auditing. Firstly, the adequate skills needed for the use of data analytics differ from the skills auditors have accumulated to date. Thus, it can be questioned whether auditors can take advantage of the techniques data analytics provides. Secondly, the analyzed data may pose challenges, as it might be unavailable to auditors. Data comes in many formats, which makes it challenging to interpret, and the integrity of data might be endangered. Lastly, an expectation gap exists between regulatory requirements and audit information users' expectations.

Hence, data analytics could provide auditors with a new, more efficient, and effective way to analyze data received in client engagements. The audit process is constructed from different phases and the role of analytics differs depending on the phase. This thesis focuses on the use of data analytics in the risk assessment phase. Balios, Kotsilaras, Eriotis, and Vasiliou (2020) argue that data analytics could prevent auditors from making wrong conclusions about clients' operating environments. Moreover, the use of data analytics enables auditors to process more data when conducting the risk assessment, reducing the audit risk. According to Werner, Wiese, and Maas (2021), it may be concluded that "data analyses play a particularly important role for gaining an understanding of the audited entity and for risk assessment" (p.5).

Current methods used by auditors need to be more efficient and effective (Werner et al., 2021). The reliability of the information provided by auditors could be questioned, as the industry has not adopted the latest technological advancements. Primary users of audit information are different stakeholders, and they need assurance that auditors are currently unable to provide. Due to technological advancements, it is evident that the procedures undertaken by auditors could be performed in a manner that responds better to clients' current practices (Appelbaum et al., 2017). However, as audit clients' businesses slowly shift toward more complex structures, tools used for information retrieval become ineffective and unreliable (Werner et al., 2021).

Furthermore, the growing amount of data generated from business operations presents both an opportunity and a challenge (Earley, 2015). It is an opportunity as it describes organizations and business environments more thoroughly, enabling more accurate conclusions (Appelbaum et al., 2017). However, it is also a challenge because the current methods are unable to process all data received from clients (Earley, 2015). Thus, some significant risks might be left undiscovered, which has a direct connection to the reliability of the audit and the audit risk (Rose, Rose, Sanderson & Thibodeau, 2017). In addition, auditing costs will increase if the methods are not updated. Therefore, methods used by auditors should be developed in a direction where they are able to tackle the challenges (IAASB, 2016a).

Wang and Cuthbertson (2015) argue that risk assessment and the evaluation of internal controls are areas where the use of data analytics would be meaningful. Earley (2015) notes that unstructured data is tolerated better in the risk assessment phase than in other phases of the audit process, and this implicates that the use of data analytics is justified. ISA 315 (IAASB, 2019) requires auditors to perform risk assessment procedures to identify and assess risks of material misstatement. Additionally, ISA 300 (IAASB, 2004b) obligates the use of analytical procedures in the planning phase. However, research in this area is scarce (Earley, 2015) and many academic papers are literature reviews without an empirical study. Previous research has concluded that data analytics is often used alongside other more traditional procedures as supplementary evidence due to the unclear guidance of standards (Eilifsen, Kinserdal, Messier & McKee, 2020). Consequently, auditors perform both data analytics and, for instance, sampling on the same set of data. Auditors are working with limited resources and, therefore, do not have time to perform both procedures. Usually, the focus is on the traditional methods, and the analytical procedures are excluded (Eilifsen et al., 2020). Thus, there is a clear need for research regarding the use of data analytics in the planning phase.

1.2 Purpose and research question

The use of data analytics in the audit process remains relatively unknown, and existing research has widely relied on literature review as the primary method to gain more knowledge in this area (Austin et al., 2021; Salijeni et al., 2018). Gepp, Linnenluecke, O'Neill, and Smith (2018) emphasize that it is necessary to bridge the gap between research and practice regarding big data techniques and audit data analytics. They highlight that especially more qualitative research is required in this field. Different applications of data analytics have received too little attention in audit practice, which has led to the fact that the effect of data analytics on the conduct of audits remains unknown (Gepp et al., 2018). Hence, the focus of this study is on how data analytics could enhance the planning phase of external auditing, as previous research has emphasized other areas of the audit. Consequently, the study aims to provide an understanding of the role of data analytics in audit risk assessment, which will be studied with the following research question:

How is data analytics used in audit risk assessment, and what are the impacts of it?

This study aims to answer the research question with a qualitative research method and several industry experts are interviewed to gather the material. The interview results are analyzed through a conceptual framework that includes assumptions derived from the existing literature.

1.3 Limitations

This study has the inherent limitations of a qualitative interview-based research. The study is limited to the data received from eight interviews with several Big Four accounting firms. Therefore, the sampling of the participants must be taken into consideration when generalizing the results. The participants work in Finland, and this could imply that the results showcase the development in audit data analytics on the Finnish market, but the participants work in global firms. Hence, the development of methods is usually done globally and not on the country level. Furthermore, interviews are always subjected to the personal views of the participant and the interviewer. Even the organizations where the participants work, and their previous work history impacts the data gathered from the interviews. The analysis and conclusions are based on the perspectives and opinions of the eight participants interviewed. Thus, all the attributes affecting the use of data analytics in auditing might not be covered in this study. Moreover, the participants may hold positive biases toward the technological advancements in auditing and, thus, see the development as more beneficial for the industry. Despite these facts, new insights are discovered, and the study is able to provide added value to the previous research.

1.4 Structure

The aim of this study has been presented in the introduction and the following sections are structured to fulfill the aim. The second section consists of the background and theory for the subject of this study, and central concepts are introduced. Previous literature is reviewed in section three in order to develop a conceptual framework for the analysis of the empirical results. The methods employed in the collection of empirical material and how this material is further analyzed are critically discussed in section four. In the fifth section, the results of the interviews are unraveled for the reader and the first categorization is conducted. The results are then further analyzed with the help of the conceptual framework in section six. The seventh section concludes the study with findings and future research needs are discussed. Lastly, the Swedish summary of the thesis is presented in section eight.

2 Background and theory

This chapter focuses on background and theory that are relevant to the subject. Definition of audit risk and its components are discussed followed by background regarding risk assessment. The other topics presented are professional judgment, definition of audit data analytics, process mining, and ISA 315.

2.1 Audit risk

ISA 200 (IAASB, 2009a) is an auditing standard that determines the objectives of an auditor and the conducting of an audit in accordance with the standards. The standard has been effective for financial statements after December 15, 2009 (IAASB, 2009a). This standard includes the definition of audit risk, as it guides auditors in their objectives. According to ISA 200 (IAASB, 2009a), audit risk describes the possibility that an auditor gives out an inappropriate audit opinion in a case where the financial statement is materially misstated. In the standard, it is defined that audit risk is reduced to a tolerable level through sufficient and appropriate evidence. Audit risk is described with the help of a model which consists of three components, and audit risk is a function of these components. These are inherent risk, control risk, and detection risk. The risk of material misstatement is formed of inherent risk and control risk since an auditor is unable to impact these. These kinds of misstatements occur due to fraud or error. On the contrary, procedures undertaken by an auditor may be insufficient and leave material misstatements undetected, which is included in detection risk. Audits are risk-based and, thus, it is vital to determine the audit risk at the beginning of the engagement.

Risks of material misstatement are, according to ISA 200 (IAASB, 2009a), at two levels which are the overall financial statement level and assertion level. With material misstatements at the overall financial statement level, it is referred to the financial statement as a whole. With assertion level, it is referred to the information disclosed in the financial statement in accordance with the framework. On the assertion level, the risks of material misstatement assist auditors in obtaining sufficient evidence to keep the audit risk at an acceptable level. There are several ways to evaluate and assess the risks of material misstatement, for instance, the audit risk model is used in mathematical terms. Chang, Tsai, Shih, and Hwang (2008) underline the fact that the design of audit strategies is directly affected by audit risk. As mentioned, the audit risk model assists auditors in the planning of the audit, resource allocation, and overall effectiveness (Helliar, Lyon, Monroe and Woodliff, 1996).

The two components of risk of material misstatement are dependent on the engagement. The risk that an assertion about a class of transaction, account balance, or disclosure is misstated in a material way is the inherent risk embedded in the risk model (IAASB, 2009a). Inherent risk is the sum of several factors. For example, complex calculations and estimations done by a client may impact the risk. Furthermore, inherent risk is subject to risks in the operating environment (IAASB, 2009a). It has to be kept in mind that the misstatement might be material individually or when aggregated. Control risk arises when the material misstatement is not captured by the internal controls and corrected or prevented (IAASB, 2009a). Thus, it is crucial to have effective controls in place, although it is impossible to completely eliminate the risk of material misstatement with the controls. This is due to human error, going around the controls, or management overriding the controls (IAASB, 2009a).

Lastly, the detection risk is introduced in ISA 200 (IAASB, 2009a) and it is impacted by auditors' chosen procedures. Thus, it can be said that detection risk arises when an auditor is unable to detect a material misstatement in the financial statement. There is an inverse relationship between detection risk and risks of material misstatements, since the higher the risks of material misstatements are, the lower the detection risk should be. This will affect the evidence gathered by auditors. According to Chang et al. (2008), more objective and correct assessment factors of detection risk will reduce audit costs. The effectiveness and application of the audit procedures are directly linked to detection risk. With a proper audit plan, engagement team, professional skepticism, and supervision the detection risk is lowered, but never completely eliminated (IAASB, 2009a).

2.2 Risk assessment

There are no explicit requirements for the audit process in the auditing standards (Werner et al., 2021), but the process has taken its form over the years and the standards refer to the different stages of the audit. Usually, the audit process is conducted according to the following stages: 1. understand the entity, 2. identify and assess risks, 3. design and execute responses to risks, and 4. conclude and communicate (Werner et al., 2021). The phases of the audit process are regulated in different international auditing standards which create a uniform whole. In ISA 200 (IAASB, 2009a) it is stated that an auditor should understand an entity and its environment, apply an appropriate response based on the risk assessment, and based on the evidence form an opinion over the financial statement. ISA 315 (IAASB, 2019) assists auditors in understanding the entity and its environment in the second stage where the risk assessment is done. In the third phase, ISA 300 (IAASB, 2004b) is followed to design the audit in accordance with the risk assessment. Lastly, ISA 700 (IAASB, 2016b) supports in forming an opinion on the financial statements and how it is issued to correct groups.

Risk assessment is a central part of the work done prior to the engagement being rolled out and guides an auditor through the process. Risk assessment guides auditor's work in different ways and there is always an option to turn back in order to revise the assessment. In the risk assessment procedures, auditors take into consideration several factors related to the client and the operating environment. To gain an understanding, an auditor will process a lot of data regarding the client. There are several standards to guide auditors in the risk assessment procedures, although professional judgment is important when weighing the findings. ISA 300 (IAASB, 2004b) defines how risk assessment provides a base on which an auditor may design and perform the subsequent audit procedures. Hence, it is critical for the audit plan to identify and assess the possible risks related to the client. Moreover, according to AS 2201 (PCAOB, 2020), risk assessment underlies the whole audit process as it is used as a tool for outlining. An auditor is able to determine significant accounts, disclosures, assertions, controls, and evidence required by relying on the assessment.

The risk assessment procedures should be sufficient from the perspective that they provide a reasonable basis for identification and assessment of the risks of material misstatement and support the remaining audit procedures. The assessment of the risks continues until the end of an engagement. When new audit evidence obtained contradicts the previous evidence used as a base for the assessment, it is necessary to revise it and adapt the audit plan accordingly. The components of the audit risk are formed based on the assessment and the information gathered from the procedures. (PCAOB, 2020, AS 2201)

ISA 315 (IAASB, 2019) guides an auditor together with other standards in the risk assessment procedures. This standard is specifically made to give guidelines in the identification and assessment of risks of material misstatement, whereas the other standards are meant to support the overall audit planning and process. The risk assessment procedures must be carefully planned as the evidence obtained shall not be biased. According to ISA 315 (IAASB, 2019), the audit procedures consist of inquiries of management and other relevant people, analytics, observation, and inspection. Bedard and Graham (2002) remark that risk identification is the sum of the client-specific risk factors and the assessment of them in order to form a judgment.

When conducting risk assessment procedures, it is not necessary to find all audit evidence that exists and could be used as a basis for the risk assessment (IAASB, 2019). On the contrary, it is important to assess the relevance and reliability of audit evidence auditors have obtained during previous audits. In ISA 500 (IAASB, 2009b) the different procedures for risk assessment are defined and explained in detail. Auditors may inspect different records or documents in various forms. Observation is used to gain evidence of the way a process or procedure is performed by the employees in the entity. Assurance can also be achieved through recalculation, reperformance, and external confirmations from third parties. Evaluation of financial data is assisted by analytical procedures which reveal relationships in financial and non-financial data. Lastly, when seeking information from different key persons, oral and written inquiries are made throughout the audit. (IAASB, 2009b, ISA 500)

Through the risk assessment procedures, an understanding of how an entity is organized is formed, including its structure, ownership, and governance. External factors such as the industry and regulations, under which the entity operates, have an effect on the risks. Additionally, the internal and external measures to assess the financial performance add to the understanding. Furthermore, an auditor is required to understand an entity's risk assessment procedures and how the management addresses the risks of material misstatements. The complexity and size of the entity determine which type of procedures are performed. (IAASB, 2019)

In accordance with ISA 200 (IAASB, 2009a), quantitative terms or non-quantitative terms are suitable to express the assessment of the risks of material misstatement. Mock and Fukukawa (2011) discuss the dependency between audit quality and risk assessment. Consequently, the auditor's choice of approach in eliciting the risk assessment will affect audit quality and may have an enhancing impact. If the auditor fails to effectively communicate the risk assessment to the audit team, further problems with quality control and monitoring of the work of the audit team will arise (Mock & Fukukawa, 2011).

2.3 Professional judgment

According to ISA 200 (IAASB, 2009a) which regulates the conduct of an audit, an auditor is required to exercise professional judgment both when planning an audit as well as while performing the audit. Professional judgment is necessary to make informed decisions that meet the ethical requirements and auditing standards. In order to make these decisions, an auditor needs relevant experience and knowledge that can be applied to the matter in question. (IAASB, 2009a)

ISA 200 (IAASB, 2009a) states that professional judgment is particularly important in decisions concerning, i.a., materiality and audit risk as well as the nature and extent of appropriate audit evidence. Appelbaum et al. (2017) explain the need and justification for the use of professional judgment in practice. During an audit, an auditor will be presented with a vast variety of different circumstances due to complex businesses in various industries and geographical locations, implementing different data structures and accounting principles, which prevents the use of preset audit rules (Appelbaum et al., 2017). Furthermore, professional judgment is strongly linked to professional skepticism which indicates that the auditor shall recognize that there might be circumstances that cause material misstatements in the financial statements (IAASB, 2009a).

2.4 Audit data analytics

The guidelines for analytical procedures are issued in ISA 520 (IAASB, 2004a) and the standard describes the nature and purpose of the analytical procedures. Analytical procedures are used for comparisons as well as to find relationships among the data. According to the standard, analytical procedures include various methods, and, thus, everything from simple comparisons to advanced statistical techniques is supported. The standard allows a wide range of options, as the choice of method and procedure is dependent on the auditor’s judgment regarding the specific client. Moreover, it is demanded from the auditor to apply analytical procedures in the risk assessment phase. With the assistance of analytical procedures, the entity and its environment may be effectively understood. ISA 520 (IAASB, 2004a) has no definitions for different analytical methods or techniques and is very broad in its guidelines leaving the decisions to the auditor. Hence, audit firms may develop standardized methods, which are applied in accordance with their audit methodology.

AICPA (2014) presents a more precise definition of audit data analytics (ADA) in an article that discusses new technologies in the auditing context. The definition of ADA is the following:

> *"Audit Data Analytics (ADA) is the science and art of discovering and analyzing patterns, identifying anomalies, and extracting other useful information in data underlying or related to the subject matter of an audit through analysis, modelling, and visualization for the purpose of planning or performing the audit"* (AICPA, 2014, p.5).

Consequently, ADA aids the auditor in focusing on risks in an effective manner and provides additional insights. With the visualizations, models, and data combinations, the auditor has more information to base their judgment on. ADA is used for planning, substantive testing, and at the end of the audit for the concluding procedures. Furthermore, two modes of ADA are distinguished, namely exploratory and confirmatory. The former is a bottom-up and inductive approach used primarily in the planning phase, as the data is examined for possible risks. The latter approach is deductive and top down since the auditor is assessing the assertions through the models built during the exploratory approach. (AICPA, 2014)

The research in this area has also formed an opinion on the definition of ADA and the methods that this umbrella term covers. Jacky and Sulaiman (2022) refer to data analytics when more complex processes are conducted during the audit process with sophisticated software and tools as well as statistical procedures. According to Salijeni et al. (2018), the function of analytical tools is to make sense of big data. Chen, Chiang, and Storey (2012) conclude that the extraction of information from data and using it for decision-making is data analytics. Analytical procedures have different purposes in the audit phases (Appelbaum et al., 2017). Titera (2013) has adapted the term audit data analysis and refers to the computer-assisted examination of the data, based on which the financial statement is created. He further describes audit data analytics as drilling down to the details of every activity underlying the financial statement. Huang et al. (2022) list regression techniques, descriptive statistics, expert systems, ratio analysis, and visualization, as ADA methods used in different phases of the audit.

Stewart (2015) is of the opinion that data analytics does the mechanics, making it easier for the auditor to form a judgment. Stewart (2015) further expresses that data analytics could be utilized for comparisons between entities' key financial ratios or cluster analysis when a more unstructured approach is taken to the data. He gradually links ADA with all the different audit procedures traditionally conducted by the auditor. According to Titera (2013), audit data analysis is simply more than just analytical procedures. Whereas analytical procedures demand an expectation, data analysis does not. This is due to the fact that data analysis does the presumptions for the auditor and discovers the activities in the data (Titera, 2013). Furthermore, multi-dimensional analyses are possible with data analysis (Titera, 2013).

2.5 Process mining

One type of audit data analytics is process mining, which improves the insights of the auditors (Appelbaum et al., 2017). Information systems process automatically, or semi-automatically, a vast amount of financially relevant transactions and process mining is an analytical tool developed to comprehend the processes and to present them in an understandable form (Werner et al., 2021). Werner et al. (2021) argue that process mining will increase the reliability of the audit statement and the robustness of the evidence used to support the statement. Jans, Alles, and Vasarhelyi (2013) discuss the possibility of exploiting the vast amount of data gathered by enterprise resource planning systems (ERP) to gain insights into business processes. They further note how process mining could be used for comparisons between the original process designs and the practical flow of the processes. The ERP systems differ from each other, and so does the data produced in them, which means that auditors are forced to create event logs depending on the particular ERP (Jans et al., 2014).

Process mining implicates a systematic analysis of automatically recorded data. Event logs are established based on the meta-data recorded by the system automatically and independently from the users. Metadata is the fingerprint left behind by the user, meaning a timestamp and the personal id of the user. The meta-data is complemented with the data entered by the auditee to construct the event log. Process mining analytics requires specific information regarding the events: the activity, the process instance, the originator, and the timestamp. Effective IT controls are necessary as the integrity of the data is a prerequisite for the analytical procedures conducted over the data. Process mining differs from the other available tools in the sense that it focuses on the path of transactions instead of the validation of the values. (Jans et al., 2014)

In addition, process mining establishes the connection between the accounts and the business processes. With process mining, auditors may create reliable business models based on the analysis of transaction processing. Manual data retrieval is recourse intensive and vulnerable to mistakes, whereas process mining would conduct the assessment of controls more efficiently and identify the events that deviate from the standard processes. This would make resource allocation more effective and expose anomalies that remain unknown with the current techniques. (Werner et al., 2021)

Accordingly, Jans et al. (2013) have noticed the advantages linked with process mining, as the audit risk model could be implemented more effectively, and this would be reflected in effective process walkthrough and analytic procedure. However, the authors also recognize the challenges with controls implemented in businesses. In general, it is normal for organizations to relax the controls with the intention to enhance the seamlessness of different processes, for example, purchase to order. For the auditor, this causes additional work because the relaxed controls are unreliable and detailed tests are necessary to cover the lacking controls. Thus, process mining reveals the consequence of relaxing the controls to auditors. The auditor is supported by process mining in the tests of details. (Jans et al., 2013)

Chiu and Jans (2019) present how controls are evaluated through the process mining analyses of event logs. An example of process mining analysis is the variant analysis, which identifies different process paths that have taken place during the audit period. These are further divided into standard and non-standard variants of the process. After dividing the variants, the auditor is able to focus more recourses on the non-standard variants that deviate from the designed business processes. The main sub-categories of non-standard variants are missing activity, activity not in the right order, and redundant activity. A materiality threshold is applied to determine which non-standard variants are further investigated. The management assertions, completeness, occurrence, and accuracy are identified with the categorization of the variants. (Chiu & Jans, 2019)

2.6 ISA 315

The revised version of the ISA 315 was issued in December 2019, and it regulates the identification and assessment of risks of material misstatement. The standard is effective for audits of financial statements for periods starting on or after December 15th, 2021 (IAASB, 2019), which means that the standard is generally applicable for audits of the fiscal year 2022. The revised ISA 315 does not change the traditional audit approach, including the audit risk model and methodology, but stresses the relevance of analytical procedures and the importance of technology (Krieger, Drews & Velte, 2021).

The revised ISA 315 also mentions automated tools and techniques as a way to perform analytical procedures and defines that when these are applied to the data, it may be referred to as data analytics (IAASB, 2019). Krieger et al. (2021) recall that the definition of automated tools and techniques in the standard is intentionally broad so that it can take into consideration the new emerging technologies. The standard includes examples of the use of automated tools and techniques, naming specifically data extraction from the client's information system, the analysis, and visualization of data as well as risk assessment procedures based on those actions (IAASB, 2019). These are only examples, and the standard does not require the use of these technologies. Therefore, Krieger et al. (2021) argue that the optionality may slow down the adoption of automated technologies.

3 Previous research

Previous research presented in this chapter has been published in academic accounting and information systems journals during the last ten years. The chapter introduces relevant aspects of the previous research, which are divided into five different topics: current practice and standards, future of audit data analytics, big data, professional judgment, and internal controls. In the conclusions, the previous research is summarized, and a conceptual framework including assumptions is formulated.

3.1 Current practice and standards

To discuss the potential of data analytics in the context of audit risk assessment, it is essential to understand current practices in the field. The practices are being developed continuously, and the Big Four accounting firms have publicly declared their ambition to improve the use of audit data analytics. Various analytical techniques are used in different phases of an audit depending on the circumstances, such as the audit task in question, data availability, and auditor's skills (Appelbaum et al., 2017). Therefore, the implementation of audit data analytics varies between different accounting firms and even between each auditor (Eilifsen et al., 2020).

AICPA (2017) has identified several potential benefits from the use of audit data analytics, one of them being the opportunity to improve understanding of an entity and its environment to identify and assess the risk of material misstatements. Eilifsen et al. (2020) interviewed five international public accounting firms in Norway and conducted a survey where 216 partners and managers answered questions regarding the use of audit data analytics in each audit phase. In the planning phase, data analytics is currently utilized to identify and assess significant risks and to perform an overall assessment of client's operations (Eilifsen et al., 2020; Titera, 2013). AICPA (2014) has specified that this assessment can be accomplished through preliminary analytical procedures combined with an evaluation of the design and implementation of internal controls as well as a test of operating effectiveness of the controls. The most promising analytical procedures include supervised approaches, unsupervised approaches, regression models, descriptive statistics, and analytical models (Appelbaum et al., 2017). However, the level of the techniques varies significantly from straightforward substantive tests to more technical and complex models that also require professional judgment (Appelbaum et al., 2017).

Despite the promising analytical models and positive attitude toward audit data analytics, previous research indicates that the use of data analytics is limited (Appelbaum et al., 2017; Eilifsen et al., 2020; Liew, Boxall & Setiawan, 2022). Appelbaum et al. (2017) remark that the use of analytics is already increasing in internal audits, but the external audits have not matched the development. According to Liew et al. (2022), the development depends partially on the process advancements within accounting firms, but quality improvements within clients' IT systems are also required. The use of audit data analytics differs between accounting firms, audit engagements, and audit phases (Eilifsen et al., 2020). Eilifsen et al. (2020) analyzed 109 engagements and described the variations in the use of data analytics in fraud risk assessment by specifying that audit data analytics was utilized from 10.5 to 36.8 percent of the engagements depending on the firm. Saljeni et al. (2018) demonstrate, how the audit methodology also affects the adoption of data analytics in risk assessment. They exemplify how the methodology can guide the auditor in situations where the auditor can with the help of ADA determine how extensive procedures have to be done (Saljeni et al., 2018).

Overall, Eilifsen et al. (2020) note that the use of audit data analytics is surprisingly low since many researchers, e.g., Perols, Bowen, Zimmermann, and Samba (2017), have emphasized the benefits of data analytics in risk assessment. Perols et al. (2017) suggest that analytical fraud risk assessment models could improve both audit planning decisions and client portfolio management. Additionally, Eilifsen et al. (2020) showcase the firms' differences in the use of audit data analytics. The participants were asked to respond on a scale of 1 to 7 – 1 meaning strongly disagree, 4 neutral, and 7 strongly agree – to questions regarding the usefulness of audit data analytics in risk assessment. When asked about the overall usefulness, the average response was 5.27, but when the question was specified to a specific engagement, the average response was lower, 4.62. This indicates that the participants see the potential of audit data analytics in risk assessment, but the implementation of it is not yet common (Eilifsen et al. 2020). Only 29 of the 109 analyzed engagements had utilized data analytics to identify and assess significant risks (Eilifsen et al., 2020).

Even though the current practice is evolving, auditing standards have not been revised at the same pace, which complicates the implementation of audit data analytics (e.g., Titera, 2013; Eilifsen et al., 2020). Appelbaum et al. (2017) have reviewed current auditing standards and their compatibility with the development of audit data analytics. Generally, the standards are perceived to make it more difficult to use data analytics even though they do not forbid the usage. In fact, the standards do not include guidance and requirements for the use of audit data analytics (Krieger et al., 2021) but define which tasks could be audited with analytical procedures in each phase of the audit (Appelbaum et al., 2017). Consequently, the use of audit data analytics requires significant professional judgment. Moreover, according to standard setters interviewed by Saljeni et al. (2018), the current standards are flexible enough to enable the use of audit data analytics, but they express their concerns when it comes to ADA's effect on understanding of materiality and risk factors.

Although the audit is mandatory for most clients of accounting firms, they still operate in a competitive environment. On the one hand, previous studies have shown that data analytics is often used as a complementary procedure (Eilifsen et al. 2020) since the competitive pricing of audit does not enable additional analytics, which makes the use of data analytics impractical or even impossible (Appelbaum et al., 2017). On the other hand, analytical procedures can be less costly than test of details, but it is considered to be less reliable by the standard setters who do not define how the analytical procedures should be performed (Appelbaum et al., 2017). Therefore, auditors are uncertain about the use of data analytics until they know how regulators will evaluate and accept the evidence produced using data analytics (Eilifsen et al., 2020). Appelbaum et al. (2017) note that it should be examined whether data analytics actually produce less reliable evidence. They propose a quantitative reliability scoring system that would rate the reliability of gathered audit evidence, and this score could be used in risk assessment (Appelbaum et al., 2017). Due to the competition in the audit market, the use of data analytics is, however, motivated as it can make the audit more effective and competitive (Krieger et al., 2021).

Titera (2013) suggests that there is also a need for an update in auditing standards regarding how data analysis is linked to audit risk and the extent of testing. Appelbaum et al. (2017) note that the standards already suggest testing of the entire population in situations where the audit procedure can be effectively performed automatically and applied to 100 percent of the population. Testing the entire population may, however, result in numerous exceptions in case the threshold definition for material deviation is too high (Appelbaum et al., 2017). According to the standards, all exceptions in a sample must be examined (Appelbaum et al., 2017) which creates the need for instructions that relate to testing of all items.

3.2 Future of audit data analytics

Previous research has introduced several possibilities for audit data analytics. As data sources, and single transactions within data are becoming more complex, the audit risk will increase if auditors continue with traditional analytical procedures that are manual and simplistic (Appelbaum et al., 2017). Audit data analytics enables the collection and comparison of data from various sources that can be both financial or non-financial (Li, 2022) as well as quantitative or non-quantitative (Appelbaum et al., 2017). However, auditors should be able to verify the quality of the data from external sources, which will become an essential part of the risk assessment process (Appelbaum et al. 2017). Such combination of information from different sources will be critical in order to understand the material risks of an entity. The use of data analytics will enhance the understanding of the entity and its environment as well as the quality of risk assessment (Appelbaum et al., 2017; Eilifsen et al., 2020). With the help of data analytics, it is possible to analyze data up to 100 percent, which results in higher-quality evidence and improves auditor reliance (Titera, 2013). In addition, the use of data analytics offers possibilities for increased audit effectiveness and thereby decreases the costs of an audit (Liew et al., 2022).

Understanding of an entity can be improved through technological advancements. Data analytics as a technique and the increased amount of data have numerous advantages that could be used to improve audit risk assessment and make it more effective. However, the vast volume of big data also poses challenges to current technologies. Excel and other basic spreadsheet tools are not able to process the volume of data and, therefore, Big Four accounting firms have developed their own smart audit tools to assist in data analytics (Liew et al., 2022). The use of advanced data analytics is still relatively rare (Eilifsen et al., 2020) but previous research has highlighted its benefits (Appelbaum et al., 2017; Jacky & Sulaiman, 2022; Liew et al., 2022).

Advanced statistical procedures enable auditors to evaluate large volumes of relevant information and even combine information from different sources to enhance the ability to assess risks (Jacky & Sulaiman, 2022). Through advanced predictive and prescriptive analytics, auditors could apply techniques that consider rules, constraints, and complexities of a specific engagement and computationally determine possible audit actions and their consequences (Appelbaum et al., 2017). The possibility to computationally analyze more data increases audit effectiveness (Titera, 2013) and improves the quality of risk assessment (Eilifsen et al., 2020).

Furthermore, Titera (2013) clarifies the changes in risk assessment due to the advancements in analytical procedures. Traditionally, analytical procedures have required an understanding of what can reasonably be expected and, thereby an acceptable level of precision has been defined. Due to the use of more advanced data analytics, auditors may not have to form an expectation, since the purpose of more advanced tools is to help auditors to gain a more precise understanding of the entity and its activities (Titera, 2013). Eilifsen et al. (2020) stress that the use of these technical advancements also requires a high system integration from client's information systems.

The increased use of more complex audit tools that utilize data analytics will lead to changes in the audit process. Auditors using these tools should understand the benefits and limitations of the tools and assess their impact on the audit procedures. The new techniques enable testing of whole populations, which can affect the dynamics of risk assessment, control testing, and substantive procedures. For example, control testing has traditionally been performed since it has been impossible to audit 100 percent of the population (Appelbaum et al., 2017). As the audit develops from this sample-driven process to a more data-driven audit, the role of risk assessment and control testing will change (Appelbaum et al., 2017). For example, in the future, data analysis could identify the exceptions in the whole data, and auditors could only focus on them instead of random sampling to find possible errors (Titera, 2013). Additionally, when sample testing is still needed, auditors could take advantage of data analytics and use risk-based sample testing which is able to identify a large number of low-value transactions that together can sum up to a material concern (Liew et al., 2022). Another changing aspect will be the time frame of audits. Traditionally, risk assessment has been regarded as a separate activity that occurs during the planning phase of an audit. As shareholders are expecting timely information, a real-time approach is adopted. Subsequently, the audit procedures can be updated based on the continuously assessed risk levels (AICPA, 2015).

3.3 Big data

Advanced processing capabilities and availability of different storage options have changed how data is captured, which has increased the amount of stored data (Earley, 2015). Appelbaum (2016) recognizes two reasons why auditors could be intrigued by big data. Firstly, the client may use big data for decision making and accounting judgments which will influence the financial statement. Secondly, big data provides auditors the possibility for "…client and industry assessments, risk analysis, confirmations, and reasonableness tests – if the data are reliable" (Appelbaum, 2016, p. 17). Nearly everything is recorded in the technological environment by information systems and applications used by organizations. It is impossible to draw any conclusions from this vast amount of unstructured data with traditional methods, and the risks within the data remain unknown without the right tools. However, the new data environment enhances assurance capabilities if the increased amount of data is utilized effectively (Brown-Liburd & Vasarhelyi, 2015).

Big data is commonly described with the aid of the four Vs; volume, variety, velocity, and veracity (e.g., Appelbaum et al., 2017; De Santis & D'Onza, 2021; Gepp et al., 2018). Volume refers to the extent of data, from the perspective of regular data handling tools that are unable to provide the capacity needed for processing. Big data is produced in various formats, and variety describes this feature of data. Big data is the consequence of the velocity at which data is produced. The last attribute of big data is veracity, as the relevance is affected by the time that passes, which is a more recent observation. Depending on the big data set being analyzed, different techniques are needed to disassemble it into something meaningful (Gepp et al., 2018).

Organizations have implemented and are implementing data analytical methods at a higher pace to understand their environment and business. Data analytics provides the management with highly valuable insights. Thus, more complex procedures are undertaken to support decision-making (Appelbaum et al., 2017). On the one hand, this creates pressure for external auditors to understand the techniques applied by organizations and to utilize compatible methods in the engagements. On the other hand, Gepp et al. (2018) conclude that auditors should take the advantage of big data techniques, even if clients are not applying them. According to them, big data techniques might even be useful when smaller data sets are being analyzed, since they give more detailed insights compared to other methods. Brown-Liburd, Issa, and Lombardi (2015) expect that several big data analytics tools will be implemented in audit and some of them are already in use. They mention, i.a., predictive and statistical analytics, machine learning, AI, and visualization techniques as well as data warehouses and distributed computing (Brown-Liburd et al., 2015). Salijeni et al. (2018) discovered in their interviews that big data could also facilitate the dialog around risk assessment between the auditor and the client.

The nature of audit evidence changes with big data, as the way evidence is collected and chosen differs drastically from previously applied methods. According to AS 1105 (PCAOB, 2020), all the information used by an auditor to reach a conclusion, on which the audit opinion is then based, is regarded as audit evidence. Audit evidence both contradicts and supports the assertions over the financial statements or internal controls (PCAOB, 2020, AS1105). Appelbaum et al. (2017) speculate the importance of testing the assertions concerning the objectives of the audit. Although tests of assertions are changed by the nature of evidence, the assertions would not inherently be altered. The audit objective remains the same, while the measures to reach it are being adjusted. Overall, an auditor must collect appropriate and sufficient audit evidence in relation to the risk of material misstatement and the quality of evidence (PCAOB, 2020, AS1105). Appropriateness is defined by relevance and reliability of audit evidence. Meanwhile, sufficiency is the amount of evidence required to reach assurance over the information provided by an entity, which is dependent on the appropriateness of the evidence.

Traditionally, evidence obtained from third parties has been considered more reliable when compared to an organizations' internal sources (PCAOB, 2020, AS1105). Big data might introduce problems to this statement with its unverifiable sources. Appelbaum (2016) identifies several deficiencies in the way data is produced and handled in electronic systems. When paper-based evidence is compared to electronic evidence, many of the characteristics perceived as strengths are turned into issues. Big data generated in third-party systems is difficult to examine for alterations, especially with insufficient controls. Additionally, Appelbaum (2016) discusses the issue of verifying the evidence for veracity, origin, and reliability. Despite these obvious problems, big data offers many possibilities for auditors. One way to tackle unreliability of a source and data integrity is to examine audit trails that data leaves behind. Data provenance refers to the origins of data, but it could offer auditors a way to audit the quality and lifecycle of data (Appelbaum, 2016). Furthermore, data lineage can also be used to find exceptions in data and to trace back past events. Hence, big data may be investigated in a manner where it can be trusted as valuable evidence. Alles (2015) notes that auditing standards are not an obstacle for the use of big data as evidence. In fact, his opinion is that auditing standards are one of the most evident facilitators for the use of big data, as the standards are open for evidence collected outside the traditional sources.

3.4 Data and professional judgment

Wang and Cuthbertson (2015) highlight the challenge of using the results produced by data analytics. Even though it is time-consuming, the analysis of the results can be the most important part of the process (Wang & Cuthbertson, 2015). Therefore, it is important to investigate how auditors interpret the results of data analytics and how it affects their professional judgment. The effects may be both positive and negative. Li (2022) suggests that the use of data analytics could improve the quality of professional judgment as well as enhance auditors' professional skepticism. As audit data analytics enables visualization of the results, it assists in the identification of material misstatements (Li, 2022).

However, Li (2022) notes that audit data analytics can also complicate the auditor's judgment. Hence, ISA 200 (IAASB, 2009) requires that the auditor is trained enough to have the competence, experience, and knowledge through which they can make reasonable judgments. The emergence of audit data analytics presents a need for new skills to ensure the quality of professional judgment. Li (2022) exemplifies that by describing how auditors' awareness regarding data relevance and data reliability can affect their professional judgment. For example, an auditor may falsely consider unstructured or internal data as less reliable compared to structured or external data, since that is the general assumption in traditional audit, where it is not possible to analyze and combine the enormous amounts of data (Li, 2022). These judgments and the applications supporting them require often advanced technical knowledge which many auditors are lacking (Brown-Liburd et al., 2015; Liew et al., 2022). Thus, auditors are cooperating to an increasing extent with IT specialists who work with large datasets and make them accessible for financial auditors (Liew et al., 2022). This showcases the importance of technical knowledge, not only from the technical standpoint, but it is also essential for professional judgments made based on data analytics. Jacky and Sulaiman (2022) recommend cautiousness when implementing audit data analytics so that professional judgment and skepticism will be taken into consideration.

Big data is changing the way auditors make decisions, evaluate audit evidence, and assess risks (Brown-Liburd et al., 2015). As the amount of data increases, auditors are challenged to make use of it in a way that considers data quality, including the relevance and reliability of the data (Brown-Liburd & Vasarhelyi, 2015). When determining the appropriate data to use, Jacky and Sulaiman (2022) emphasize the auditor's professional judgment and critical thinking, which will be necessary regardless of the use of data analytics. Even the most advanced audit tools will not be able to make decisions for the auditor alone, since the big data environment has its limitations that require professional judgment. For example, despite the ability to identify patterns, technological tools are unable to evaluate whether the results are relevant for audit (Brown-Liburd et al., 2015). Subsequently, they are used to assist in decision-making, but the auditor needs to interpret and analyze the results using professional judgment (Brown-Liburd et al., 2015).

Auditors' competencies and capabilities needed to make professional judgments will be challenged by the information overload that big data is creating (Hamdam, Jusoh, Yahya, Jalil & Abidin, 2022). Hamdam et al. (2022) introduce a conceptual framework that identifies cognitive aspects that might affect auditors' judgment when they are working in the big data environment. Similarly, Brown-Liburd et al. (2015) note that a big data environment causes several limitations for auditors' information processing, including information overload, information relevance, pattern recognition, and ambiguity. Information overload is linked to task complexity. Technological developments produce the vast amount of data that is more complex (Hamdam et al., 2022). The data originates from multiple sources and can be both structured and unstructured which makes it harder to judge the relevance of information (Brown-Liburd et al., 2015).

Data complexity will also change the way auditors analyze data so that the analysis is done effectively (Hamdam et al., 2022). However, Hamdam et al. (2022) suggest that technical advancements can make data analytics more effective and even lead to better judgments, as analytics can reduce the effect of auditors' limitations, and technology can assist in making less unbiased judgments. Therefore, the quality of decisions made based on data analytics depends more on auditors' ability to handle big data rather than on their experience or knowledge. These limitations and potential issues regarding professional judgment might be a reason why big data is not yet integrated into the audit (Hamdam et al., 2022).

The results of data analytics can be presented in different ways. Wang and Cuthbertson (2015) discuss whether the format of the output can affect auditors' judgments and interpretations. Data visualization has evolved in the big data environment to help auditors in their decision-making through graphics and visuals (Hamdam et al., 2022). Generally, the assumption is that data visualization integration will improve auditors' judgment (Brown-Liburd et al., 2015;

Hamdam et al., 2022; Liew et al., 2022). As data visualization combines data from several sources and illustrates the underlying data, it can visualize hidden patterns in the data and detect key insights. Hence, data visualization can assist auditors in identifying the relevant patterns for decision-making. (Hamdam et al., 2022) Through data visualization even auditors without strong technical or data-science knowledge can interpret the results of data analytics (Liew et al., 2022). Nonetheless, it is important to consider which visualization techniques are applied so that they can complement the traditional audit approaches (Hamdam et al., 2022).

The risk assessment process can become even more complex, as the unstructured nature of big data adds to the ambiguity (Brown-Liburd & Vasarhelyi, 2015). Brown-Liburd et al. (2015) specify that audit data analytics are suitable for audit tasks that require more subjective judgment from the auditor, such as fraud risk assessment. Even though fraud risk assessment is required in every audit, traditional audit methods are not very effective in fraud risk identification, as auditors are using standard planning programs and checklists (Brown-Liburd et al., 2015). Data analytics, on the contrary, enables the use of big data in risk assessment and has been proven to be effective in fraud risk identification (Brown-Liburd et al., 2015). Fraud risks may be, for instance, identified if data analytics detect a negative correlation between financial and nonfinancial information (Brown-Liburd et al., 2015).

3.5 Internal controls

AS 2110 (PCAOB, 2020) includes the procedures for risk assessment and one important procedure is to gain an understanding of internal controls over financial reporting. Internal controls are able to either increase or decrease the auditor’s workload. Effective controls mitigate the risk of material misstatement, whereas ineffective controls increase the risk, and more evidence has to be obtained by the auditor (PCAOB, 2020, AS 2201). When an organization’s controls over the information used are effective, the reliability of that information increases (PCAOB, 2020, AS 1105). Appelbaum (2016) derives the same opinion regarding electronic systems where the credibility of electronic documents relies on the controls within the system. Werner et al. (2021) observe in their article that still today a vast majority of clients’ internal processes and controls are manually analyzed. These manual tasks include inquiring the process owners, reviewing process documentation, and sample testing. According to Werner et al. (2021), the present-day audit is limited and inefficient, as the procedures are unable to provide reliable information over information that is processed by the applications where the system controls are automated as well.

One of the respondents in the study by Jacky and Sulaiman (2022) concludes that in data-driven audits the robustness of the IT general controls has a critical role. In addition, the respondent emphasizes the essentiality of the IT application controls, which are specific to each system used by an organization. In the same study, the researchers noted, that several respondents were of the opinion that some of the risks associated with data analytics rise during the generation of the data. Liew et al. (2022) discuss the same problem in their paper, and they observe an issue with using data analytics if the IT controls have deficiencies. The consequences of these deficiencies are data integrity problems and a reduction in audit quality. Daglienė and Klovienė (2019) suggest that auditors apply more detailed audit procedures on the information systems if they perceive the data to be untrustful. Thus, the quality of IT controls has to improve, if data analytics is applied by auditors (Liew et al., 2022). According to Liew et al. (2022), the parallel use of data analytics and traditional methods is the result of poor controls in IT systems. This makes the adaption of data analytics less desirable as the effectiveness gains are lost.

The effectiveness of control procedures can be assessed with the help of data analytics, providing evidence of the controls (Daglienė & Klovienė, 2019; De Santis & D'Onza, 2021; Wang & Cuthbertson, 2015). For instance, according to Wang and Cuthbertson (2015), data analytics could be performed "…to verify authorization, perform limit tests, and evaluate segregation of duties" (p. 157). Jacky and Sulaiman (2022) have identified a concern from their respondents regarding the evidence collected with data analytics from the controls. The sufficiency of the evidence gathered with analytical methods is being questioned by the respondents. Daglienė and Klovienė (2019) observe that the standards require the use of analytical procedures when estimating the internal control system, but the complexity of this system varies depending on the size of a client.

The clients' systems produce financial and non-financial information that the auditor needs to analyze to attain a certain level of assurance. Since these systems and their logic differ radically from the previously used paper-based records, the auditor needs to be careful when placing trust in the data. Jans et al. (2012) introduce the concept of process mining which is an analytic method used to systematically review the data recorded by the information systems. The effectiveness of IT controls can be analyzed with the help of the logs recorded by the systems

(Appelbaum, 2016). These logs include information on the dynamics, activity flows, and events in a system. In other words, the logs leave an audit trail with the possibility of retrospective reviewing (Jans et al., 2012). Consequently, all the alterations may be inspected by auditors to ensure the reliability of the data produced in the systems. Process mining gives the auditor an effective tool to analyze the control environment and the log files (Jans et al., 2012). As a result, auditors are able to place trust in the data and use it for further testing.

3.6 Conclusions of the previous research

The previous literature agrees to a high degree that ADA will impact the audit industry to some extent. The existing body of literature is not unanimous about how quickly the change will take place and what the concrete consequences will be. The changing role of the auditor is at the center of many articles, and it is contemplated how the future might look like for the occupation. The audit process is broken down into the well-distinguished phases in order to see how data analytics is shaping these. The previous research indicates that the use of ADA in the planning phase and risk assessment is limited (Appelbaum et al. 2017; Eilifsen et al. 2020; Liew et al., 2022) but data analytics as a tool has been studied as it relates to other phases of the audit process as well as its benefits and disadvantages.

Potential benefits identified are, for instance, an increased understanding of the entity (Eilifsen et al., 2020) and better fraud risk assessment (Perols et al. 2017). Additionally, there are already promising tools to be used in data analytics but problems with competence and data availability might prevent the implementation (Appelbaum et al., 2017). The previous research concludes that one prerequisite for ADA utilization in audit is the integration of clients' ERP systems and IT systems in general (Eilifsen et al., 2020; Liew et al., 2022). Liew et al. (2022) note in their article the difficulties with the controls in clients' IT systems. If the control deficiencies are not solved and the system quality remains poor, the full potential of data analytics is not gained (Liew et al., 2022).

Even though the factors affecting the use of ADA have been studied in previous research, information regarding the actual use of ADA in the planning phase and risk assessment is lacking. Eilifsen et al. (2020) discovered in their study how the usefulness of ADA in risk assessment is recognized but not implemented in practice. Therefore, it is hard to make assumptions based on previous research how ADA actually is being implemented in risk assessment. Previous research has identified data analytical tools and technologies, but they are mostly used in other phases of the audit. Consequently, it can be assumed that the use of ADA in the planning phase is not yet very extensive but there are possible techniques to be used also in the planning phase. In other words, the previous research suggests that ADA could be implemented in the planning phase as well, but there are unsolved matters to be resolved and researched.

On the contrary, the effect of auditing standards in the use of ADA has been researched by several studies and it affects the implementation of ADA in risk assessment (e.g., Appelbaum et al., 2017; Eilifsen et al, 2020; Krieger et al., 2021; Titera, 2013). The overall tone of the previous research regarding the standards is fairly negative although the discussion regarding standards is divided. Some of the articles see standards as inhibitors for the use of ADA (e.g., Titera, 2013; Jacky & Sulaiman, 2022), whereas other articles conclude that the standards actually make it possible to use ADA (e.g., Salijeni et al., 2018). For example, Salijeni et al. (2018) interviewed professionals from IAASB who were of the opinion that the current ISA standards are flexible enough for ADA utilization. However, Jacky and Sulaiman (2022) observed in their study that the lack of authoritative guidance was the main inhibiting factor for ADA. Appelbaum et al. (2017) in turn consider both ends of the spectrum.

Currently, duplicated work is still conducted in several cases and there are many factors affecting this – one being the auditing standards (Eilifsen et al., 2020). According to Eilifsen et al. (2020), the uncertainty of the regulators' perspective often leads to data analytics being a complementary procedure performed alongside tests of detail. Even though the topic has been discussed in several studies, the effect of standards on the ADA used in risk assessment remains unclear. In light of the previous research, it is expected that the standards may affect the use of ADA in the planning phase both positively as well as negatively. As the contrast in previous research is so significant, it is an interesting aspect from the perspective of this research. Thus, this study investigates reasons why the opinions present two extreme ends of the spectrum.

Though, the previous research acknowledges that the use of ADA in practice remains in its infancy (Appelbaum et al. 2017; Eilifsen et al. 2020; Liew et al., 2022), it has identified needs for the use. According to Daglienė and Klovienė (2019) usually, large audit clients are the first to apply big data and data analytics to their operations. Thus, audit firms are the followers in the adaption of new developments. The increasing amount of data being produced challenges the quality and effectiveness of the audit, but advanced analytical tools have been considered as a solution (Titera, 2013). Brown-Libuard et al. (2015) stress the importance of being prepared for the problems which arise when big data is integrated into the audit process, as audit judgments should be based on reliable information. On the one hand, the authors highlight the potential of big data to improve audit judgment and audit quality. On the other hand, big data should not be used as the only source of evidence. Brown-Libuard and Vasarhelyi (2015) argue that the concept of audit evidence is changing with big data. To answer the new requirements such as the increasing amount of data as well as audit effectiveness and quality, it is expected that the use of ADA will become more common in risk assessment. This leaves a gap to research the perceived advantages of ADA, in the opinion of auditors, when facing new requirements.

Previous research has already identified several possibilities for ADA. They have investigated solutions for the increasing amount of data, such as the possibility to combine data from different sources (Appelbaum et al., 2017; Li, 2022), nalyzing the whole population (Titera, 2013), and technical advancements (Appelbaum et al. 2017; Jacky & Sulaiman 2022; Liew et al., 2022). These advancements have the possibility to increase audit effectiveness (Titera, 2013) and improve audit quality (Eilisen et al., 2020). Moreover, ADA could enable improvements in risk assessment as advanced tools could, for example, be used to perform risk-based sampling rather than random sampling. However, Eilifsen et al. (2020) note that the developments require high data availability and system integration. Additionally, aspects regarding auditors' competence requirements have been lifted up by previous research. Liew et al. (2022) discuss how accounting graduates are required to possess stronger digital aptitude compared to their predecessors. Li (2022) highlights the changes in professional judgment as the auditor has to evaluate what data is relatable and relevant. Based on previous research it is to be expected that data analytical tools will be evolving, and more advanced applications suitable for risk assessment will be introduced when the use of ADA increases in phases other than just testing. In addition, it can be assumed that ADA will change professional judgment in risk assessment. These changes are of interest when analyzing the results and the aim is to discuss how the changes affect the audit.

4 Methodology

This chapter introduces the chosen research method and the approaches used to conduct the empirical part of the study. Research method selection, data acquisition, and analysis as well as data validity, reliability, and research ethics will be discussed.

4.1 Research method

The research method is determined by the combination of data availability and research goals (Bloomfield, Nelson & Soltes, 2016). Traditionally, the method selection is done between quantitative and qualitative research methods, and accounting research has focused on quantitative research methods. However, some research questions are not able to be answered with quantitative methods, as there may not be extensive data regarding the researched topic (Kriefer et al., 2021; Himick, Johed & Pelger, 2022).

Qualitative research methods are usually built on data that includes detailed descriptions (Bryman & Bell, 2015). Since the aim of this study is to explore the role of audit data analytics in practice, qualitative research methods can provide a desirable understanding of the actual use of data analytics in audit risk assessment. In other words, qualitative research is an approach in which the collection and analysis of data are the basis for the categorization of the data and to formation of a theory (Bryman & Bell, 2015).

We will apply an interview-based approach by interviewing industry experts. This is reasoned as we aim for a broader understanding of the subject instead of just a single case (Krieger et al., 2021). As the study aims to explore current audit practices and possibilities for the future, we have chosen to do semi-structured interviews. Semi-structured interviews allow the researcher to ask broad open-ended questions and focus on new aspects that emerge during interviews (Bryman & Bell, 2015). Due to the exploratory nature of this research, semi-structured interviews are a suitable method as they enable follow-up questions regarding interesting topics that arise during an interview (Eilifsen et al., 2022). Hence, the interviews may not exactly follow the interview script, but for the most part, all the questions will be asked using the same wording in every interview (Bryman & Bell, 2015). Therefore, semi-structured interviews are an appropriate method choice to ensure the interviews are comparable if several persons are doing the fieldwork (Bryman & Bell, 2015). This is of high importance as the interviews, except the first one, were conducted individually by either of the writers.

4.2 Data acquisition

Research data were obtained through eight semi-structured interviews. The selection of interview objects is important in qualitative research. The interviewees are professional auditors from Big Four accounting firms operating in Finland. Big Four firms are considered particularly suitable for the study since they have more resources to train specialists and develop audit systems that utilize data analytics compared to smaller audit firms (Krieger et al., 2021). According to Liew et al (2022), all Big Four firms have already developed their own in-house systems that are used internationally, which further motivates the choice to concentrate on them. Additionally, the in-house development of audit tools enables cooperation between auditors and system developers (Krieger et al., 2021). In the context of the Big Four firms, Finland has a smaller economy than many of their other markets but many of the IT applications are developed globally, which makes auditors on the Finnish market valid for the study.

We interviewed several professionals in audit from different levels of the organizations. The research objects were chosen with purposive sampling, meaning auditors with relevant experience and knowledge in relation to the research question were approached (Bryman & Bell, 2015). More experienced auditors and IT specialists are essential, as they can describe how the audit industry has evolved during their time in the field. Auditors at lower organizational levels are also valuable, as they can provide information regarding the current implementation situation. (Liew et al., 2022) As we have personal relationships with several Big Fours, we contacted experts in the field who recommended possible interviewees to avoid convenience sampling. All the interviewees asked to participate agreed to an interview.

The interview script was developed based on previous research and professional literature. The interviews were conducted in Finnish, which was the mother tongue of all the interviewees. The interviewees were first asked about their roles, core tasks, and experience related to data analytics. The following questions were divided into three categories: current use of audit data analytics, changes in the use of audit data analytics, and the effect of auditing standards. The English version of the interview script is provided in Appendix A followed by the Finnish script in Appendix B. As the interviews were semi-structured, the interviewees were able to focus more on different questions based on their knowledge and experience. The interviews took from 33 minutes to 53 minutes, on average 45 minutes. All interviews were done online via Microsoft Teams and recorded with the permission of the participants.

4.3 Data analysis

Grounded theory is the most common method to analyze qualitative data. The theory is regarded particularly good in "facilitating theoretical work in substantive areas that have not been well researched by others" (Bryman & Bell, 2015, p. 593). Since previous research has not studied the use of audit data analytics in the planning phase and there have been technological advancements in the field of data analytics, the use of grounded theory is reasonable. Additionally, grounded theory differs from other research methods, since the data is not analyzed through an existing theory, but the data is used to generate new theories or develop existing theories (Strauss & Corbin, 1994), which makes the theory suitable for our thesis.

Grounded theory is based on systematically gathered and analyzed data. Soon after the initial data is gathered, data analysis is started by coding the data. The data is coded into component parts which are then grouped into concepts. Followingly, the concepts are elaborated into categories that are central to the phenomenon being studied. Throughout this process, the data is constantly compared and contrasted to identify similarities and differences within the data. The coding of data and collection of data will continue until theoretical saturation is reached. Thereafter, a substantive theory is specified based on the key categories and connections between them. (Bryman & Bell, 2015)

As with many other studies, our thesis incorporates some features of grounded theory but not all of them. To specify, the transcribed interview data were coded according to grounded theory and thereby different concepts were generated. Both writers analyzed the transcripts separately by using the same codes to group the data into similar concepts. The key concepts were then used to create broader thematical topics, that can be regarded as categories. However, the grounded theory is not followed in all stages, and after forming the thematic topics the collected data is analyzed based on the conceptual framework presented in chapter 3.6.

Chapter 3.6 concludes the previous research introduced in chapter 3 and presents assumptions that were established from the previous research. Moreover, the chapter introduces the key concepts and variables related to the problem which were identified in the previous research. Based on these assumptions, concepts, and variables as well as relationships between them, a conceptual framework is developed. The conceptual framework is the theoretical basis for this thesis and guides the collection of data and its analysis. The results of the interviews are analyzed in the light of the conceptual framework and thereby connected to the previous research.

4.4 Reliability, validity, and replicability

Qualitative research is often linked to concerns regarding reliability and validity. However, qualitative researchers have questioned the relevance of reliability and validity in qualitative research. Both reliability and validity can be divided into internal and external parts. External reliability refers to replicability, which is hard to achieve with interviews that happen in a social situation. Replication is particularly difficult as the results of qualitative research are easily influenced by the researcher's subjective perspective and learnings. (Bryman & Bell, 2015) To avoid the researcher's own interpretation, it is important to record the observations as concretely as possible (Silverman, 2017). In this thesis, the minimal inferences are acknowledged by doing verbatim transcripts of the interviews and interpretating the results based on previous research. Internal reliability, in turn, is used to describe mutual understanding about the observations between members of the engagement team. (Bryman & Bell, 2015)

Validity as a term refers to the interpretation of the observations (Silverman, 2017). Internal validity emphasizes the connection between the observations and theoretical ideas developed whereas external validity stresses the importance of generalization of the findings (Bryman & Bell, 2015). In the context of research, generalizability is measured based on the extent to which the results of the study can be generalized to other settings (Ghauri & Grønhaug, 2010). Qualitative research is often conducted with a small number of individuals, which makes the generalization arguably impossible. Therefore, in qualitative research, the findings should be generalized to theoretical reasoning rather than to populations. (Bryman & Bell, 2015)

Even though the relevance of qualitative studies has been questioned by some researchers, qualitative methods are considered effective to answer questions such as "how" (Doz, 2011). Moreover, qualitative research can be applied to research where the aim is to describe how something is done in practice (Doz, 2011). Furthermore, validity and reliability are taken into consideration in the selection of interview objects. The participants are experienced professionals in audit and IT, which increases the validity of the gathered data. Eilifsen et al. (2020) observe that there are significant differences in the use of audit data analytics between the Big Four accounting firms. Thus, we will interview professionals from several Big Four accounting firms to ensure that the results can be generalized.

4.5 Research ethics

Knowledge of ethical principles is crucial in business research. Firstly, the researcher has to consider the possible harm to the participant and the minimization of it. Confidentiality and anonymity are a big part of this as the identities of the participants and organizations must be maintained confidential if they request that. In qualitative research, anonymity is particularly important as the sample sizes are small. (Bryman & Bell, 2015) The use of data analytics and different data analytical tools are regarded as a competitive advantage and the content of the interviews is confidential. Therefore, it is extremely important to anonymize all individuals and organizations as well as the name of systems and adopted IT tools so that they are unidentifiable. Due to confidentiality and the rather small number of experts in the field, we have not divided the interviewees by the organization they work for.

The other ethical principles are lack of informed consent and invasion of privacy. Informed consent relates to the participant's decision to make an informed decision whether to participate in the study. (Bryman & Bell, 2015) The participants were informed about the research subject and the estimated duration of the interview before deciding to agree to the interview. They were also promised anonymity and the possibility to not answer questions they would not want to answer. Additionally, they were aware that we wished to record the interviews. Invasion of privacy refers to the extent to which privacy isolations could be condoned and is linked to the other principles already discussed (Bryman & Bell, 2015).

5 Results

In this chapter, the interview results are interpreted, and they are divided into different thematical topics in order to draw conclusions. Background information regarding the participants and how the interviews were conducted are presented. After the background information a more detailed unraveling of the interviews is conducted with the help of the thematic topics. Firstly, the current situation of ADA in the interviewed organizations is presented, where the focus is on how ADA is used and what kind of ADA is utilized. Secondly, the reasons for ADA usage in auditing are introduced and the factors affecting the usage. Thirdly, the changes and developments in ADA are discussed, as well as what measures have been taken to enable the utilization. Lastly, the impact of auditing standards on ADA is touched upon.

5.1 Interviewed professionals

Individuals with different roles are important for the research as the responsibilities vary between each organizational level (Liew et al., 2022). Partners and senior managers focus on the bigger picture and interact with clients regarding the audit and additional sales. Experienced managers often lead the audit team and focus on the operational details, whereas those with less experience do the practical analyses and report to the other team members about their findings (Liew et al., 2022). Several Big Four firms in Finland have a specialized team for IT audit, which complicates the dynamics a little, since the data analysts often do the data analytical procedures and send it to the financial auditors to go through and analyze the results. We have interviewed specialists from different organizational levels, with different roles and experiences, as presented in Table 1.

Interviewee	Role	Experience (Audit)	Experience (DA)
Participant 1	Manager	6 years, *	5 years
Participant 2	Manager	5 years, *	22 years
Participant 3	Partner	11 years, *	8 years
Participant 4	Senior Manager	11 years, *	11 years
Participant 5	Manager (IT Auditor)	8 years	3,5 years
Participant 6	Senior Associate (Data Analyst)	2 years	2 years
Participant 7	Manager (IT Auditor)	7 years	3 years
Participant 8	Partner	20 years, *	7 years

Table 1. Introduction of the participants. * Refers to the participant being an authorized public accountant.

5.1.1 The background of the professionals

The participants are shortly introduced to give an understanding of their background and suitability for the aim of this study. All the participants work for Big Four Firms, in either financial auditing or IT auditing. Most of the participants are authorized public accountants. In addition, the participants are to some degree experienced with data analytics and have applied data analytics in their work. The participants have different positions which gives insights into different levels of organizations and how the situation is perceived. Hence, two partners, one senior manager, four managers, and one senior associate were interviewed.

P1, P4, and P8 have mostly focused on auditing in their career but have also played a part in the technical development. P1 and P4 have, for instance, internal roles in teams that aim to improve the technical solutions available and other areas where these solutions are involved. Furthermore, these participants have seen practical advancements in data analytical tools over the years, as they have been applying them throughout their careers. P3 has shifted from auditing to data analytics during the past years and has deep insights into both areas. P2 and P6 have a background in analytics but have expanded their skillset to auditing. P5 and P7 have worked with internal auditing and are currently mainly focusing on IT auditing. The participants and companies were granted anonymity, and this is respected in the background information.

5.2 The present use of ADA

During the interviews, the participants described the present use of ADA from different viewpoints. These are divided under several topics: timeline of development, risk assessment, controls, standardized procedures, data analytical tools, and the effect of a new engagement.

5.2.1 Timeline of development

In order to form a better understanding of the use and starting point of ADA, the participants were asked about the historical timeline of ADA development. When they were asked how long data analytics and other analytical tools have been used for auditing in the organization, the participants hesitated to answer straight away within a certain number of years, as analytics comes in many forms. Analytical procedures have been used for several years now and are also regulated by auditing standards. Thus, the definition of data analytics is an important factor when it is determined for how long it has been used. P4 and P3 concluded that it depends on where the mark for data analytics is drawn. For example, P4 and P8 talk about audit command language (ACL) which has been used according to P8 for over 20 years. ACL was used when the data mass was too large for Excel to process. P2 agrees also that data analytics has been supporting auditing since the beginning of the 1990s.

P1 and P8 specify that general ledger analysis as an analytical tool has been used for auditing since 2016 or 2017, but it is not as sophisticated as the newer tools. The more sophisticated tools have been adopted during the last five years according to the majority of the participants. P3 believes the major steps took place within the past three years. P4 believes the pace of development has been exponential and more and more tools are being implemented to practice. P5 and P6 were unable to respond to the question concretely. P6 was of the opinion that data analytics has not been utilized for that long, as the skill set of auditors is not compatible, and P6 thinks that competitors are using data analytics at a larger scale. P5 referred to their role and to the narrow visibility it gives to audit planning and other audit procedures. To conclude, analytics has been used for a long time in auditing, but data analytics is a more recent form of analytics in auditing.

5.2.2 Risk assessment

The focus of the interviews was to understand if data analytics is already implemented in the planning phase, specifically in risk assessment, at the current moment. The answers received from the participants differ to some degree, which entails that the use of data analytics varies across different organizations. Based on the interviews one reason for the variation is the firm's audit methodology. For example, P4 refers to the audit methodology based on which the audits are conducted in the firm and how it guides auditors to use data analytics in the planning phase and it is a mandatory procedure. On the contrary, P2 discusses how the audit methodology lacks specific data analytical measures for the planning phase and risk assessment.

According to P3, data analytics is only used in some of the engagements, and it is utilized for individual items. P3 describes how some auditors have the ability to use data analytics in planning and risk assessment but others lack the skills. An understanding of the content of the items would be a prerequisite for further procedures. P3 uses revenue as an example that could be understood better with the help of the data and the IT environment. Moreover, P3 concludes that this is something lagging behind and it would be crucial to understand at the beginning of the engagement how the items are connected to the data. The risk levels and, followingly, the required procedures may drastically differ from each other depending on the specific item and its inherent risk. This type of understanding is of high importance for risk assessment.

Data analytics is already used to detect deviations in the financial statement and other financial data. According to P1, data analytics, in fact, can assist auditors in the analytical assessment of the company when auditors are inspecting the income statement and balance sheet for deviations. If deviations are detected, P1 explains how data analytics makes it possible to investigate the core of the problem. P4 describes how the risk determination is first done on the total level in order to identify the areas where the risk may lie. Data analytics becomes even more relevant when the details are analyzed on the second level. For example, the transaction flows are taken through the tools to see if they match the expected values which may indicate possible risks. When the detected deviations or risks are material, they are taken into consideration in risk assessment as there has to be an assigned procedure that responds to the risk.

P8 discusses the use of data analytics in connection to process analysis. In the planning phase, the number of transactions per account is assessed with analytics to see which accounts are relevant for further analytical procedures and which ones may be inspected with the traditional methods. The processes must be identified to detect the accounts with a high number of transactions. In addition, the persons making the entries for the account are identified. These analyses assist auditors when the auditee is interviewed as the answers are compared to the data and to what it makes evident. In addition, it is possible to specifically discuss the deviations found through data analytics with the auditee to understand what has caused them.

5.2.3 Controls

The effectiveness of controls has a huge impact on audit risk and, therefore, control identification is a key part of risk assessment. As process controls and IT controls are critical for the integrity of the data, this study is concerned with the controls influencing the quality and general usefulness of data produced in the IT systems by the auditees. Thus, a question about the controls was presented to the participants. Data analytics is not only relevant for testing of data but also for testing of controls. P7 stresses the importance of functioning IT controls and process controls since both of these affect the reliability and usability of the data. The more trust is placed in the material produced by the system, the more critical the IT controls are. Therefore, the consequence of failed IT controls might be serious for the audit plan. According to P7, the failing of IT controls changes the audit plan in the sense that manual methods are required when the integrity of the data is compromised. In other words, the workload of the auditor increases, and the effectivity benefits are lost.

P8 draws a line between accounting controls and IT controls. To demonstrate, P8 explains how data analytics is used to identify the IT controls in the systems, leaving the accounting controls as a dilemma. The accounting controls do not necessarily leave a trace behind that could be audited afterwards. P4 explains how an analytical tool is applied in practice to an ERP system. With the data analytical tool, the IT controls and system-specific application controls are identified. The effectiveness of the controls may be assessed through the data, but here the use of data analytics remains partial. In addition to data analytics, other measures are required, to gain assurance over the control effectiveness. However, this tool is specific to only one type of ERP system and is not yet a generalizable solution.

Even other participants imply that there are challenges facing the data analytical testing and identification of controls in the systems. P1 describes the difficulty of identifying the controls from the data as they are not necessarily included in the financial data. Thus, the controls may be part of the process but excluded from the data. In addition, P1 notes the customized nature of controls, meaning that the controls are client specific particularly when something else than the general ledger is considered.

5.2.4 Standardized procedures

The answers regarding standardized analytical tools present two opposite extremes. The participants were asked if there are standardized analytical tools mentioned in the audit methodology for risk identification, assessment of internal controls, and testing of internal controls. According to P2, the problem with data analytics is that it is not standardized, and data analytics is not systematically conducted in the risk management and planning phase. P3 makes a distinction between the engagements and notes how the systematic and standardized way of using analytics varies. Standardized data analyses are more common in the testing phase. P3 agrees with P2 about the fact that standardized tools are more present in the testing than in the planning. P7 has also similar thoughts as it might be difficult to identify controls with data analytics in the planning phase but indicates that there are standardized tools for the testing of the controls. P6 lifts up the problem with the data analytical procedures, as they are not done in a united manner but more depending on client and item being analyzed. P2 talks about the methodology and concludes that only a few ready-to-use data analytical procedures are included.

The opposite end is presented by P1, according to whom, only standardized tools and procedures are used. Other tools and procedures are not forbidden but the premise is to conduct the audit with standardized procedures. Similarly, P4 answers that standardized tools are in place and there are certain most commonly employed tools that are even mandatory to apply in the engagements. Additionally, P8 talks about standardized workpaper templates where the data is imported for further analysis. Auditors are obligated to follow the firm-specific methodology in their actions and if the methodology has not been updated after data analytics has become more common, the opportunities to take advantage of it are limited.

5.2.5 Data analytical tools

During the interviews, the participants lifted up two specific data analytical tools that have already been implemented in audit risk assessment. Both general ledger analysis and process mining will be discussed in more detail.

5.2.5.1 General ledger analysis

The general ledger analysis is applied to the customer's general ledger data, which is analyzed in different ways. The general ledger analysis was raised by more than one participant as a suitable analytical tool for audit risk assessment. P3 links the understanding of the general ledger data to the planning phase since it clarifies the connection between the financial statement item and the risks included in the specific item. The general ledger analysis enables broader insights whereas if, for example, only billing data or warehouse data are inspected, the bigger picture might be left unclear.

When the starting point is the general ledger, the procedures are more logical. P6 describes the information available in the general ledger and why it guides auditors. All the entries are visible and thus the different entry chains entail if something deviates from the usual. If a suspicious number of entries is made by one person, the tracing is made through the general ledger. Hence, the general ledger could guide auditors to the areas with the most risk with the help of data analytics. P3 agrees with this view and adds that after analyzing the general ledger it is easier to comprehend which subsystems are relevant to the assessed information. In general, the navigation through the data becomes more understandable when this approach is utilized.

Moreover, P7 identifies the effectivity gains with general ledger analysis, as it reduces the amount of auditing work required when the material areas are found more effectively. According to P7, the general ledger data is one of the largest datasets assessed. P2 depicts how the account-specific income statement and balance sheet are analytically inspected every month through the general ledger. Based on the interviews, the general ledger analysis is already proved useful, but more advanced data analytics could enhance the auditors' resource allocation.

5.2.5.2 Process mining

During the interviews, process mining as a solution for the process and control identification and testing was mentioned by several participants. For this reason, the relevance of process mining as one data analytical tool has been recognized in this study. Some of the participants have been using process mining concretely in their work and have practical insights about the applicability to real clients. P1, P2, and P4 discuss their experiences with process mining in practice and share the current obstacles and development potential.

P1 is concerned about the standardization of the tool when the systems are still inspected case-by-case and the data demands case-by-case consideration. According to P4, process mining is only used in a handful of clients and to different extents. On the one hand, P4 believes in the potential of process mining and is sure that the use cases will increase. On the other hand, P4 acknowledges a significant issue with process mining which could undermine the usability. The data mass left to assess is extensive and the auditor might be overwhelmed. The processes in the systems are long and vary depending on the case, which makes it challenging to define the relevant areas. Examples of deviating sales processes are cases where the order is canceled or modified. In addition, all the sales will never reach the general ledger due to these alterations on the way. Despite these hinders, P8 describes how easy the validation of some simple controls is through process mining - the transaction flow through the control point is visible, segregation of duties, and any modifications to master data may be assessed. P2 explains how process mining eliminates the "normal processes" and the focus is shifted to the unusual process paths. According to P2, this has risk-minimizing effects.

P5, P8, and P7 give more insights into the future and requirements of process mining. A critical challenge with process mining is the form of the metadata and event logs. Different systems produce different kinds of data, and some processes are run across several systems. P7 emphasizes the amount of work required to process the data into consistent and readable form. For specific ERP systems, this problem has already been solved and there are existing models used for process mining. P7 makes the notion that if process mining would be able to define processes going through the legacy systems, it would bring the most added value. Specifically, the processes going through legacy systems are the longer processes crossing several systems. According to P5, there must exist enough lines of data if process mining is used, which leaves out rarely executed processes.

P8 believes in the power of process mining and sees the increasing demand in the future coming from clients. Clients are expressing their interest in process mining as it makes the deviating transactions visible in the processes. Moreover, auditors are able to effectively test the data masses with only a few tests, and more resources are left for the deviating cases in the opinion of P8. An assumption made by P8 indicates an increase in the reporting made with process mining, as clients benefit from this information in their operations.

5.2.6 The effect of a new engagement

Another observation made during the interviews was how new clients affect the use of data analytics in the planning phase. Audit evidence is cumulative in nature and the knowledge of the client's operations grows every year. Thus, P1 suggests that auditees are divided into two "baskets": reoccurring audits and new audits. From reoccurring audits, auditors have accumulated audit evidence to support the data analytical procedures. However, this is not as straightforward with new clients. P1 claims that expectations based on the data from the first few months are not reliable enough. Hence, data analytics might prove partially useless right at the beginning of the first financial year being audited. Risk assessment is therefore made with qualitative methods, such as interviews and operational environment assessment, according to P1.

The same experience is shared by P2 who emphasizes the amount of work solely a takeover of a new client demands, leaving the analytical procedures to a minor role. P2 observes how the use of data analytics is impacted by the available data in the planning phase. If auditors are unaware of the different data types the client will provide, a trial-and-error approach is taken. P2 talks about "dry runs" which enable the first tests to see how the data could be analyzed later. Nowadays, clients have an increasing number of different systems supporting financial administration. It takes a couple of financial years to gain an understanding of the client, the systems, and what kind of data it is possible to retrieve from the systems. P2 acknowledges the difficulty of inquiring data when the auditor is unaware of what would need to be asked. After the get-to-know phase data analytics provides useful features. P7 considers the possibility of gaining access to the data from previous periods already in the planning phase. Consequently, the use of data analytics could in fact be meaningful for new auditees.

5.3 Reasons for the use of ADA

The interviews revealed several reasons for the utilization of ADA in different parts of the audit. ADA may support auditors in various areas and increase the effectiveness of the audit process. The factors driving ADA usage are discussed in detail in the following sections.

5.3.1 Benefits for risk assessment

The participants were asked why data analytics is used in risk assessment. P1 thinks data analytics provides additional assurance in the planning of the audit, as auditors have their own vision about the situation, but it might lack support. Usually, auditors have an expectation of which areas contain more risks than others. With data analytics the expectations of auditors are given a concrete background and, thus, the relevance of the expectations is higher. P1 gives an example of a situation where the auditor has noted in the discussions that there is something suspicious in the entries. For example, it is possible that a questionable number of entries was made at the end of every month, and this would be visible with data analytics. If the suspicion proves to be correct, the items are flagged and considered in risk assessment. Another reason raised by P1 is the quantifiable nature of data which makes it easier to see if the risk is material.

P8 observes how auditors like to think they know everything, when, in fact, the reality might be very different. With data analytics, the accounts are skimmed through and the relevant accounts with a large number of transactions are identified. P8 raises the reporting aspect of auditing since clients and audit overseers are interested in seeing the documentation behind the judgments. Furthermore, after data has accumulated over the years, the trend is visible, and this supports auditors when the reports are shown to clients. Effectivity benefits are drawn from the trends that data analytics provides, since auditors see where the exceptions are and where the focus must be directed.

Auditors aim to minimize the risks while conducting the work, and data analytics support this attempt. Thus, one reason for the use of data analytics is risk minimization. P2 believes that process mining has risk minimizing effect as it shows that the main data masses have followed the pre-determined processes and controls. It gives assurance to auditors over the data and pinpoints the deviating items. P2 gives a practical example regarding the general ledger that may include millions of lines of data, which are impossible to manually verify. If process mining works effectively, the risk will be smaller according to P2. P7 and P8 note how data analytics even brings added value when all the transactions go through the tools, and this has a reassuring effect. P7 compares this to sample taking where the sample should be statistically representative but, in reality, several deviations might be overseen. Even though data analytics might not reveal everything, it gives a broader overview compared to sampling.

With data analytics, auditors are able to gain a better understanding of the bigger picture and this reduces the risks of not identifying material misstatements. P2 claims that the most meaningful benefit of data analytics is the overall picture it gives, instead of dealing with the individual samples. P2 believes the overall view is also clearer when data analytics is used. P4 accompanies the opinion of P2 as the audit teams have a better understanding of the auditee from the beginning. P5 underlines how data analytics is in the first place utilized for large masses of information and a consequence of this is a better overview of the organization and its operations. P5 even compares the use of data analytics to interviews and exemplifies the concrete difference between these two – what data tell versus what a human tells.

5.3.2 Effectivity

The participants were asked if data analytics reduces the work of auditors and whether this could be a reason for the implementation of ADA. The answers received were not straightforward and they showcase the current stage of adaption. It was noted in the interviews that an important factor is the experience of the user. In the interviews with P1, P3, P4, and P6 the experience factor was stressed from the effectiveness perspective. P3 mentioned the size of the company and the high number of employees working in audit. This number of employees fits different types of skills and knowledge, and, thus, the scale is wide. P1 explains the possibility for resource savings when an experienced auditor is utilizing data analytics, and this further reduces the work required on the total level. In contrast, in the hands of an inexperienced auditor data analytics could even lead to additional work. Even though this might be the case in general with data analytics, the amount of evidence gathered in one hour has increased considerably according to P1. Hence, in the long-run data analytics will pay itself back and has clear effectiveness benefits.

P4 explains the requirement for more experienced auditors in the data analytics context through the validity of the analysis. In order to make a relevant analysis, based on which conclusions are possible to draw, experience is a necessity. If the staff conducts the analysis, it may be impossible to make conclusions based on the information. P6 also raises the problem of the segregation of work assignments. This leads to analyzing irrelevant information from the audit perspective and unnecessary work spent on making too complex analyses. According to P4, P6, P7, and P8, a consequence of this is making double work. Either the staff is unable to conduct the analysis, or the analysis is invalid and consequently, the traditional samples are taken on top of the analysis. P4 concludes how data analytics will surely reduce the workload when implemented correctly and it will take time to gain the desired benefits. P8 stresses the fact that it might be hard to let go of the old methods and trust the new ones.

The effectiveness benefits are still dependent on the specific engagements. P3 admits how far extremes there still are in the engagements when it comes to ADA usage. In some specific engagements, ADA optimizes the work, even if ADA is only used partially in the execution. P3 has noted the profitability advantages of these engagements. The other extreme is the engagements where the auditors think they should use analytics, but the reasons remain unclear. The consequence is again double work, as the analytics was conducted "just for the sake of it". The profitability declines in these engagements. P5 shares this view and stresses the importance of the planning phase as the risks and the proper tools to tackle these risks should be identified there. Analytical procedures are costly safety precautions for the auditors, and they should have a clear purpose in the engagement.

The third factor influencing the effectiveness benefits of data analytics is the understanding of the auditor. P2 describes that many feel like ADA only causes additional work. P2 further explains how the perception of data analytics remains incomplete, as auditors are unsure what it replaces from the traditional procedures. This creates uncertainty among auditors, which leads to the incapability to make decisions regarding the right methods, and it feels easier to rely on the traditional procedures.

5.3.3 Other internal and external factors

Additionally, of interest is understanding the internal and external factors affecting the use of ADA, and the participants were asked to list these factors in the interviews. First, the external factors are represented and then the internal factors. P1, P3, and P4 agree that there is pressure from clients to modernize the audits and utilize more analytical tools. P1 refers to the trendiness of data analytics and how this is reflected in clients. P4 observes clients' desire for additional value and expectation for new technologies used in the audit. P3 believes clients expect the audits to be broader and more detailed. P5 assumes that pressure stems from competitors who are developing their tools toward incorporating data analytics. P7 suggests the pricing pressure is a factor affecting the adaption of ADA as the competition is hard on the field.

Nearly all the participants thought the effectiveness benefits were the most important internal factors affecting the ADA implementation to operations. P1 states there are clear effectiveness benefits from analytics. P3 refers to the workload of auditors and thinks analytics could reduce it and make the work assignment efficient. P4 thinks data analytics makes the procedures more straightforward and in general harmonize the procedures inside the firm. Even P5 talks about the cost-effectiveness benefits arising from data analytics.

In addition, the audit quality could increase with data analytics and organizations are interested in this. P4 claims audits made with the help of data analytics have higher quality. P3 agrees with P4 that ADA usage all the way from the planning phase affects audit quality positively and this drives the implementation. Risk assessment is more accurate and audit procedures are better aimed when more data is processed, and this is reflected in the quality. P5 implies that high-quality audits require ADA implementation since the data gives a solid background.

Lastly, ADA has made the work of the auditors more meaningful. P1 thinks it is sensible to conduct the audit procedures with ADA. P4 has recognized that people think the audits are performed more conveniently through analytical tools. P3 concretely describes how the meaningfulness of the work content increases when ADA takes over the monotonous and mandatory tasks. With ADA the work is spread throughout the year according to P4 and this could also have positive effects on the meaningfulness of the work.

5.4 Challenges

Not only did the participants discuss the benefits and possibilities of audit data analytics but also some challenges. There are certain challenges that most of the participants referred to: collaboration between the financial auditor and data analyst, problems with data, as well as challenges with competence shortage and shifting content of the work.

5.4.1 Cooperation between the financial auditor and data analyst

Based on the interviews, the auditors are experiencing challenges within their organizations. P2, P6, P7, and P8 all mention the gap between the financial auditor and data analyst. P2 explains the problematics behind this gap as financial auditors do not always understand what data analytics is capable of. P2 is more concerned about the factor that financial auditors have excessive expectations of data analytics whereas P6 stresses the other end of the spectrum and is more concerned that the financial auditors are unaware that something could be audited more effectively with data analytics. P6 discusses the importance of cooperation in the planning phase. If the financial auditors and data analysts would plan the procedures together it would be easier to identify which procedures could be done with data analytics and where it is necessary to rely on traditional procedures. However, P6 clarifies that this kind of cooperation is still regrettably rare.

P7 and P8 discuss the issue from a control standpoint but identify a similar gap in the understanding. According to P7, the control testing requirements are unclear for the auditors in some instances. This is due to the fact that data analytics conducts substantive testing of data, which implies that the testing of controls is an unnecessary procedure. Similarly, P7 explains the importance of remembering this in the planning phase, since data analytics can cover the whole data set and auditors do not necessarily have to plan to conduct any control testing in that process. P8 shares this opinion by emphasizing that it does not matter whether some control is effective or not if the whole dataset can be audited. However, P8 concludes that when the audited data is taken from system, the IT controls should in fact be checked. Otherwise, the data is considered unreliable which according to P8 often is forgotten by financial auditors.

5.4.2 Challenges with data

When working with technical solutions, it is to be assumed that there are some technical challenges, especially with data. When the participants were asked what is hindering the use of analytics, many of them named the challenges with data. Several participants referred to the importance of data availability. P2 stresses that not only is it crucial that there is available data, but the data must be in a suitable format. P4 specifies the requirements for the format and explains that the data has to contain the right kind of data points that are relevant to the analysis. P8 agrees with P4 and emphasizes the importance of high-quality data. P6 has also experienced problems in data availability as clients might not always understand the added value of data analysis and might therefore complicate data retrieval. P6 expresses that data retrieval would be easier if the client would give auditors the rights to the systems so the chances of receiving the right kind of data would be higher, which often is not the case.

P4 also discusses the challenges in practical data retrieval. According to P4, Finnish companies use several different ERPs which complicates data retrieval, as every ERP is different. Followingly, the auditor or data analyst is often forced to use a lot of time to understand what kind of data is available and how the data practically may be retrieved. P4 also mentions some ERPs that in their experience do not enable the retrieval of right kind of data. These considerations require comprehensive system understanding. P2 mentions that the data format may be so difficult to understand that its processing and interpretation require experience. P8 echoes this opinion and thinks that an inadequate understanding of the data is one of the most central obstacles to the use of data analytics.

5.4.3 Competence shortage

Traditionally financial auditors have had a business background. However, as the use of data analytics becomes more common, auditors are required to master new skills. P1 discusses the change in the content of auditors' work and their worry that auditors' skills are not compatible with the requirements of the job. P1 names this as one of the challenges that must be overcome in the future, as it is now slowing down the implementation of data analytics since ADA-driven audit requires a totally different analytical mindset compared to the traditional audit. P4 also recognizes this impairment in auditors' skills and explains how the expectations of new associates' skillset are much higher than the knowledge required from the new associates when P4 began as an associate.

P1 discusses the alternatives to solve this competence shortage. On the one hand, the solution could be recruiting people that already have the required skills through education or previous experience. On the other hand, it is also possible to train those experts in-house, but P1 comments that this requires a lot of resources and must be expensive. P3 comments on the profitability of the engagements from a competence perspective. P3 explains that the implementation of new procedures, such as data analytics, with which the engagement team is not familiar, might weaken the profitability of audit. P1 predicts that one possibility is that there will be separate groups of people with data analytical skills and people with financial audit experience, as the required skillset will otherwise be too wide.

5.5 The changes and developments in ADA

The aim of the interviews was also to comprehend how data analytics and the use of data analytics have developed after the first implementations. The pace of development has increased exponentially during the past few years and the solutions are becoming increasingly complex and sophisticated. Even if data analytics has existed in some form already from the 90s, the difference between past solutions and today’s solutions is drastic. Thus, the comparison of these solutions might not be meaningful. The analytical tools available today provide opportunities for completely different analytics than the past tools.

5.5.1 Planning and risk assessment

Not only is the focus of this study in understanding the past development of data analytics, but also the future developments of data analytics in the planning phase and specifically in risk assessment. In the opinion of P1, the data analytics in the risk assessment has become more precise and will continue to develop in this direction in the future. P1 describes how, at its core, auditing is identifying risks and responding to the risks. Thus, data analytics would make both the risks and the procedures more specific. According to P8 data is analyzed at an earlier stage of the year when previously it was viewed for the first time in the fall. Now data is a part of the planning, and a basic understanding can be received earlier. Followingly, P8 thinks the analysis of data could be spread out through the year more evenly in the future.

P4 recalls how individual audit teams were responsible for the use of data analytics when it was not yet implemented in the methodology. Hence, data analytics was left out of the planning phase and was supporting other stages of the audit, for example, evidence inspection. After the new audit methodology, analytics has become a part of planning and risk assessment. There is more guidance on the use of analytics and where it should be utilized. P4 concludes how the audit teams are able to gain a thorough picture of the client and its operations. Even though data analytics generally improves understanding, data analytics has not, according to P4, identified any new relevant risks in the engagements but it has deepened the knowledge of the existing ones.

P3 discusses the changed way of thinking in connection to data analytics. Data analytics has a supporting nature in audit, and it may be used at the beginning stage of a task, for example, the first assessment in planning. The latter part could still be done manually if data analytics is a too complex tool for the task. P6 believes analytics has a future in planning and risk assessment. A challenge remains, according to P6, in how data analytics are developed and utilized. The cooperation is deficient, and auditors have the knowledge required for meaningful analytics. Therefore, cooperation in the development of analytics would benefit everyone.

5.5.2 Development of data analytical tools

During the interviews, data analytical tools and their development were discussed with the participants. According to P2, the tools are going through constant change, and they are changing more than the actual analyses. Nowadays Excel has stepped aside, and other tools are at the center, which even advances visualization opportunities. P1 agrees to this and adds how reporting to clients has developed with the new tools. Furthermore, observations made with the tools have higher significance than before. The tools are utilized at a broader scale in the audits when auditors' skills have developed. P3 also identifies the development in the tools during the past few years. According to P3, process mining has seen significant advancements in process identification. Additionally, the standardization of data analytical tools used for sub-ledgers is, in the opinion of P1, a favorable future direction.

For auditors the development toward user-friendliness of the tools is important and this was noted in the answers. P1 describes the intuitiveness of the newer tools compared to the older ones. Once the tools are intuitive enough, even less experienced auditors have the ability to produce useful analyses and conclusions based on the data. P1 predicts the tools will go through massive changes in the future and they are more straightforwardly implemented. P4 agrees that the tools are becoming more user-friendly, and the analysis field will be broader. With standardized data analytical tools, possibilities for straightforward analyses grow, according to P7. In fact, analyzing tools conduct everything for the auditor with the inbuilt models. The firm has invested a lot of resources in the development of data analytics and in this way supported the change.

P8 gives a thorough explanation of the development stages. First came the general ledger data analysis and from there it expanded to other areas. Thereafter sales, current assets, and salaries could be analyzed with data analytics. For investment companies, a separate data analytical tool was developed which understood the investments. P8 notes how nowadays data analytics are a natural part of the audit whereas 20 years ago it felt unnatural. The challenges with data quality were harder to overcome as the lack of compatible skills was severe. Thus, the auditors could not be sure if the analysis had succeeded or not.

The participants were asked to suggest if there are tools, they are still unable to use, and the majority thought they have already an extensive set of tools at hand. P1, P2 and P8 were exceptions as both identified tools that could elevate the process. P1 thinks standardized statistical tools would help in the analyzing of data. P1 assumes regression-based procedures will become more common in the future. P2 and P8 were interested in the development of process mining and the tools it could introduce to the field. P6 speculated how there might be an analytical tool where both auditors and clients may leave comments. This would increase interactivity and support the overall documentation.

A few participants expressed in the interviews their beliefs regarding the automatization of the data analytical tools and the possibilities for intelligent tools, which would reduce the manual work. P2 notes the fact that current analyses are still very mechanical in nature. There are some implementations already, but the benefits are marginal, and auditors are obliged to conduct the overview. The general ledgers are difficult to analyze with artificial intelligence because organizations have different ways of making entries. P2 suggests a possibility for intelligent deviation analysis where the tools raise suspicious entries for the auditor to observe. In practice, the people working with data analytics could do the analyses in advance and hand out these to auditors for further assessment. According to P4, automatization is under constant development. The target of these developments is resource-intensive monotonous tasks. P7 assumes artificial intelligence could even make judgments in the future when the legislation allows this.

Revised audit methodologies support the development of data analytical tools and procedures. Some of the participants think the largest measure taken by their firm to enable the utilization of data analytics is the new audit methodology. The new methodology is the base for digital audits where data is used to a high degree. These participants see the revising of audit methodology as a huge investment and change of mindset. Besides the revised audit methodology, extensive in-house training has taken place in some of the firms. P6 disagrees with the current methodology since it insists unnecessarily on broad inspections. P6 suggests the inspection could be based on the level of the risk and not on the amount of the material.

5.5.3 Data

The handling and understanding of data have gone through changes over the years and will continue to improve. P4 describes how data was first stored on auditors' computers with structured query language (SQL), then in servers, and nowadays in the cloud. P8 talks about the past problems with retrieving the client data when the auditors were responsible for it. Nowadays specific data specialists conduct the retrieving and structuring of data instead of auditors. In addition, P7 explains that data is exported through standardized tools installed by the client and the analyzing models are pre-defined. Thus, the technical side lies in the hands of technical experts rather than auditors.

Auditors' capacity to analyze has increased with the different storage opportunities. P2 sees an opportunity for automated data handling where data is automatically retrieved from the client's systems. In addition, automated structuring of data and intelligent databases are the future possibilities meaning that the software could automatically retrieve the data from the database in real-time. P4 stresses the growing amount of data which challenges the capacity of the analyses and requires powerful tools. P1 and P4 see as a future challenge the transportation of other than general ledger data to the tools, for example, ERP system or control data. In contrast, P3 stresses the challenges of understanding the data and standardizing the procedures.

P2 and P3 discuss in detail developments in database management and the benefits this creates. The participants mention centralized databases for the client data where the data is standardized and ready for analyzing. P3 identifies effectivity benefits when the auditors are able to just take the chosen analyses with the press of a button and the intervening discussions with a separate analytics team are avoided. P2 shares the idea of application interface access to the most common accounting systems. Through the application interface, the data retrieving process would be simplified and shifted to real-time retrieval. In reality, this requires a significant number of working hours as well as permissions from the client which might complicate the practical use of that kind of application.

5.5.4 Required competence

P1, P3, and P6 discuss the developments made within firms to attain the skills and knowledge required for data analytics. During the past years, data analytics teams have been established to support the auditors with the change. Thus, people with compatible understanding are developing analytical tools and producing analyses for auditors. The firms are investing in hiring more people that fall under the analytics umbrella. P1 mentions that people with data engineering skills are also part of the new analytical teams. P3 observes the benefits gained through the restructuring of different teams dealing with IT and analytics. Thus, required knowledge is available more efficiently and the coordination is straightforward. According to P6, the aim is to connect people with knowledge of the standardized analyses and people with knowledge of the customized analyses in order to educate different professionals about the purposes of data analyses.

The auditors' professional judgment has to evolve with the new procedures and increasing amount of data. P2 gives an example where the samples are replaced with analyses. For the auditors, the consequences might remain unclear, and judgment is required to solve the issues. The auditor has to decide what the data analyses are able to replace without compromising the quality of the audit. P6 further contemplates how the analyses give a better bigger picture, but auditors must still recognize the unusual items. The timeframe auditors have for the analyzing is tight and puts pressure on the judgment.

5.6 The impact of standards

Based on the previous research, the auditing standards are one of the most significant factors related to the implementation of data analytics, so we also asked the participants about their views regarding the auditing standards. None of the participants were of the opinion that the current standards would prevent the use of ADA, but thoughts about the future of the standards differed amongst the participants. In the current stage, the participants seem to refer more to their own audit methodology than to the standards.

However, there is a clear connection between the standards and the methodology. P2 notes that analytical tools are mentioned in the standards, but the standards do not specify how the actual procedures should be done. Therefore, P2 suspects that this is the reason why data analytical tools have been included in their internal audit methodology on to a certain extent. P4 shares the opinion by concluding that the use of technology is more precisely defined in their own methodology when compared to the standards. P4 continues with an example and explains that standards contain requirements for the audit which can be fulfilled according to the auditor's own judgment. That judgment can be that the requirements are most effectively fulfilled by using ADA. Additionally, P3 stresses that the changes in standards are always taken into consideration and updated in the methodology.

The difference in answers regarding future development is significant but can also depend on the fact that some participants may be more familiar with the auditing standards than others. When it comes to data analytics, P2 thinks that the standards will not be changing, since too detailed standards would leave too little space for practical application and, therefore, will not affect the use of ADA. P4 also anticipates that the standards will stay at a quite general level since the audited firms differ enormously and the same standards have to be applied to all of them. This relatively neutral opinion is shared by P7 who thinks the standards do not prohibit the use of ADA but do not either guide the use of it. P7 adds that future changes might have a bigger effect on IT audits as the data has to be reliable. P6 did not want to comment on the standards as they were not too familiar with them.

P8 does not either see any prohibiting factors in standards but recalls an incident in some other country, where the evidence provided through audit data analytics was not enough for regulators, as the data used as evidence did not contain enough data points, and the documentation of the procedure was not precise enough. P3 discusses the developments in regulation. They believe that regulation will tighten, as it has been doing in the past. Moreover, P8 predicts that regulation will not allow for much latitude but will not prevent the use of ADA. Followingly, P8 thinks some procedures might have to be done more precisely to meet future standards, which could increase the workload in that aspect. P1 echoes the fact that the regulatory requirements will probably be increasing especially when it comes to gathering enough audit evidence. P1 mentions also the challenges in implementing the new requirement which in some cases might be hard. Additionally, they expect changes in ISA 520 that will regulate the use of ADA.

A few participants shared even more specific thoughts about the changes in risk assessment. P3 explains how the recent changes in the standards have shifted the focus of the audit more toward risk assessment and planning phase overall. According to P3, ADA is a suitable solution for that shift: in some cases, it is more difficult to evaluate the exact correctness of a certain financial statement item with ADA, but the analytical way of working suits risk assessment well. Through data analytics, the auditor can assess what an item consists of, what kind of transactions have taken place, and what risks may be associated with the item. Therefore, P3 calls for wider use of ADA in risk assessment as it is an effective way to meet the requirements of the standards. P1 predicts that requirements for documentation of risk assessment will increase significantly as it relates to the revised ISA 315 and IT auditing as well as ADA.

All participants were specifically asked whether the revised ISA 315 will affect audit risk assessment. P1, P2, P7, and P8 share the opinion that the revised standard will not have a direct effect on audit data analytics as it mostly requires an assessment of the risks associated with the IT systems. According to P3, the standard takes the work in the direction that the auditor needs to understand the big picture and risks better, including the system environment and understanding data flows from beginning to end. P3 thinks ADA could be helpful to fulfill those requirements within risk assessment. P4 does not either see a major effect in risk assessment but thinks the revised standard has an impact on the quality of the data and thereby also affects ADA. P5 and P6 did not want to comment on the effect of the revised ISA 315. All in all, the participants do not expect big changes in the applicable standards within the next 5 years.

6 Analysis of results

The results are analyzed in this section through the conceptual framework built in section three based on the previous research. The results are related to the findings and conclusions previously made in this field of research in order to derive novel interpretations. The results were categorized under several thematic topics in section five and with the help of the conceptual framework the results are analyzed under different thematic areas. The aim of this study is to study the role of data analytics in the risk assessment phase of an audit, and which impacts the implementation might have on the audit overall. Altogether eight participants contributed to the study and the answers vary to some extent, which introduces space for further contemplation. Part of the reason is due to the fact that the participants were from different Big Four accounting firms.

6.1 ADA in the planning phase

Based on the previous research it is expected that ADA is implemented in the planning phase and appropriate tools are developed by the audit firms. According to the previous research, in the planning phase and risk assessment the purpose of analytical procedures is to “enhance the auditor’s understanding of the client’s business and its transactions or events and identify areas that may indicate probable risks to the audit” (Appelbaum et al., 2017, p.4). On the contrary, Appelbaum et al. (2018) discuss if more complex analytics could challenge the traditional analytical procedures, which are not a new invention in the auditing field. Thus, the previous literature is used as starting point to see how far the practice has come and how ADA is utilized in the planning of audits. The results of the interviews show that the auditors recognize the distinction between analytical procedures and more novel data analytics. Analytical procedures are familiar already from the 90s, but sophisticated data analytical tools have formed during the past five years. This emphasizes the importance of understanding the difference between these two and what their capabilities are in the data processing. During the past five years, Big Four accounting firms have developed more complex analytics to better understand the data and the risks. Analytical procedures have become more integrated into the audit process and the program characteristics are evolving constantly to a more user-friendly direction.

The interviews reflect the previous research (e.g., AICPA, 2017; Eilifsen et al., 2020; Titera, 2013; Werner et al., 2021) as it is clear that data analytics enhance auditors' understanding of the entity, its environment, and risk assessment. When the data is thoroughly analyzed, the assumptions generated of the auditees have additional support. From a client perspective the backed-up assumptions have more relevance, and auditors may concretely visualize their opinions. With data analytics, the auditees are first analytically assessed before moving on to other procedures. Consequently, auditors have a stronger understanding of the auditee and a clearer overview to base the audit on. This understanding is also required by the auditing standards (IAASB, 2019, ISA 315) as risk assessment relies on understanding. The first assessment of data reveals areas with risk after which the data is further aggregated to see if the risks are material. If the risks are material, risk assessment is adjusted accordingly. The interviews provide empirical results to showcase how this is done in practice. Usually, the first assessment is done with standardized analytical tools or general ledger analysis followed by more complex tools such as process mining to identify the processes.

Eilifsen et al. (2020) conclude in their study that the usefulness of ADA in risk assessment is recognized while the practical implementations and tools remain unknown. The authors discovered two strategies for ADA implementation, and they represent opposite ends of the spectrum. On the one hand, the firms are still waiting to see where the development is going but on the other hand, the firms are deeply involved in the facilitation of ADA (Eilifsen et al., 2020). A similar spectrum emerged from the interviews and the central meaning of firm-specific audit methodology was recognized in this context. Eilifsen et al. (2020) argue that the limited use of ADA will continue until it is incorporated into the firm-specific audit methodologies.

The results of this study confirm this suggestion as the participants in this study referred mostly to the audit methodology when they spoke about the data analytical tools used in the planning phase. In the interviews, one participant discussed the firm's updated audit methodology, which relies on data analytics in risk assessment and gives detailed guidance for the auditors. Followingly, the participant expressed that this methodology update has increased the use of ADA in risk assessment. On the contrary, some participants admitted the deficiencies regarding the guidance over the tools in the methodology and were more hesitant to use ADA in risk assessment. The results agree with the observations made previously by the researchers, as Saljeni et al. (2018) have also noted in their study the effect audit methodology has on the adoption of data analytics.

Controls are of interest for two reasons in this study. Firstly, effective controls assure the reliability and quality of data produced in the systems. Secondly, the assessment of controls with data analytics would increase the effectivity of the audit. According to the participants, the data analytical assessment of controls is still challenging and there are several challenges facing this process. Systems are assessed for IT controls that relate to the system access, changes implemented to the systems, and automatic system controls. In the interviews, the importance of these controls was stressed since the data reliability relies on functioning controls. If auditors move toward data-driven procedures, the assessment of controls becomes an integral part of the planning. Wang and Cuthbertson (2015) discuss how traditionally the controls are only tested at one point in time and how data analytics could be used to ensure the operation of the controls for a whole period of time. A similar concern is visible in the results of this study since IT auditors conduct the testing at a specific time point and have no knowledge of changes made before or after this time point, which compromises the reliability of the data. The ineffective and unreliable controls are sorted out at the beginning of an audit, and this directs the audit planning as the control risk is an essential part of audit risk.

Jacky and Sulaiman (2022) have derived corresponding results in their study and concluded that robust IT controls are a necessity for data-driven audits. However, the data analytical assessment of control effectivity remains deficient according to the interview results. Even the analyzing of the business processes is related to the controls and supports the understanding of the auditors. According to Eilifsen et al. (2020), a mapping of business processes is done with ADA in the planning phase, and this was mentioned in the interviews since the processes for accounts with a high number of transactions must be identified. For some systems a partial assessment is possible but in general, the controls are manually tested. Thus, it may be concluded that ADA tools for control assessment are still being developed and are used for certain systems. Usually, the controls and processes in these systems are pre configurated by the system provider which enables standardized ADA tools to be effectively used in all the engagements where the same systems are used.

The previous research regarding ADA usage in control assessment and the importance of effective controls is not very extensive. Usually, it is concluded in the literature that functioning IT controls increase data reliability and unreliable data could compromise the data analytical assessment of auditees. For example, Liew et al. (2022) note that the quality of IT controls must improve if data analytics is used in the audits. Therefore, this study has contributed to the literature by studying the practical situation of control testing and identification with ADA. The potential of ADA for the control assessment is recognized by the results of this study and some analytical tools are already applied in practice. In addition, the auditees have shown interest in the data received from the analytical assessment of controls.

The systematic use of data analytics is still developing, and the procedures are dependent on individual clients. Based on the results, previously the decision to use data analytics has been on the shoulders of individual teams and team-specific competence has determined the usefulness of data analytics. However, the firms have developed standardized tools for certain procedures, and these are now used according to methodology. Specific ADA applications discovered in the interviews were general ledger analysis and process mining. These tools were also mentioned in the literature, but research on the practical implementations was scarce. Namely, the previous research merely listed these tools, and in which phases they might be applicable. Therefore, this study was able to discover how the tools are utilized in practice, especially in the planning phase of the audit.

General ledger analysis is, according to the interviews, a suitable tool for risk assessment procedures, since all the entries are visible in the general ledger and the analytical tools reveal the connections between financial statement items and the risks included in the individual items. After analyzing the general ledger, auditors comprehend the upper level of the information and can effectively target the details. General ledger analyses are relatively easy to standardize, and the information is comparable which assists in detecting deviations from the usual. Werner et al. (2021) emphasize the importance of the role data analyses play when auditors are gathering an understanding of the auditee, and the general ledger is a central source of information for the tools. Since the general ledger is a huge dataset, the data analytical analysis of it has effectivity and reliability benefits, as the risks of material misstatements can be analyzed from the whole dataset at once.

Process mining is applied for the process and control mapping and testing by the auditors. Werner et al. (2021) have researched process mining as one complementary analysis tool and discovered in their study how limited the data analytical inspection of controls is still today. The same phenomenon is recognized in the interviews since the participants were unsure about the data analytical identification of controls and processes. The major problem seems to be the nature of the clients' systems. The assessment is dependent on the specific system as the controls are customized. This introduces problems in developing a tool that could effectively find processes and controls from different systems. As an example, one participant mentioned the high number of different ERP systems solely in Finland. The effectivity gains are lost if the tool has to be altered separately for every system.

The previous research has also identified the problem with several systems and argues it is one prerequisite for the utilization of ADA (Eilifsen et al, 2020; Liew et al., 2022). This implies direct development challenges for the data analytical tools as the tools are unable to process and understand data from various systems. Despite these evident problems, the study identifies the potential of process mining. Werner et al. (2021) discuss the usefulness of process mining for risk assessment in the sense that reliable information about the relevant risks is gathered with the tool. In the interviews, process mining was mentioned by several participants as a means to tackle the process and control assurance. The control verification with process mining minimizes the risks embedded in the processes. Process mining is already being applied by some of the firms but only in specific engagements where the use is reasonable from the resource perspective. The results indicate a belief in the development of process mining and the demand from clients for this type of analytical technique. To conclude, ADA is applied in the planning phase by the firms, but the extent of ADA usage differs between the actors to some degree.

Appelbaum et al. (2017) recognize the effect of insufficient competencies on ADA utilization. They imply that there are analytical tools available, but the use is prevented by the inadequate skills of the auditors. In the interviews, this concern was also raised by the participants since some auditors are capable of using the analytical tools while others lack the ability. If the firm-specific audit methodology still mainly encourages the use of traditional audit methods and has not been revised, auditors are not demanded to update their technical skills, whereas an updated methodology would require advanced analytical skills from auditors. Consequently, the audit methodology has an impact on the auditors' competencies.

The overall requirements for new auditors have changed tremendously during the past years (Liew et al., 2022). The participants compared today's requirements to the requirements they faced when applying for their position. Nowadays technical and analytical skills are needed in addition to financial auditing skills. Saljeni et al. (2018) discovered in their study that a lack of skills prevents the process-wide use of data analytics. This leads according to Saljeni et al.

(2018) to forming specialized teams with analytical knowledge. This finding was made also in this study and the firms have established teams that support the auditors with data management and analyzing. Although data analytical tools are becoming more intuitive and software for automatic data retrieval is improving, the need for dedicated experts is not diminishing. Speculation around the future of the occupancy is inevitable and the participants had different visions of the possible solutions. Firstly, the existing professionals could be trained in-house to master the novel audit tools. Secondly, recruiting new experts with analytical skillset could improve the situation. Lastly, the current model with two separate teams is continued and people with other than business backgrounds could join the data analytics team.

6.2 Standards

Previous research has quite extensively discussed how auditing standards affect the development of ADA, but the opinions of the researchers are polar opposites. However, an absolute majority of previous research views the effect of standards negatively, meaning that the standards complicate the use of ADA even though they do not prevent it. Jacky and Sulaiman (2022), for example, argue that the lack of authoritative guidance is the number one reason inhibiting the use of ADA. On the contrary, some studies refer to standards as an enabling factor. Therefore, the explanation for this contradiction is of interest when analyzing the results.

In contrast to previous research, the participants have a positive outlook on the effect of standards. Firstly, previous research stresses the slowness of updating standards as a limiting factor for ADA (e.g., Titera, 2013; Eilifsen et al., 2020). The professionals interviewed in this study recognize the situation but do not see it as a significant factor prohibiting the use of ADA. Instead of standards, the participants argue that organizations' internal audit methodology has a bigger impact. Secondly, previous research insists that procedures performed with ADA are considered less reliable by the standards setters (Appelbaum et al., 2017), and the auditors are followingly unsure if they can use procedures performed with ADA as evidence (Eilifsen et al., 2020). Based on our study, this uncertainty has decreased significantly as the audit methodologies have evolved. The participants explain how they can rely on the methodology and trust that if they perform the audit procedures according to the methodology, the procedures will also fulfill the requirements of the standards. Therefore, the uncertainty about the sufficiency of the evidence has decreased notably.

Lastly, previous research has identified the problem of conducting data analytics as a complementary procedure to the traditional methods due to the uncertainty in regulation and competitive pricing (Eilifsen et al., 2020). The participants mentioned the problem with overlapping procedures but do not implicate that the standards would be the reason for the overlap. According to the participants, the methodology guides their daily work, and even though the standards do not define how data analytics should be used, the methodology defines it in more detail. Therefore, there is no need for precautionary procedures. However, our study shows that lack of experience and knowledge has a bigger role in the discussion.

Based on the interviews, when data analytics has become more common and trendy, it may even be used without thinking about why it is used, which can lead to unnecessary complementary procedures. Even though the participants' attitude toward the standards is quite positive or at least neutral, the participants mentioned some aspects they are concerned about. The audits are yearly randomly quality checked by regulators and the participants expressed their concerns when it comes to procedures performed with ADA. One participant even shared an example where the evidence produced by ADA was not enough for regulators and complimentary procedures should have been needed. Thereby, the concerns regarding overlapping work expressed in previous research seem reasoned.

This study provides a new contribution regarding the effect of standards on the ADA used in risk assessment since it has not specifically been studied in previous research. The results show that recent changes in the standards are shifting the focus of the audit to the planning phase and risk assessment. The problems with the evidence are not the same in risk assessment and, therefore, ADA meets well the requirements of standards set for risk assessment. Participants see several possibilities for ADA in risk assessment as it can effectively improve auditors' understanding of the entire data and transactions within it as well as assist in recognizing risks. This contradicts the results of Saljeni et al. (2018) who mention that the standard setters are concerned about the ADA's effect on the understanding of materiality and risk factors.

The results imply that auditors do not expect significant changes in standards, that will affect the use of ADA, in the near future. The overall consensus is that the standards tend to tighten but they have to be broad enough to be suitable for all kinds of audits. The revised ISA 315 has not affected the use of ADA in risk assessment, according to the participants.

6.3 ADA as a solution to meet the new requirements of audit

This study has identified new requirements audit is facing with the changing business environment where the auditees interact. Even though the requirements challenge the audit process, they also present new opportunities for audit firms. In this study, the focus has been on three main factors affecting the traditional audit, namely, big data, audit effectivity, and audit quality. When ADA is harnessed effectively the requirements presented by these factors are satisfied according to the interview results. Even previous research has made the conclusion that with data analytical tools big data could be turned into an advantage (e.g., Titera, 2013). The adaption of ADA in risk assessment will become more common when the obvious benefits are recognized at a large scale.

Previous research has identified that audit firms are the followers in big data utilization and, therefore, also in the implementation of data analytics (Daglienė and Klovienė, 2019). Our study makes a notion that this might be due to the data availability, format, and retrieval. Hence, the auditees are able to analyze their own data more efficiently, while audit firms have to handle every auditee separately depending on their systems. This fact was stressed by several participants during the interviews which imply that big data is both a facilitator and an obstacle for data analytics. For instance, Appelbaum et al. (2017) state in their article that "big data provides almost limitless opportunities to the external auditor to utilize advanced analytics" (p.4).

According to the interviews, the large amount of available data enables auditors to draw a detailed picture of the client which assists in different phases of the audit. Followingly, a higher assurance could be reached which is supported by the previous literature (e.g., Brown-Liburd & Vasarhelyi, 2015). In the interviews, the amount of data was interpreted as a positive phenomenon, as different trends are visible over the years, and these developments in the trends are effectively communicated to the auditees with data analytical tools. Similar findings are discovered in the article by Salijeni et al. (2018), where the effective communication of risk assessment is discussed. Consequently, the results of the study correlate with the previous research but also contribute with findings regarding auditors' opinions over the changing data environment.

This study has gathered first-hand experience regarding the effectivity benefits of ADA. The results strongly support the assumption that one of the main reasons for ADA implementation are the effectivity gains. The previous literature reflects this conclusion and depicts a future with digitized audits (e.g., Krieger et al. 2021). Vast amounts of data are analyzed with less manual work. The amount of evidence accumulated per hour has increased remarkably, which solely proves the effectivity of ADA. This study discovers that the relationship between ADA and effectivity is not straightforward in every case, as other factors interfere. Namely, the experience of the auditor is an important factor when effectivity is pursued. Another central factor is the engagement to which analytics is applied, since, for example, the size of the auditee affects the effectivity benefits. This study is able to conclude that effectivity is both dependent on the individual auditor and on the auditee. In practice, less experienced auditors lack the ability to make meaningful analyses and easily rely on traditional methods in addition to the data analytical tools, whereas experienced auditors reduce the overall workload by deriving relevant analyses in an effective manner.

There is an ongoing debate regarding audit quality and the impact of ADA. On the one hand, more data is thoroughly analyzed to form the assessment, while on the other hand, the tools are not entirely trusted. In contrast, Daglienė and Klovienė (2019) have recognized pressure from regulators to apply advanced analytical tools as it increases audit quality. The results support the view that ADA would in fact have quality-enhancing characteristics. The quality of individual stages is increased, and this improves the overall audit quality. It can even be stated that ADA is required to maintain the level of audit quality and without ADA the quality will decrease. Previous research has studied the relationship between ADA and audit quality and agrees that ADA will improve the quality (Daglienė and Klovienė, 2019; De Santis D'Onza, 2021; Earley, 2015).

6.4 Future development

Previous research refers to the possibility of more advanced data analytical tools that would enhance risk assessment without particularly defining these tools. The results indicate that auditors believe in the future possibilities of ADA. The participants expect that data analytics will lead to more precise risk assessment, which is in line with previous research that has identified the quality advantages of ADA due to a better understanding of the entity (Appelbaum et al., 2017; Eilifsen et al., 2020). Further improvements to the understanding are expected via new advanced tools that, according to the interviews, will take huge steps forward in future. The results specify several advancements in risk assessment, the most central ones being standardization of data analytical tools and process mining.

It is clear that the firms are in different stages in the implementation of these but there is a common interest to form a better understanding of clients' data and use it to improve and enhance risk assessment. Liew et al. (2022) have identified that Excel and other spreadsheet-based tools are not suitable to process the enormous amount of data which is confirmed in the interviews as the participants call for more advanced tools. Automatization of the tools is under constant development and the participants see potential in more intelligent tools that could reduce the manual monotonous work. The participants argue that improved risk assessment as well as automated tools offer possibilities for increased effectiveness, as discussed also by Liew et al. (2022). Thereby, this study has identified new possibilities within ADA which are in line with the expectations of the previous research.

The results address changes in the accessibility of the ADA. As the tools are becoming more user-friendly, ADA will be accessible for less experienced auditors. Another way to make ADA more accessible is automated data handling and structuring of data. The auditors discuss the possibility of intelligent and centralized databases where the data is standardized and ready for analyzing. This would enable the possibilities of ADA that were identified in the previous research, such as the collection and comparison of data from various sources (Appelbaum et al, 2017; Jacky & Sulaiman, 2022; Li, 2022) which could enhance the risk assessment. AICPA (2015) presumes that risk assessment will adopt a real-time approach where the risk levels are assessed continuously, and the procedures are updated accordingly. Based on the interviews, auditors do not yet see additional value in real-time risk assessment but explain that if data is analyzed earlier, the analysis of data could be spread more evenly throughout the year.

Previous research suggests that ADA could improve both the quality of professional judgment but also complicate the use of auditor's judgment in some situations (Li, 2022). In the planning phase of an audit, it is important to decide, which procedures are done by using ADA and what kind of data analyses result in the best quality while being as efficient as possible. This decision requires professional judgment, and the results of the interviews indicate that there are huge differences in auditors' abilities to make this judgment. Using judgment does not only include making sure the evidence and quality are sufficient but the evaluation of the reliability of the data. Brown-Liburd et al. (2015) argue that these judgments require advanced technical knowledge that many auditors lack. In other words, data analytical tools are perceived as complex and the data formation in the systems is not grasped by auditors. However, the results of the interviews show that auditors can in many situations rely on the firm's audit methodology which takes the mentioned considerations into account. Additionally, the teams specialized in data analytics are able to help with the assessment of data relevancy.

Based on the interviews, the auditors perceive that more experienced auditors are able to do better data analyses as they have more experience to base their judgment on. This contradicts the previous research, as Hamdam et al. (2022) argue that an auditor's ability to handle big data has greater impact on the quality of the decisions than the experience of the auditor. However, Liew et al. (2022) express that the increasing cooperation with IT specialists enables the analysis of large datasets, and the analysis is made accessible for less experienced financial auditors through data visualization. The participants acknowledge the possibility to form a better understanding of data but stress the fact that auditors must still recognize unusual items which requires experienced professional judgment.

Additionally, experienced auditors understand the transaction flows and how the entries are made to the systems, and this understanding supports the analyzing of the data. Hamdam et al. (2022) introduce a possibility for less biased judgments through data analysis which could reduce the effect of auditors' limitations in analyzing the vast amount of data. As a concrete solution, the participants of this study suggest that, in the future, artificial intelligence could make judgments instead of auditor when it is legally possible. Consequently, it is clear that the use of ADA affects professional judgment, but professional judgment continues to be a crucial part of audit even though the data analysis can identify potential risks. Judgment is required in the planning phase when deciding which procedures are compatible with the assessed risks as well as when interpreting the results.

7 Conclusions

The focus of this study is on researching how the changing business environment is affecting auditing and how the industry could respond. Technical advancements and a growing amount of data are shaping the industry toward a new era. As the industry is facing several concerns and challenges, this study examines the possibilities of ADA to tackle the new requirements. The aim of this thesis is to study the role of ADA in risk assessment to understand how it could impact the whole audit process. Followingly, the research question "how data analytics is used in audit risk assessment and what are the impacts of it?" has guided the study.

Wang and Cuthbertson (2015) discuss in their article issues on data analytics that could be researched in the future and the role of data analytics in risk analysis is one of them. The authors note the lack of information regarding practical implementations and what the impacts might be on the overall audit engagement. Thus, our study has combined different aspects of ADA studied before, and applied the existing knowledge together with new empirical findings to a less researched area. Appelbaum et al. (2018), call for more research in the domain of analytics in external auditing, as they have made a broad literature review of 301 papers mentioning analytical procedures in the context of public audit engagements. Even though a vast body of research exists in this area, research about ADA's practical implementation by audit professionals is scarce (Appelbaum et al., 2018). However, the material gathered for this study has revealed practical implementations of ADA in the planning phase and is able to answer the research needs identified previously. While previous research has been unable to contribute with such findings, this study contributes to the existing literature with findings of the progress made in practice and what the future might look like in the opinion of industry experts.

As the focus has been on the use of ADA in risk assessment, the central findings are derived from this area. Previous research has made significant findings of ADA usage in the testing phase as it is in auditors' interest to lower the detection risk. Hence, the capabilities of ADA in assisting auditors in risk determination has not received attention to the same degree. This study has discovered that the Big Four accounting firms have implemented ADA to some extent, but the overall usage and advancements in audit tools vary across the firms and individual auditors. Audit methodology is the primary source of guidance and, therefore, it impacts the possibilities to rely on ADA. This implies that ADA is used to a higher degree if the methodology has been recently updated. In addition, the ability to use ADA effectively relies on clients' systems, and better system integration would enhance the possibilities to apply ADA. The most evident factor affecting ADA usage is auditors' competencies regarding analytical tools. The firms aim to tackle this challenge by allocating resources to in-house training and forming dedicated teams skilled in analytics.

Currently, in risk assessment, ADA supports auditors in generating an overall understanding of the auditee, which then guides the planning of the audit procedures. As ADA enables the processing of vast amounts of data, the understanding of the client is improved, and this affects the following audit procedures. ADA does not make any decisions on behalf of the auditor but guides the auditor to target the riskiest financial statement items. Consequently, ADA produces high-quality information that supports the professional judgment. The Big Four accounting firms have already implemented ADA applications such as general ledger analysis, process mining, and other standardized and non-standardized tools developed in-house. The use of ADA in risk assessment streamlines the audit process and eliminates resource-intensive manual tasks. ADA enables the designing of more precise audit procedures that stem from risk assessment, improving the effectivity of the whole audit process.

The use of ADA is regulated by auditing standards which have been considered as a prohibitive factor for the usage in previous research. However, the results show that the interviewed auditors do not echo this perspective since they see that their firm-specific audit methodology has a bigger effect on how ADA is used in risk assessment. The firm-specific audit methodology takes into account regulations and auditors trust that procedures made according to the methodology also fulfill the requirements of the standards. Therefore, the results contradict earlier findings and demonstrate that auditors are not concerned about the standards when deciding whether to use ADA in risk assessment. If anything, the recent changes in standards are shifting the focus to risk assessment.

The results indicate that the firms have increased and are increasing the use of ADA in risk assessment. The data analytical tools are becoming increasingly sophisticated and drawing analyses requires less experience from the auditor. The results suggest that this will have a positive impact on audit quality and effectivity, as ADA reduces the manual work required for data processing. Additionally, the increased use of ADA in risk assessment affects and changes professional judgment. On the one hand, auditors will have stronger support for their judgments. On the other hand, auditors have to evaluate the suitability of analytical procedures, the results of them as well as the suitability and reliability of the data being used. Consequently, the auditors are equipped to answer the changed expectations of clients and other stakeholders. Even though analytical tools have already advanced tremendously, there is a clear ambition to further develop them and use them in risk assessment.

7.1 Future research

One central limitation of this study is that the implementation of ADA in risk assessment has only started in recent years and the use of ADA will develop significantly in the future. Therefore, the topic could be further researched after the industry has implemented more sophisticated analytical tools and the use of them is more common. In particular, future research could focus on the audit of controls, as the use of ADA in that area is not yet very established. The use of ADA in assessing controls is increasing in the near future when, for example, process mining advances or another solution is developed. Another interesting field for further research is the evolution of professional judgment. ADA could be combined with sophisticated technologies, such as AI, that have the ability to make judgments independently. This has the potential to significantly change the dynamics of professional judgment.

The majority of previous research as well as our thesis has implemented an interview-based approach when studying the use of ADA in practice. Some studies have also had the access to documentation and have conducted a content analysis but research regarding the daily application of ADA by auditors is limited if even non-existing. Therefore, we suggest that future research could study the use of ADA in risk assessment through observation and investigate how auditors actually make the decision whether to use ADA or not, how it is implemented, and how the results influence the rest of the audit process.

Lastly, we want to highlight further research needs on the relationship between financial auditors and IT auditors. Bauer, Estep, and Malsch (2019) have studied the impact of the relationships within the whole audit team, and the importance of mutual value and respect, which, according to them, is not always achieved. Our results indicate also that there might be problems in this relationship which can decrease both the effectivity and quality of the audit. In the light of risk assessment, this is important as Allen, Hermanson, Kozloski, and Ramsay (2006) show the importance of both skillsets in risk assessment. Even though financial auditors may think that they are capable to identify risks related to IT systems, Allen et al. (2006) are of the opinion that collaboration with IT specialists is crucial as IT expertise has a greater effect on the accuracy of auditors’ system related inherent and control risk assessments than general audit experience.

8 Summary in Swedish – Svensk sammanfattning

Dataanalysens roll i revisionsriskbedömning

8.1 Inledning och problemdiskussion

Det huvudsakliga målet för revision är att uppnå rimlig säkerhet att det reviderade bokslutet inte innehåller väsentliga felaktigheter (Appelbaum, 2016). Eftersom mängden data som produceras av företag har ökat exponentiellt, måste revisorerna också reagera på denna förändring. Om revisionsmetoderna och revisionsverktygen inte uppdateras, ökar revisionsrisken samtidigt som pålitligheten av revisionen minskar, eftersom de nuvarande metoderna inte är tillräckligt effektiva. Dataanalys kunde stödja revisorerna för att bemöta de nya krav som stordata ställer. Implementering av nya metoder kommer dock medföra ytterligare utmaningar, eftersom revisionsbranschen är starkt reglerad av lagar och standarder.

Revisionsprocessen består av olika faser som innehåller olika användningsändamål för dataanalys. I denna studie undersöks dataanalysens roll i planeringsfasen, särskilt i riskbedömning. Wang och Cuthbertson (2015) anser att riskbedömning och utvärdering av interna kontroller är områden där användningen av dataanalys kunde vara meningsfullt. Ostrukturerade data tolereras bättre i planeringsfasen än i andra faser av revisionen, vilket förstärker dataanalysens möjligheter i riskbedömningen (Earley, 2015). Även om det enligt revisionsstandarder är obligatoriskt att använda analytiska granskningsåtgärder under planeringsfasen, är tidigare forskning inom detta område begränsad. Tidigare forskning har påpekat att revisorer är osäkra om analytiska granskningsmetoder räcker som bevis. Därför finns det en tendens att göra överlappande granskningsåtgärder. Revisorernas begränsade resurser leder dock till prioriteringar, vilket oftast innebär att endast traditionella granskningsåtgärder görs och de analytiska åtgärderna utelämnas. Detta lämnar ett tydligt behov för forskning om dataanalys i revisionens planeringsfas.

8.2 Syfte

Tidigare forskning om användningen av dataanalys i revisionsprocessen är inte heltäckande, eftersom forskningen har koncentrerat sig på andra granskningsmetoder och andra revisionsfaser än planeringsfasen. Därför är avhandlingens fokus på planeringsfasen och målet är att undersöka hur dataanalys kan förbättra granskningen i planeringsfasen. Syftet med studien är således att analysera dataanalysens roll i revisionsriskbedömning, vilket kommer att studeras med följande forskningsfråga:

Hur används dataanalys i revisionsriskbedömning och vilka påföljder har det?

8.3 Metod

Studien utförs med en kvalitativ forskningsmetod, eftersom syftet är att studera dataanalysens roll i revision i praktiken. Kvalitativa metoder möjliggör forskning av praktiska tillämpningar. Materialet samlas in med semistrukturerade intervjuer för att få mångsidigt material som stöder studiens syfte. Semistrukturerade intervjuer skapar ett utrymme för nya frågor som uppstår under intervjun, vilket stöder forskning av ett relativt nytt fenomen (Bryman & Bell, 2015). Därmed har studien ett intervjubaserat tillvägagångssätt som bygger på åtta intervjuer med olika sakkunniga inom branschen.

En central aspekt i kvalitativa forskningar är urvalet av intervjuobjekt. I denna studie har intervjuobjekten valts från Big Four-revisionsbolag som är verksamma i Finland, eftersom de stora bolagen har resurser för utveckling av nya granskningsmetoder och verktyg. Även tidigare forskning stöder detta perspektiv och därmed valet av bolagen. De intervjuade personer arbetar med revision på olika nivåer i bolagen. Intervjuobjekten valdes med målinriktad urvalsmetod, vilket betyder att personer med relevanta erfarenheter och kunskaper för studiens syfte kontaktades. Intervjuguiden är uppbyggd på basis av tidigare forskning och annan facklitteratur. Frågorna är indelade i fyra teman för att skapa en tydlig struktur för intervjuer. Först diskuteras allmänna frågor om deltagarnas bakgrund. Detta följs av frågor om nuvarande användning av dataanalys och framtida förändringar i användningen. Till sist diskuteras inverkan av revisionsstandarder.

För analys av det empiriska materialet tillämpas grundad teori och ett konceptuellt ramverk med utgångspunkt i tidigare forskning. Enligt grundad teori kategoriseras materialet innan det analyseras. Grundad teori skiljer sig från andra forskningsstrategier i det att materialet inte analyseras genom ett existerande teori utan materialet används för att utforma nya teorier. Denna studie inspireras av grundad teori, men teorin tillämpas inte i dess hela utsträckning. Efter att materialet har kategoriserats på ett meningsfullt sätt, analyseras det med hjälp av det konceptuella ramverket. Antaganden som utformar ramverket har skapats utifrån tidigare forskning.

8.4 Tidigare forskning

Tidigare forskning är i hög grad enig om att dataanalys kommer att påverka revisionsindustrin i viss utsträckning. Däremot finns det olika uppfattningar om förändringens takt och påföljder. Överlag är forskning om dataanalysens roll i planeringsfasen begränsad (Appelbaum, Kogan & Vasarhelyi, 2017; Eilifsen, Kinserdal, Messier & McKee, 2020; Liew, Boxall & Setiawan, 2022). Trots detta har tidigare forskning identifierat flera potentiella fördelar med dataanalys (Eilifsen et al., 2020; Perols, Bowen, Zimmermann & Samba, 2017). Därtill finns det redan färdiga verktyg som står till förfogande, men revisorerna saknar kompetens för att tillämpa dessa (Appelbaum et al., 2017). Ett annat hinder för implementering av dessa verktyg är ineffektiva systemkontroller (Liew et al., 2022). Därutöver anses revisionsstandarderna påverka möjligheten för vidsträckt användning av dataanalys, men åsikterna i litteraturen är varierande. Å ena sidan ses standarderna som ett hinder (Titera, 2013; Jacky & Sulaiman, 2022), och å andra sidan anses de möjliggöra tillämpning av dataanalys (Salijeni, Samsonova-Taddei &Turley, 2018).

Titera (2013) diskuterar i sin artikel hur den växande datamängden utmanar både revisionskvalitet och effektivitet medan Brown-Liburd, Issa och Lombardi (2015) anser att stordata har potential för ökad revisionskvalitet. Då mängden data ökar, behöver revisorn använda professionellt omdöme i högre grad för att avgöra pålitligheten av data (Li, 2022). Dataanalys har även egenskaper som bidrar till riskbedömning, eftersom avancerade analytiska verktyg kan användas för att utforma riskbaserade sampel i stället för slumpmässiga sampel.

Med utgångspunkt i tidigare forskning har följande antaganden utformats för att stödja analysen av det empiriska materialet. På basis av tidigare studier kan det antas att användningen av dataanalys är begränsad i planeringsfasen, men det existerar verktyg som motsvarar planeringsfasens behov. Det kan förväntas att revisionsstandarder kan ha både positiv och negativ inverkan på användningen av dataanalys, vilket gör det ett intressant område för forskning. Användningen av dataanalys i riskbedömningen antas att öka, och därmed uppstår det ett behov för forskning som studerar påföljderna. Till sist kan det förväntas att de nuvarande analytiska verktygen kommer att utvecklas och att det uppstår avancerade lösningar för speciellt riskbedömning. Dataanalys antas påverka revisorernas professionella omdöme i framtiden.

8.5 Resultat

Intervjuresultaten kategoriseras och analyseras under olika teman för att svara avhandlingens forskningsfråga och syfte. Teman som diskuteras är dataanalysens roll i riskbedömningen, revisionens förändrade krav, effekten av revisionsstandarder och framtidsutsikter.

Resultaten från intervjuerna visar att även om olika analytiska verktyg har använts sedan 1990-talet har mera avancerade analysverktyg utvecklats under de senaste fem åren. Big Four-revisionsbolagen har allokerat resurser för utvecklingen av verktyg som möjliggör djupare insikter i kundernas data och risker. Enligt resultaten har analytiska procedurer blivit bättre integrerade i revisionsprocessen och verktygen utvecklas åt ett användarvänligare håll. Resultaten stämmer överens med tidigare forskning (AICPA, 2017; Eilifsen et al., 2020; Titera, 2013; Werner, Wiese & Maas, 2021) som också visar att dataanalys förbättrar revisorernas uppfattning om det reviderade bolaget och därmed riskbedömningen.

Eilifsen et al. (2020) sammanfattar att dataanalysens fördelar har identifierats i tidigare forskning men studier om dess praktiska implementering i riskbedömning saknas. Denna studie har identifierat praktiska användningsändamål och befintliga verktyg som används av Big Four-revisionsbolagen. Såsom tidigare studier också visar, finns det stora skillnader i utvecklingstakten mellan de olika revisionsbolagen. Vissa bolag är väldigt insatta i utvecklingen medan andra väntar på vart utvecklingen är på väg. Resultaten visar att den bolagsspecifika revisionsmetodologin har en central roll i användningen och utvecklingen av dataanalys. De intervjuade bolagen har redan skapat vissa standardiserade verktyg som används i olika revisionsfaser i enlighet med metodologin. Huvudboksanalys används då en första bedömning av bolaget görs för att skapa en helhetsbild av data och möjliga risker. Därtill utnyttjas processmining för att identifiera och revidera olika processer och kontroller.

Kraven på revision har förändrats under de senaste åren, vilket har medfört vissa utmaningar. Denna studie har identifierat flera nya krav som industrin behöver bemöta. De intervjuade deltagarna diskuterade hur revisorer saknar analytiska och tekniska kunskaper. Därmed har kraven på nya revisorer också ökat i hög grad. Utöver kompetensproblem nämndes stordata, effektivitet och revisionskvalitet som faktorer som kommer att förändra den traditionella revisionen. Dataanalys har dock egenskaper som hjälper att lösa utmaningar med de nämnda faktorerna. I denna studie studeras även hur kontroller påverkar möjligheten att implementera dataanalys i riskbedömningen. Om databaserade revisioner blir allt vanligare, ökar kraven för effektiva kontroller. Dataanalys kunde vara ett lämpligt sätt för kontrollrevidering och därmed bli en del av planeringsfasen.

Resultaten gällande attityder mot revisionsstandarder avviker från tidigare forskning som betonar standardernas negativa påverkan. Deltagarna har nämligen en positiv attityd gentemot inverkan av standarder. Resultaten visar att metodologin i praktiken har en större effekt på användningen av dataanalys än revisionsstandarder. I litteraturen har det diskuterats att standarder orsakar överlappande arbete, men resultaten från denna studie stöder inte denna uppfattning. Studien bidrar till forskningen, då det inte förut har undersökts hur standarderna påverkar utnyttjandet av dataanalys i riskbedömning. Resultaten indikerar att fokus i standarderna kommer att flyttas till planeringsfasen och speciellt till riskbedömningen men inga stora förändringar förväntas på kort sikt.

Resultaten indikerar att revisorer är övertygade av de fördelar som dataanalys kommer att medföra i framtiden. Deltagarna antar att dataanalys leder till noggrannare riskbedömningar, vilket är i linje med tidigare studier, eftersom dataanalys förbättrar revisorernas uppfattning om de reviderade bolagen (Appelbaum et al., 2017; Eilifsen et al., 2020). Enligt resultaten kommer de mest centrala framstegen tas i standardisering av verktyg som kan användas för riskbedömning. Verktygen blir lättare att använda, vilket innebär att mindre erfarna revisorer också kan utnyttja analyserna. För tillfället har erfarna revisorer eller separata team utfört analyserna, eftersom de kräver mycket professionellt omdöme. Även om verktygen blir lätthanterligare, har professionellt omdöme fortfarande en viktig roll i revisionen.

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Attachment 1 - Interview guide in English

The aim of this study is to research the role of data analytics in the planning phase of the audit and specifically in risk assessment. In addition, the paper is interested in researching the effects of data analytics on the whole audit process. The environment, where auditors conduct their work, has changed faster than the available methods, for instance, the amount of data has increased notably, and the systems used by clients are more complex.

Please find below the interview questions used and it is possible to discuss other areas and themes if they become relevant. We hope you agree to the recording of the interview.

Introduction

- What is your position and the main responsibilities of your role?
- How many years have you spent as an audit professional?
- How many years have you been in your current work position?
- Do you have any certifications relevant to your profession?
- Do you have any other relevant working history in regard to data analytics?

Current use of audit data analytics

- How long has your company been using data analytics and other data analytic tools? How long have you personally used data analytics?
- How is data analytics implemented in the planning phase of the audit process, especially risk assessment?
- Does your firm have standardized data analysis tools according to your firm's audit methodology in the planning phase for risk identification, assessment of internal control, internal control testing etc.?
- Why are you using data analytics in audit risk assessment? (why not?)
- What internal and external factors drive your company's use of audit data analytics?
- Is the use of data analytics currently causing additional work or reducing the workload?

Changes in the use of audit data analytics

- How has the use of data analytics changed in audit risk assessment?
- How has the use of data analytics developed / how could it be developed?
- What actions have been taken to favor the use of data analytics in your organization? Based on your opinions, what are the most important factors favoring the utilization of data analytics? And what are those hindering the use of data analytics?
  How has the increase in the use of data analytics affected the planning phase and risk assessment?
- Are you seeing major changes coming within the next 5 years regarding the use of data analytics?
- Are there some analytical tools that you would like to use but you can't yet?

The effect of auditing standards

- What is your perception of auditing standards and regulations regarding the use of data analytics in auditing?
- How does ISA 315R affect the use of data analytics?
- Do you expect any changes in the regulatory framework in form of regulators responding to the emergence of audit data-analytics?

Attachment 2 – Interview guide in Finnish

Tutkimuksen tarkoituksena on tutkia data-analytiikan roolia tilintarkastuksen suunnitteluvaiheessa ja erityisesti tilintarkastusriskin arvioinnissa ja määrittelyssä. Lisäksi tutkimme mitä vaikutuksia data-analytiikan käytöllä on tilintarkastukseen kokonaisuutena. Ympäristö, jossa tilintarkastajat toimivat on muuttunut nopeammin kuin käytössä olevat metodit, esimerkiksi datan määrä on kasavanut huomattavasti ja asiakkaiden järjestelmät ovat monimutkaisempia.

Ohessa haastattelua tukevia kysymyksiä, voimme keskustella myös muista aiheista ja osa-alueista, mikäli ne ovat relevantteja. Toivomme, että suostutte haastattelun tallentamiseen.

Yleistä

- Mikä on asemasi ja mitkä ovat roolisi päävastuualueet?
- Kuinka monta vuotta olet tehnyt töitä tilintarkastuksen parissa?
- Kuinka monta vuotta olet ollut nykyisessä tehtävässäsi?
- Onko sinulla joitakin työsi kannalta merkittäviä sertifikaatteja/pätevyyksiä?
- Onko sinulla muuta relevanttia työkokemusta data-analytiikkaan liittyen?

Data-analytiikan käyttö tilintarkastuksessa nykyään

- Kuinka kauan data-analytiikkaa ja muita analyyttisia työkaluja on käytetty yrityksessänne? Miten pitkään olet itse käyttänyt data analytiikkaa?
- Miten data-analytiikkaa käytetään tarkastuksen suunnitteluvaiheessa, erityisesti riskien arvioinnissa?
- Onko yrityksessänne käytössä standardisoituja data-analyyttisiä työkaluja, joita käytetään suunnitteluvaiheessa riskien tunnistamiseen, kontrollien tunnistamiseen, kontrollien testaukseen jne.?
- Miksi käytät data-analytiikkaa tilintarkastusriskien arvioinnissa? (miksi et?)
- Mitkä sisäiset ja ulkoiset tekijät ohjaavat yrityksesi data-analytiikan käyttöä?
- Aiheuttaako data-analytiikan käyttö tällä hetkellä lisätyötä vai vähentääkö se työmäärää?

Muutokset data-analytiikan käytössä

- Miten data-analytiikan käyttö on muuttunut tilintarkastusriskin arvioinnissa?
- Miten data-analytiikan käyttö on kehittynyt / miten sitä voitaisiin kehittää?
- Mitä toimenpiteitä on tehty data-analytiikan käytön edistämiseksi organisaatiossasi? Mitkä ovat mielestäsi tärkeimmät data-analytiikan hyödyntämistä edistävät tekijät? Ja mitkä ovat tekijöitä, jotka estävät data-analytiikan käytön?
- Miten data-analytiikan käytön lisääntyminen on vaikuttanut suunnitteluvaiheeseen ja riskien arviointiin?
- Uskotko, että data-analytiikan käytössä tapahtuu suuria muutoksia seuraavan viiden vuoden aikana?
- Onko olemassa joitakin analyyttisiä työkaluja, joita haluaisit käyttää, mutta et vielä saa?

Standardien vaikutus

- Mikä on käsityksesi tarkastusstandardeista ja -sääntelystä, jotka koskevat data-analytiikan käyttöä tarkastuksessa?
- Miten ISA 315R vaikuttaa data-analytiikan käyttöön?
- Odotatteko standardeissa ja sääntelyssä tapahtuvan tulevaisuudessa muutoksia data-analytiikan käytön yleistymisen vuoksi?