An Extended Study on the Usage of Audit Data Analytics within the Accountancy Sector

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***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 audit approach within the accountancy sector is necessary. Research demonstrates that technology can contribute to an improvement of audit quality, by enhancing audit effectiveness and efficiency. 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. This paper extends the previous research [1], including a more detailed literature review, data collection, analysis and results. 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 [2]–[5]. 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 [6]. 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 audit approach within the accountancy sector is necessary [7]. Research demonstrates that technology can contribute to an improvement of audit quality [8].

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” [9]. 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 [10]. 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” [11]. 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][7].

Previous research shows that technology/ADA can contribute to an improvement of audit quality [8]. 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 [8][9]. Additionally, previous research increasingly recognizes that ADA is likely to transform the conduct of the audit significantly [12]–[14]. 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" [12]. To support the individual and personal judgement of the auditor, ADA could provide a solution. ADA is a method of using data 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 [15]. 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 [16].

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 [17]. 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 [18]. 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 [18]. However, this research focuses not only on the use of ADA, but also on the sequentially of its use.

To analyze the sequential use of ADA, process mining will be used [19] [20]. Process mining is a technique used to analyze and visualize end-to-end processes, by ordering the events based on the timestamps/event logs. Ordering these events is a crucial step for understanding the sequence of activities within a process and to detect possible deviations from the expected process [19] [20]. As van der Aalst (2011) stated: "Process mining aims to discover, monitor and improve real processes by extracting knowledge from event logs" [20]. The initial stage in process mining involves the utilization of event logs, which document individual activities or events associated with specific cases. These events, arranged in chronological order, collectively represent a single "execution" of the process [21].

For the use of this research process mining algorithms from the Python package 'Pm4py', a Process Mining package for Python, were used [22]. In specific, the heuristic miner will be used. A heuristic analysis simplifies the information by removing redundant details and exceptions, concentrating on the primary behaviors [23].

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) sequence, 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 [24], 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 [25]. 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 [26]. 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 [27]. The VTA model also includes the three types of process mining as described by Van der Aalst (2011): discovery, conformance and improvement [28]. The VTA model is a tool to classify data analytics into different categories [29] 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.

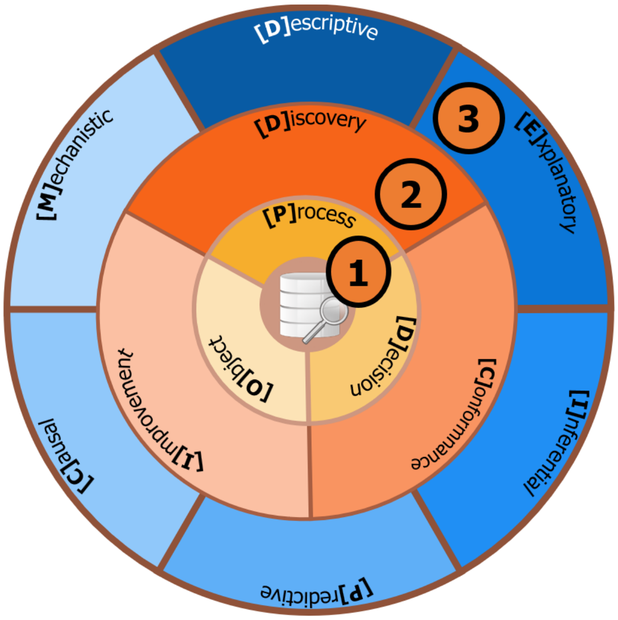

Figure 1. Value Through Analytics model [26]

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 [29]. An example of this is shown in Figure 2, in which the questions are set against audit organizations. 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 [29].

The survey questions were set up by dr. Mantelaers (chartered auditor) and dr. Zoet, founder of the VTA model [26], based on the analysis quotient. 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).

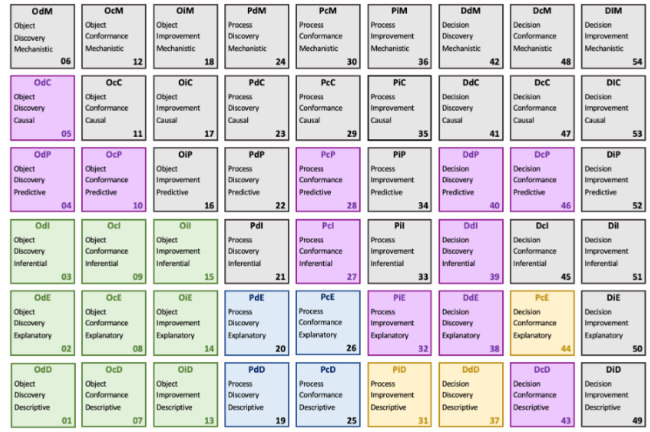

Figure 2. Periodic system types of analyses [29]

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 questions were arranged in chronological order, following the sequence and complexity of ADA types. This means that the data analysis types embedded in these questions are used systematically in the expected chronological sequence. This approach of progressing step by step improves the clarity and relevance of the data analysis, making it a more methodical and understandable exploration of the subject matter. With this set up, we expect that ADA types with lower complexity, such as 2, will be utilized more frequently than the more intricate ADA types like 37 or 43. Furthermore, considering the hierarchy of complexity in ADA types, proficiency in

ADA type 5 should imply competence in performing ADA type 7 as well.

The sequence 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 [23].

IV. DATA COLLECTION AND ANALYSIS

The survey was distributed to a population of 7,008 respondents in total, of which initially 203 responded, a response rate of 2.90%. 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). Based on the initial results some first analysis was carried out, this paper includes the total dataset and expands the earlier analysis/research. The final dataset consists out of 609 respondents, a response rate of 8.69%. *The respondents consist out of 488 males, 119 females and 2 (none of) both. Within the respondents there are 198 chartered auditors and 133 accounting consultants. Around 20% works for one of the Big 4 auditing firms.* 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.

The overall 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 an NBA perspective this can be considered a representative response rate. The survey was distributed in the first half of 2021.

TABLE II. WORK EXPERIENCE RESPONDENTS

Work experience (in years)	Initial dataset - Number of respondents	Final dataset – Number of respondents
< 5	3	8
5 - 10	22	64
10 – 20	72	201
20 – 30	58	194
> 30	48	142
Total	**203**	**609**

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

A. Initial Results

The initial 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.

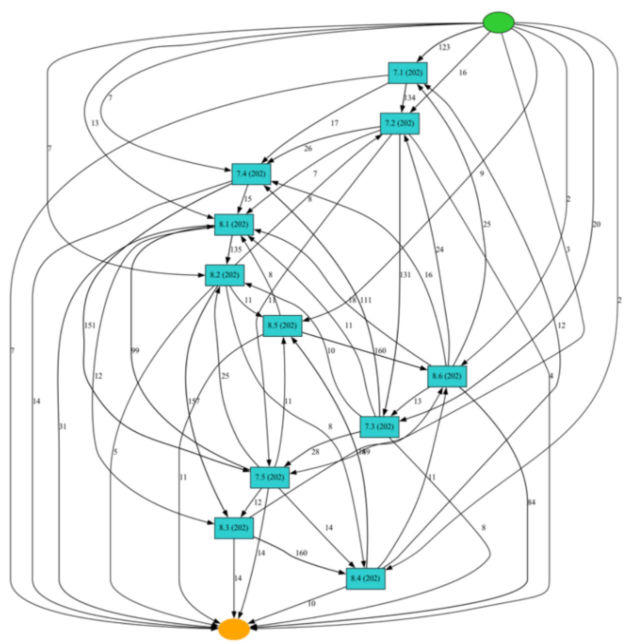

Figure 3. Result heuristic miner.

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. The results are shown in Figure 4.

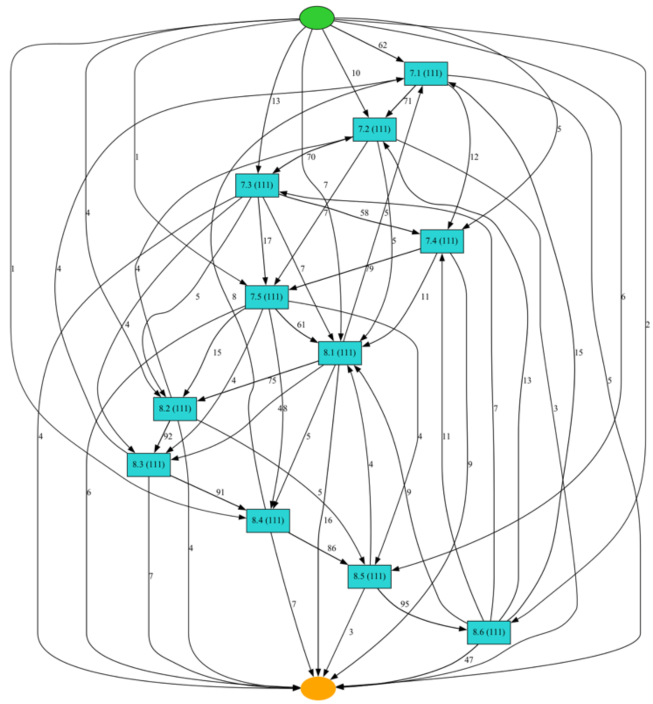

Figure 4. Result heuristic miner external auditors.

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).

B. *Subsequent analysis*

In addition to the initial analysis, the analyses were repeated based on the expanded survey (n=609). The analysis based on the expanded survey distinguishes 357 unique variants within a total of 609 respondents (58.6%).

A total overview of the data analysis types in order of usage is shown in Figure 5.

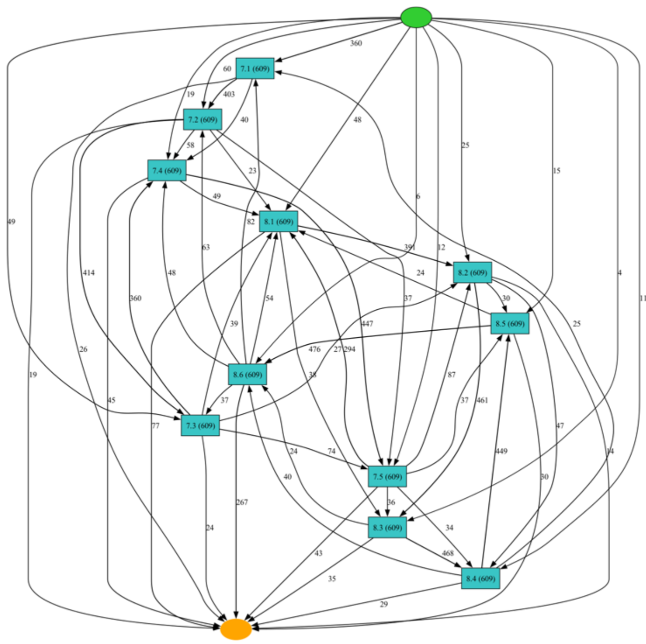

Figure 5. Results heuristic miner – subsequent analysis

Due to the high number of unique variants (58.6%), an overview of the top ten variants is shown in Table V. For clarity purposes, the number of occurrences per unique variant is added.

TABLE V. TOP 10 VARIANTS – SUBSEQUENT ANALYSIS

												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	179
Variant 2	7.1	7.2	7.3	7.4	7.5	8.2	8.3	8.4	8.5	8.6	8.1	12
Variant 3	8.1	8.2	8.3	8.4	8.5	8.6	7.1	7.2	7.3	7.4	7.5	11
Variant 4	7.1	7.2	7.3	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.4	8
Variant 5	7.1	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	6
Variant 6	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.1	5
Variant 7	8.1	7.1	7.2	7.3	7.4	7.5	8.2	8.3	8.4	8.5	8.6	4
Variant 8	7.1	7.2	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.3	4
Variant 9	7.1	7.2	7.3	8.1	8.2	8.3	8.4	8.5	8.6	7.4	7.5	4
Variant 10	7.1	7.2	7.3	7.4	7.5	8.5	8.6	8.1	8.2	8.3	8.4	4

The most frequent variant, referred to as variant 1, appears 179 times. Chronologically, this variant aligns logically with the sequential order of questions (7.1 to 8.6). Consequently, the data analysis types embedded in these questions are employed in the expected chronological sequence. However, this pattern is applicable to only 29.4% of the respondents (n=179). The occurrences for other variants are widely dispersed, ranging from twelve to four instances for variants two through ten.

Due to the significant variation in results, a supplementary analysis will be carried out focusing solely on the external auditors (who are anticipated to possess the most extensive audit experience. The expanded sample consists of 332 external auditors. Based on the external auditor sample, 195 unique variants were identified (58.7%). This closely reflects the variance observed in the total population. Nevertheless, the anticipated chronological order is acknowledged by only 105 respondents (31.6%). This percentage is marginally higher among external auditors when compared to the total sample. A total overview of the data analysis types in order of usage for the external auditors is shown in Figure 6.

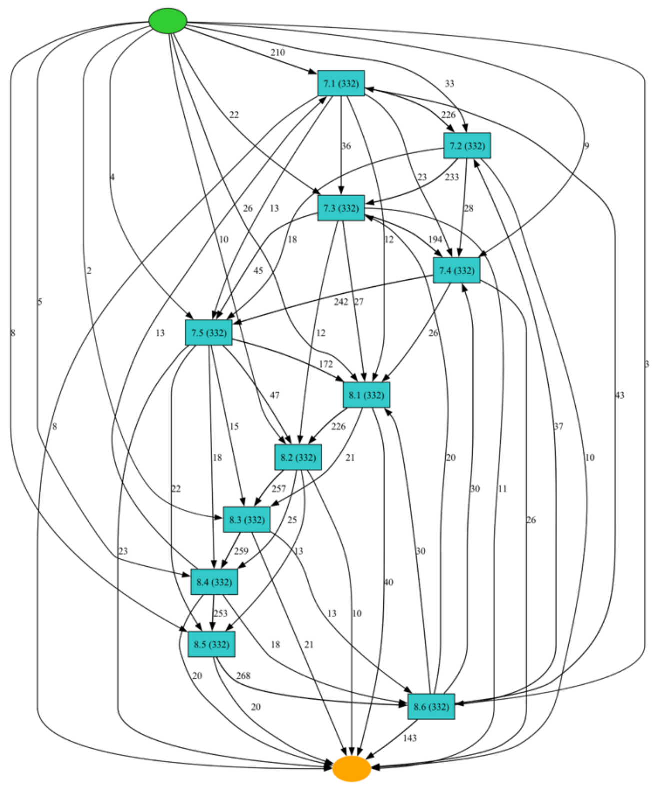

Figure 6. Results heuristic miner external auditors– subsequent analysis

Due to the high number of unique variants (58.7%), an overview of the top ten variants is shown in Table VI. For clarity purposes, the number of occurrences per unique variant is added.

TABLE VI. TOP 10 VARIANTS EXTERNAL AUDITORS – SUBSEQUENT ANALYSIS

												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	105
Variant 2	8.1	8.2	8.3	8.4	8.5	8.6	7.1	7.2	7.3	7.4	7.5	6
Variant 3	7.1	7.2	7.3	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.4	6
Variant 4	7.1	7.2	7.3	7.4	7.5	8.2	8.3	8.4	8.5	8.6	8.1	6
Variant 5	7.1	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	5
Variant 6	8.1	7.4	7.1	7.2	7.3	7.5	8.2	8.3	8.4	8.5	8.6	3
Variant 7	7.1	7.2	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.3	3
Variant 8	7.1	7.2	7.3	7.4	7.5	8.5	8.6	8.1	8.2	8.3	8.4	3
Variant 9	7.2	7.3	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.1	7.4	2
Variant 10	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.1	2

The most common variant, variant one, is observed 105 times. It follows a chronological alignment with questions ranging from 7.1 to 8.6, wherein the embedded data analysis types are logically applied in the expected sequence. Notably, this pattern is found in only 31.6% of the respondents (n=105). Occurrences for other variants are widely scattered, with instances ranging from six to two for variants two through ten.

C. Final analysis

Initially, both responses 'I don't know' and 'Not relevant' were categorized under '1- I never use it.' However, in our effort to refine and clarify the dataset, we are revisiting this classification.

To establish a more distinct differentiation, the decision has been made to equate 'Not relevant' with '1 – I never use it.' This choice is grounded in the understanding that 'Not relevant' implies a lack of usage for the particular item. Conversely, 'I don't know' will undergo a dedicated analysis. We recognize that this response cannot be seamlessly linked to the Likert scale without potentially introducing distortions to the overall data overview. This approach allows for a nuanced separation between explicit non-usage, represented by 'Not relevant,' and uncertainty, as indicated by 'I don't know.' By doing so, we aim to preserve an accurate understanding of the dataset, while acknowledging the intricacies associated with the 'I don't know' response. This reconsideration is intended to enhance the overall reliability and interpretability of the data.

First, a descriptive analysis will be performed on the usage of 'I don't know.' On average, each respondent answered 'I don't know' to 0.90 questions. In addition, 17 respondents (out of the 609 total respondents) answered 'I don't know' to all 11 questions. The frequency of 'I don't know' responses for each question is presented in Table VII.

TABLE VII. ANALYSIS RESPONSE 'I DON'T KNOW'

Question	Occurences of 'I don't know'	ADA description	ADA type
7.1	57	Object – Discover – Explanatory	2
7.2	48	Object – Discover – Predictive	4
7.3	56	Object – Discover – Causal	5
7.4	37	Object – Discover – Descriptive	7
7.5	43	Object – Discover – Explanatory	8
8.1	41	Process – Discover - Descriptive	19
8.2	48	Process – Discover – Explanatory	20
8.3	41	Process – Conformance – Descriptive	25
8.4	55	Process – Conformance – Explanatory	26
8.5	61	Decision – Discover – Descriptive	37
8.6	63	Decision – Conformance - Descriptive	43

To enhance clarity, the results are visualized in Figure 7. This shows that for the first questions, relatively more 'I don't know' responses were registered. From question 7.4 onwards, a drop is visible, indicating a decreasing frequency of 'I don't know' responses. However, a notable trend emerges beyond this point, revealing an increasing amount of 'I don't know' responses as the complexity of the data analysis types rises.

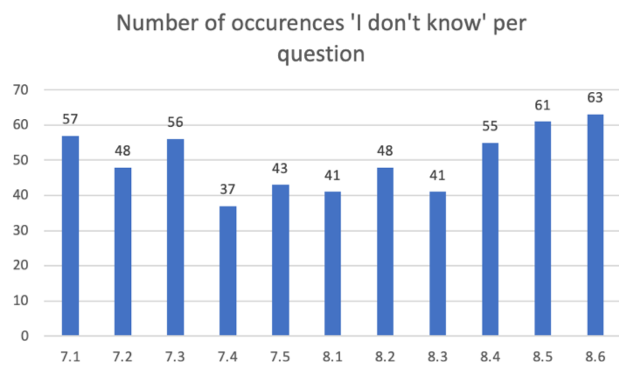

Figure 7. Number of occurences response 'I don't know' per question.

These results indicate that respondents initially grapple with uncertainty in the early questions, possibly due to the novelty of the survey or the initial learning curve. The observed drop in 'I don't know' responses from question 7.4 may suggest a level of familiarity or increased confidence among respondents in handling less complex data analysis types. However, the subsequent rise in 'I don't know' responses from question 7.4 onwards suggests a growing challenge for respondents as the survey progresses into more intricate aspects of data analysis. This pattern underscores the need for targeted support or training in the latter stages of the survey, where the complexity of questions seems to pose a greater difficulty for participants.

Based on the refined dataset, the heuristic process mining algorithm will be reapplied to analyze the results. The refined dataset is identical to the dataset used in the subsequent analysis (V. Results – B), excluding responses labeled 'I don't know' to eliminate noise. This analysis will be conducted on both the entire sample and the subset of external auditors. The entire sample comprises the 609 respondents, excluding the 17 who answered all questions with 'I don't know' (n=592). The analysis based on the expanded survey distinguishes 374 unique variants within a total of 592 respondents (63.2%). A total overview of the data analysis types in order of usage is shown in Figure 8.

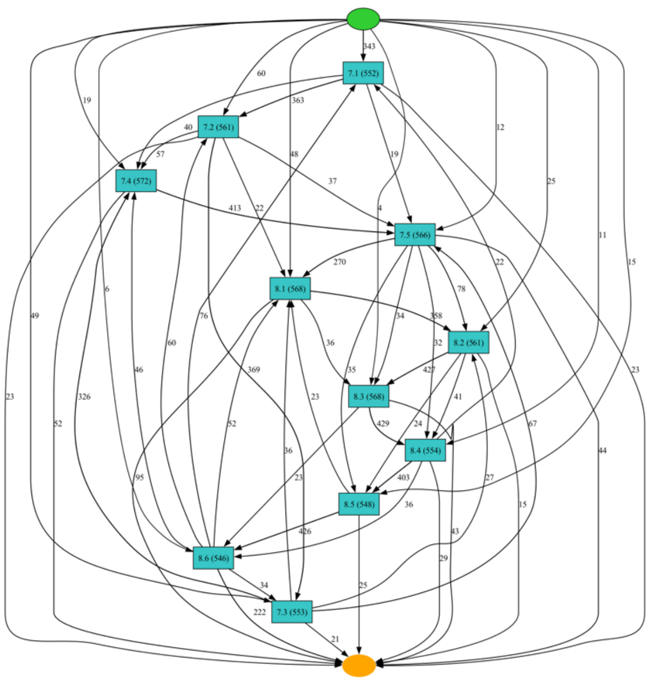

Figure 8. Results heuristic miner – final analysis

Due to the high number of unique variants (63.2%), an overview of the top ten variants is shown in Table VIII. For clarity purposes, the number of occurrences per unique variant is added.

TABLE VIII. TOP 10 VARIANTS – FINAL ANALYSIS

												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	158
Variant 2	7.1	7.2	7.3	7.4	7.5	8.2	8.3	8.4	8.5	8.6	8.1	12
Variant 3	8.1	8.2	8.3	8.4	8.5	8.6	7.1	7.2	7.3	7.4	7.5	9
Variant 4	7.1	7.2	7.3	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.4	7
Variant 5	7.1	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	6
Variant 6	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.1	4
Variant 7	7.1	7.2	7.3	8.1	8.2	8.3	8.4	8.5	8.6	7.4	7.5	4
Variant 8	7.1	7.2	7.3	7.4	7.5	8.5	8.6	8.1	8.2	8.3	8.4	4
Variant 9	7.3	7.4	7.5	7.1	7.2	8.1	8.2	8.3	8.4	8.5	8.6	3
Variant 10	7.1	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	7.3	7.4	3

Appearing 158 times, variant 1 stands out as the most frequent. It conforms chronologically to the order of questions (7.1 to 8.6), where the associated data analysis types are logically employed in the anticipated sequence. However, this specific pattern is evident in just 26.7% of the respondents (n=158). The occurrences of other variants are widely distributed, with instances varying from two to four for variants two through ten.

The analysis based on the expanded survey, solely focused on the external auditors, distinguishes 200 unique variants within a total of 323 respondents (61.9%). A total overview of the data analysis types in order of usage is shown in Figure 9.

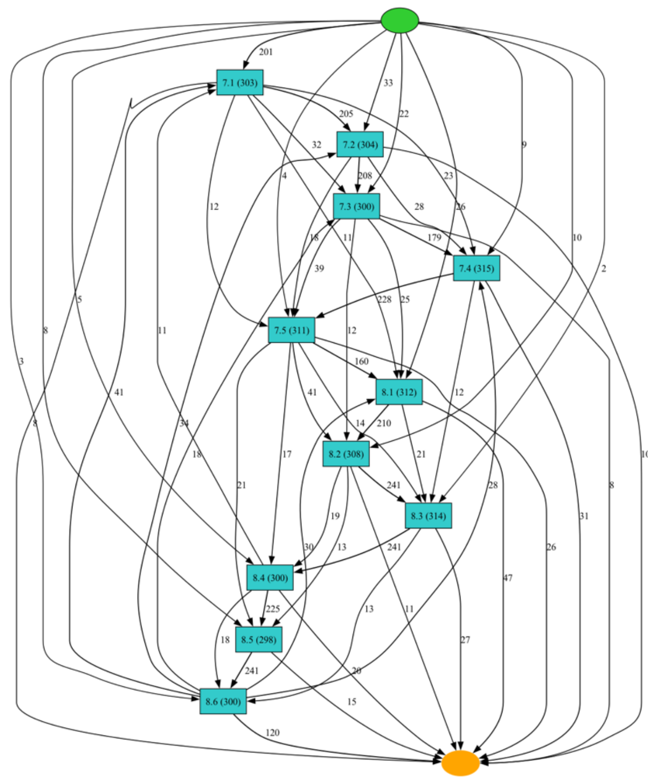

Figure 9. Results heuristic miner external auditors – final analysis

The top ten variants are shown in Table IX. For clarity purposes, the number of occurrences per unique variant is added.

TABLE IX. TOP 10 VARIANTS EXTERNAL AUDITORS – FINAL ANALYSIS

												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	95
Variant 2	8.1	8.2	8.3	8.4	8.5	8.6	7.1	7.2	7.3	7.4	7.5	6
Variant 3	7.1	7.2	7.3	7.4	7.5	8.2	8.3	8.4	8.5	8.6	8.1	6
Variant 4	7.1	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	5
Variant 5	7.1	7.2	7.3	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.4	5
Variant 6	7.1	7.2	7.3	7.4	7.5	8.5	8.6	8.1	8.2	8.3	8.4	3
Variant 7	8.1	7.4	7.1	7.2	7.3	7.5	8.2	8.3	8.4	8.5	8.6	2
Variant 8	7.2	7.3	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.1	7.4	2
Variant 9	7.2	7.3	7.4	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.1	2
Variant 10	7.1	7.5	8.1	8.2	8.3	8.4	8.5	8.6	7.2	7.3	7.4	2

With a frequency of 95 occurrences, variant 1 emerges as the most prevalent. Sequentially, this variant aligns with the order of questions (7.1 to 8.6), showcasing a logical utilization of data analysis types in the expected sequence. It's noteworthy that this pattern applies to only 29.4% of the respondents (n=95). The instances of other variants are dispersed widely, ranging from two to four occurrences for variants two through ten.

D. Summary results

All results, combining initial, subsequent and final analyses, are summarized in Table X.

TABLE X. SUMMARY RESULTS

Analysis	Sample size	Variance (% unique variants)	Number of occurences of anticipated sequence	% of occurences of anticipated sequence
Initial analysis - total	203	65.0%	58	28.6%
Initial analysis - external auditors	111	71.2%	31	27.9%
Subsequent analysis - total	609	58.6%	179	29.4%
Subsequent analysis - external auditors	332	58.7%	105	31.6%
Final analysis - total	592	63.2%	158	26.7%
Final analysis - external auditors	323	61.9%	95	29.4%

The results from both the initial and subsequent analyses exhibit a considerable degree of similarity. The anticipated sequence in the utilization of data analysis is observed in only 28-30% of the respondents. Even after refining the data by excluding 'I don't know' responses in the final analysis, the percentage of the expected sequence remains within the range of 26-30%. Additionally, all analyses indicate a high percentage of variance, exceeding 58%. Despite the increase in variances resulting from the elimination of 'I don't know' responses in the final analysis, the overarching trend remains consistent.

VI. CONCLUSION AND FUTURE WORK

In this article, we aimed 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 in conjunction with the non-chronological order of the data analysis types, indicate the presence of a misinterpretation or possible gap in comprehending the data analysis types utilized in the survey and their appropriate chronological order. This discrepancy raises questions about the competence and understanding of the survey participants in applying these data analysis techniques in a correct and coherent manner. 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 follow up on the answers: *'I don't know' or 'Not relevant'* to identify the underlying reasons and expand our results/knowledge.

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REFERENCES

[1] L. Verhoeven, E. Mantelaers, and M. Zoet, "Usage of Audit Data Analytics within the Accountancy Sector," in Proc. eKNOW, 2023, pp.14-19.

[2] MCA, "Accountancy Monitoring Committee." Accessed: Mar. 24, 2023. [Online]. Available: https://www.monitoringaccountancy.nl/

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

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

[5] AFM, "Research reports on supervision of audit firms | Audit firms | AFM Professionals." Accessed: Mar. 24, 2023. [Online]. Available: https://www.afm.nl/nl-nl/sector/accountantsorganisaties/rapporten-publicaties

[6] D. Brydon, "Assess, assure and inform: improving audit quality and effectiveness," UK Government, 2019.

[7] Future Accountancy Sector Committee, "Reliance on Audit," *Ministerie van Financiën*, 2020.

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

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

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

[11] 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.

[12] 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 Journal of Practice & Theory (2022)*, vol. 41, no. 1, pp. 25–48, 2022, [Online]. Available: https://doi.org/10.2308/AJPT-19-064

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

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

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

[16] AFM, "Legislative letter." 2021.

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

[18] A. Eilifsen, F. Kinserdal, W. F. Jr. Messier, and T. E. McKee, "An Exploratory Study into the Use of Audit Data Analytics on Audit Engagements," *American Accounting Association*, pp. 1–23, 2020.

[19] M. Jans, P. Soffer, and T. Jouck, “Building a valuable event log for process mining: an experimental exploration of a guided process,” *Enterp Inf Syst*, vol. 13, no. 5, pp. 601–630, May 2019, doi: 10.1080/17517575.2019.1587788.

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

[21] W. van der Aalst, “Process Mining,” *ACM Trans Manag Inf Syst*, vol. 3, no. 2, pp. 1–17, Jul. 2012, doi: 10.1145/2229156.2229157.

[22] A. Berti, S. van Zelst, and D. Schuster, “PM4Py: A process mining library for Python,” *Software Impacts*, vol. 17, p. 100556, Sep. 2023, doi: 10.1016/j.simpa.2023.100556.

[23] A. J. M. M. Weijters, W. M. P. van der Aalst, and A. K. A. de Medeiros;, “Process Mining with the HeuristicsMiner Algorithm,” *Beta working papers*, no. May, 2006.

[24] R. Likert, “A Technique for the Measurement of Attitudes,” *rchives of Psychology*, no. 140, pp. 1–55, 1932.

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

[26] M. Zoet, “VTA-model,” 2018. Accessed: Feb. 01, 2023. [Online]. Available: https://martijnzoet.com/2018/10/22/het-value-through-analytics-vta-model/

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

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

[29] E. Mantelaers and M. Zoet, “Data-analysis (III).” Accessed: Mar. 27, 2023. [Online]. Available: https://www.accountant.nl/vaktechniek/2021/1/data-analyse-nader-geanalyseerd-iii/