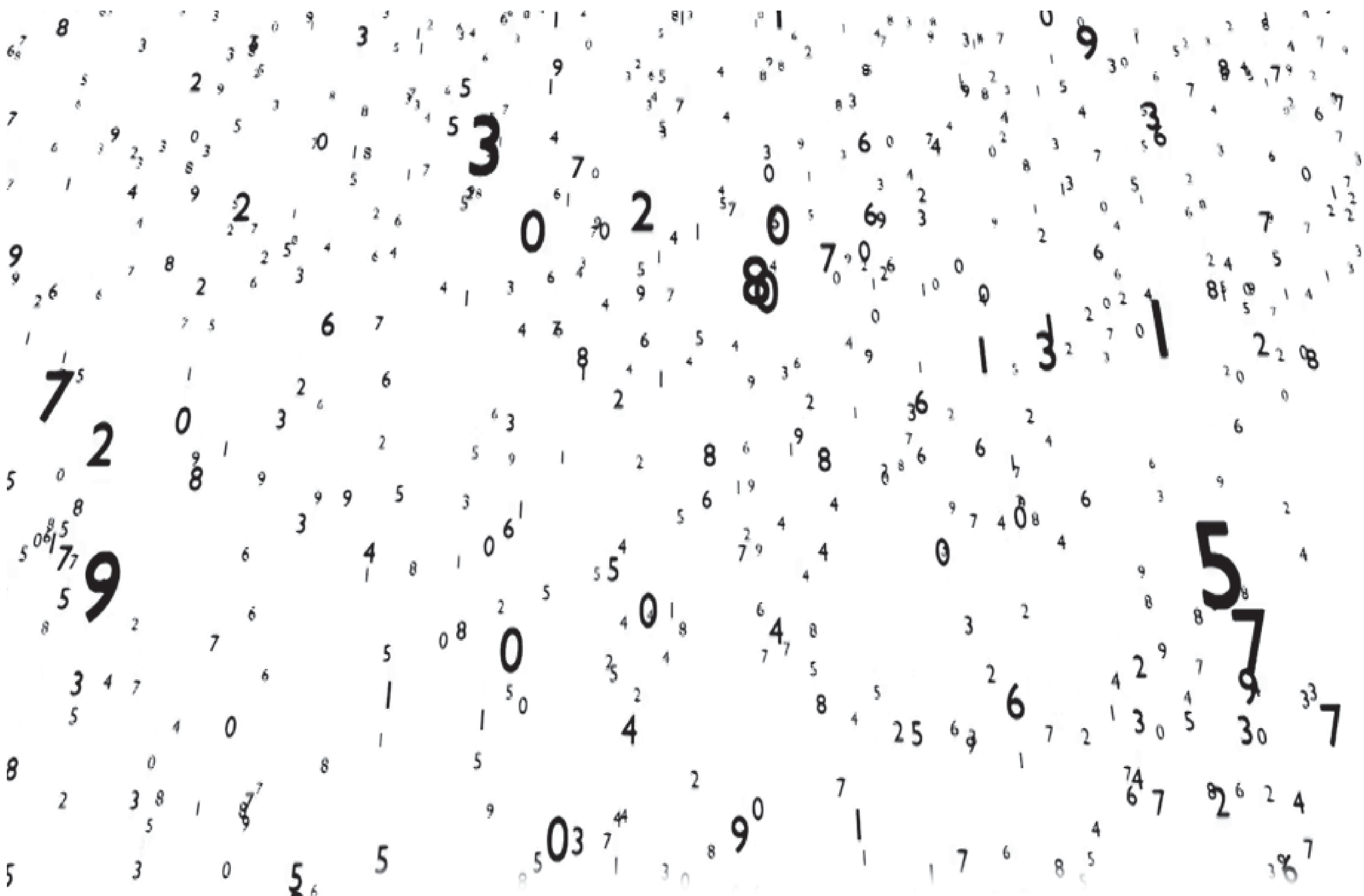

DATA ANALYTICS IN FINANCIAL STATEMENT AUDITS

Identification of the Key Challenges in Implementing Data Analytics in Financial Statement Audits under the International Standards on Auditing

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RESUMÉ

Stigende digitalisering og automatisering i samfundet har de senere år medført et massivt fokus på og investering i implementering af dataanalyse i finansiel revision. Revisionsbranchen er dog underlagt en række love og standarder, hvorfor det må tilsikres, at implementeringen sker i overensstemmelse med den relevante regulering på området. I denne afhandling er det derfor undersøgt, hvordan begrebet dataanalyse benyttes i den nuværende debat, hvor branchen er på nuværende tidspunkt i processen med at implementere dataanalyse, samt hvor de væsentligste problemstillinger forbundet med at implementere dataanalyse under de gældende internationale standarder om revision (ISAerne) opstår.

Det er fundet at dataanalyse, som begrebet anvendes i revisionsbranchen i dag, omfatter en rækker metoder og værktøjer til at analysere mønstre, tendenser og afvigelser i data, til formål for opnåelse af revisionsbevis. Sådanne værktøjer kan i stigende grad automatisere analyseprocessen og analysere på store mængder af data. Revisionsbranchen er dog på et tidligt stadie i implementeringen af dataanalyse, idet de anvendte værktøjer fortsat anses som relativt simple og som oftest anvendes på traditionelle typer af finansiel information. Branchen bevæger sig dog gradvist mod at udvikle og anvende mere komplekse teknologier og andre typer af information. For nuværende anvendes dataanalyse dog primært i tillæg til eksisterende revisionshandlinger inden for risikovurdering og substansrevision. Traditionelle handlinger er endnu ikke i videre omfang erstattet af dataanalyse grundet usikkerhed i om, hvordan nye værktøjer og metoder kan anvendes til at give revisionsbevis.

Det er fundet at de væsentligste udfordringer ved at implementere dataanalyse under de gældende internationale standarder om revision, rangeret efter deres betydning i praksis, relaterer sig til følgende fire områder:

- *Relevans og pålidelighed af data*: Det anses som en væsentlig udfordring i praksis at vurdere typen og omfanget af handlinger der kræves i ISA 500 for at sikre relevans og pålidelighed af data, når datamængderne stiger og nye fejlkilder opstår som følge af, at data udtrækkes på nye måder og fra nye kilder.
- *Dokumentation*: Dataanalyse medfører, at revisor i højere grad end tidligere baserer sig på automatiserede processer i dataanalyseværktøjerne. Det er en udfordring at der i dag ikke er klare retningslinjer i ISA 230 for, hvilken dokumentation der kræves af revisor til at påvise at værktøjerne behandler informationen efter intentionen.
- *Typen af opnået revisionsbevis*: Nye dataanalytiske handlinger, såsom test af fulde populationer af store mængder transaktioner, er udfordrende at knytte op til de eksisterende, anerkendte typer af handlinger i ISA 500. Når ikke handlingen er klart defineret, vanskeliggøres fastlæggelsen af, hvilken type revisionsbevis der opnås og som følge heraf også vurderingen af, hvornår tilstrækkeligt egnet revisionsbevis er opnået.
- *Håndtering af afvigelser*: Analyse på fulde populationer af store mængder transaktioner medfører ofte store mængder afvigelser, som revisor ikke praktisk har mulighed for at teste. Hvordan afvigelser bør behandles vanskeliggøres dog af, at sådanne handlinger ikke entydigt kan defineres under de metoder for udvælgelse af elementer til test, der er anerkendt i ISA 500.

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1 INTRODUCTION

Technological development in society has happened at a previously unseen pace in recent decades. As a result, technological capabilities now exceed those of humans by far, which has brought along inventions most people would have thought were impossible only a few years back. Such inventions include brain chips to move a robotic arm by thought, technologies that can make diagnoses that are more precise than what doctors can do, as well as the self-driving car which drives more safely than human drivers.

Buzzwords in the discussion of the recent technological development include digitalisation, robotics, artificial intelligence, and big data. Some argue that we are in the midst of a 'digital revolution' and characterise this period in time as the 'digital age' or the 'information age'. Irrespective of the label, society and the economy as we know it has changed and will continue to change at a fast pace.

From a business perspective, these changes also require companies to change. It is observed that the technological advancement varies significantly from industry to industry, but no industry is completely unaffected by the digitalisation. Furthermore, new products are developed which in turn create new industries. The digitalisation, furthermore, changes the types and volumes of accessible information. This puts pressure on companies to find ways to utilise this information as a competitive advantage. They are therefore developing smarter ways to collect, store, and analyse information in order to improve their business.

For the audit industry, this implies a need to follow the technological development in order to be able to audit financial information, irrespective of the type of company it comes from and how the information is generated. Furthermore, as for other businesses, technological development provide opportunities for competitive differentiation and improved efficiency. Some even argue that the technological development will change the role of the auditor substantially in the future.

This discussion of the role of the auditor is often connected to a discussion of data analytics, which has been intense in recent years. Audit firms are currently investing heavily in developing data analytics tools and capabilities, and a common expectation is that data analytics will significantly impact the way audits are conducted. It is discussed how audit quality and efficiency will be impacted, as well as whether auditors have the right skill sets to appropriately apply data analytics to audits.

A prerequisite for implementing data analytics, as well as any other initiative in any given industry, is that it can be applied in compliance with relevant regulation. The audit industry is subject to a range of sources of regulation internationally and locally. Therefore, part of the debate naturally concerns regulative matters. As a result of this debate, standard-setters are now looking into whether the recent focus on data analytics implies a need for revision of auditing standards. These standard-setters include the International Auditing and Assurance Standards Board (IAASB), the American Institute of Certified Public Accountants (AICPA), and the Public Company Accounting Oversight Board (PCAOB). The latter two are, additionally, working on separate application guidance.

1.1 FIELD OF STUDY

This study takes a regulative approach to the current debate about whether auditing standards need revision or separate guidance is needed. It seeks to build on the current initiatives taken by the IAASB in order to provide relevant input for the further work at the IAASB.

In 2015, the IAASB established the Data Analytics Working Group (DAWG) to examine developments in technology, their impact on audits and how and when the IAASB should respond to these new technologies (IAASB DAWG 2016). In September 2016, the DAWG issued the report "Request for Input: Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics", from now on referred to as the RfI (ibid.). This report summarise the challenges preliminarily identified by the working group related to implementation of data analytics in audits and requesting input from stakeholders for further analysis and consideration.

The RfI and the input received from it constitutes the basis of this study. The current debate on the need for updating auditing standards implies that auditors face challenges in implementing new data analytics tools and techniques. This study seeks to analyse the challenges specifically related to implementing data analytics under the International Standards on Auditing (ISAs), which are stipulated by the IAASB.

1.2 PROBLEM STATEMENT

Based on the field of study described above, it is determined that the primary purpose of this thesis is to answer the following question:

'What are the key challenges in implementing data analytics in financial statement audits under the ISAs?'

To assist in answering the problem statement above, the following sub-questions are considered relevant:

1. *What defines data analytics in financial statement audits and how is it different from traditional audit techniques?*

In order to answer the problem statement, it is important to establish an understanding of the concept of data analytics as it is used in the audit industry today. This sub-question seeks to establish this common ground for the further analysis. This question is addressed in section 3.2 and 4.1.

2. *To what extent has new data analytics tools and techniques been implemented in financial statement audits?*

In the notion of key challenges in the problem statement is an implicit element of importance, which requires an understanding of status quo. This sub-question addresses to what extent data analytics is used today in order to identify the most relevant challenges at the time this thesis is written. This understanding is obtained in section 3.2 and 4.2.

3. *What are the main challenges identified in the RfI and the received comment letters in relation to data analytics and the ISAs?*

As results of further analysis of the RfI and the received comment letters is yet to be seen, it is used as the starting point of this thesis in identifying the key challenges. The initial identification of top challenges is included in section 5.

4. *How can the identified main challenges be explained by reference to the ISAs?*

This question seeks to provide insights into the requirements of the ISAs in the areas identified as challenging and explain where the challenges may arise from a theoretical perspective. This question, thus, elaborates on the challenges identified in the preceding section. This analysis is performed in section 6.

5. *Are the identified main challenges considered critical in the implementation of data analytics in financial statement audits in practice?*

The problem statement refers to key challenges in the implementation of data analytics. This implies that the identified challenges should be considered critical in the audit industry's current efforts to extend the use of data analytics. This sub-question seeks to analyse the perception of the relevance and significance of the identified challenges within the audit industry in section 7.

The first and second research questions seek to establish the context in which the study is performed and applicable. The purpose of research question three to five seek to ensure that the conclusions to the overall problem statement is sufficiently linked to the ISAs and takes into account difference perspectives on the topic.

1.3 DELIMITATIONS

Certain relevant perspectives on the implementation of data analytics are left out as it is assessed that they would require separate analysis beyond the scope of this study. These considerations are described below.

Benefits and limitations of data analytics

When considering challenges in implementing data analytics, it could be relevant to consider the benefits to the audit quality and efficiency from implementing data analytics, as well as its limitations, such as whether data analytics has the potential to address all relevant audit assertions. This thesis, however, does not challenge or test these claimed benefits nor address the limitations, but accepts that all larger audit firms are investing heavily in introducing data analytics tools and techniques in audits and assumes they will continue to do so.

The expectation gap

There is a recurring debate in the industry about the expectation gap between users of the financial statements and auditors in their perceptions of the level of assurance obtained from an audit. It has been argued that data analytics impacts the expectations among the users of financial statements. Due to the limitations of the scope of this thesis, this area is left for separate analysis.

Other regulative requirements

This study focus on regulative requirements stipulated in the ISAs. Other regulation stipulate further requirements of the auditor such as local statutory requirements, alternative sets of auditing standards, and data privacy regulation. This regulation could also pose a challenge to implementation of data analytics, but is not within the scope of this study.

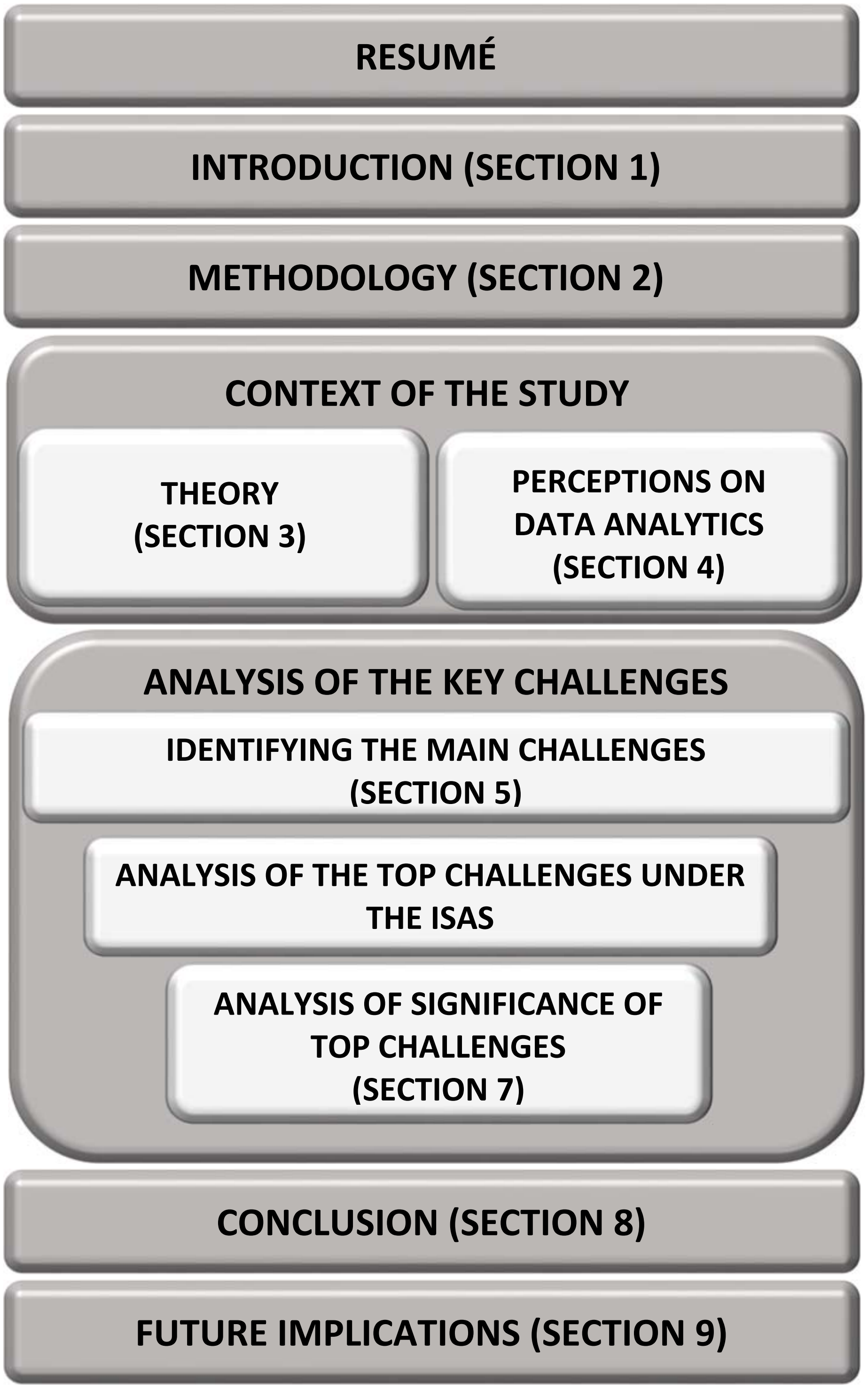
Skill set of auditors

A debate is observed about whether data analytics implies a need to revise the required skills of an auditor to prepare for the technological development. It is argued that auditors will need more statistical and IT-technical knowledge. This educational perspective, is considered a separate matter of discussion and is not discussed in this thesis.

Practical challenges

Auditors meet a range of practical challenges in implementing data analytics. These may include resistance to provide access to systems or technical challenges in extracting, storing, and processing large volumes of data. It is assessed that such challenges are independent of the ISAs. Therefore, they are not included in the further analysis.

1.4 STRUCTURE OF THE THESIS

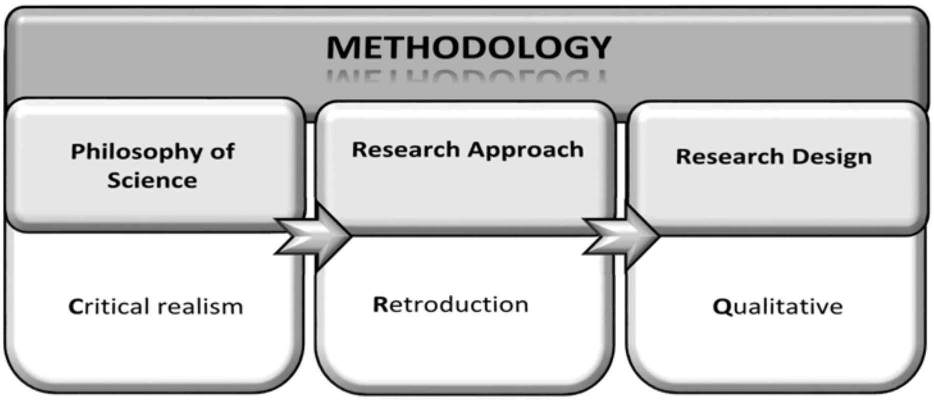


2 METHODOLOGY

This section outlines the methodological considerations of this study. The selected methodology is shown in fig. 1. This section address the considerations of the philosophy of science and the underlying ontology and epistemology in section 2.1, the research approach in section 2.2, and the research design in section 2.3, including an outline of the relevant data as well as the data collection and analysis.

These elements combined comprise the methodological approach by which the study is conducted. The choices made in terms of methodology, including considerations of limitations in the approach, is determining for the quality of the research and thereby the applicability of the conclusions. Reflections on the quality of the study is included in section 2.4.

Figure 1 Research Methodology



Source: The author's presentation.

2.1 PHILOSOPHY OF SCIENCE

Philosophy of science refers to the beliefs and assumptions about what constitutes knowledge and how it can be obtained, by which the research is conducted. Scientific philosophies acknowledged in the literature are referred to as paradigms (Saunders, Lewis and Thornhill 2016).

This study is based on the critical realism by which reality and the causation are assumed to be related to deeper structures that are not directly observable (Fuglsang, Olsen og Rasborg 2014). Research, thus, seeks to explain the causal connections of the observed phenomenon by obtaining a holistic understanding of the underlying mechanisms.

Paradigms within philosophy of science are further explained by their ontology and epistemology, which is considered in the subsequent sections.

2.1.1 ONTOLOGY

Ontology refers to assumptions made about the nature of reality (Saunders, Lewis and Thornhill 2016). These assumptions are important to define in order to determine an appropriate research design. The ontology of social sciences under critical realism recognises that society is an ever-changing and complex system (Jespersen 2014).

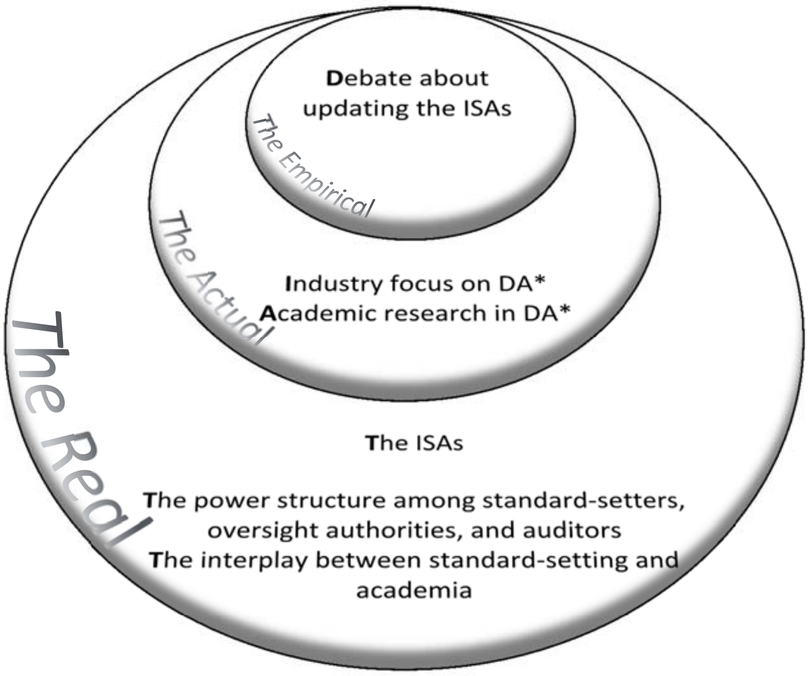
The ontology of the specifically studied domain is typically stratified into three domains in the critical realism (Saunders, Lewis and Thornhill 2016, Jespersen 2014):

6 . The empirical: Observable events or experiences, i.e. data.

7 . The actual: Trends and events caused by 'the real', which may or may not be observable.

8 . The real: Underlying causal structures and mechanisms which are, at least partly, not observable.

Figure 2 Stratified Ontology



* DA refers to 'Data Analytics'

Source: The author's presentation.

Fig. 2 depicts the stratified ontology applicable to this study. It is assessed that the real domain includes several layers. The ISAs are in an observable layer in this domain and is a product of the deeper non-observable power structure of the industry.

2.1.2 EPISTEMOLOGY

Epistemology refers to assumptions about what constitutes acceptable, valid, and legitimate knowledge (Saunders, Lewis and Thornhill 2016).

Critical realism recognises that structures and mechanisms are uncertain (Jespersen 2014). The uncertainty arise from the acknowledgement that structures and mechanisms are non-determinable as they are ever-changing, at least partly, non-observable, and as it involves subjectivity to disclose these underlying elements (ibid.). Hence, conclusions reached about them will be time-specific and historically dependent (Saunders, Lewis and Thornhill 2016). Due to this contextual nature of societal knowledge, studies in this field can seek 'reasons to believe', but cannot discover certain knowledge (Jespersen 2014).This is an implicit limitation of critical realism.

The conclusions of this study are, therefore, specific to the time and context in which the study is conducted. Despite methodologies that seek to strengthen the arguments of the identified causation, there is an implicit risk that conclusions are coincidental or do not disclose all relevant causations.

2.2 RESEARCH APPROACH

The methodological approach to the research shall reflect the research philosophy. Approaches can be deductive, inductive, retroductive, or abductive in nature (Jespersen 2014). For this study, a retroductive analysis is considered the most appropriate approach considering the philosophy of critical realism.

By the retroductive analysis, an observable phenomenon is analysed in order to identify the underlying mechanisms that produces the observed phenomenon (ibid.). The approach draws on elements from the inductive and the deductive methodologies (ibid.). This study incudes an initial analysis, which is inductive in nature as it seeks to identify the challenges in implementing data analytics underlying the current debate about whether the ISAs should be updated. Based on these findings, a further inductive analysis is performed to address how these challenges can be explained by underlying mechanisms, such as the ISAs.

Based on these initial inductive analyses, the retroductive approach draw from the deductive approach by empirically testing the hypotheses of causation identified in the initial analysis (Fuglsang, Olsen og Rasborg 2014). In this study, the identified challenges and their causes are treated as implicit hypotheses, which are empirically tested by interviewing a range of relevant stakeholders.

2.3 RESEARCH DESIGN

The research design outlines the data at which the study is based, how data has been selected, obtained and analysed. This is the part that links the research question of the study, the philosophy of science, and the research approach in such a way that meaningful conclusions can be reached.

In determining the appropriate research design, the purpose of the study must be considered. This study is based on an observation that there is an ongoing debate about whether the ISAs should be updated to reflect the increased use of data analytics, which implies that there are currently challenges in applying the ISAs. The purpose of this study is to identify and explain the key challenges in implementing data analytics in financial statement audits. Thus, the study is explanatory in nature.

Based on the perception of the adopted research philosophy that societal knowledge is a social construction, the perspectives of the actors cannot be neglected in the explanatory study (Jespersen 2014). Therefore, qualitative research methods are considered appropriate in this context. The means to analysing qualitative information depends on the nature of the data involved, which is outlined below.

2.3.1 DATA

The nature of the data is, along with the selected research philosophy and research approach, decisive for designing an appropriate approach to collecting and analysing data. Data can be primary or secondary. Primary data involves empirical data obtained for the purpose of the study in question and has not been processed by others. Secondary data, on the other hand, is data collected and processed by others. The relevant data to this study are outlined for each category below.

Primary data

For this study, primary data is obtained from interviews conducted for the purpose of this study. The selection of respondents is based on the power structure of the industry, in which the IAASB represent the standard-setting power for audits where the ISAs are adopted. Local oversight authorities constitutes the judicial power and, finally, practicing auditors represent the executive power. Furthermore, academic research has a role in the standard-setting agenda.

Respondents have been selected to reflect perspectives from the judicial power, the executive power, and academia. Due to prior experience in the industry, some respondents may provide broader perspectives from previous roles they have had as well as from international experience. Perspectives provided from the US are considered relevant to this study, despite the AICPA and the PCAOB as the main standard-setters, as the US Generally Accepted Auditing Standards and the PCAOB standards are generally aligned with the ISAs. It is emphasised that the statements made by respondents represent individual perspectives and not official statements from the organisations they are affiliated to. The respondents are presented below:

Jon Beck is a state authorised public accountant, partner at KPMG in Denmark, and leads its department of professional practice. He is, furthermore, part of the audit technical committee at Danish Auditors, the trade organisation of auditing, accounting, tax and corporate finance in Denmark. Jon Beck is responsible for the implementation of data analytics tools at KPMG in Denmark and is involved in initiatives related to data analytics at a Nordic level. He is, furthermore, responsible for US accounting and reporting engagements delivered from KPMG Denmark.

Jesper Drud is a state authorised public accountant and senior manager at BDO in Denmark. Jesper Drud works in the development centre within the department of professional practice at BDO in Denmark and has previously worked within the knowledge centre. He specifically works with implementation of data analytics tools in the Danish BDO practice and theoretical education of auditors in the use of such tools.

Trevor Stewart retired from his partner position at Deloitte LLP in 2009 after 38 years with the firm, where he has worked in Johannesburg, Amsterdam, London, and New York. He established and led Deloitte's global Audit Technology Research and Development Center in Princeton, led the global development and implementation of the first two generations of integrated audit software in the network, of which the latest is still in use, and he has designed and written Deloitte's Statistical Techniques for Analytical Review software, which includes multiple regression analysis techniques. After his retirement, he continues to assist Deloitte on analytics-related projects as a consultant. He is, furthermore, a Senior Research Fellow in the Accounting and Information Systems department at Rutgers Business School, part of the Continuous Auditing & Reporting Lab (CarLab), the Rutgers AICPA

Data Analytics Research Initiative (RADAR) working group and a member of the task force at the AICPA developing the AICPA Audit Data Analytics Guide.

Miklos Vasarhelyi is a Professor of Accounting Information Systems and serves as director at the Rutgers Accounting Research Center and CarLab at Rutgers University, the State University of New Jersey, US. He is, furthermore, involved in the RADAR working group as well as in a working group at the AICPA, which is working on developing an AICPA Audit Data Analytics Guide. The professor has published more than 200 journal articles and 20 books and directed more than 40 Ph.D. theses. He is, furthermore, one of the most cited authors on the topic of data analytics in auditing and accounting.

Martin Samuelsen is a state authorised public accountant with a background from Deloitte and Mazars. He is currently responsible for the Danish Public Oversight of Auditors and audit firms at the Danish Business Authorities. Furthermore, he represents the Danish oversight authorities at the International Forum for Independent Audit Regulators (IFIAR) and the Committee of European Auditing Oversight Bodies (CEAOB).

Secondary data

To this study, the most important secondary data are:

- The RfI
- Selected comment letters to the RfI
- The ISAs

The comment letters are selected based on a documented evaluation of credibility and scale of the respondents. The selection is made by preference to international organisations and organisations that have demonstrated noticeable insight into the topic of data analytics in the audit industry.

Other secondary literature include academic literature on the topic of data analytics, other relevant publications on data analytics from, as examples, audit regulators, oversight authorities and trade organisations, as well as academic literature on philosophies and methodologies of science. This literature is included to obtain an understanding of the subject of data analytics and the context in which it is applied at the time of this study as well as to support methodological considerations.

2.3.2 DATA COLLECTION AND ANALYSIS

This section addresses the specific methodology for collecting and analysing the primary and secondary data. It is divided into interviews, as the methodology for primary data, and document analysis, as the methodology for secondary data. Finally, there is a section on synthesis, i.e. the approach to combine the collection and analysis of both types of data.

Interviews

The interviews are conducted by a semi-structured approach. This approach is relevant as it follows an initial research on the topic, from which a general understanding of the topic has been obtained and the field of study has been narrowed down to an implicit set of hypotheses. Hence, the purpose and scope of the interviews are defined but in order to be open to new perspectives and information from the interviewees, the interview is not fully structured.

The scope of each interview is outlined in an interview guide in order to ensure consistency in the data obtained from the interviews and ensure that the purpose of the interviews is met. Guides are sent out to the respondents before the interviews in order for them to consciously or unconsciously prepare for the interview.

The interview guide is prepared on the basis of the problem statement and supporting research questions and includes the topics below:

- Introduction of the respondent
- Presentation of the study and the role of the interview
- Definition of data analytics as the concept is currently used
- Current stage of implementation of data analytics in the audit industry
- Perceptions on relevance and significance of challenges identified from analysis of the RfI and comment letters
- Future perspectives on solving the challenges

In order for the respondents to express themselves freely, the interviews are conducted in Danish for the respondents working in Denmark and in English with the respondents situated in the US. The interview guide is also prepared in Danish for the Danish respondents. Upon approval from the interviewee, the interview is recorded for later reference.

During the interview, brief notes are made under each point of the interview guide. Afterwards, the recording is further analysed to get an overview of the perspectives and opinions of the interviewee, and the notes are elaborated.

When the interviews have been analysed, all direct and indirect quotes are gathered for each respondent and forwarded to them for validation and confirmation. There is a risk that perspectives and opinions do not come across clearly in verbal communication. The validation ensures that the information used in the analysis reflects the perspectives and opinions of the interviewees.

Document analysis

The analysis of secondary data is centred on the RfI, relevant comment letters and the ISAs. The secondary nature of the data and the qualitative methodology selected requires a systematic approach to this analysis. This approach is outlined below.

Initially, the RfI and relevant comment letters are analysed in order to identify the challenges in implementing data analytics. The RfI is systematically analysed in order to identify all challenges noted related to standard-setting. These challenges are then extracted, listed, and given an identification number.

Following this step, an overview is made of the respondents submitting comment letters to the RfI. From this list, relevant comment letters are identified. These comment letters are systematically analysed to identify mentioned challenges. Each identified challenge is compared to the list of challenges identified in the RfI. If it matches one of the existing challenges identified, this is recorded as a confirmation of the challenge. If it does not match an existing challenge, it is put on a separate list of additional challenges in order to ensure that all relevant challenges are considered. If additional challenges are identified more than once, the number of confirmations is recorded.

In order to establish an initial understanding of the importance of the identified challenges, the number of confirmations are ranked and the top five challenges are extracted for further analysis in the study.

The further analysis of the top challenges is made by reference to the ISAs. The analysis is based on an analogous approach and recognises arguments included in the comment letters to explain the grounds of the challenge.

An alternative to this structured analysis of secondary data would be further collection of primary data. This is not considered feasible for the scope of this thesis considering the conducted collection of primary data, which supports the document analysis.

Synthesis

Upon collection and analysis of primary as well as secondary data, the observations and perspectives obtained are synthesised into one understanding of the studied subjects as the outcome of the study. This is done by comparing and evaluating perspectives with the purpose of being able to reach a relevant and well-founded conclusion.

2.4 QUALITY OF RESEARCH

This section addresses reflections on the quality of the research. Initially, it was noted that the quality needs to be evaluated by the understanding that there are certain limitations implicit in the critical realism. The perspective of critical realism implies that knowledge obtained is always conditional to undisclosed elements of the underlying structures and mechanisms, which may impact the studied empirical observations (Jespersen 2014). Despite this limitation, the study seeks conclusions that are anchored to empirics to the degree possible.

For qualitative studies, Saunders, Lewis and Thornhill (2016) suggests assessing the quality of the research based on the four criteria listed below:

- Dependability
- Credibility
- Transferability
- Authenticity

In the following, they will each be addressed.

Dependability

Dependability refers to how well the process of the study is documented in order for the reader to understand how data is obtained and analysed (Saunders, Lewis and Thornhill 2016). It is attempted to describe the process of how data is obtained and analysed in detail throughout the thesis in order to emphasise the context in which the study is performed and by which conclusions are dependent.

Credibility

Credibility refers to how it is ensured that the socially constructed reality reflects the intentions of the participants (Saunders, Lewis and Thornhill 2016). When analysing comment letters, credibility is ensured by analysing a larger number of letters in order to ensure that all relevant perceptions are included. When analysing interviews, credibility is ensured in that each respondent has confirmed the direct and indirect quotes made to the interview in order to ensure that the individual's perceptions have been reflected as they were intended.

Transferability

Transferability refers to the extent to which the conclusions of the study can be applied in another setting, i.e. are transferable (Saunders, Lewis and Thornhill 2016). This study seeks to accommodate this by explaining in detail the research questions, design, context, and findings. The author recognises, however, that based on the nature of the study, conclusions are specific to the time in which the study is conducted.

Authenticity

Authenticity seeks to ensure that all views are represented and that this is done without bias (Saunders, Lewis and Thornhill 2016). As the author has a role in the audit industry as an auditor with four years of experience, the risk of bias is recognised. This is sought to be overcome by selecting respondents, both in the analysis of comment letters and interviews, who represent various roles in the audit industry in order to ensure that all relevant perspectives are reflected. Where possible, input from several respondents with similar roles in the industry have been included in order to ensure the completeness of relevant perceptions to the degree possible.

Overall, the quality of the research is considered acceptable given the explained attempts to fulfil the four criteria of quality above as well as the nature of the research and conclusions reached.

3 THEORY

This section seeks to establish an understanding of the context in which this study is performed, which provides the basis for the further analysis as well as for the understanding of the context in which the conclusions are reached. This includes an initial understanding of relevant concepts as well as of the structures and mechanisms that impact implementation of data analytics in the audit industry.

Initially, an introduction of the ISAs and the audit risk model is provided in section 3.1 along with an introduction to the audit process as this is the framework in which the role of data analytics is studied. This is followed by a theoretical review in section 3.2 of the concept of data analytics and the context in which the term is used today, as this is decisive for the applicability of later findings. This involves a description of the theoretical implications of data analytics on the audit process and procedures as well as a description of the current use of data analytics in the industry, including the involved types of data and technologies. Finally, as the current debate revolves around whether the ISAs should be updated, an outline is provided of the current level of recognition of the use of technology in the ISAs in section 3.3. This is included in order to understand the current standpoint of the ISAs and the basis for potential updates.

Hence, this section provides the theoretical basis for further identification and analysis of challenges currently experienced in the implementation of data analytics under the ISAs.

3.1 THE INTERNATIONAL STANDARDS ON AUDITING

This section briefly outlines the framework by which audits are conducted. This is included as an understanding of the ISAs as a framework is important in order to understand the current debate and challenges involved in implementing data analytics. In order to fully understand the implications of data analytics in auditing, an outline of the audit process is also provided.

The ISAs are adopted by more than 100 countries and are issued by the IAASB, an independent standard-setting body (Eilifsen, et al. 2014). The IAASB is supported by the International Federation of Accountants (IFAC), which, as of November 2016, had 175 members and associates across 130 countries, representing three million accountants (IFAC 2016).

The ISAs provide a framework for conducting audits and is based on the risk-based audit model. They contain objectives, definitions, requirements, application guidance, and other explanatory material including relevant appendices to assist auditors in meeting the overall objective of the audit:

"*To obtain reasonable assurance about whether the financial statements as a whole are free from material misstatement…*" (ISA 200, para. 11(a)).

3.1.1 THE RISK-BASED AUDIT MODEL

In order to understand the audit process, an understanding is required of the model by which the ISAs and the audit process are based.

Until the audit model was challenged and changed between the 1950s and 1970s, audits involved detailed testing of all transactions and balances (ICAEW 2016). Since then, the risk-based audit model has set the standard in the industry, introducing, among other concepts, materiality, risk analyses, and controls testing (ibid.).

Today, audits do not provide assurance that no misstatements exist in a set of financial statements. Rather, audits are planned and conducted to reduce the audit risk to a sufficiently low level to conclude that the financial statements do not include a material misstatement (ISA 200, para. 17).

The audit risk is explained by the function below (ISA 200, para. 13(c)):

$$\text{AUDIT RISK} = \text{RISK OF MATERIAL MISSTATEMENT} \times \text{DETECTION RISK}$$

Audit risk refers to the risk that the auditor express an inappropriate audit opinion when the financial statements are materially misstated (ibid.). Risk of material misstatement (RoMM) is, in turn, a function of inherent risk, i.e. the susceptibility of an assertion about the information to be materially misstated, and control risk, i.e. the risk that material misstatements are not prevented or detected and corrected by internal controls (ISA 200, para. 13(n)). The detection risk refers to the risk that audit procedures performed do not detect material misstatements (ISA 200, para. 13(e)).

3.1.2 THE AUDIT PROCESS

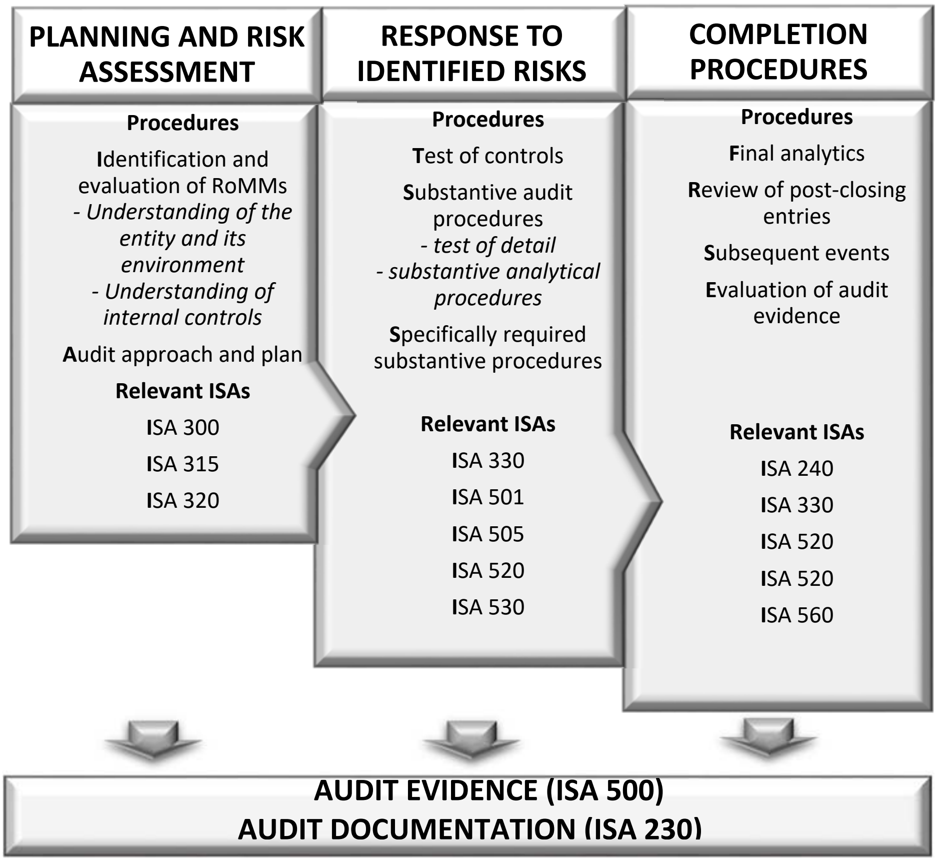
In order to analyse the implications of and challenges in implementing data analytics in audits, one must have a basic understanding of the process of auditing and the link to the ISAs. The ISAs include separate standards for different audit topics and do not strictly follow the audit process. The overall link of the audit process to the ISAs is provided in this section.

Overall, an audit involves five steps (Sudan, et al. 2013):

- Preliminary client and engagement acceptance
- Planning and risk assessment procedures
- Procedures performed as a response to identified risks
- Audit completion procedures
- Reporting.

Preliminary steps are made before the actual audit is commenced, and the reporting is the final product of the audit. The audit process in the further analysis, therefore, refers to the steps covering the primary conduct of the audit, i.e. the three steps in the middle.

Figure 3 The Audit Process



Source: The author's presentation.

Fig. 3 illustrates the audit process and how it links to relevant standards. The figure is prepared for the purpose of providing an overview of the overall process. Not all ISAs are included either because they do not link directly to the three steps or because they cover general principles applicable throughout the audit. The most significant of these general principles is that of professional judgment. This concept along with the concepts of audit evidence and audit documentation is considered central in the understanding of an audit. Therefore, their definitions are included below.

Audit evidence

"*Information used by the auditor in arriving at the conclusions on which the auditor's opinion is based. Audit evidence includes both information contained in the accounting records underlying the financial statements and other information*" (IAASB 2015, p. 15).

Audit documentation

"*The record of audit procedures performed, relevant audit evidence obtained, and conclusions the auditor reached (terms such as 'working papers' or 'workpapers' are also sometimes used)*" (IAASB 2015).

Professional judgment

"*The application of relevant training, knowledge and experience, within the context provided by auditing, accounting and ethical standards, in making informed decisions about the courses of action that are appropriate in the circumstances of the audit engagement*" (IAASB 2015, p. 32).

3.2 DATA ANALYTICS IN FINANCIAL STATEMENT AUDITS

Data analytics is a wide-ranging concept as the data in use and the analytical techniques vary greatly depending on the purpose and context of the analysis. Some industries already explore and exploit the opportunities within Big Data, Artificial Intelligence, Robotics, etc., all of which are buzz-words in the modern business world and relate somewhat to the concept of data analytics.

This thesis focuses on data analytics in the context of external financial statement audits and its correlation with the ISAs. Hence, a common understanding of what data analytics mean to the audit industry and where the industry is currently at in its technological advancement is important.

This section provides the theoretical definitions of the concept of data analytics as well as a theoretical outline of the context in which the concept is used today. This involves the implications of data analytics on the audit process and procedures as well as the advancement in the current use of data and technologies.

3.2.1 DEFINITIONS

Data analytics comprise, as the name of the concept suggests, all sorts of analyses of a set of data. What is interesting in this thesis is how data analytics are defined in the context of auditing.

The IAASB DAWG defines it as:

"*Data analytics, when used to obtain audit evidence in a financial statement audit, is the science and art of discovering and analyzing patterns, deviations and inconsistencies, and extracting other useful information in the 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*" (2016, p. 7).

It is noted that this definition is based on, and largely identical to the wording of the definition developed by the AICPA (2015).

The Institute of Chartered Accountants in England and Wales (ICAEW) defines data analytics as "*Data analytics consists of tools that extract, validate and analyse large volumes of data, quickly. The tools are applied to complete populations, 100% of the transactions, i.e. 'full data sets', and they can be used to support judgements, draw conclusions or provide direction for further investigation. Data visualisation, such as bar and pie charts, and cluster diagrams, is used to analyse data, bring it to life and help users understand the significance of the findings. Improvements in interfaces mean that data analytics can be used by non-specialists*" (Chaplin 2016). Specifically in audit, the ICAEW elaborates that data analytics enable auditors to "*improve the risk assessment process, substantive procedures and test of controls. It often involves very simple routines but it also involves complex models that produce high-quality projections*" (ICAEW 2016, p. 3).

The definitions of the IAASB DAWG and the AICPA defines data analytics as an art and science of analysing data to obtain audit evidence, whereas the ICAEW definition defines the data analytics toolbox within auditing. Except for the notion of validating data in the ICAEW definition, the definitions are not considered contradictory.

3.2.2 ADVANCEMENT OF DATA ANALYTICS

Data analytics is a popular term in the audit industry today. In order to analyse the challenges involved, it is important to understand how data analytics contribute to audits in practice and the development within data analytics, including the underlying drivers of development. Hence, this section seeks to describe the context in which the concept of data analytics is used today.

Data analytics have always been part of the audit process (Stewart 2015). Skimming through financial statements, comparing results among industry peers, and scanning journals for unusual entries are examples of normal audit procedures performed even before audit documentation was made electronical and which technology over time has made easier with the use of, for instance, Excel, IDEA, and ACL (ibid.). When significant and continuously increased focus has been paid to data analytics in recent years, it is driven by extraordinary developments in data science, computer power, and volumes and accessibility of data, which provide opportunities for performing data analytics in a new way by use of new tools and technologies (ibid.).

Procedures

The first step in understanding the context of the use of data analytics is to understand its contribution to the conduct of audits. This section outlines how data analytics contribute to the overall audit process, the correlation between data analytics and traditional audit procedures, and provides practical examples of audit procedures performed by use of data analytics techniques.

A distinct feature of data analytics tools and techniques, is that they can be applied on larger sets of audit-relevant data and is relevant to more steps in the audit process than the traditional way of performing analytical procedures would (IAASB DAWG 2016). Data analytics has the potential to transcend the traditional phases of the audit process within, at least, risk assessment, test of controls, substantive audit procedures and blur the traditional boundaries between them by its iterative nature (ibid.).

As examples of how data analytics is used in practice, the ICAEW (2016) suggests the procedures below as some of the typical procedures to be performed by use of new data analytics techniques:

- Three-way matches between sales orders, goods received notes, and invoices;
- Gross margin analyses for identification of sales with negative margins;
- Detailed recalculations of depreciation on fixed assets by item and based on the exact dates; and
- 'Can do did do tests' of whether segregation of duties are in place and, if inappropriate accesses are given, whether they have been used.

The procedures themselves are not uncommon to traditional audit. The news is the availability to auditors of technology that makes it achievable to perform those traditional procedures to an extent that has traditionally been impractical. Traditionally, the auditor would select a sample for testing.

The data analytics tool developed and gradually implemented in the audit profession in recent years makes it possible to test 100 pct. of the items included in a data set in a fast and cost-effective manner (Byrnes, et al. 2015).

Thus, data analytics techniques have implications throughout the audit process as well as for the way in which traditional audit procedures can be performed.

Data

The increased volumes and availability of data is often mentioned as a key driver of the use of data analytics and it is an area in rapid development. In order to understand the context in which data analytics is currently used, this section outlines the types of data used for data analytics procedures in audits today.

Traditionally, analytical procedures have been based on historical accounting and financial data (Alles and Gray 2016). Although the mass and complexity of this information has developed, it is not to be confused with Big Data. Big data involves vast amounts of data, which is constantly updated and changing, and it includes quantitative and qualitative data, financial and non-financial data, and structured as well as unstructured data (Alles and Gray 2016).

Thus, big data provides potential for more real-time continuous monitoring and assurance of data and implicitly a shift from the retroactive audit approach to a reactive and predictive audit approach (Bumgarner og Vasarhelyi 2015). Although the industry will eventually have to adapt to the use of big data as it becomes more widely implemented by auditees, such opportunities have not yet been exploited, and it is considered too early to consider it characteristic of the current use of the data analytics concept within auditing.

Hence, it is recognised that the increased volumes, complexity, and accessibility of data are key drivers in the development of data analytics tools. However, the full potential of incorporating analyses of big data in audits has not yet been explored. Thus, data analytics today focus primarily on traditional financial data in larger volumes, although examples of more complex technologies are observed such as regression analysis.

Technologies

As part of obtaining an understanding of the context of the use of data analytics in audits, it is relevant to understand the advancement of the technologies applied in this industry. This section describes the perception of technology in the standards, examples of tools and technologies used in practice as well as the current state of development in those technologies.

Data analytics techniques for auditing are referred to under many names in the industry and in literature. The concept used in the ISAs, and therefore also in much literature, to refer to such technologies is 'computer-assisted auditing techniques' (CAATs). The IAASB defines CAATs in rather generic terms as:

"*Applications of auditing procedures using the computer as an audit tool (also known as CAATs)*" (IAASB 2015, p. 17)

Omoteso (2013) elaborates on the use of CAATs:

"CAATs revolve around the use of special software packages in viewing the overall business operations and examining a large volume of data files within a very short time. CAATs permit the auditor to carry out data interrogations by using historical data to identify anomalies for further investigation of the specific area(s) concerned thereby enhancing the credibility of audit evidence…" (Omoteso 2013, p. 69).

The definitions of CAATs or data analytics techniques are, thus, not specific to a certain technology or software. The rapid technological development allow for a continuous stream of new software tools to be introduced with widely different distinctive features, which could all be labelled CAATs. Hence, the CAATs toolbox is undefined and inconstant.

In order to define where the advancement of CAATs is currently at in a simple way, Alles and Gray (2016) talk about traditional versus extended data analytic techniques. Traditional techniques include Excel, ACL, and IDEA, which are primarily used to analyse individual sets of financial data, whereas typical features of extended techniques include visualisation and predictive analyses, which involves analysis of several sets of data at once (ibid.). Various techniques are available to assist auditors in visualisation and predictive analyses, for example by use of tools to perform statistical predictions such as regression analyses. Visualisation tools are available and used today, such as Tableau (ibid.). Predictive techniques are also being implemented in the industry (ibid.).

Despite heavy investments in developing the tools applied in the audit industry, those tools remain relatively simple compared to other industries. Cognitive technologies, for instance, could facilitate big data analytics, as such techniques are able to process structured and unstructured data of both financial and non-financial nature. However, it is observed that the audit industry and academia has not yet developed and implemented such tools to a noticeable degree.

Figure 4 Status on use of Data Analytics

		DATA ANALYTICS TOOLS	
		Simple	**Complex**
APPLIED DATA	**Financial information**	*Current State*	
	Non-financial Information		

Source: The author's presentation based on input from Alles & Gray (2016).

Fig. 4 includes a presentation of the current stage of implementation of data analytics in the audit industry, which is characterised by an ongoing transition to more advanced use of technologies to, among other features, visualise and predict data. However, the technologies involved remain relatively simple in comparison to other industries. Furthermore, the analysed data currently remains based on primarily traditional financial data with little observable movement towards utilising the value of non-financial data.

Summary

In summary, data analytics can be used to perform analyses throughout the audit process. It involves primarily traditional audit procedures performed in new ways. Such new data analytics techniques are driven by and accommodate increasing volumes of data. It is found that, despite availability of new types of complex and untraditional data referred to as big data, the current use of data analytics is applied merely to traditional financial data. Furthermore, it is found that the technology applied in the audit industry does not yet involve complex technology such as cognitive technology, as is observed in other industries.

3.3 THE CORRELATION BETWEEN DATA ANALYTICS AND THE STANDARDS

The further analysis seeks to identify key challenges in the link between data analytics and the ISAs. Each of these concepts are outlined in the preceding sections. This section seeks to outline the extent to which data analytics is recognised in the ISAs today.

The term data analytics is not used in the ISAs. Instead, the ISAs use the concept of CAATs to refer to the use of technology, as noted in section 3.2.2. The ISAs mostly refer to the use of CAATs in ISA 240 'The auditor's responsibilities relating to fraud in and audit of financial statements'. However, some references are given on the use of CAATs throughout the audit to identify and address risks other than those specifically related to fraud.

The ISAs refer to the use of CAATs in obtaining audit evidence over operating effectiveness of controls (ISA 330, A27), obtaining an understanding of controls around journal entries and identification of non-standard journal entries (ISA 315, A91), and in analysing transactions among related parties (ISA 550, A36). The most specific acknowledgement of how CAATs can be used in audits is given in ISA 330 A16, in which CAATs are suggested as a means to select samples, sort data, and test entire populations.

As the ISAs is a principle-based framework for auditors, it does not prohibit the use of data analytics in areas where it is not directly referred to. However, as the ISAs refer to CAATs only to a limited extent, there may be perceived barriers to implementing data analytics techniques as an alternative way of meeting the objectives of the ISAs (IAASB DAWG 2016).

4 PERCEPTIONS ON DATA ANALYTICS

In section 3.2, the questions of how data analytics is defined and to what extent it has been implemented in audits were addressed from a theoretical perspective by observations made in the existing literature. It is noted that there is often a gap between theoretical definitions and understandings reached in the literature on one hand and on the other hand, the perception in practice of the same matters. This sometimes leads to inconsistent use of concepts.

Perceptions of data analytics in practice has been obtained from the conduct of interviews with relevant actors in the audit industry. This section, therefore, firstly addresses how data analytics is perceived as a concept and secondly addresses to what extent new data analytics tools and techniques are implemented in audits today. The section, thus, contributes to the establishment of the concept of data analytics and status quo in the process of implementation, which are important elements of the context in which this study is performed.

4.1 THE CONCEPT OF DATA ANALYTICS

Interviewees have been asked to describe their understanding of the concept of data analytics. As the term data analytics is not new, interviewees have also been asked to explain how the concept, as it is used in the audit industry today, is different from how it has been used previously. The section is therefore divided into an analysis of the basic definitions of data analytics among interviewees and an analysis of how the concept is used in the industry today.

4.1.1 DEFINITION

In order to establish an understanding of the concept of data analytics, the interviewees have been asked to share their understanding of the concept as it is used today.

Trevor Stewart is the developer of the definition of data analytics in auditing used by the AICPA, and largely by the IAASB, which is mentioned in section 3.2.1. His perception of the concept is, therefore, naturally, aligned with this theoretical definition. In the interview with Trevor Stewart (2017), however, he comments that there is generally a lot of confusion about data analytics. He clarifies the concept as follows:

"*I think you've got to think about data analytics as just really being an approach to analysing data. It is a set of techniques, a set of methodologies, and I think what happens is that it tends to get confused with audit procedures themselves and they are really not. They are just ways of performing audit procedures*" (Stewart 2017, 2:20).

Jon Beck's perception of data analytics is somewhat aligned with that of Trevor Stewart. He adds to the explanation:

"*Data analytics is, in my opinion, something we have done in the past 50 years or more. It is analyses of data, as the concept says*" (Beck 2017, 4:14).

He further explains that traditionally, those analyses have been performed in many ways, whether it is manually scanning a sub-ledger in order to identify transactions of interest, or whether you get an extract in excel and sort on specific variables with the same purpose, it is data analytics (ibid.). However, what drives the development in data analytics, he explains, is the volumes of data, which is significantly larger today than 50 years ago, and which makes, for instance, the analysis of sub-ledger data challenging.

Specifically the element of large volumes of data is a defining characteristic of data analytics, in the definitions provided by Jesper Drud and Martin Samuelsen. They explain data analytics as:

"…*Generally, it is a question of analysing large volumes of data in an automated process, where you, to a certain extent, define what is to be analysed, but a very automated analysis and typically very large volumes of data"* (Drud 2017, 3:20).

"*…I understand data analysis as being a concept used when you talk about using large volumes of data, and analysis hereof, to obtain audit evidence"* (Samuelsen 2017, 1:40).

These definitions all mention data analytics as ways of analysing data in order to obtain audit evidence, but some variations are noted. The interpretation of the author is that Trevor Stewart and Jon Beck takes a theoretical stand when asked to describe data analytics as a concept, whereas Jesper Drud and Martin Samuelsen seek to explain that data analytics, as the concept is used today, is driven by increased volumes of data. This is supported by the acknowledgement by Jon Beck that increasing volumes of data is a driver of the development in data analytics, which is a characteristic of data analytics in Jesper Drud and Martin Samuelsen's view. The author notes, however, that data analytics tools are not only applicable to entities with large volumes of data, but that this is often mentioned as a differentiator from traditional tools. Jesper Drud adds the automation of the analytics to the definition, which is considered part of the development noted by both Trevor Stewart and Jon Beck as well.

It is inferred from the interviews that the perception of data analytics is that it basically comprise all methodologies to analyse data with the purpose of obtaining audit evidence. However, the concept of data analytics is currently used when considering increased automation of analytics and the opportunity to analyse larger volumes of data.

4.1.2 USE OF THE CONCEPT OF DATA ANALYTICS

Data analytics has gotten significant attention in the audit industry in recent years and it is often discussed how data analytics will change how audits are performed. As noted above, however, the basic definition of the concept is rather generic and comprise methodologies that have already been applied for many years. This implies that new meanings have been ascribed to the concept of data analytics. The interviewees have, therefore, been asked to explain what data analytics mean in the context in which it is used today and how it is different from previous use of this concept.

Martin Samuelsen (2017) does not believe data analytics is a new subject, but that it is a matter of a change in focus due to audit firms' focus on enhancing efficiency in the audit process as well as being able to cope with the increased digitalisation of their clients.

This is in line with the view of Jon Beck, as noted above, and of Trevor Stewart (2017) who provides an example of how data was analysed even before the time of computers, which is similar to the example from Jon Beck in section 4.1.1. He notes that back then, data analytics was just a manual process of paging through a physical ledger and look for unusual items to guide the focus of the audit. The full population testing, for instance, made possible by new technologies and tools, is just a new way of performing such audit procedures.

The new ways of performing audit procedures by use of technology is also aligned with the perception of Jesper Drud (2017), who explains that the difference to traditional analytical procedures revolves around the automation of the analytics as well as significant software involvement in the process.

Similarly, Jon Beck (2017) notes that the new tools provide new opportunities for obtaining audit evidence, such as the opportunity to match different data populations as opposed to analysing individual data sets separately.

Thus, the interviewees are considered consistent in their views that data analytics as it is used now is a matter of performing audit procedures in a new more automated way by use of new technology and tools. This makes full population testing as well as the match of several data populations more feasible to perform than previously.

4.2 STATUS OF THE USE OF DATA ANALYTICS

As established above, data analytics in the context it is currently discussed in the industry, is a matter of a development in the availability and use of data analytics technologies in the audit process. In order to identify relevant challenges in the implementation of data analytics it is relevant to establish status quo by determining how far the audit industry has come, so far, in implementing such new data analytics tools in the audit process. All interviewees have therefore been asked to what extent data analytics tools are currently being used in the audit industry.

4.2.1 STAGE OF IMPLEMENTATION

This section seeks to outline, overall, where the audit industry is currently at on the journey to fully exploit the potential of new data analytics tools.

Martin Samuelsen (2017) and Jesper Drud (2017) both explain that in their views, data analytics techniques are generally used as an add-on to traditional audit techniques and not as a replacement to base conclusions on solely. Jon Beck (2017) finds that the data analytics techniques currently used are simple, and that the outcomes are not used to place reliance on as audit evidence. Trevor Stewart (2017) indirectly supports this view as he describes that the use of data analytics is not quite as advanced as it could be.

Finally, Miklos Vasarhelyi (2017) explains that the industry is at a very early stage in terms of implementing data analytics tools and techniques. He acknowledges that it is an area in development, and one where audit firms invest heavily by stating:

"*What I have observed is that firms have been working very hard on developing analytical capabilities, but in the end, most of the capabilities are being applied in the consultancy side of the business - not in the audit side of the business*" (Vasarhelyi 2017, 12:00).

It is inferred from the responses above that the audit industry is in an early phase of implementing data analytics tools and technologies in a way in which it can provide audit evidence. Hence, the audit industry is currently far from experiencing the full potential of data analytics in the audit process.

4.2.2 REPLACEMENT OF PROCEDURES

In order to understand the notion of an early stage, it is relevant to obtain a further understanding of the expected potential use of data analytics in the future and how the industry specifically has come in the implementation.

Some respondents describe that results from procedures performed with data analytics techniques are currently not used as audit evidence to a very large extent. It is also referred to as an add-on to traditional audit procedures. In this discussion it is relevant to consider the types of audit procedures performed by such new tools and techniques, and the potential for replacing some traditional methodologies with data analytics methodologies.

In the following sections, this is discussed further as the use of data analytics techniques is considered for each stage of the audit. The stage of responses to identified risks is divided into controls testing and substantive testing as this is clearly separated types of procedures in the audit process.

Risk assessment

Jesper Drud (2017) explains that data analytics can support and to some extent replace some substantive procedures, but the auditor cannot rely fully on data analytics for controls testing nor risk assessment purposes.

He elaborates on this statement by noting that he has not yet seen software capable of analysing all transactions flows from an entity at once in order to base the risk assessment on data analytics. Thus, the auditor needs to perform some initial risk assessment in order to target the data analytics procedures to specific areas and sub-populations of the data.

Jon Beck (2017), however, notes that data analytics techniques are currently used primarily for risk assessment procedures, although it is still at an early stage. In his view, the industry is not currently at a stage where data analytics techniques in general provide audit evidence by themselves, but mainly assist in focusing the audit at relevant areas (Beck 2017).

The author further notes that tools do exist, and are being used to a limited extent, which can visualise unusual transaction flows based on the entire transaction flow of an entity. This a strong tool in the risk assessment phase of an audit. Furthermore, by visualising and analysing specific sub-data sets, data analytics can further substantiate the risk assessment. These observations are considered supported by the statement from Jon Beck. It is noted, however, that Jesper Drud does not seem to have been introduced to such tools to perform initial analysis of transaction. This would indicate that such tools are not yet widely used.

Hence, some replacement of risk assessment procedures is currently being introduced in audits. However, it is not yet considered widely used.

Controls testing

Jesper Drud (2017) explains that data analytics techniques cannot replace controls testing completely, as the tools themselves imply a need to understand and evaluate controls around data validity when using data analytics techniques. This would refer to general IT controls and application controls to ensure data integrity.

Although data analytics may imply a need for testing controls to ensure reliability of the analysed data, it does not mean that some controls tests could not be performed by data analytics. However, no interviewees mention ways in which such controls testing is performed in practice, and it is therefore assessed that this is an area where data analytics techniques are, at least currently, not used to a noticeable extent.

Substantive testing

The respondents provide slightly different views on whether substantive audit procedures are currently being replaced by data analytics. Trevor Stewart (2017) notes that in his view, procedures from data analytics tools are not always being used only as an addition to existing procedures. As an example of data analytics techniques used to provide audit evidence, he mentions that a regression analytics tool, which he took part in developing, is used extensively at Deloitte.

According to Jon Beck (2017), however, what the industry is working towards but has not yet reached, is the state where audit evidence is obtained from more sophisticated data analytics techniques, including regression analyses and cognitive analyses. No other interviewees mention the use of such techniques in practice. While there may be differences among countries, Trevor Stewart mentions regression as an example where audit evidence is currently obtained, as an exception to the general observation that results of data analytics procedures currently do not provide audit evidence. Therefore, it is not assessed that complex data analytics tools provide audit evidence for substantive procedures to a considerable extent.

Instead, interviewees often mention methodologies to test full populations of data, which is currently being tested as to how they can provide audit evidence. As an example, Jon Beck (2017) describes how the valuation of trade receivables can be evaluated by matching the list of trade receivables by customer with credit information, in order to identify debtors that have gone bankrupt or have a negative credit record. Another example, he explains, is obtaining evidence for the existence of revenues by matching the full population of sales transactions against receipts of payments in the bank. Currently, however, such procedures are mostly af a test-phase and not widely used to obtain audit evidence.

While a wide range of opportunities to perform traditional audit procedures in smarter ways have been identified, it is not considered a general perception in the industry that data analytics have yet replaced substantive testing to a significant extent.

Completion procedures

No respondents mentioned specific potential or actual use of data analytics in the completion stage of an audit. Rather, completion procedures will directly be affected by use of data analytics in earlier stages of the audit as this stage includes evaluation of audit evidence obtained throughout the audit. Data analytics is, thus, not yet considered applicable to replace procedures in the completion stage of an audit.

Overall, it is inferred from the preceding analysis that data analytics tools and techniques are most widely used for risk assessment purposes and, in some instances, as an addition to traditional substantive audit procedures. The use of data analytics for controls testing is not yet noticeable and is not currently considered relevant to replace procedures in the completion stage of the audit.

4.3 SUB-CONCLUSION

It is identified that there are some variances in the way the basic concept of data analytics is used and interpreted among the interviewees. Some consider data analytics a concept covering all sorts of analysis of data, which can comprise simple and manually performed analyses as well as complex analyses that are impractical to perform without the use of technology. Others assess the concept as merely referring to the latter complex types of procedures.

There seem to be a general consensus, however, that the way the concept is used in the industry today, is driven by developments in the data volumes at clients as well as technological advancements. Hence, new tools are developed, which in a more automated manner are capable of analysing larger volumes of data. Therefore, the methodologies discussed today refers mostly to the possibilities of performing more complex and comprehensive analyses than what have traditionally been feasible to perform.

It is found that those complex data analytics tools and techniques are only implemented in audits to a limited extent. The audit industry is currently testing how such new tools and methodologies can be used to provide audit evidence and either support or replace traditional procedures. It is found that data analytics techniques, such as visualisations of trends and patterns of large data sets and 100 pct. tests of data sets, are mostly used in addition to traditional audit procedures in the risk assessment and substantive testing phases of the audit.

Hence, the basis for further analysis is a situation, in which the audit industry is investing in and testing how new data analytics tools and techniques can provide audit evidence. However, at this stage no general industry practice has developed, and the procedures performed by new tools and technologies are mostly used in addition to traditional audit procedures.

5 IDENTIFYING THE MAIN CHALLENGES

Some preliminary analysis have been performed by the DAWG in order to identify issues with new data analytics tools and techniques relevant in the standard-setting agenda. As this thesis seeks to add input to the work currently being done and planned to be done in this area from a standard-setting perspective, the further analysis will build on this preliminary research conducted by the DAWG. The DAWG's RfI and relevant comment letters obtained will, therefore, be analysed in order to identify the main perceived challenges in implementing data analytics under the ISAs.

In section 5.1 the preliminary research of the DAWG is introduced. The relevant potential challenges related specifically to the ISAs are then extracted from the RfI and presented below. Section 5.2 presents the selection of which of the comment letters to the RfI to include in the further analysis. Section 5.3 outlines the challenges considered most important as inferred from the analysis of the RfI and the relevant comment letters. Finally, a summary of the findings of this section is provided in section 5.4.

5.1 IAASB DATA ANALYTICS WORKING GROUP'S REQUEST FOR INPUT

The DAWG issued the RfI in September 2016 as a step in exploring the field of data analytics and collecting insights from stakeholders for further analysis (IAASB 2016). The RfI is based on preliminary analyses made by the DAWG. In order to focus this thesis on the most important challenges, it builds on the the preliminary work of the DAWG. This section describes how the RfI is used to focus the further analysis in this study.

The RfI identifies considerations relevant to the use of data analytics in financial statement audits covering regulative challenges in terms of compliance with the ISAs, data protection, and privacy laws, but also ethical considerations on the storage of client-sensitive data and the possible need for collaboration with the International Ethics Standards Board for Accountants. Other mentioned challenges related to the skills and competences of auditors and oversight authorities today in the light of increased used of complex technologies and more practical challenges related to data acquisition and processing. This thesis seeks to address challenges in implementing data analytics in financial statement audits under the ISAs specifically. Therefore, the following analysis of the RfI and relevant comment letters will include only the comments and considerations related to the current ISAs and potential changes to them.

From the RfI all challenges related to the ISAs have been identified and extracted. The identified challenges are listed in Appendix 2. 18 questions have been identified in total. Some questions and challenges overlap but have been included, as they represent different aspects and details of the challenges.

The number of challenges itself does not provide much insight into the relative importance of the identified challenges. Furthermore, the purpose of the RfI was to obtain further insights. Among other questions, it asks:

"*Is our list of standard-setting challenges accurate and complete?*" (IAASB DAWG 2016, p. 5).

This indicates that the list might not be exhaustive as there may be other relevant and important challenges, which are not identified in the RfI.

5.2 RESPONDENTS

As of 20 September 2017, 51 responses had been submitted from audit firms, trade organisations, standard setters and oversight authorities. Appendix 3 includes an overview of the respondents and the type of organisation the response represent. The institutions and organisations submitting comment letters vary significantly in size, geographical scope, and credibility. In order to rule out observations specific to only one country or small group of individuals, the further analysis is based on comment letters from respondents who either represent global audit firms, international associations of relevant stakeholders in the industry, or who have contributed noticeably to the implementation of data analytics internationally or to the global research agenda in this area.

The selected respondents represent different stakeholders including practitioners, regulators, and academics in order to ensure that all relevant perspectives are considered. The selection in each category is outlined below.

5.2.1 AUDIT FIRMS

The work initiated by standard-setters to assess whether updates are needed to accommodate data analytics is a response to the changes audit firms are currently implementing in the audit methodology. It is, therefore, natural to include the perspectives of auditors, as they face the challenges first hand in their efforts to implement data analytics in practice.

Global audit firms currently invest significantly in developing data analytics tools as well as in interpreting the auditing standards in the light of newly developed methodologies. These global networks, furthermore, audit the largest companies in the world. The global audit networks are, therefore, considered the most insightful and representative of the practitioners.

In order not only to obtain perspectives from the Big Four in the industry, the top ten global audit firms were considered relevant. Of the ten largest global audit firms, according to ICAEW (Doherty 2017), only seven have provided responses to the DAWG's RfI, representing Deloitte, PwC, EY, KPMG, BDO, Crowe Horwath International, and Baker Tilly.

In addition to the largest global audit firms, the response from Accountancy Europe was included. This trade organisation informs the European policy debate on auditing and represents professional organisations across Europe (Accountancy Europe n.d.). Due to the specific purpose of influencing the regulation and the outreach of the members, the considerations from this organisation is considered a relevant alternative perspective from the eyes of the practitioners.

Furthermore, the response from ICAEW has been included. The ICAEW presents itself as a global professional body for chartered accountants (ICAEW n.d.). Furthermore, the ICAEW has published several articles and publications on the topic of data analytics in auditing, including the report 'Data Analytics for External Auditors' (ICAEW 2016), which proves the institute's commitment and knowledge in this area.

5.2.2 AUDIT REGULATORS

To represent the view of regulators and standard-setters, responses from AICPA, IFIAR, and the Financial Reporting Council (FRC), have been included.

The AICPA is responsible for issuing the Generally Accepted Auditing Standards (GAAS) applicable in the US. The GAAS are overall converged to match the ISAs (AICPA 2014) and in order to maintain a consistent approach to auditing, it is considered relevant to consider the views of the AICPA. Furthermore, AICPA has put significant efforts into analysing and addressing issues related to implementation of data analytics in audits. This has resulted in the publication of the book 'Audit Analytics and Continuous Audit: Looking Toward the Future' (AICPA 2015), Audit Data Standards to assist auditors in extracting data for analysis (AICPA n.d., (a)), and the organisation will soon publish an Audit Data Analytics Guide (AICPA n.d., (b)). Hence, the AICPA has gained a comprehensive knowledge on the topic of data analytics, which is relevant to consider in addition to the thoughts of the DAWG.

The IFIAR represent audit regulators of 52 jurisdictions (IFIAR n.d.), and is therefore considered a relevant and credible source for input in the analysis.

Finally, the response of the audit regulator of the UK, the FRC, has been included due to the insights obtained from the work conducted in order to publish the 'Audit Quality Thematic Review: The Use of Data Analytics in Audit of Financial Statements' (Financial Reporting Counsil 2017). The publication has been referred to by several other respondents as relevant to the work of the DAWG, which confirms its relevance and credibility.

5.2.3 ACADEMICS

Only two responses from academics were identified. One is from a class of audit graduates at Hunter College and the other from the CarLab at Rutgers, the State University of New Jersey.

As only the CarLab has previously contributed considerably to the body of literature on the topic, only their response has been included. It is noted, furthermore, that the CarLab represents some of the most cited authors on this topic including Professor Miklos Vasarhelyi and Professor Alexander Kogan.

5.2.4 SUMMARY

This selection results in 13 relevant responses representing seven global audit firms, two international associations of audit practitioners, three standard-setters and regulating institutions, and one academic institute.

5.3 ANALYSIS OF REPONSES

First of all, the responses were analysed for confirmation of the challenges identified by the DAWG in order to assess the accuracy of the list and the relative importance of the identified challenges. In Appendix 2, the challenges identified by the DAWG are linked to the number of respondents who confirms that the specific challenge is relevant to the considerations of standard-setting and in practice.

The RfI asked for input on whether the list of challenges is accurate and complete. Hence, the comment letters could include additional relevant challenges to consider. Appendix 4 includes an overview of additional challenges identified in the responses and the respondents who identified the challenge.

It is assessed that analysis of the five most widely recognised challenges would be appropriate in order to identify the key challenges. As noted in Appendix 2, three challenges were confirmed eight times and three challenges were confirmed in seven responses. However, two of them relate to relevance and reliability of data used for data analytics, with the angles of information produced by the entity and external data respectively. As the comment letters often refer to them in combination, they are combined in the further analysis.

Table 1, thus, summarises the top five challenges identified in this preliminary analysis sorted from highest to lowest by the number of confirmations identified in the comment letters to the RfI.

Table 1 Top Five Challenges

Challenge	Challenge description
Documentation	How can the documentation requirements be fulfilled when using data analytics based on the iterative nature of the process to reach a conclusion and what is the extent of the required documentation?
Relevance and reliability of data	What procedures should the auditor perform to evaluate the relevance and reliability, including completeness and accuracy, of information used in data analytics procedures?
Outliers	What is an appropriate level of work to be performed over outliers when testing 100% of a population, in order to determine if the outlier is an exception?
Classification of audit procedures	How should evidence obtained from data analytics be classified as either risk assessment procedures, test of controls, or substantive procedures? Is the classification even relevant when using data analytics?
Nature of audit evidence	What is the nature of the audit evidence obtained via data analytics in response to identified risks when the risk identification and response occurs in one step?

Source: The author's presentation of challenges confirmed in responses from EY (2017), KPMG (2017), Deloitte (Buss 2017), PwC (Sextion 2017), BDO (Smith 2017)*, Crowe Horwath International* (Chitty 2017)*, Baker Tilly* (Ginman 2017)*, Accountancy Europe* (Schneider and Boutellis-Taft 2017)*, ICAEW* (ICAEW 2017)*, AICPA* (Coffey 2017)*, IFIAR* (van Diggelen 2017)*, FRC* (McLaren 2017)*, and Rutgers University* (CarLab 2017) *and linked by the author to the relevant challenges.*

5.4 SUB-CONCLUSION

From the RfI, the author identified 18 challenges related to the ISAs. From the 51 submitted comment letters, 13 respondents were selected representing seven global audit firms, two international associations of audit practitioners, three standard-setters and regulating institutions, and one academic institute.

From the analysis of these comment letters, the five top challenges confirmed concerns:

- Documentation
- Relevance and reliability of data
- Outliers
- Classification of audit procedures
- Nature of audit evidence

6 ANALYSIS OF TOP CHALLENGES UNDER THE AUDITING STANDARDS

Five main challenges related to standard-setting were identified in the preceding section based on analysis of the RfI and selected comment letters. The RfI and the comment letters mention general challenges in implementing data analytics under the ISAs. However, they do not provide much insight into what elements of the ISAs they consider the root of the challenge. Nor do they provide many examples of how data analytics make these challenges particularly relevant.

By analysing each of the five main challenges identified in section 5, this section seeks to provide this insight of the regulative origin of the challenges as well as clarify the context in which they appear. This section, thus, seek to elaborate on the challenges whereas a later section discusses the practical significance of the challenges. The analysis is performed based on relevant ISAs and insights from the RfI, relevant comment letters, and relevant literature on the topic of data analytics.

6.1 DOCUMENTATION

Identified challenge:

"*How can the documentation requirements be fulfilled when using data analytics based on the iterative nature of the process to reach a conclusion and what is the extent of the required documentation?*"

Documentation requirements are specifically addressed in ISA 230 Audit Documentation (IAASB 2015) and assists the auditor in meeting the objective of preparing:

"*documentation that provides:*

a) A sufficient and appropriate record of the basis for the auditor's report; and

b) Evidence that the audit was planned and performed in accordance with ISAs and applicable legal and regulatory requirements" (ISA 230, p. 151).

Further specific documentation requirements are noted in other ISAs and summarised in the Appendix to ISA 230.

Data analytics are not specifically mentioned in the standards, but as data analytics become more widespread and as oversight authorities get a chance to review documentation of data analytics procedures, a norm emerges. The FRC (2017), the audit regulators and oversight authority in the UK, however, has published a thematic review on data analytics in which findings from their review of audit files for audit engagements covering financial years ending in 2015 are disclosed among findings from interviews and other requests. The report mentions three identified instances from three different audit firms, where the documentation included in the audit files were insufficient to fully understand the procedures performed by data analytics specialists (ibid.). As examples of matters that caused the documentation to be insufficient, the report mentions lack of recording of analytics criteria and parameters put into data analytics tools, audit evidence produced by IT specialists were documented outside the audit file, audit file tools were not capable of archiving relevant evidence (ibid.). The findings emphasise that documentation requirements are yet to be calibrated in order for auditors to confidently apply data analytics.

The RfI notes that documentation requirements do not necessarily need to be different for data analytics specifically, but acknowledge that challenges arise in terms of applying the documentation requirements (IAASB DAWG 2016). The DAWG specifically questions whether all data and details of all performed routines need to be included in the documentation as well as whether data used in data analytics, but not used directly as audit evidence to base conclusions on, should be retained (ibid.).

By analysis of the challenges noted in the RfI, relevant comment letters, and of ISA 230, the following parts of ISA 230 are considered the main sources of uncertainty in relation to documentation of data analytics in the implementation phase;

- Para. 8: "*The auditor shall prepare audit documentation that is sufficient to enable an experienced auditor, having no previous connection with the audit, to understand: (Ref. Para. A2-A5, A16-A17)*
    a) *The nature, timing and extent of the audit procedures performed to comply with the ISAs and applicable legal and regulatory requirements; (Ref. Para. A6-A7*)…" (ISA 230, p. 152).
- Para. 9: "*In documenting the nature, timing and extent of audit procedures performed, the auditor shall record:*
    a) *The identifying characteristics of the specific items or matters tested; (Ref. Para. A12)…"* (ISA 230, p. 152).

What is relevant to notice is the notion of the 'experienced auditor' in paragraph eight and of 'identifying characteristics' in paragraph nine. These two elements of ISA 230 are analysed further below.

6.1.1 THE EXPERIENCED AUDITOR UNDERSTANDING

There is an issue related to the notion in ISA 230 of an experienced auditor (Smith 2017) and the ability to understand the nature of the performed procedures. The experienced auditor is defined in ISA 230 para. 6 as:

"*An individual (whether internal or external to the firm) who has practical audit experience, and a reasonable understanding of: (i) Audit processes; (ii) ISAs and applicable legal and regulatory requirements; (iii) The business environment in which the entity operates; and (iv) Auditing and financial reporting issues relevant to the entity's industry"* (IAASB 2015, p. 151).

Currently, data analytics is at a stage of development and implementation. Hence, the level of practical experience with and understanding of these types of procedures vary significantly among practitioners. Often when data analytics are used, it is supported by IT specialists, which would further imply that auditors' knowledge and competencies in this area are somewhat limited.

Questions arise in terms of what to expect of the experienced auditor with regards to experience with and understanding of how data analytics contribute in the audit process at this stage of implementation. It is worth considering whether a certain level of knowledge should be expected or whether the level and detail of documentation should reflect the early stage of implementation and thus be more extensive now, and gradually be adjusted over time as the 'general auditor' gains more experience with the use of data analytics. Requiring a high degree of detail in the documentation could contribute to the development of a common understanding of data analytics. However, as noted in the response from Deloitte (Buss 2017), extensive documentation requirements may hinder the implementation of data analytics as the cost of meeting the requirements could provide arguments in favour of traditional audit techniques with lower documentation requirements.

6.1.2 IDENTIFYING CHARACTERISTICS

ISA 230 para. 9 requires the auditor to document 'identifying characteristics' of tested items when documenting the nature and extent of the performed procedures. It is not required to retain all information used in selecting items to test and upon which the auditor does not reach conclusions, but the characteristics of the tested items must be retained. Challenges arise from this requirement, as it is considered uncertain whether it should be interpreted as a requirement to retain documentation that allow reperformance of the audit or not.

ISA 230 A12 states that identifying characteristics depend on the nature of the audit procedure and items tested and lists examples of identifying characteristics for a number of documents and procedures. For a sampling procedure, for instance, the auditor could identify the tested documents by recording their source, starting point and sampling interval (ibid.). However, no examples are currently provided for data analytics procedures.

The response from the FRC notes that the documentation requirements would traditionally allow reperformance of the audit procedures and that this might not currently be possible in relation to data analytics procedures (McLaren 2017). The FRC further comments that auditors do not keep the entire captured datasets and that the setup of the audited entities' accounting systems may not allow extraction of the accounting information in the same format and by the same way at a later point in time (ibid.).

In line with the comments in the RfI on this matter, the responses from FRC, ICAEW, and EY specifically question whether scripts or programming used to extract the data should be retained and/or whether the entire data sets should be retained (Ernst & Young Global Limited 2017).

6.2 RELEVANCE AND RELIABILITY OF DATA

Identified challenge:

"*What procedures should the auditor perform to evaluate the relevance and reliability, including completeness and accuracy, of information used in data analytics procedures?*"

The consideration of relevance and reliability stems from the objective in the audit process of obtaining sufficient appropriate audit evidence. This objective is defined in ISA 200 on the 'overall objectives of the independent auditor and the conduct of an audit in accordance with international standards on auditing' and is one of the defining elements in the conduct of an audit. The notion of sufficient appropriate audit evidence is therefore mentioned throughout the ISAs.

The relevance and reliability of the audit evidence in supporting drawn conclusions determine the appropriateness of the audit evidence obtained, which is also referred to as the quality of the audit evidence (ISA 200, para. 13 (b)ii). Conversely, sufficiency of audit evidence refers to the quantity of evidence. The required quantity of evidence is dependent on the assessed risk of material misstatement and the quality of the documentation (ISA 500, A4). In determining the quality, relevance concerns whether the information is logically relevant for the purpose of the procedure to be performed and the assertion to be tested (ISA 500, A27). Reliability is influenced by the source and nature of the information and the context under which it is produced (ISA 500, A31, ISA 200, A30).

ISA 500 para. 7 requires the auditor to consider the relevance and reliability of information to be used as audit evidence regardless of the source. However, the standard includes examples of sources and circumstances that affect reliability of information. For instance, the standard mentions that the reliability of audit evidence is increased when it is obtained from independent sources outside the entity (ISA 500, A31).

Apart from the generally required consideration of relevance and reliability of audit evidence, ISA 500 sets out specific considerations to be made and evidence to be obtained when information to be used as audit evidence is prepared by the entity. First of all, the auditor must obtain audit evidence over the accuracy and completeness of the information (ISA 500, para. 9(a)) and secondly, the auditor must evaluate whether the information is sufficiently precise and detailed for the purpose of the procedure (ISA 500, para. 9(b)).

Based on the requirement in ISA 500 para. 7 described above, the auditor must consider relevance and reliability of information analysed by use of data analytics tools and techniques. Still, it may be relevant to consider if the ISAs remain appropriate in the context of rapid development in the volume and complexity of data, the increased accessibility of data from various sources as well as the use of new complex data analytics tools. Accountancy Europe notes that data analytics procedures are often based on data extractions from the entity's underlying databases and not on system-generated reports, which would be covered by the information produced by the entity definition (Schneider and Boutellis-Taft 2017). Furthermore, EY notes that apart from the risk related to the validity of the data in these databases, the auditor and the specialists involved in the data extraction further introduce an extraction risk to the process, which should be considered (Ernst & Young Global Limited 2017).

These circumstances and new ways of working introduce new risks that the auditor need to consider, but there is currently no guidance in the ISAs on how to address them. It is questioned whether these risks should be addressed directly in the ISAs. The new ways of extracting and processing data may imply a need to extend the requirements to obtain audit evidence of completeness and accuracy of information produced by the entity to all data used to obtain audit evidence irrespective of the source. Some auditors may, by their own professional judgment consider completeness and accuracy of data, but requirements would facilitate consistency in the considerations to make before placing reliance on a data set.

In addition to the general considerations of relevance and reliability of data, the RfI and the comment letters furthermore notice a challenge in this area specific to information obtained from external sources. It is questioned whether the assumption in ISA 500 that reliability is generally increased for data from external sources remains relevant.

6.3 OUTLIERS

Identified challenge:

"What is an appropriate level of work to be performed over outliers when testing 100% of a population, in order to determine if the outlier is an exception?"

ISA 500 para. 10 requires the auditor to determine means of selecting items for testing when performing test of details or test of controls. The means available to the auditor, according to ISA 500 A52, are:

- Selecting all items (100 pct. examination)
- Selecting specific items
- Audit sampling

The first issue occur in determining how data analytics fit the means of selecting items for testing stipulated in the ISAs as there may be a need for applying new methodologies. After that, challenges arise in developing such methodologies in practice, which would meet the objectives of the ISAs and be feasible to apply in practice. These two areas are addressed below.

6.3.1 MEANS OF SELECTING ITEMS FOR TESTING

This section seek to establish the requirements of each of the means of selecting items for testing and show how some data analytics procedures may be challenging to place within the three methodologies.

Selecting all items

Applying 100 pct. examination is mostly relevant when performing tests of detail and involves testing of all items in a given population. That might be all transactions that make up an account balance, such as all sales transactions that make up revenues. It could, however, also be a sub-population for which the auditor wish to obtain separate audit evidence, such as sales transactions only for sales of a specific product, where the risk of material misstatement is considered higher.

ISA 500 A53 lists examples where this approach may be appropriate, which include situations where the population is comprised of few items of high value and when automatic calculation or processing by an information system makes 100 pct. examination an effective approach.

Selecting specific items

Specific items testing involves judgemental or haphazard selection of items. This method is not statistical and therefore the tests performed provide evidence only over the tested items. The results can, thus, not be statistically projected to the full population and the auditor needs to address the risk of material misstatement in the untested part separately.

Sampling

Sampling involves a systematic selection of items for testing, which allows the results of the tests performed to be projected to the full population (ISA 500, A55-56). Specific considerations to sampling are addressed in ISA 530 Audit Sampling.

Audit sampling is defined in ISA 530 para. 5(a) as:

"*The application of audit procedures to less than 100% of items within a population of audit relevance such that all sampling units have a chance of selection in order to provide the auditor with a reasonable basis on which to draw conclusions about the entire population*" (IAASB 2015, p. 456).

When testing by means of sampling, ISA 530 para. 12 specifically requires the auditor to investigate any deviation or misstatement identified and evaluate the effect on the audit procedure being performed as well as other areas of the audit.

Selecting items for testing in data analytics procedures

From the RfI, comment letters, the body of academic literature on data analytics, as well as from the interviews conducted by the author, it is observed that one of the features most widely referred to when discussing data analytics, is the opportunity to test full populations of large volumes of data.

As noted above, ISA 500 assumes that full population testing is only feasible if the population consists of few items or if the transactions involved is highly standardised. Data analytics, however, makes it feasible to test populations consisting of billions of individual items irrespective of whether they are standardised. Such data analytics procedures, thus, resembles the 'selecting all items'-methodology, but in a new context.

Data analytics will examine the population based on a set of defined assumptions and parameters. An example would be the assumption that certain data elements, such as quantity and price, shall agree across a sales order, delivery documentation, and the issued invoice in the sales process. However, variances from such assumptions may occur for various natural reasons and not necessarily be reflective of an error in the recorded transaction. Hence, without further investigation, the auditor cannot conclude that all differences identified by data analytics tools constitute misstatements and thereby conclude on the population.

Testing the full population of, for instance, sales transactions, will for many companies involve testing of millions or billions of transactions. Such data analytics procedures can therefore easily produce thousands of outliers, i.e. variances from the assumptions and criteria put into the analytics tools (ICAEW 2016). Upon investigation it is often found that many of outliers do not reflect misstatements, i.e. the analytics flag false positives (ICAEW 2016).

The challenge for the auditor occurs in determining how to handle large numbers of outliers. In traditional 100 pct. examination, the auditor would investigate all identified variances. However, it is impractical for auditors to investigate thousands of outliers individually. Therefore, other methodologies are needed to analyse the outliers and limit the detailed investigation of outliers to a level, which is feasible in practice and at the same time sufficient to conclude on the full population. Such methodology, thus, involve elements of the 100 pct. examination approach as the full population is subject to analysis, but the investigation of outliers will have to draw on elements of either the specific items testing, sampling approach, or analytical procedures, which is normally an alternative to test of details.

Developing these new methodologies and techniques pose challenges to the auditors as they are not reflected directly in the ISAs. Deviating from the standard methodologies of the ISAs will require the auditor to exercise professional judgment, which is currently difficult as auditors, in general, are inexperienced in the use of new data analytics tools and as there is no official guidance available.

6.3.2 METHODS TO ADDRESS OUTLIERS

The DAWG asks in the RfI whether the most appropriate approach to outliers would be to test each individual outlier identified in a full population analysis individually, to reach a conclusion based on tests of a sample of the outliers, or whether testing of outliers should be performed until the amount of untested outliers are reduced to a level that could not include a material misstatement, which resembles the specific items testing (IAASB DAWG 2016). Thus, the DAWG suggests that outliers are addressed as a separate population.

The CarLab (2017) comments that simple sampling might not result in an appropriate sample to conclude on all outliers, but suggests instead to apply risk-based filters to identify what they refer to as "exceptional exceptions", i.e. riskier transactions which are likely to represent misstatements. For further detail on this approach, the group refers to a study performed by Hussein Issa (2013), which proposes a framework for dealing with such outliers, titled "Exceptional Exceptions". Furthermore, the group informs in their response to the RfI that the RADAR is working on a systematic approach for prioritising outliers (ibid.).

Issa (2013) suggests a framework in which the rules and assumption underlying the analytical procedure are weighted in terms of the significance a breach would have. In the test, each item tested would be assigned a suspicion score based on the types of rules that have been breached, if any, and the relative weight of those rules. Hence, if the item does not classify as an outlier, it would have a suspicion score of zero, and the more rules of significance that are breached the higher a score will be assigned (ibid.). The auditor can then arrange the outliers by their scores and thereby focus the further investigation in a prioritised manner on the so-called 'exceptional exceptions'. In a similar manner, the RADAR is currently working on a Multidimensional Audit Data Selection (MADS) project which seeks to develop a framework to assist auditors in dealing with outliers by prioritising them and focusing the further investigation on outliers likely to reflect misstatements (AICPA n.d., (c)).

Hence, research has been and is currently being conducted on the topic of developing frameworks for auditors to apply on outliers. However, there is currently no well-recognised framework available in the audit industry. As noted above, the ISAs do not provide guidance on how to treat outliers appropriately either. Thus, uncertainty remains in the audit industry as to which methodologies would be appropriate and acceptable under the ISAs. Auditors may seek to overcome these challenges by applying professional judgment, but there is a risk that it may result in widely inconsistent approaches to outliers. The ICAEW (2017) indicates that there is already a gap in the interpretations and judgments made in this area among audit firms and audit regulators.

6.4 CLASSIFICATION OF AUDIT PROCEDURES

Identified challenge:

"*How should evidence obtained from data analytics be classified as either risk assessment procedures, test of controls, or substantive procedures? Is the classification even relevant when using data analytics?*"

As inferred from section 3.2.1, data analytics procedures may become relevant across the phases of an audit. Moreover, data analytics introduce new ways of performing audit procedures and may involve a more iterative process than what the ISAs currently contemplate. This could include single procedures which could support the auditor's risk assessment, but also provide audit evidence for the evaluation of controls and the substantive procedures. Therefore, it has been questioned whether data analytics procedures undermine the relevance of such distinct categorisation of procedures.

The following analysis seeks to identify, first of all, to what extent the ISAs approve of concurrent performance of risk assessment procedures, controls testing, and substantive procedures. Secondly, an example is given to illustrate how a data analytics procedures could meet the objectives of each type of procedure. Finally, based on the requirements of the ISAs and the identified example, it is outlined how data analytics may make the classification of audit procedures less relevant.

6.4.1 CONCURRENT PERFORMANCE OF AUDIT PROCEDURES

Traditionally and in line with the ISAs, risk assessment procedures have been performed with the purpose of obtaining an understanding of the entity and its environment in order to be able to identify and evaluate risks of material misstatement. This process is defined in the ISAs as:

"*… A continuous, dynamic process of gathering, updating and analysing information throughout the audit*" (ISA 330, A1).

This definition implies a somewhat iterative process, which is also a characteristic of many data analytics procedures.

Analytical procedures are, furthermore, required to be performed as part of the risk assessment in addition to inquiries, observation, and inspection (ISA 315, para. 6(b)). Analytical procedures may include financial as well as non-financial data and may assist the auditor in identifying unusual patterns and trends, which can be used as the basis for identifying risks of material misstatement (ISA 315, A14-15). Data analytics tools can, thus, naturally contribute to the risk assessment, as it is characterised as dynamic analysis of various types of data.

The ISAs stipulate that risk assessment procedures by themselves do not provide sufficient appropriate audit evidence on which to base the audit opinion (ISA 315, para. 5). However, a risk assessment procedure may provide audit evidence over account balances, disclosures, and related assertions as well as the operating effectiveness of controls, although the procedure was not planned as a substantive procedure or test of operating effectiveness (ISA 315, A2). ISA 330 A23, furthermore, states that test of controls and test of details may be performed concurrently over the same transaction if they address each purpose of the test separately.

Hence, it is found that data analytics procedures could naturally contribute to the risk assessment. Furthermore, it is observed that the ISAs directly allow the auditor to perform risk assessment procedures, controls testing, and substantive audit procedures concurrently, as long as the objectives of each class of procedures are addressed separately.

6.4.2 EXAMPLE OF A TRIPLE PURPOSE PROCEDURE

An example of such a triple purpose procedure, would be an analysis of the three-way-match of volumes and prices across sales orders, delivery documentation, and sales invoices for the full population of revenue transactions.

If revenues is considered a significant area in the initial planning of the audit, the auditor will need to identify and evaluate risks of material misstatement. The initial understanding of the process and control environment could be obtained from inquiries with relevant personnel and, for instance, inspection of supporting documentation of the flow of a sales transaction. The risk assessment could, furthermore, be supported by the analysis of three-way-matches in the full population.

Such an analysis would highlight if some transactions follow a different flow than the one explained by the client. Thus, the auditor can use the analysis to identify additional risks areas or to support the risk assessment made, as it also shows if the process works as expected. If separate flows of significance to the audit are identified, the auditor would go back and perform inquiries and inspections again to strengthen the understanding of the process and the risk assessment.

For the transactions following the tested flow, however, the full analysis of the three-way-match could, in addition to the risk assessment, provide audit evidence for the operating effectiveness of an automatic three-way-match control as well as substantive audit evidence for recorded revenues, as all transactions are analysed. The analysis, thus, becomes a triple-purpose-test. At the same time, it represents an iterative process as the auditor needs to re-perform some steps in the process if such analysis identify additional transactions flows to address separately.

6.4.3 RELEVANCE OF CLASSIFICATION

The ISAs already allow concurrent performance of the three classes of procedures and stipulates elements of continuous, dynamic analysis throughout the audit. However, as the example shows, data analytics tools may allow performance of procedures, which address the objectives of each class of procedures at once, to a larger extent than previously. Yet, the auditor still has to document how the performed work classify as a risk assessment procedure, controls testing, as well as a substantive audit procedure.

It is questioned whether the classes of procedures in the current audit model remain relevant as more procedures will cover the objectives of each type of procedure. An alternative could be a more holistic approach to auditing in the ISAs by enhancing that the process to obtain sufficient appropriate audit evidence is iterative and transcends the existing categories of procedures.

6.5 NATURE OF AUDIT EVIDENCE OBTAINED

Identified challenge:

"*What is the nature of the audit evidence obtained via data analytics in response to identified risks when the risk identification and response occurs in one step?*"

This identified challenge links into the challenge related to categorisation of audit procedures and how data analytics can provide evidence across those categories. However, it relates more to the challenges in determining the nature and evaluating the audit evidence obtained from data analytics procedures, including the assessment of when sufficient appropriate audit evidence has been obtained.

6.5.1 SUBSTANTIVE AUDIT EVIDENCE

ISA 330 para. 4(a) divides substantive procedures into tests of details and substantive analytical procedures. Auditors are challenged in categorising audit procedures performed by data analytics tools as either tests of detail or substantive analytical procedures and, thus, in determining the nature of the audit evidence obtained and how to appropriately obtain the evidence.

Defining substantive audit procedures

The ISAs do not provide a clear definition of tests of details. Substantive analytical procedures, however, are defined in ISA 500 A21 on audit evidence and ISA 520 para. 4 on analytical procedures as:

"…*Evaluations of financial information through analysis of plausible relationships among both financial and non-financial data. Analytical procedures also encompass such investigation as is necessary of identified fluctuations or relationships that are inconsistent with other relevant information or that differ from expected values by a significant amount*" (IAASB 2015, p. 400, p. 447).

This definition of substantive analytical procedures above implies that the auditor develops expected values in order to identify variations from them. ISA 520 sets out specific requirements for substantive analytical procedures. ISA 520 para. 5(c) requires the auditor to form expectations of recorded amounts or ratios and para. 5(d) requires the auditor to determine a monetary amount above which differences between actual and expected values must be investigated. This threshold depends on materiality, the desired level of assurance from the procedure, and the assessed level of risk of material misstatement (ISA 520, A16).

Classifying data analytics procedures

It is assessed that the distinction between tests of details and substantive analytical procedures have traditionally been clearer. Tests of details would typically involve selection of a sample of items which would then be vouched against supporting documentation, such as physical order copies or invoices, i.e. tested in detail as the concept suggests. Substantive analytical procedures, however, would mostly involve numerical analysis of data such as comparison of account balances to prior year or budget information.

In the example of full population testing of three-way-match in sales transactions, the data analytics tools automatically vouches each item to information from other supporting data sets presenting information on orders, deliveries, and invoices. This resembles the traditional test of details as the tested items are vouched to supporting information, although the process is automated and the supporting evidence is in the form of other data extracts.

At the same time, however, it could be argued that it should classify as a substantive analytical procedure, as the auditor sets expectations to the relationships among financial and non-financial information, which the data analytics tool then analyse and highlight fluctuations and inconsistencies.

The distinction between test of details and substantive analytical procedures impacts the assessment of appropriate approaches to address variations, as further discussed in section 6.3 on outliers. Furthermore, ISA 330 para. 21 requires that if a significant risk is identified and relevant controls are not tested, the substantive audit approach has to include test of details. If procedures cannot clearly be defined, it becomes challenging to determine whether this requirement is fulfilled.

Hence, procedures performed in new ways by use of data analytics makes it more difficult for auditors to determine the nature of the procedures performed and, thus, the appropriate approach to address variations identified in the procedures as well as to determine if sufficient appropriate audit evidence has been obtained.

6.5.2 PROCEDURES TO OBTAIN AUDIT EVIDENCE

Another challenge in evaluating audit evidence obtained from data analytics procedures arise from the fact that such new procedures are currently not recognised in the ISAs.

ISA 500 A2 notes the following procedures for obtaining audit evidence:

- Inspection
- Confirmation
- Recalculation
- Reperformance
- Analytical procedures
- Inquiry

Some procedures performed by data analytics tools may well fit within the existing recognised procedures. An example would be to automatically perform a full recalculation of the annual depreciation based on information of asset acquisition dates, asset types and the depreciation policy. Such a procedure would naturally categorise as a recalculation, and the general auditor would have experience in evaluating the evidence obtained from such procedures.

The example from the preceding section of the three-way-match, however, would not necessarily fit just as well into the listed procedures. As noted above, it may be categorised as an analytical procedure, but it can also be argued that it is not. If it is not an analytical procedure, however, there is no obvious category to which such procedure would belong.

As each of the procedures differ in terms of the strength of audit evidence they can provide, as determined partly in the ISAs and partly by industry practice. New procedures, thus, challenge the auditors in how the audit evidence should be evaluated as there is no normal practice to lean on. Furthermore, auditors may fear that oversight authorities will not concur with the individual professional judgments made, if a direct link cannot be made to the procedures recognised in the standards. Hence, auditors may be of the perception that the value for the audit quality of such procedures is not fully recognised.

There are, therefore, challenges for auditors in determining the nature of the procedures performed by data analytics, whether it is in defining it as a test of details or a substantive analytical procedure within substantive testing or among the general procedures to obtain audit evidence. This affects how variations should be addressed, whether specific requirements of the ISAs are fulfilled, and how the auditor would evaluate the audit evidence obtained and determine when sufficient appropriate audit evidence has been obtained.

6.6 SUB-CONCLUSION

The analysis of the key challenges in the context of the ISAs revealed critical areas of uncertainty and concerns with regards to interpretation and application of the ISAs when seeking to implement data analytics techniques, which are summarised below for each of the challenges.

Documentation

Challenges arise primarily from two requirements in ISA 230. The first one is the notion of the experienced auditor. How to set expectations for the experienced auditor's knowledge on the use of new data analytics technologies and adjust the documentation accordingly is difficult, as the knowledge in practice vary significantly among auditors. The second is the requirement to record identifying characteristics of tested items. Uncertainties have been expressed as to whether the requirement of documenting identifying characteristics of tested items implies that the documentation should allow reperformance of the procedures.

Relevance and reliability of data

As auditors seek to increase reliance on audit evidence obtained from analytics performed by use of new data analytics tools and methodologies, which themselves impose new extraction and manipulation risks, relevance and reliability of analysed information becomes even more critical. Challenges arise in determining how to validate data from other sources and extracted in other manners than what have been used previously, as there is currently no clear requirements on this matter. Furthermore, it is questioned whether these circumstances imply a need to make the specific requirements for validation information produced by the entity in ISA 500 applicable to all information used for data analytical procedures, irrespective of the origin. Finally, assumptions in the ISAs regarding reliability may be obsolete, such as the assumption that reliability is increased when the information is obtained from external sources.

Outliers

Challenges arise in handling extensive volumes of outliers in an analysis of 100 pct. of a population by use of data analytics techniques, as such procedures would not clearly fit into either the sampling nor the 100 pct. examination approaches to selecting items for testing mentioned in the ISAs. Research has been and is being conducted to develop frameworks to handle outliers in such procedures. However, no consistent approach has developed in the industry, and it remains a challenge to determine which methodologies will be accepted as appropriate under the ISAs.

Classification of audit procedures

It is identified that the iterative nature of procedures performed by use of data analytics techniques challenges auditors in terms of classifying it in the boxes of risk assessment, controls testing or substantive procedures. Furthermore, it is questioned whether the classes remain relevant in all situations or if the ISAs should reflect a more holistic approach to meeting the objectives of an audit as opposed to the current prescriptive boxes.

Nature of audit evidence

Some valuable procedures that data analytics techniques allow the auditor to perform, do not fit easily as either test of details or substantive analytical procedures within the category of substantive procedures nor among the recognised procedures to obtain evidence in general. Hence, auditors experience difficulties in determining the nature of the audit evidence obtained from such procedures. This, furthermore, implies challenges for the auditor in determining how to respond to variations identified, whether requirements of the ISAs to perform specific types of procedures are met, and in the subsequent evaluation of the audit evidence. Eventually, it challenges the auditors' judgment of when sufficient appropriate audit evidence has been obtained, as the neither the standards nor industry practice can be referred to. Auditors, therefore, fear that oversight authorities will not recognise the value of such procedures for the audit quality.

7 ANALYSIS OF THE SIGNIFICANCE OF THE TOP CHALLENGES

In the section above, the identified five top challenges were analysed from a theoretical perspective based on input from the comment letters to the RfI and analysis of the ISAs. However, the RfI and comment letters provide only limited input on the role and effect of the identified challenges in practice.

This section, therefore, adds analysis of the practical relevance and importance of the identified top challenges based on conducted interviews. The input is analysed in order to determine whether the identified challenges reflect merely theoretical and hypothetical challenges in matching the use of data analytics to the standards with little practical implication, or whether they represent relevant challenges in practice, which might impede the process of implementing data analytics in the audit industry. From the identified top challenges this section, thus, seek to analyse which of the challenges can be considered key challenges in implementing data analytics.

Below, the identified challenges are analysed in the same order as in the preceding analysis. The order is not indicative of the relative importance as this is what this section seeks to identify. The challenges relate to:

- Documentation
- Relevance and reliability of data
- Outliers
- Classification of audit procedures
- Nature of audit evidence

For each challenge, interview input is analysed to assess the perceived significance of the challenge. Where relevant practical examples are provided by interviewees in addition to those mentioned in section 6, they are included to clarify the challenges. Finally, a brief summary is provided of the perceptions of each challenge.

7.1 DOCUMENTATION

As noted in section 6.1, challenges in documenting the use of new data analytics tools and techniques arise from the uncertainty about the level of required documentation due to the notion of the experienced auditor in the standards as well as about whether the requirement of documenting 'identifying characteristics' of tested items in practice means that the documentation should allow reperformance.

7.1.1 SIGNIFICANCE OF THE CHALLENGE

The comments made by the interviewees are analysed in order to determine how critical the identified challenge is perceived by stakeholders.

Jesper Drud (2017) ranks documentation as the second most important of the five identified challenges. Trevor Stewart (2017) acknowledges that all the identified challenges are important, but ranks the one concerning documentation last. Similarly, Jon Beck (2017) explains that he does not consider documentation a critical issue today, but that it will become critical as data analytics tools become too sophisticated for the general auditor and for oversight authorities to understand in detail, how they work. Documenting how data has been obtained, however, is not difficult, according to Jon Beck (2017) and Jesper Drud (2017). Hence, the challenges of documenting identifying characteristics and determining whether it should allow reperformance is not considered significant.

From the interviews of Miklos Vasarhelyi, Trevor Stewart, and Martin Samuelsen it is interpreted that challenges in preparing documentation is not their primary focus. This might be due to their role as academics and due to the limited extent to which data analytics is currently used to provide audit evidence. As a professor, Miklos Vasarhelyi does not face the challenges of documenting audit procedures in practice. Likewise, Trevor Stewart works mostly in academics and as an advisor in developing data analytics tools at Deloitte. Hence, he no longer meets the documentation challenges in practice. As auditors do not yet place much reliance on data analytics and as there is a time lag between audits and the quality reviews conducted by oversight authorities, Martin Samuelsen might not yet have been much exposed to documentation of data analytics either. This might explain why Martin Samuelsen does not currently see significant challenges in this area.

Hence, it is assessed that documentation of new data analytics tools and techniques is considered an increasingly important challenge for practitioners. As tools and technologies develop and more reliance is to be placed on them as providers of audit evidence, the more relevant the challenge will become. However, due to the current limited use of such methodologies to provide audit evidence and the role of some interviewees, this area is not top of mind for all respondents.

7.1.2 THE CHALLENGE IN PRACTICE

As discussed above, the interviewed practising auditors assess that there are challenges and potential future challenges related to documentation of data analytics. These challenges related to documentation of different elements, which are elaborated and discussed below.

Integrity of data analytics tools

Jesper Drud explains that the main documentation challenges relate to documentation of the automated process of performing analyses by use of data analytics tools, i.e. documenting how these tools process the data and determines whether there are variances (Drud 2017). He describes the reasons for the challenge:

"*I believe what makes it somewhat difficult to use data analytics today is that no one really knows the documentation requirements and the understanding of what is actually going on*" (Drud 2017, 30:20).

He notes that this documentation can be quite burdensome as it can easily become very technical and that a balance is needed in how these procedures are documented (ibid.). Yet, he emphasises that documentation is critical and that if the auditor has not understood the process and cannot document it, it cannot be used as audit evidence anyway (Drud 2017).

Jon Beck (2017) furthermore explains that oversight authorities might require local documentation for tools developed centrally in global audit networks. It may be required that local member-firms of global networks keep documentation of how those tools operate and how it is locally ensured that they do what they are intended to do (ibid.). For local member-firms in smaller countries with limited resources and capabilities in this area, this can be a challenge (ibid.).

It is assessed that the challenges in understanding and documenting how such data analytics tools process the data are important and will become increasingly important as they become increasingly complex and used more extensively to provide audit evidence.

Audit procedures

It was discussed in section 6.1.1, how the notion of the experienced auditor in the documentation requirements of the ISAs would affect the documentation of audit procedures performed by use of data analytics tools.

Jesper Drud (2017) notes that currently, most auditors are relatively inexperienced in the use of such techniques. He further states that:

"*…It will definitely be my expectation that the requirements to document what has happened in the data analytics process are higher today than they will be in, say, five years, because it will become more commonly used*" (Drud 2017, 24:23).

However, Jon Beck (2017) notes that some data analytics tools are already used in practice and that the use, naturally, requires documentation. As a simple example, he mentions test of journal entries by use of analytical tools. In this procedure, the auditor starts out with a large data population and from that identifies journal entries associated with a high risk based on certain criteria, which need to be tested further. This process of filtering the data, he notes, is already being documented as part of standard audit engagements today. Hence, the general auditor already has some experience in documenting rather simple data analytics procedures, which can be built on to document more complex procedures.

The author, furthermore, notes that documentation challenges is part of the everyday work of an auditor. Auditors will, and have always, faced audit areas of higher and lower complexity. The more complex the area and the higher the risk involved, the more comprehensive the documentation needs to be, and it is up to the professional judgment of the auditor to determine the appropriate level.

Hence, new data analytics procedures may require more consideration in determining how to appropriately document them. Furthermore, in the implementation phase, a higher level of documentation may be required than what would be expected at a later stage. However, determining the appropriate level of documentation of data analytics procedures is not considered unique and critical to the implementation of data analytics, as this consideration is an ordinary part of an audit.

7.1.3 SUMMARY

This area is considered challenging mostly by practitioners, which is considered natural as only practitioners directly face the challenges of actually preparing audit documentation. It is identified that challenges are expected in determining the appropriate level of documentation when auditors start placing more reliance on those procedures as audit evidence. It is noted, however, that auditors already face documentation challenges frequently in their ordinary work and have already gained some experience in documenting simple data analytics procedures.

The critical challenge observed in practice relates, however, to documentation of how new complex data analytics tools process data and generates analyses. Especially for local members of global audit networks, who use centrally developed data analytics tools, it is considered a challenge to prepare documentation that supports the use and quality control of such tools.

7.2 RELEVANCE AND RELIABILITY OF DATA

From the previous analysis, it is identified that there is a challenge in determining the requirements for testing relevance and reliability of data as more reliance will be placed on data analytics. Challenges were identified in validating data from untraditional sources and data extracted in new ways. It was, furthermore, questioned whether the specific requirements for validation of information produced by the entity should be applicable to all analysed information, irrespective of the source. Finally, it was questioned whether the assumption in the standards that external data is more reliable than internal data remains relevant.

7.2.1 SIGNIFICANCE OF THE CHALLENGE

The challenges of relevance and reliability is considered one of the most important among the interviewees. The interviewees have therefore been asked to elaborate on the reason for the significance of this challenge in the implementation of data analytics.

Jesper Drud (2017) notes that the high level of automation in the new data analytics process makes considerations of reliability crucial and he sees this as the most important challenge in implementing data analytics.

Similarly, Martin Samuelsen (2017) comments that implementation of data analytics implies greater reliance on the data. He further notes:

"*All else equal, this must mean that you have to be more firm on whether the system actually generates the right data and how it gets into the system and out again*" (Samuelsen 2017, 27:47).

Jon Beck (2017) also considers this challenge the most significant along with the challenge related to outliers. He confirms that this area might be more critical than it has been previously due to the large volumes of transactions analysed and based on the principle that "if garbage goes in, garbage will also come out" (Beck 2017, 38:42).

Trevor Stewart (2017) also supports the opinion that this challenge related to data reliability is one of the most important ones to consider in the implementation of data analytics due to the increased reliance on data.

Hence, there is strong indications among the interviewees that this in area of high importance in the industry when implementing data analytics.

7.2.2 THE CHALLENGE IN PRACTICE

The statements above mostly states why the importance of relevance and reliability increases with data analytics. In this section, input from the interviewees on where challenges are observed is discussed.

Reliability

As an example of the challenges related to reliability, Jon Beck (2017) mentions 100 pct. population test of three-way-match for sales, where data on sales orders, delivery documentation, and sales invoices are matched by use of data analytics techniques. Traditionally such procedures involved inspection of underlying documents which, as part of the procedure, would give an indication of the reliability of the tested information. The full population analysis performed by data analytics tools will show whether information agrees across data sets, but it will not ensure that the analysed information is reliable (ibid.). Therefore, he notes, practitioners today discuss the 'four-way-match', in which a fourth match to external bank data is added in order to reduce the risk related to reliability of the data. Such solutions, however, are not easily found for all new types of procedures.

Jesper Drud (2017), furthermore, notes that his experience in practice is that there is a lack of understanding among auditors of the importance of validating data input when implementing new data analytics tools and techniques.

Hence, it is observed that auditors experience challenges in verifying reliability of the information they place reliance on as it is increasingly data-driven. This requires new methodologies, which may involve inclusion of addition data of higher credibility.

Relevance

Miklos Vasarhelyi (2017) comments that the development in data analytics tools and techniques will change the perception of relevant data in audits dramatically. He explains that exogenous data will be considered relevant to a much larger extent than it has been previously (ibid.). Exogenous data in this context refers to data external to the audited entity. He explains the relevance of exogenous data by:

"*A lot of external information tells you something about the company. I think the trend is that you do less 'in the company data analysis' and more 'linking it to the environment data analysis'. Sources like weather data, local econometrics data, social media of different source, and news pieces basically give firms confirmatory data about the company*" (Vasarhelyi 2017, 22:30).

He further comments on the reliability of such data:

"*Exogenous data is much more reliable than endogenous data. And I think what you consider relevant data will change pretty dramatically"* (Vasarhelyi 2017, 24:20).

Trevor Stewart (2017) also comments that in addition to reliability of data, auditors must also consider relevance to a larger extent. As an example, he notes the use of predictive analyses, where the auditor needs to carefully consider the relevance to the current year data of the predicting variables and the data used to develop the predictive model (Stewart 2017, 26:20).

Thus, as opposed to the discussion in section 6.2, the interviewees does not consider the assumption that external data is more reliable than internally generated data obsolete. Rather, they observe challenges for auditors in identifying and assessing relevant data to include in data analytics procedures. Especially if information is obtained from untraditional sources, it may be difficult to include due to the lack of industry recognition of the credibility of such information.

7.2.3 SUMMARY

There is a general consensus among interviewees that increased use of new data analytics tools and techniques increases the importance of assessing relevance and reliability of the analysed data. Challenges arise in developing new methodologies to verify the reliability of data, as no clear requirements are yet stipulated in this area.

It was found that the assumption that external data is more reliable than internally generated data was not considered obsolete among interviewees. On the contrary, new data analytics techniques will require auditors to more carefully assess the relevance of applied information and may need to include new types of external data. However, it may be challenging to include types of information which are currently not widely recognised as relevant.

The increased importance of these considerations might imply a need for the ISAs to reflect this as an important focus area as well as accommodate the use of new types of relevant data in obtaining audit evidence.

7.3 OUTLIERS

It is identified that one of the most widely discussed benefits of data analytics tools is the opportunity to analyse 100 pct. of a selected data population in an automated manner. However, this form of testing does not fit the traditional distinction between acknowledged means of selecting items for testing in the ISAs. Therefore, it does not provide guidance on how to address, potentially, thousands of outliers identified in such procedures.

7.3.1 SIGNIFICANCE OF THE CHALLENGE

Among the interviewees, there are mixed views on whether outliers constitute a significant challenge. The arguments for each interviewee are outlined and analysed below in order to evaluate whether challenges in this area are critical to the implementation of data analytics.

Martin Samuelsen (2017) does not find this area critical and refers to general principles of the auditor's professional scepticism towards deviations and variations. Yet, he notes that the time spent on analysing outliers could reduce the advantage of using data analytics from a time and effectiveness perspective. Likewise, Jesper Drud (2017) assesses that this is an area where, as for all other audits, it is a question of when the auditor believes sufficient appropriate audit evidence has been obtained in order to form an opinion.

Jon Beck (2017), however, recognises outliers as one of the most widely discussed challenges in the implementation of new data analytics tools. Likewise Trevor Stewart (2017) refers to outliers as currently being a big unsolved problem. The issue, as he explains it, is that you get a lot of outliers and know most of them are false positives, but you cannot just ignore them (ibid.). Despite the already conducted research, such as that of 'exceptional exceptions' mentioned in section 6.3.2, he does not believe that there is yet a final well thought-through solution available to overcome this problem (ibid.).

Miklos Vasarhelyi (2017) concurs with the perception that there are significant challenges in this area and encourages the industry to start thinking differently of this matter to accommodate the use of data analytics. He comments that the idea of extrapolation from a sample and judgemental sampling to assess the value of the population does not fit well with the very large data sets of billions of transactions that auditors face today. In his view, this focus on the standards on such methods is the cause of the challenge. He observes that auditors, despite the focus of the standards, feel that in order to reduce their audit risk sufficiently, they need to do other things such as full population testing. However, he notes that the standards require you to examine exceptions and variances irrespective of whether you perform test of details or substantive analytical procedures, but explains that if you get thousands of exceptions, it is not feasible to test each of them (ibid.).

In terms of significance, it is also noted that outliers is a topic discussed and analysed specifically in the RADAR working group's MADS project, as described in section 6.3.2. The project seeks to develop a framework for handling outliers. Furthermore, it has been a matter of much discussion in the RADAR working group's work on the development of the AICPA Audit Data Analytics guide. This indicates that a substantial number of stakeholders, at least in the US, consider it a highly relevant challenge to address by standard-setters.

It is noted that the US, in general, is considered highly regulated. This might partly explain the difference from Miklos Vasarhelyi's and Trevor Stewart's significant focus in this area to the general reference to the auditor's professional judgment by Jesper Drud, who is a Danish auditor, and Martin Samuelsen, who is responsible for the Danish Public Oversight. Furthermore, as noted above, Jon Beck, who participates in international collaborations on implementation of data analytics and is also a US GAAP accredited, also recognises this area as a significant matter of discussion.

As the challenge is confirmed to be highly discussed and analysed internationally both in audit firms and by standard-setters and academics, the challenge is concluded to be considered of high importance.

7.3.2 SUMMARY

It is found that research is being conducted in order to develop sound frameworks for handling outliers in audits. However, such methodologies would currently not link directly to the auditing standards due to the challenges in linking 100 pct. examination procedures to the ISAs.

In Denmark, such methodologies are expected to be implemented mostly by reference to the auditor's professional judgment in determining if the audit evidence is sufficient and appropriate. In highly regulated countries, however, this missing link to the standards may pose a significant challenge to implementation of new methodologies, which is evidenced by the discussions of this topic internationally. It is therefore concluded that the challenge is significant, but based on the perspective on applying professional judgment, it is not considered the most critical of the identified challenges.

7.4 CLASSIFICATION OF AUDIT PROCEDURES

The audit process is a somewhat iterative process by nature. It is argued, however, that the use of many new data analytics tools and techniques emphasizes this iterative characteristic. Yet, the standards clearly distinguished between risk assessment procedures, controls testing, substantive procedures and completion procedures. It may be challenging, and perceived as irrelevant, to categorise all new data analytics procedures as one or the other, as they would often address objectives within several categories at once.

7.4.1 SIGNIFICANCE OF THE CHALLENGE

The opinions in this area are diversified among the interviewees. Differences primarily arise in the assessment of whether challenges in the iterative nature of an audit are intensified by data analytics, or if the challenge is the same as for all audits, irrespective of the use of data analytics. The arguments of the interviewees are outlined below.

Jon Beck (2017) and Jesper Drud (2017) are both of the opinion that this is not a challenge specific to data analytics implementation. Jon Beck (2017) explains that he considers the classification of audit procedures a natural part of the audit model. He elaborates by explaining that the standards mention these classes of procedures to clarify, for instance, that controls testing is not in itself sufficient in order to address an identified risk. Furthermore, he emphasises that auditors already use a range of dual-purpose procedures. Thus, he does not consider this area a significant challenge in the implementation of data analytics, as the challenge in categorising dual-purpose procedures is not new.

Martin Samuelsen (2017) agrees with Jon Beck that the classification of procedures is in line with the audit process. However, he questions the future relevance of some of the requirements to perform specific types of procedures. As an example, he questions whether it remains relevant in the future to require that substantive audit procedures are performed whenever a significant risk of material misstatement is identified. With increased focus on data analytics, validation of data, and audit of systems, he suggests that controls testing over IT systems could possibly provide sufficient audit evidence in the future. As an example, he questions the benefit of performing additional substantive procedures over revenue, in the future, if a system-based audit approach could ensure that the information flowing through the system is accurate.

Trevor Stewart (2017) also recognises that the audit process has always been iterative to some extent. However, he explains that data analytics techniques may highlight the iterative aspect of the process. He explains that the initial stage of the audit involves exploratory analysis to which new data analytics tools are likely to contribute significantly. For instance, the use of visualisation is highly relevant for this purpose. Previously, he notes, the exploratory stage would typically involve skimming through the latest financial statements and talking to Management. Hence, new data analytics tools make the exploratory analyses more visible and he, therefore, asks whether such exploratory analytics need to be documented in the audit file.

Miklos Vasarhelyi (2017), on the contrary, is clear in his view that the stages of the audit are going to blend together with data analytics and, therefore, the classification of procedures will not make sense in this 'new world'.

Thus, there are differing views among the interviewees as to whether the classification of audit procedures pose a specific challenge to the implementation of data analytics or not. In order to reach a conclusion from these responses they are further analysed below.

Assessment of arguments

It is noted that Martin Samuelsen's question of whether controls testing could provide sufficient audit evidence was mentioned after he concurred to the perception that the classification, overall, makes good sense in the audit model. The question of requirements when identifying significant risks of material misstatements is, therefore, considered merely an example of a challenge related to this area, which is expected to be more relevant in the future. Based on the context in which it was asked, however, it is assessed that Martin Samuelsen does not consider the mentioned example critical to implementation of data analytics.

Likewise, from the way in which the challenge in documenting exploratory analytics noted by Trevor Stewart was framed, it is assessed that, although he sees a practical challenge in this area, he does not consider it critical to implementation of data analytics.

Jon Beck and Jesper Drud, who are both audit practitioners, do not consider it critical to implementation of data analytics. Likewise, it is inferred above that neither do Martin Samuelsen or Trevor Stewart consider the area critical to implementation, although they could provide some examples of related challenges. Miklos Vasarhelyi is the only respondent who clearly expresses a sense of importance in the identified challenge. Based on the other respondents' input and the findings in section 4.3 of the current stage of implementation it is assessed, however, that it might be too early to talk about a 'new world' as mentioned by Miklos Vasarhelyi. His view is, therefore, considered more relevant in the future.

7.4.2 SUMMARY

It is found that this challenge is currently more of a theoretical discussion with limited practical relevance. As data analytics tools become more prevalently used, it is likely to become a relevant discussion and require reconsideration of the entire audit framework in the standards. At this early stage, however, it is not considered a significant challenge in the implementation of data analytics.

7.5 NATURE OF AUDIT EVIDENCE

The ISAs note that procedures to obtain audit evidence are inspection, observation, confirmation, recalculation, reperformance, and analytical procedures. Furthermore, they classify substantive procedures into test of details and substantive analytical procedures. Under test of details, the ISAs recognise means of selecting items for testing as selection of all items, selection of specific items, and sampling. Some new data analytics tools and techniques do not fit easily into these recognised methodologies and procedures. Therefore, it becomes a challenge for auditors to determine the nature of the audit evidence obtained and, consequently, to assess when sufficient appropriate audit evidence has been obtained.

7.5.1 SIGNIFICANCE OF THE CHALLENGE

Among the interviewees, there seem to be consensus that data analytics do not fit well into the traditional procedures recognised in the standards. However, the respondents provide different perspectives on whether it constitutes a significant challenge for auditors specifically to implement data analytics. Some consider it a more theoretical discussion than a challenge in practice, while others consider the, to some degree, missing link between theory and practice a challenge to auditors, as the value to the audit quality of data analytics might not be appropriately recognised. The arguments are presented and analysed below. In order to keep the overview, the arguments are divided into groups.

Professional judgment

Jesper Drud is of the opinion that this area is merely a theoretical discussion and not a significant challenge in practice. He explains:

"*What is important is whether you have sufficient documentation for the work performed and that sufficient work has been performed to form the conclusion. Whether you name it under one or the other type of audit procedure is not important*" (Drud 2017, 31:35).

In determining whether sufficient audit work has been performed when using new data analytics tools, he refers to the general principle that this is determined by the auditor's professional judgment, as for all other procedures (Drud 2017).

Jon Beck (2017) comments that currently, this is not a critical challenge. However, he acknowledges that when auditors start placing reliance on data analytics, there may initially be a challenge in making the judgment of evaluating the nature of the audit evidence obtained in the absence of a well-established industry practice. As an example, he notes that full population testing should, naturally, provide stronger audit evidence than testing a sample, but that this might not currently be reflected in the ISAs.

By reference to the findings in section 4.3, it is observed that the audit industry is currently in a testing phase of how data analytics can be used to provide audit evidence. Based on this observation, it is assessed that the challenges identified by Jon Beck are likely to become relevant in the near future.

According to the practising auditors interviewed, it remains up to the auditor's professional judgement to determine when sufficient appropriate evidence has been obtained, irrespective of whether the method used fits directly into the procedures in the standards. However, it is important to acknowledge the observation that noticeable challenges will arise in evaluating the audit evidence from data analytics techniques when auditors start using data analytics to obtain audit evidence. It is, furthermore, noted that these challenges may become relevant in the near future.

The quality implications of data analytics

In line with Jon Beck, both Miklos Vasarhelyi and Trevor Stewart use the example of 100 pct. analysis of large data sets as an example of a procedure made available by new data analytics tools, which is not easily classified as either test of details or substantive analytical procedure. They both note that it might be something in between.

Trevor Stewart explains:

"… And I think it's when you start getting into that debate, you end up with a, I think, fairly sort of sterile debate about 'so is this a test of details or is it an analytical procedure' and actually it doesn't really matter. I mean, what you're trying to do is gather audit evidence in the best way you can, and now there are a bunch of different ways of doing it. It may be covered by analytical procedures and it may be covered by test of details, but maybe it's just a different way of going about gathering the evidence" (Stewart 2017, 6:12).

He later adds that:

"*I think the classification is not so important as understanding what the various data analytics are and how they can be used for a variety of different purposes"* (Stewart 2017, 45:41).

In order to recognise the strength of audit evidence of such procedures, he believes that either the auditing standards or the standards on quality control should set an expectation that auditors are using the most effective technique rather than just the most efficient one (Stewart 2017). By effective, he refers to the quality of the audit evidence, and by efficient, he refers to the requirement to conduct audits through efficient use of auditors' resources. Hence, he acknowledge that it is challenging for auditors to implement data analytics procedures, if the standards do not fully recognise the implications on audit quality, when it cannot be linked directly to standards (ibid.).

Thus, it is acknowledged that it is a challenge for auditors that the standards do not clearly recognise the quality implications of audit evidence from such new procedures, either by a general clause or by specifically accommodating such new procedures.

Oversight and standards

Martin Samuelsen, however, is not worried that the challenges in determining the nature of data analytics audit procedures will impede implementation of audit procedures. He explains that, in Denmark at least, the audit firms and the oversight authorities have a close ongoing dialogue on the introduction of new technologies and methodologies. The oversight authorities do not pre-approve any new data analytics methodologies, but gets a chance to raise concerns in the process. In terms of what is important to auditors in practice, he comments:

"*I actually think that what is also important to the audit firms is what oversight authorities around the world think of what they do"* (Samuelsen 2017, 34:28).

Hence, he believes that the understanding among auditors as well as oversight authorities of the value added from data analytics tools and techniques is important to facilitate use of data analytics implementation.

Trevor Stewart (2017), however, notes that practitioners, generally, are somewhat scared of starting to audit in new ways, which have not been tried and tested. The reason, he explains, is that they operate in highly regulated environments and do not know how oversight authorities will react.

Comparing the statements by Martin Samuelsen and Trevor Stewart would indicate that there are differences in the relations between auditors and oversight authorities from country to country, which is in line with the notion that some countries are more strictly regulated than others, as discussed in section 7.3.1. This observation implies that misfits between audit procedures and standards are more challenging in some countries than in others.

It is observed that the interviewed Danish auditors tend to refer to the auditor's professional judgment to cope with the unclear link to the standards. The view of the Danish auditors fit well with the opinion of Martin Samuelsen, as responsible for the Danish Public Oversight of Auditors, that the auditor's professional judgment and the recognition of the quality of the work performed is important in implementing new tools.

Due to the differences in rigidity of oversight authorities, however, this attitude is expected to be different in other countries, which is supported by the observation by Trevor Stewart, who finds it challenging for auditors that the standards do not recognise the value of new methodologies. This would support the observation that the attitude is different in larger countries, as Trevor Stewart is the only one of the respondents who have worked as an auditor and is still affiliated to an audit firm in the US.

7.5.2 SUMMARY

The difficulties in determining the nature of procedures performed by new data analytics tools and techniques under the ISAs, and thereby evaluate the audit evidence obtained, are generally recognised.

It is found that the challenge is highly relevant to auditors in strictly regulated countries such as the US, where the oversight of the industry is perceived as placing more focus on strict compliance. It is observed that in Denmark the challenge is not currently perceived as critical since it, to a large extent can be overcome by applying professional judgment and communicating with the Danish oversight authorities. However, it is expected that the challenge will become more relevant, also in Denmark, in the near future, as auditors will use data analytics to obtain audit evidence more prevalently.

7.6 SUB-CONCLUSION

It is found that there are areas of the identified theoretical challenges with little impact in practice. Furthermore, some aspects of the challenges are not unique for data analytics but reflect general challenges in the audit process when facing new technologies. Those elements are, therefore, not considered key challenges in implementing data analytics. Below, the significance of the identified top challenges are summarised. The summaries are provided in order from the most to the least significant challenges in practice, based on the perspectives obtained in the preceding analysis.

Relevance and reliability of data

It is assessed that what is perceived as the most important challenge in practice is the one related to relevance and reliability of data. By increasing the reliance on data analytics, considerations of data relevance and reliability becomes increasingly important. However, the general auditor currently has little experience and understanding of how to address these matters as the volumes of data are massive compared to traditional analytics, and the types of data and sources they come from are increased continuously. Furthermore, there is currently little guidance available on this matter outlining, for instance, whether reliance on data analytics would require specific forms of IT controls testing and how to determine when sufficient evidence has been obtained to conclude that the data is sufficiently reliable.

Documentation

Regarding the challenge of documentation it is found that documentation is considered a rather natural part of using data analytics tools and techniques, as it documents the thought process to form a conclusion, which is no different than from what auditors normally do. As long as data analytics tools and techniques are in their early stage of implementation, this will naturally require a rather high level of documentation to ensure that the general auditor will understand it. However, significant challenges specific to data analytics are identified in the local documentation of how it is ensured that data analytics tools process the data as expected. These challenges are considered highly relevant in practice, as general auditors currently do not have sufficient technical knowledge to understand and document complex data analytics tools.

Nature of audit evidence

The determination of the nature of the audit evidence obtained from data analytics and the subsequent assessment of when sufficient appropriate audit evidence has been obtained, is also considered an important challenge in practice. It is widely recognised that some audit procedures performed by use of data analytics tools, such as the 100 pct. examination, does not fit well with the procedures stated in the ISAs. It is observed that the Danish interviewees tend to be of the opinion that this is not critical as it does not change the founding principle that it is up to the auditor's professional judgment to determine whether sufficient appropriate audit evidence has been obtained. This is, furthermore, also the principle the Danish oversight authorities lean on, and the expectations of sound professional judgment is aligned through continuous dialogue between auditors and the oversight authorities.

The interviews, however, indicate that the fear of being criticised by oversight authorities might be more severe in other countries, where oversight authorities have a reputation of being more bound to the specifics of the standards than the general principles of professional judgment. Hence, Danish auditors experience challenges to some degree in assessing the nature of the audit evidence, but the challenges are perceived as more critical internationally.

Outliers

The challenge of outliers is heavily discussed internationally. However, new challenges tend to be solved by reference to professional judgment to a larger extent in Denmark than in more strictly regulated countries. The high focus internationally on how to handle outliers in accordance with the standards, however, implies that this is an important area. However, due to the element of applying traditional professional judgment, it is not considered the most critical challenge to implementation of data analytics.

Classification of audit procedures

It is found that data analytics tools and techniques may enhance the existing iterative process of auditing, which might further blur the lines between risk assessment and response procedures, and between the recognised types of responses. Thus, the classification of the procedures in the current audit framework might need revision when data analytics become more prevalently used, and some requirements could already be relevant to reconsider. However, at the current limited level of use of data analytics, this is merely considered a theoretical discussion and not a critical challenge in the implementation of data analytics.

Hence, it is concluded that the challenges related to ensuring relevance and reliability of data, documenting the integrity of new tools, evaluating the nature of the audit evidence obtained, and handling outliers are considered significant in practice and may impact the process of implementing data analytics. The interviews indicate, however, that the challenges regarding outliers and nature of the audit evidence are considered more critical in more strictly regulated countries. It is assessed that the classification of audit procedures currently reflects merely theoretical challenges rather than critical challenges in practice. It may become more relevant as data analytics becomes more widely used. However, it is not considered a key challenge in the implementation phase.

8 CONCLUSION

The examined research questions were divided into two purposes. The first research questions were asked to establish the context in which the study is conducted, and in which the conclusions reached are applicable by defining the concept as it is used today, and the extent to which data analytics is currently applied in the audit industry. These areas are addressed separately below. The last research questions were asked with the purpose of ensuring that the overall problem statement is answered based on a structured analysis and taking into account all relevant perspectives. The findings from these research questions are therefore included below, as part of the conclusion on the overall problem statement of identifying key challenges in implementing data analytics under the ISAs.

Defining data analytics

Data analytics in audits comprise all methodologies to analyse data with the purpose of obtaining audit evidence. It refers to an art and science of discovering and analysing patterns, deviations and inconsistencies, as well as to extract other useful information from data relevant to the audit matters through analysis, modelling and visualisation. Hence, data analytics is not applicable to specific steps in the audit process.

The concept as it is currently used in the industry refers to increasing automation of the analytics and growing opportunities to analyse larger volumes of data at a more detailed level due to new data analytics tools and techniques.

Current implementation of data analytics

Audit firms are currently investing heavily in developing and implementing new tools and technologies to be applied at procedures referred to as data analytics. The procedures currently implemented, however, remain based mostly on traditional types of audit procedures but performed in new ways. These new ways are often described as being more iterative by nature than traditional ways of auditing.

The technologies currently applied in audits are, compared to other industries, still relatively simple as they are typically used to visualise data sets or match specific parameters of a number of different data sets. These tools, however, are more automated and complex than analyses traditionally performed in, for instance, Excel. Hence, the industry is moving towards implementation of increasingly complex tools. Similarly, the data analytics procedures currently performed are based primarily on traditional financial information. The industry, however, is gradually seeking to introduce new types of relevant data in audits.

Thus, the industry is at an early phase of implementing data analytics tools and techniques and is currently testing how such methodologies can provide audit evidence. Therefore, data analytics procedures are currently being performed mostly in addition to traditional audit procedures rather than replacing them. Currently, the data analytics methodologies used in practice primarily involve various visualisations of data sets to support risk assessments and ways to analyse full populations by matching several data sets as an alternative way of performing traditional substantive audit procedures.

Key challenges in implementing data analytics under the ISAs

The work of auditors is subject to quality control by oversight authorities, who assess whether auditors are in compliance with, apart from statutory requirements, the ISAs. It is observed that the early adoption phase of new data analytics tools implies significant challenges for auditors to ensure that new ways of auditing are compliant with the ISAs and, thereby, acceptable to oversight authorities. Such challenges may impede the pace of innovation in the audit industry.

It is found that, starting with the most important, the key challenges in implementing data analytics under the ISAs concern:

- Relevance and reliability of data
  ISA 500 requires considerations to be made of relevance and reliability of all information to be used as evidence. The ISAs, however, do not require specific procedures to be performed when applying data analytics tools and techniques. Considerations specifically of completeness and accuracy of information, furthermore, is only directly required for information produced by the entity. Increased reliance on analysis of large data sets, however, implies a need for further validation of the analysed data. Furthermore, new risks are faced as data is extracted in new ways and obtained from an increasingly wide range of sources. In the absence of guidance in the ISAs and of a well-established industry practice in the area, it is considered challenging to determine appropriate and consistent approaches to ensuring relevance and reliability of analysed data.

- Documentation
  ISA 230 requires documentation sufficient to enable an experienced auditor to understand the work that has been performed. No specific requirements are stipulated for documentation of data analytics tools and techniques. Applying new data analytics tools, however, implies challenges in documenting the integrity of such tools, i.e. how it is ensured that the tools process the data the way they are intended to. Especially when tools are developed internationally in audit firm networks or acquired externally, it is challenging for audit firms with limited resources and capabilities within software development to prepare such documentation for local oversight authorities.

- Nature of audit evidence
  Challenges are identified in linking relevant procedures made available by data analytics techniques, such as full population testing, to the ISAs as either test of detail or substantive analytical procedures, as stipulated in ISA 500. Nor do such procedures link clearly to the procedures available to obtain audit evidence from, as stipulated in ISA 500. The lack of a clear link causes difficulties in determining the nature of audit evidence obtained, which in turn makes it difficult to assess the strength of audit evidence obtained, and eventually conclude when sufficient appropriate audit evidence has been obtained. These assessments will always be based on professional judgment. However, exercising professional judgment becomes more difficult in the absence of an established acceptable industry practice, which is the case at the current implementation stage. Especially in strictly regulated countries this is a concern when implementing new techniques.

- Outliers

  It is identified that new data analytics procedures, which can test and analyse full populations, often produce large numbers of outliers. When billions of transactions are analysed, this might result in thousands of outliers. It is known that some outliers will be false positives, and that it is not feasible for auditors to manually test each outlier. However, as such procedures do not clearly fit within the means of selecting items for testing stipulated in ISA 500, finding the appropriate approach to address these outliers is challenging. Academics are developing methodologies to handle this, but a generally acceptable industry practice has not yet developed. As auditors need assurance that their methodologies are acceptable to oversight authorities, availability of academically developed methodologies is not in itself sufficient to implement them in practice. This an area of concern, especially in strictly regulated countries.

Since these challenges potentially impede innovation in the audit industry, they are important to recognise, consider, and address in the further debate and analysis of whether the ISAs need revision, or if other initiatives should be made to facilitate innovation in the audit industry.

9 FUTURE IMPLICATIONS

With the establishment of the most critical challenges in the current implementation of data analytics tools and techniques, the natural next step is to determine the right approach to address them and facilitate further implementation of data analytics.

Each of the interviewed stakeholders have strong opinions with respect to how the industry and standard-setters should approach data analytics. While each of the interviewees express that they find it very positive that the IAASB and other standard-setters show interest in data analytics, their views differ in terms of what would be the better approach now from a standard-setting perspective. In this section, their arguments are presented in order to invite further debate among relevant stakeholders on the basis of the findings of this thesis.

Arguments for update of the ISAs

As a starting point, it is noted by Martin Samuelsen (2017) that the IAASB has been challenged for not providing standards that are up-to-date. He assesses that the industry is not waiting for updated standards in order to implement data analytics as they, to a large extent, are principle-based and, thus, applicable in all circumstances. However, he recognises that the IAASB should start revising the standards in order to take into account the possibilities for using data analytics to obtain audit evidence. The issue with this, he explains, is that it typically takes four to seven years to update standards and by that time, they may already be outdated due to the fast pace of development.

Trevor Stewart (2017) observes that the use of data analytics is not quite as advanced as it could be, as the standards do not encourage it and as practitioners operate in highly regulated environments and do not know how oversight authorities will react. He, therefore, concurs with the view that the standards need to be updated. He explains this by saying:

"..*I think the problem with the ISAs, and standards generally, is that they were written a long time ago. Relatively, I mean. And there have been so many changes just in the last five or six years and I think the standards need to be constantly refreshed as analytics become more important. And I think they will need to be refreshed so that it becomes easier for auditors to understand the important role that analytics plays. And I think there needs to be more recognition in the standards that there are new ways of gathering evidence, and standards need to be able to deal with it in one way or another*" (Stewart 2017, 59:04).

He notes that a solution could be to write the standards in an even more general way and then have separate guidance on how to apply data analytics under the standards, which are more frequently updated (Stewart 2017). In terms of updating the standards, however, he warns the profession against jumping straight to standard-setting without prior appropriate research in the area, such as the research conducted in the RADAR initiative (ibid).

Miklos Vasarhelyi has a more dramatic view on the preferred direction of the development of the standards. He comments:

"*… Audit regulation has to change substantially. My guess is that - if that would be possible, I don't think it's possible - what should be done, is create a whole parallel set of regulations from a white* *piece of paper and start some engagements in that direction of progressively understanding better what that entails…*" (Vasarhelyi 2017, 32:10).

He elaborates that changes will have to be made in partnership between regulators, auditors, and auditees (Vasarhelyi 2017). This could be in the form of projects like one he is involved in in Australia, which involves performance of parallel audits to experiment with different ways to audit by use of data analytics tools. He notes, however, that this will happen in baby steps as this is currently the only feasible way to go about it.

Arguments against update of the ISAs

As already indicated by Martin Samuelsen above, one might argue that data analytics should not impact the standards as they are prepared as a principle-based framework and not a detailed guidance. Jon Beck elaborates on this view by saying:

"The beautiful thing about the auditing standards, I think, is that they are relatively universal in nature and can be tailored to fit all sorts of companies as they are principle-based" (Beck 2017, 01:02:16).

He further explains, that before making any changes to the standards or even developing separate non-authoritative guidance, the audit industry needs to develop good practice itself (Beck 2017). The only way to develop such practice, he explains, is by trial and error in trying to obtain audit evidence from data analytics in practice.

In many ways, Jesper Drud (2017) agrees to the perception that the audit industry needs to figure out itself, how to solve many of the challenges related to data analytics, and he supports the principle-based framework of the standards. He acknowledges, however, that there may be some elements of the standards that could be revised already. Yet, in order to facilitate data analytics, he believes it would be more appropriate to issue non-authoritative guidance on how to apply data analytics techniques in practice.

As stated above, Martin Samuelsen (2017) notes that the industry will not wait for the auditing standards to be updated. What is most likely, he believes, is that data analytics techniques will be implemented and the standards will be updated retrospectively. On the quality of the audits performed in this intermediate stage, he states that he is confident that the audit industry is sufficiently self-regulating, as auditors are risk averse and, generally, do not sign off accounts if they are not confident in the conclusion.

Next steps

As noted above, there are stakeholders arguing in favour of immediate update of the ISAs and, if possible, even a complete revision of the framework in the light of data analytics. On the other hand, there are stakeholders arguing that the ISAs are sufficiently principle-based already, but if updates are initiated, thorough research and solid experience from the use of data analytics in practice should be established in order not to stop or impede the innovation in the industry.

The right approach is likely to be somewhere in between keeping the ISAs up to date while allowing and facilitating innovation in the industry. How that could be achieved and the appropriate role of the ISAs in a digitalised world is left for further analysis beyond the scope of this thesis.

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APPENDICES

Appendix 1: Abbreviations

Appendix 2: Identified challenges and confirmations

Appendix 3: Respondents to the RfI

Appendix 4: Additional challenges identified by respondents

Appendix 5: Recording of interview with Martin Samuelsen, 3 October 2017 (provided on USB)

Appendix 6: Recording of interview with Jesper Drud, 10 October 2017 (provided on USB)

Appendix 7: Recording of interview with Miklos Vasarhelyi, 10 October 2017 (provided on USB)

Appendix 8: Recording of interview with Jon Beck, 12 October 2017 (provided on USB)

Appendix 9: Recording of interview with Trevor Stewart, 12 October 2017 (provided on USB)

APPENDIX 1 ABBREVIATIONS

Abbreviations used throughout the thesis are explained below:

AICPA: The American Institute of Certified Public Accountants

CAAT: Computer-assisted Auditing Technique

CarLab: The Continuous Auditing & Reporting Lab at Rutgers University

CEAOB: The Committee of European Auditing Oversight Bodies

DAWG: Data Analytics Working Group (in the IAASB)

FRC: The Financial Reporting Council

IAASB: The International Auditing and Assurance Standards Board

ICAEW: The Institute of Chartered Accountants in England and Wales

IFAC: The International Federation of Accountants

IFIAR: The International Forum for Independent Audit Regulators

ISA: The International Standards on Auditing

MADS: Multidimensional Audit Data Selection project

PCAOB: The Public Company Accounting Oversight Board

RADAR: Rutgers AICPA Data Analytics Research Initiative

RfI: The DAWG's 'Request for Input: Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics'

RoMM: Risk of Material Misstatement

APPENDIX 2 IDENTIFIED CHALLENGES AND CONFIRMATIONS

ID	Challenge	No. of responses positively confirming the challenge
1	How does data analytics contribute to the auditor's identification and assessment of the risk of material misstatement?	1
2	Can data analytics provide substantive audit evidence, and if so, should it be classified as test of details or substantive analytical procedures?	3
3	Does data analytics affect the evidence required from other substantive audit procedures or test of controls?	5
4	What is the minimum level of General IT Control testing and what is the impact of the results of such tests when data analytics is used in the audit?	5
5	What is the impact of any deficiencies in general IT controls and application controls which the auditor intends to rely in order to conclude that the data from IT systems is sufficiently reliable?	1
6	What procedures should the auditor perform to evaluate the relevance and reliability, including obtaining evidence about accuracy and completeness, of information produced by the entity?	8
7	What procedures should the auditor perform to evaluate the relevance and reliability of information from third-party sources?	7
8	How should evidence obtained from data analytics be classified as either risk assessment procedures, test of controls, or substantive procedures? Is the classification even relevant when using data analytics?	7
9	What is the role of controls testing when auditors can analyse 100% of the transactions in a particular area of the audit?	6
10	What is the nature of the audit evidence obtained via data analytics in response to identified risks when the risk identification and response occurs in one step?	7
11	What is an appropriate level of work to be performed over outliers when testing 100% of a population, in order to determine if the outlier is an exception?	8
12	When all transactions in a particular area for the entire period have been analysed, how do the auditor demonstrate or corroborate that unexpected transactions have been addressed?	0
13	How can the documentation requirements be fulfilled when using data analytics based on the iterative nature of the process to reach a conclusion and what is the extent of the required documentation?	9

14	Which quality control processes need to be in place in audit firms in order to place reliance on new data analytics technology and tools, whether they are internally developed or third-party technologies and tools are applied?	4
15	What benefits and challenges does data analytics impose in terms of risk of confirmation bias, professional judgement and professional scepticism?	2
16	How does the use of centralised specialised expertise in data analytics in Audit Delivery Models affect the need for direction and supervision?	3
17	Are there specific implications of data analytics on group audits if scoping can be improved, analytics of non-significant components can be more effective and more of the audit procedures can be centralised?	4
18	What are the implications of data analytics on the audit of estimates?	3

Source: The author's presentation of challenges identified in the DAWG's (2016) RfI and linked by the author to confirmations from responses from EY (2017), KPMG (2017), Deloitte (Buss 2017), PwC (Sextion 2017), BDO (Smith 2017)*, Crowe Horwath International* (Chitty 2017)*, Baker Tilly* (Ginman 2017)*, Accountancy Europe* (Schneider and Boutellis-Taft 2017)*, ICAEW* (ICAEW 2017)*, AICPA* (Coffey 2017)*, IFIAR* (van Diggelen 2017)*, FRC* (McLaren 2017)*, and Rutgers University* (CarLab 2017) *and linked by the author to the relevant challenges.*

APPENDIX 3 RESPONDENTS TO THE RFI

No.	Respondent	Type of organisation
1	Shigeto Fukuda. CISA (Japan)	Local auditor
2	Advanced auditing class at Hunter College Graduate Programme (US)	Students
3	Crowe Horwath International	Global audit firm
4	Financial Reporting Council (UK)	National regulator
5	Institut der Wirtschaftspruefer in Deutschland e.V. (IDW) (Germany)	National trade organisation for auditors and audit firms
6	Office of the Auditor-General of New Zealand (NZ)	National public auditor
7	International Association of Insurance Supervisors (IAIS)	International association for insurance regulators
8	National Association of State Boards of Accountancy (NASBA) (US)	National association for audit and accounting regulators and practitioners
9	International Forum of Independent Audit Regulators	International audit regulator association
10	Institute of Management Accountants (IMA) (US) Association of Accountants and Financial Professionals in Business	International association for accountants (non-audit)
11	Institute of Singapore Chartered Accountants (Singapore)	National trade organisation for accounting professionals
12	CPA Canada	National trade organisation for accounting professionals
13	Chartered accountants Australia and New Zealand	National association for leaders in business and finance
14	Accountancy Europe	European trade organisation for professional organisations for auditors and accountants
15	Pennsylvania Institute of Chartered Accountants (US)	National trade organisation for accounting professionals
16	South African Institute of Chartered Accountants (SAICA)	National trade organisation for accounting professionals
17	New Zealand Auditing and Assurance Standards Board (NZAuASB) (NZ)	National regulator
18	CPA Australia (AU)	National trade organisation for accounting professionals
19	Auditor General of Alberta (Canada)	Local public auditor
20	Deloitte Touche Tohmatsu Limited	Global audit firm
21	Moore Stephens LLP (UK)	Global audit firm

22	PricewaterhouseCoopers International Limited	Global audit firm
23	The Malaysian Institute of Certified Public Accountants (Malaysia)	National trade organisation for accounting professionals and regulator
24	European Federation of Accountants and Auditors for small and medium-sized enterprises (EFAA)	European trade organisation for national accountants and auditors
25	Grant Thornton International Limited (UK)	Global audit firm
26	Auditing and Assurance Standards Board (AASB) (Canada)	National regulator
27	The American Institute of CPAs (AICPA) (US)	International trade organisation and standard-setter
28	BDO International Limited	Global audit firm
29	Ernst & Young Global Limited	Global audit firm
30	EXPERTsuisse (Switzerland)	National trade organisation for accounting professionals
31	PKF International Limited	Global audit firm
32	The Institute of Chartered Accountants of Scotland (ICAS) (UK)	National trade organisation for accounting professionals and regulator
33	KPMG	Global audit firm
34	Institute of Chartered Accountants in England and Wales (ICAEW)	National trade organisation for accounting professionals
35	The Chartered Institute of Public Finance and Accountancy (CIPFA) (UK)	International trade organisation for public finance professionals
36	Rutgers Continuous Audit and Reporting Laboratory (CarLab)	Academics
37	The Japanese Institute of Certified Public Accountants (Japan)	National trade organisation for accounting professionals and regulator
38	Association of Chartered Certified Accountants (ACCA)	International trade organisation for accounting professionals and students
39	Baker Tilly International	Global audit firm
40	Inflo Software	Audit software developer
41	Royal Netherlands Institute of Chartered Accountants (NBA) (Netherlands)	National trade organisation for accounting professionals
42	Tom Koning	National individual advisor to audit firms in the Netherlands
43	Harvest Investments Ltd.	Securities valuation specialist

44	IFAC Small- and medium sized practices committee	International trade organisation for accounting professionals
45	Malaysian Institute of Accountants	Regulator
46	CFA Institute	International trade organisation for investment management professionals
47	Denise Silva Ferreira Juvenal (Brazil)	Local auditor
48	Australian Auditing and Assurance Standards Board (AUS)	National regulator
49	Independent Regulatory Board for Auditors (South Africa)	National regulator
50	The Compagnie Nationale des Commissaires aux Comptes (CNCC) and the Conseil Supérieur de l'Ordre des Experts-Comptables (CSOEC) (France)	National regulators
51	Haut Conseil du Commisariat aux Comptes (France)	National regulator

Source: The author's presentation based on the comment letters submitted to the DAWG (2016).

APPENDIX 4 ADDITIONAL CHALLENGES IDENTIFIED BY RESPONDENTS

Audit firm	Challenge
EY	How can data analytics be used in identifying and assessing risks of fraud in revenue recognition?
EY	When identifying a significant risk, does it remain relevant in all cases to obtain an understanding of the entity's controls and whether they have been implemented?
EY	When data analytic tools allow the auditor to assess the effect of all journal entries on account balances the selection of high-risk journal entries for testing is improved. Is it then relevant in all audits to understand management's controls around journal entries?
EY	As data analytics facilitate analysis of populations at a more granular level, the existing challenge of applying performance materiality in determining the nature, timing and extent of audit procedures becomes even more relevant.
EY	When data analytics improve risk assessment procedures, does it remain relevant to perform substantive procedures over material account balances if the risk of material misstatement is very low?
EY	How can prior period information, adjusted for expected changes, be used to form expectations when performing analytical procedures by use of data analytic tools and should this be clarified in ISA 520?
PwC	Could the new techniques eliminate the need for audit sampling and extrapolation of identified errors and be sufficient on their own in responding to identified risks, for example when analysing an entire population of transactions from initiation through to settlement?
PwC	Can data analytics eliminate the need for sampling and, thereby, make data analytics appropriate in itself to respond to identified risks?
KPMG, BDO and Accountancy Europe	What is the impact the auditor's ability to place reliance on work performed by internal audit functions that use data analytics.
Accountancy Europe	What are the criteria for situations where use of data analytics is appropriate and when it is not?
Baker Tilly	How should auditors address relevance and reliability of open-source data in Management's analyses?
CarLab	What considerations should auditors make in relation to cyber-attack risks?
CarLab	When continuous monitoring becomes reality, what is the implications on ISA 240?

Source: The author's presentation of additional challenges identified in comment letters from EY (2017)*, KPMG* (2017)*, PwC* (Sextion 2017)*, BDO* (Smith 2017)*, Accountancy Europe* (Schneider and Boutellis-Taft 2017)*, Baker Tilly* (Ginman 2017)*, and the CarLab* (2017).