Usage of Audit Data Analytics within the Accountancy Sector

Lotte Verhoeven and Eric Mantelaers
Research Centre – Future-proof Auditor
Zuyd University of Applied Sciences & RSM Netherlands Accountants N.V.
Sittard/Heerlen, the Netherlands
lotte.verhoeven@zuyd.nl
eric.mantelaers@zuyd.nl

Martijn Zoet
Research Centre – Future-proof Financial
Zuyd University of Applied Sciences
Sittard, the Netherlands
martijn.zoet@zuyd.nl

***Abstract*— Evidence from the various reports and articles as well as the importance of the audit process shows that adjustment and/or improvement of the current approach within the accountancy sector is necessary. Research demonstrates that technology can contribute to an improvement of audit quality. Additionally, previous research increasingly recognizes that audit data analytics is likely to transform the conduct of the audit significantly. The goal of this research is to study how Audit Data Analytics is currently used within the audit. In order to answer this question, a survey was distributed via the Dutch National Accountants Association, focusing on how Audit Data Analytics is used in the accountancy sector. However, the results and the non-chronological order of the data analysis types indicate a misinterpretation or lack of understanding of the data analysis types (implemented in the survey) and their chronological order.**

Keywords-audit data analytics; audit quality; process mining; process mining algorithms.

I. INTRODUCTION

Audit quality consistently received substantial attention from regulators and academics over the past years due to numerous audit scandals. Caused by a lack of independent oversight and enforcement, various accounting and audit scandals took place in the beginning of the 21st century. Recent reports from the Dutch Authority for the Financial Markets (AFM), and recent published reports from, among others, the Future Accountancy Sector Committee (CTA) and the Accountancy Monitoring Committee (MCA), show that the quality of annual audits is inadequate [1]–[4]. Internationally the lack of audit quality is also visible. In the Brydon report, Brydon states that the audit quality is insufficient and improvements including new reporting duty with respect to fraud and more auditor transparency are recommended [5]. Evidence from the various reports and articles as well as the importance of the audit process shows that adjustment and/or improvement of the current approach within the accountancy sector is necessary [6]. Research demonstrates that technology can contribute to an improvement of audit quality [7].

This research, therefore, focuses on the current usage of Audit Data Analytics (ADA) within the audit. The goal of this research is to achieve a view of the application of ADA within the financial audit. To achieve this, this paper answers the following main question: *How and to what extent is Audit Data Analytics currently used by auditors/accountants?*

The remainder of the paper is organized as follows: Section II describes the relevant literature regarding audit quality and ADA. In Section III, the research method is described, followed by the data collection and analysis in Section IV. Finally, the results, conclusion and future work are presented in Sections V and VI respectively.

II. LITERATURE REVIEW

Audit quality is a very broad concept and can be defined in various ways. DeAngelo describes audit quality as “the market assessed joint probability that a given auditor will both discover a breach in the client’s accounting system and reports the breach” [8]. Whereas the Government Accountability Office uses a more extensive approach and states that high audit quality is achieved when performed according to the corresponding standards and no material misstatements due to error or fraud are present [9]. The legal definition of audit quality is on the other hand very concise, as it states audit quality as either “audit failure” or “no audit failure” [10]. In conclusion, audit quality is a broad concept and difficult to summarize in a single definition. Next to that, these different definitions show that audit quality is not yet recognized universally across the world. As mentioned before, evidence from the various reports and articles as well as the importance of the audit process shows that adjustment and / or improvement of the current approach within the accountancy sector is necessary [1]–[4][6].

Previous research shows that technology/ADA can contribute to an improvement of audit quality [7]. By automating certain audit analyses, more time and resources can be allocated to the interpretation of these analyses. This maximizes the dual aspects of audit quality: independence and expertise [7][8]. Additionally, previous research increasingly recognizes that ADA is likely to transform the conduct of the audit significantly [11]–[13]. As Barr-Pulliam et al. state: “The use of advanced testing methods such as ADAs can occur at any stage of the audit and can significantly transform the process of auditing financial statements, resulting in enhanced audit effectiveness and audit efficiency – both elements and signals of audit quality” [11]. To support the individual and personal judgement of the auditor, ADA could provide a solution. ADA is a method of using data

 ISBN: 978-1-68558-082-7

analysis techniques to evaluate financial information and assess the accuracy and reliability of an organization's financial statements. This involves collecting and examining large amounts of data, and using statistical and computational tools to identify patterns, trends, and anomalies that may indicate potential problems or issues. Data-driven audits are becoming increasingly familiar within the accountancy sector, due to innovation, increase in technology/data and the pursuit of continuous assurance [14]. Data-driven 'control' is also used by the AFM (regulator), as they want to implement data-driven supervision to enhance the efficiency and effectivity of the supervision of audit firms. To achieve this, the AFM will structurally request data from the audit firms to gain insight into the current quality control and risk characteristics [15].

Despite the fact that the use of ADA within the audit practice is relatively new, various previous research has been performed. The Financial Reporting Council (FRC), regulator to auditors, accountants and actuaries and setter of UK's Corporate Governance and Stewardship Codes, conducted a review of the use of technology in the audit of financial statements. Within this review, the FRC found that ADA was currently used mostly for risk assessment and the audit of revenue and that advanced ADA was only used sporadic [16]. This was also highlighted by Eilifsen et al. who explored the use of ADA in current audit practice in Norway. Eilifsen et al. found that despite the positive attitude with regards to the usefulness of ADA, the use of 'advanced' ADA is rare [17]. Eilifsen et al. also found that this is caused by its complexity and lack of implementation guidelines and confidence in the ability of ADA to provide sufficient and appropriate audit evidence. It is suggested that this is likely to persist until ADA will be incorporated in the audit methodologies and ADA is explicitly supported and accepted by supervisory bodies and standard-setters [17]. However, this research focuses not only on the use of ADA, but also on the sequentially of its use.

III. RESEARCH METHOD

The goal of this research is to study how ADA is currently used within the audit. In order to answer this question, a survey was distributed focusing on how ADA is used in the accountancy sector. The survey is distributed via the Dutch National Accountants Association (NBA) across members of the Accounttech working group, a total of 7,008. The members of the NBA are spread over several accountancy firms in the Netherlands and consists out of accounting consultants/auditors (AA in Dutch), chartered auditors (RA in Dutch) and people working in the accountancy sector.

The survey consists of 20 questions which are divided into seven subsections. These subsections relate to 1) composition/descriptive (general), 2) the scope of ADA, 3) assessing the possibility to detect misstatements, 4) sequentially, 5) possibility to assist decisions, 6) materiality and 7) phase of the audit in which ADA is used. The questions are answered on a likert-scale basis [18], in which answers range from '1 – I never use it', to '7 – I always use it'. Likert scales are considered a good fit for analytical purposes, due to their relatively large number of categories [19]. In addition, the respondents were able to answer: 'I don't know' or 'Not relevant'. For the purpose of this research the latter two are classified as '1 – I never use it'.

By formulating the survey questions, the Value Through Analytics (VTA) model from Zoet is used [20]. This model concretizes data analytics into subtypes. The VTA model incorporates the six different types of analyses from Leek and Peng (2015), namely: The 1) descriptive, 2) explanatory, 3) inferential, 4) predictive, 5) causal, and 6) mechanistic [21]. The VTA model also includes the three types of process mining as described by Van der Aalst (2011): discovery, conformance and improvement [22].

The VTA model is a tool to classify data analytics into different categories [23] and is shown in Figure 1. The VTA model distinguishes 54 different types of data analysis which can be derived by walking through the three circles within the model. The inner circle starts with the question: "What do I want to analyze?" In which a 1) process, 2) decision or 3) object can be chosen. The second circle questions "Why do I want to analyze?" Which can be answered by 1) discovery, 2) conformance, and 3) improvement. Finally, the outer circle asks the question "To what extent do I want to analyze it?" The last question indicates the choice to the following types of data analytics: 1) descriptive, 2) explanatory, 3) inferential, 4) predictive, 5) causal, and 6) mechanistic. Additionally, the types of analysis within the VTA model are layered in sequence, which indicates that if an inferential analysis can be carried out, one should also be able to carry out a descriptive and explanatory analysis.

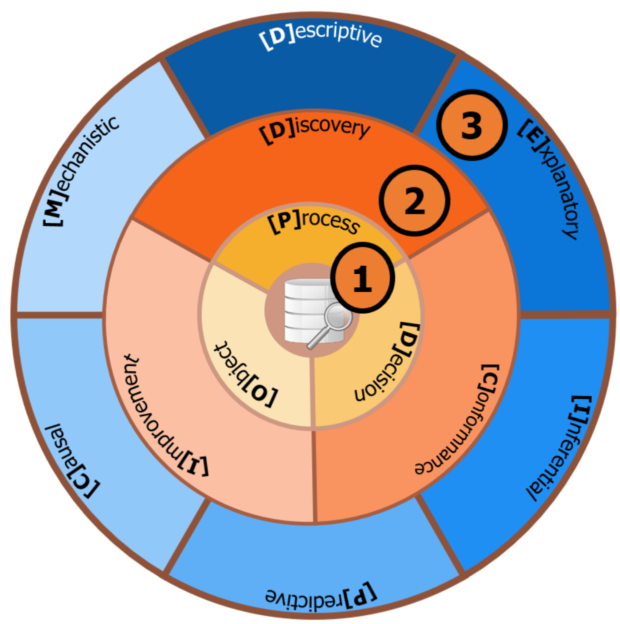

Figure 1. Value Through Analytics model [20]

To assess which competences can be utilized with the help of ADA, a so-called analysis quotient can be computed, which visualizes the type of questions that can be answered [23]. An example of this is shown in Figure 2, in which the questions are set against audit organizations. Grey indicates that an audit organization cannot perform the analysis, green indicates that the type of analysis is standard procedure within each audit. Blue indicates that the analysis is used within every audit, but expertise is needed. Purple indicates that the analysis is executed by only one employee for their own use, but the results are not communicated throughout the team. Finally, yellow indicates that it is not executed for every audit [23].

The survey questions were set up by Dr. Mantelaers (chartered auditor) and Dr. Zoet, founder of the VTA model [20]. In order to validate and refine the survey questions and to ensure the correct questioning a pilot test was conducted by five master students (Accounting and Control – Maastricht University). Moreover, the pilot test was executed by two members of the Accounttech group, of which one is related to the Post-Master IT-Auditing & Advisory (Erasmus University Rotterdam).

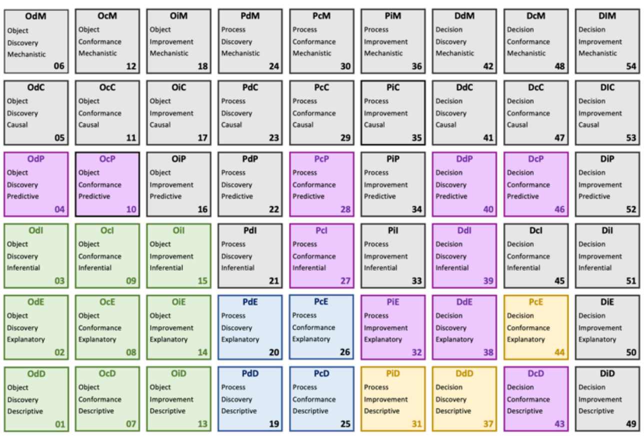

Figure 2. Periodic system types of analyses [23]

Within the survey questions, a particular sequence is followed related to several 'levels' of ADA usage in practice, which can be linked to the data analysis types/levels in the VTA model. In Table I the survey questions are linked to the type of data analyses derived from Figure 2. Each question focuses on the frequency of use of the ADA types as mentioned in Table I. As the questions and data analysis types, are listed in a chronological order, this implies that if an auditor uses ADA type five, the auditor will also be expected to be able to perform ADA type two and four.

TABLE I. SURVEY DESIGN

Survey question	ADA type	ADA description
7.1	2	Object – Discover – Explanatory
7.2	4	Object – Discover – Predictive
7.3	5	Object – Discover – Causal
7.4	7	Object – Discover – Descriptive
7.5	8	Object – Discover – Explanatory
8.1	19	Process – Discover - Descriptive
8.2	20	Process – Discover – Explanatory
8.3	25	Process – Conformance – Descriptive
8.4	26	Process – Conformance – Explanatory
8.5	37	Decision – Discover – Descriptive
8.6	43	Decision – Conformance - Descriptive

The sequentially of the data from the survey will be analyzed with the help of process mining algorithms. For the use of this research, a heuristic analysis will be performed due to the scope of possible responses and outcomes. A heuristic analysis eliminates any redundant details and exceptions and focuses on the main behavior [24].

IV. DATA COLLECTION AND ANALYSIS

The survey was distributed to a population of 7,008 respondents in total, of which 203 responded, a response rate of 2,90%. The response rate is relatively low, possibly caused by the non-committal nature and scope of the survey. Moreover, surveys are frequently distributed within the Accounttech working group and NBA, which also causes the low response rate. From a NBA perspective this can be considered a representative response rate. The survey was distributed in the first half of 2021. The respondents consist out of 167 males and 36 females, of which 72 are a chartered auditor (RA in Dutch) and 39 accounting consultants (AA in Dutch). Around 25% of the respondents works for one of the Big 4 Auditing Firms (EY, PWC, Deloitte and KPMG). The most common jobs within the respondents are external auditor (chartered auditor and accounting consultants), accountant in business or public/internal auditor. However, the work experience varies across the respondents as is shown in Table II.

TABLE II. WORK EXPERIENCE RESPONDENTS

Work experience (in years)	Number of respondents
< 5	3
5 - 10	22
10 – 20	72
20 – 30	58
> 30	48
Total	**203**

To analyze the outcomes of the survey a heuristic process mining algorithm is applied by using three input variables. These input variables consist out of 1) case concept name, represented by the respondents ID, 2) concept name, represented by the question number and 3) the timestamp, represented by the answer based on the likert scale. To ensure the chronological order a timestamp is added to the data by converting the likert scale. In which '7 – I always use it' is matched to the earliest timestamp, as it is always used (used now). '1 – I never use it' is matched to the latest timestamp, since its use will be furthest in the future. The options in between (two to six) are matched accordingly.

V. RESULTS

The analysis distinguishes 132 types of unique variants within a total of 203 respondents (65.0%). A total overview of the data analysis types in order of usage is shown in Figure 3. The numbers 7.1 until 8.6 refer to the questions of the survey, the link to the data analysis types is shown in Table II. As the likert scale was converted to a timestamp in order to perform these analyses, the order of the questions depends on the usage of the specific ADA. For example, question 7.1 relates to the use of data analysis: Object – Discover – Explanatory. 60.6% of the respondents (n=123) indicated that this analysis is always used (likert scale – 7). Due to the rating of '7 – I always use it', this data analysis type is matched to the earliest timestamp and therefore shown at the start of the path in Figure 3.

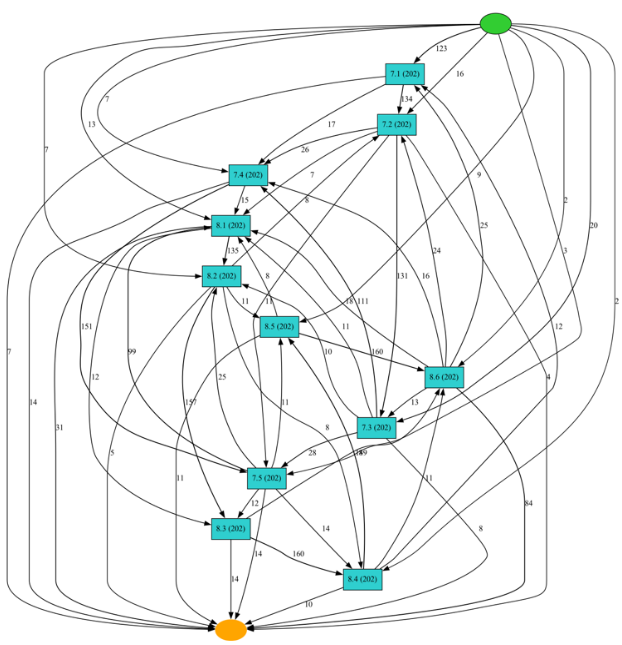

Figure 3. Result heuristic miner.

Due to the high number of unique variants (65,0%), an overview of the top ten variants is shown in Table III. For clarity purposes, the number of occurrences per unique variant is added.

TABLE III. TOP 10 VARIANTS

												Number of occurences
Variant 1	7.1	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	58
Variant 2	7.1	7.2	7.3	7.4	7.5	8.2	8.3	8.4	8.5	8.6	8.1	4
Variant 3	7.1	7.2	7.3	8.1	8.2	8.3	8.4	8.5	8.6	7.4	7.5	3
Variant 4	8.1	8.2	8.3	8.4	8.5	8.6	7.1	7.2	7.3	7.4	7.5	2
Variant 5	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.1	2
Variant 6	7.1	7.3	8.1	8.2	8.3	8.4	8.5	8.6	7.2	7.4	7.5	2
Variant 7	7.1	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	2
Variant 8	7.1	7.2	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.3	7.4	2
Variant 9	7.1	7.2	7.3	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.4	2
Variant 10	7.1	7.2	7.3	7.4	7.5	8.5	8.6	8.1	8.2	8.3	8.4	2

The most common variant (variant 1) occurs 58 times. This variant is, also chronologically seen, the most logical variant, as the occurrence of the questions are in a chronological order (7.1 to 8.6). This means that the data analysis types, intertwined in the questions, are used in the (expected) chronological order. However, this is only applicable to 28.6% of the respondents (n=58). The number of occurrences for the other variances is widely spread as can be seen for variant two to ten (max. four occurrences per variant). The results from variant two show that question 8.1 (related to data analysis type Process – Discover – Descriptive) is used less compared to question 8.2 to 8.6 (related to the more advanced data analysis types). In variant three to ten a non-chronological order is also apparent, indicating that the more 'basis' analysis types are carried out less frequently than the more 'advanced' types. However, variant four indicates that analyses with regards to a process and/or decision (questions 8.1-8.6) are frequently used, and analysis regarding an object (questions 7.1-7.5) less frequently, despite the fact that most of the analyses regarding 'Objects' are expected to be used standard in every audit, as can be derived from Figure 2.

As the results vary widely, an additional analysis solely on the external auditors (chartered auditor and accounting consultants) as they are expected to have the most experience with regards to audits. Within the total sample, 111 external auditors and 79 unique variants are identified (variance of 71.2%). Compared to the total sample, an even higher variance can be recorded.

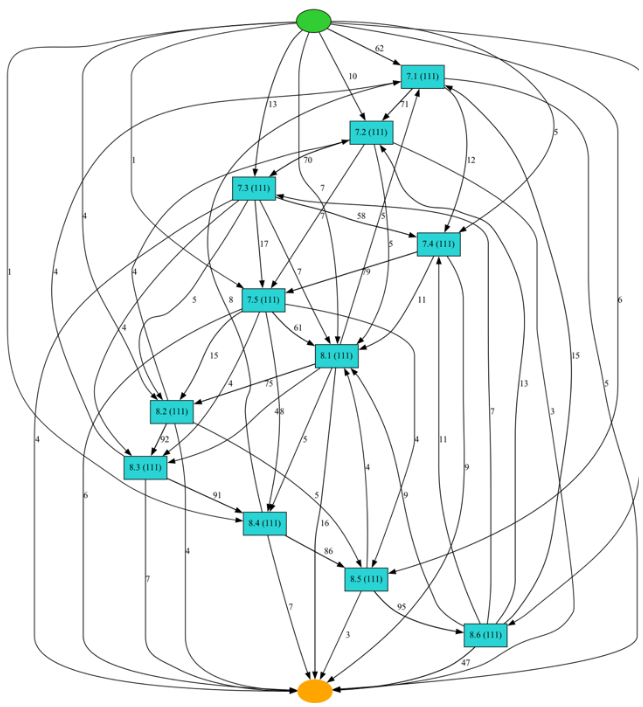

Figure 4. Result heuristic miner external auditors.

Due to the high number of unique variants (65.0%), an overview of the top ten variants is shown in Table IV. For clarity purposes, the number of occurrences per unique variant is added.

TABLE IV. TOP 10 VARIANTS EXTERNAL AUDITORS

												Number of occurences
Variant 1	7.1	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	31
Variant 2	7.1	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	2
Variant 3	7.1	7.2	7.3	7.4	7.5	8.2	8.3	8.4	8.5	8.6	8.1	2
Variant 4	8.6	8.5	7.2	7.1	7.3	7.4	7.5	8.2	8.3	8.4	8.1	1
Variant 5	8.6	7.2	7.3	7.1	7.4	7.5	8.1	8.2	8.3	8.4	8.5	1
Variant 6	8.5	8.6	8.2	8.3	8.4	7.2	7.5	7.3	7.4	8.1	7.1	1
Variant 7	8.5	8.6	8.1	8.2	8.3	8.4	7.1	7.2	7.5	7.4	7.3	1
Variant 8	8.5	8.6	7.3	7.5	8.1	8.2	8.4	7.1	7.4	7.2	8.3	1
Variant 9	8.5	8.6	7.1	7.2	7.3	7.5	8.2	8.3	8.4	8.1	7.4	1
Variant 10	8.5	8.6	7.1	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	1

The most common variant (variant 1) occurs 31 times. This variant is, also chronologically seen, the most logical variant, as the occurrence of the questions are in a chronological order (7.1 to 8.6). However, this is only applicable to 27.9% of the respondents (n=31). The number of occurrences for the other variances is widely spread as can be seen for variant two to ten (max. two occurrences per variant).

VI. CONCLUSION AND FUTURE WORK

In this article, we aim to answer the main question: *"How and to what extent is Audit Data Analytics currently used by auditors/accountants?"* With the help of a survey distributed across members of the NBA working group Accounttech, an overview was given of the use (and its extent) of ADA. The insights derived from our study provide a better understanding of how and to which extent ADA is currently used by auditors/accountants and specific external auditors. However, the results and the non-chronological order of the data analysis types indicate a misinterpretation or possible lack of understanding of the data analysis types (implemented in the survey) and their chronological order. Remarkable are the similar results within the external auditor group, as they are expected to have the most experience regarding audits. Future research could therefore focus on concretizing (and creating an understanding of) the data analysis types. This could be achieved by creating a more practice-oriented survey. Moreover, in future research we would like to include the answers: *'I don't know' or 'Not relevant'* in the results and follow up on these answers to identify the underlying reasons and expand our results/knowledge.

ACKNOWLEDGEMENTS

We would like to thank Michelle van Wamelen for collecting the data. Moreover, we would like to thank the NBA working group Accounttech for collaborating on this survey.

REFERENCES

[1] MCA, "Accountancy Monitoring Committee," 2020. https://www.monitoringaccountancy.nl/ (accessed Mar. 24, 2023).

[2] Future Accountancy Sector Committee, "Confidence in Control Final Report of the Committee on the Future of the Accountancy Sector | Parliamentary Document | Central Government," 2020. https://www.rijksoverheid.nl/documenten/kamerstukken/2020/01/30/vertrouwen-op-controle-eindrapport-van-de-commissie-toekomst-accountancysector

[3] AFM, "AFM supervisory agenda 2022," 2022.

[4] AFM, "Research reports on supervision of audit firms | Audit firms | AFM Professionals." https://www.afm.nl/nl-nl/sector/accountantsorganisaties/rapporten-publicaties (accessed Mar. 24, 2023).

[5] D. Brydon, "Assess, assure and inform: improving audit quality and effectiveness," UK Government, 2019. [Online]. Available: https://www.gov.uk/government/publications/the-quality-and-effectiveness-of-audit-independent-review

[6] Future Accountancy Sector Committee, "Reliance on Audit," *Minist. van Financ.*, 2020, [Online]. Available: https://www.rijksoverheid.nl/documenten/kamerstukken/2020/01/30/vertrouwen-op-controle-eindrapport-van-de-commissie-toekomst-accountancysector

[7] E. Mantelaers, "An Evaluation of Technologies to Improve Auditing," Open University, 2021.

[8] L. E. DeAngelo, "Auditor Size and Audit Quality," *J. Account. Econ.*, vol. 3, no. 3, pp. 183–199, 1981, doi: https://doi.org/10.1016/0165-4101(81)90002-1.

[9] Government Accountability Office, "Public Accounting Firms: Required Study on the Potential Effects of Mandatory Audit Firm Rotation," Government Printing Office, Washington D.C., 2003.

[10] J. R. Francis, "What do we know about audit quality?," *British Accounting Review*, vol. 36, no. 4. pp. 345–368, 2004. doi: 10.1016/j.bar.2004.09.003.

[11] D. Barr-Pulliam, H. L. Brown-Liburd, and K. A. Sanderson, "The Effects of the internal control opinion and use of audit data analytics on perceptions of audit quality, assurance, and auditor negligence.," *A J. Pract. Theory*, vol. 41, no. 1, pp. 25–48, 2022, [Online]. Available: https://doi.org/10.2308/AJPT-19-064

[12] G. Salijeni, A. Samsonova-Tadderu, and S. Turley, "Big Data and changes in audit technology: contemplating a research agenda," *Account. Bus. Res.*, vol. 49, no. 1, pp. 95–119, 2019.

[13] M. Cao, R. Chychyla, and T. Stewart, "Big Data analytics in financial statement audits," *Account. Horizons*, vol. 2, no. 29, pp. 423–429, 2015.

[14] J. van Buuren and W. Wijma, "On quality assurance of data-driven control methodology," *Maandbl. Voor Account. en Bedrijfsecon.*, vol. 96, no. 1/2, pp. 15–25, 2021.

[15] AFM, "Legislative letter." 2021. [Online]. Available: https://www.rijksoverheid.nl/documenten/kamerstukken/2021/04/21/kamerbrief-wetgevingswensen-dnb-en-afm

[16] FRC, "The use of technology in the audit of financial statements," 2020.

[17] A. Eilifsen, F. Kinserdal, W. F. J. Messier, and T. E. McKee, "An Exploratory Study into the Use of Audit Data Analytics on Audit Engagements," *Am. Account. Assoc.*, pp. 1–23, 2020.

[18] R. Likert, "A Technique for the Measurement of Attitudes," *rchives Psychol.*, no. 140, pp. 1–55, 1932.

[19] L. H. Kidder, C. M. Judd, and E. R. Smith, *Research methods in social relations*, 5th ed. CBS College Publishing, 1986.

[20] M. Zoet, "VTA-model," *2018*. https://martijnzoet.com/2018/10/22/het-value-through-analytics-vta-model/ (accessed Feb. 01, 2023).

[21] J. Leek and R. D. Peng, "What is the question?," *Science Magazine*, pp. 1314–1315, 2015.

[22] W. M. P. Van Der Aalst, "Process Mining," in *Discovery, Conformance and Enhancement of Business Processess*, 2011, pp. 215–217.

[23] E. Mantelaers and M. Zoet, "Data-analysis (III)," 2021. https://www.accountant.nl/vaktechniek/2021/1/data-analyse-nader-geanalyseerd-iii/ (accessed Mar. 27, 2023).

[24] A. J. M. M. Weijters, W. M. P. van der Aalst, and A. K. A. de Medeiros;, "Process Mining with the HeuristicsMiner Algorithm," *Beta Work. Pap.*, no. May, 2006.