Applying machine learning in audit techniques:

Towards (near) real-time assurance

IT Audit, Compliance and Advisory Program

VU VRIJE UNIVERSITEIT AMSTERDAM

SCHOOL OF BUSINESS AND ECONOMICS

BDO

This white paper is a brief report of a study that BDO Digital and Vrije Universiteit Amsterdam jointly conducted.

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1. Introduction

Today's audit view is clearly associated with digitalization and its impact on business strategies across the globe. The center of this digital journey is dominantly filled by the far-reaching deployment of advanced technology. The intensive and massive use of this evolutionary capability empowers reinventing business models, improving customer experience, optimizing processes and operations, reshaping trade with partners, and more. It is now necessary to remain attractive in modern digital chains and survive in the current ever-demanding marketplace. It has visibly become a technology-driven environment that no longer appears to tolerate the large distances between the traditional physical world and the new digital world. We are entering a contactless economy in which technology defines the bright future, affects the behavior of society, and dictates how we conduct business (Shahim 2017). This irreversible transformation has obviously not left the audit profession unaffected. Currently, it is increasingly challenging to live up to the faster adoption of technology and apply it boldly as an instrument of change (Sun et al. 2015; Eulerich and Kalinichenko 2018; Knudsen 2020; Korhonen et al. 2020).

Operating in online business environments requires organizations to modernly manage and frequently improve various kinds of business processes and activities. It is an opportunity and a challenge for the audit profession, which jointly calls for a new operating model. Opportunities arise from increasing reliance on information technology (IT) and real-time data processing environments by which information can be provided instantly after events take place and transactions are recorded. Challenges are concerned with a prevailing need for cost-cutting activities and budget constraints, increased risk exposure, a rapidly changing complex regulatory landscape and growing stakeholder demands (Hardy and Laslett 2015; Weins et al. 2017).

1.1. Revamped audit approach

The traditional annual examination of financial statements is not fit for the digital era since it hinders timely and relevant assurance reporting (Kuhn et al. 2014). Two common reasons are mentioned to establish a certain image of the critique of the traditional approach. First, the manual audit focuses on records in identified risk areas and therefore may fail to capture all relevant data (AICPA 2015). Second, performing an audit only once a year may result in fraudulent activity going undetected for up to a year or more in the case that internal control of the organization itself does not adequately function. In this way, traditional audit practices uncover intentional and unintentional errors; however, only after they have possibly had a detrimental effect on the organization (Flowerday et al. 2006). Critical decisions by investors, creditors, top management, and other stakeholders are then based on outdated information rather than current audited facts, raising the risk of making less than optimal decisions. (Kuhn et al. 2014).

Therefore, in today's business climate, the need to implement new audit approaches to keep pace with the changing and modern business environments is stronger than ever before (Eulerich and Kalinichenko 2018). It has become a necessity for auditors to deploy automated tooling to conduct the planned audit faster, more efficiently and in more depth. Data-driven auditing techniques reenter the scene, such as continuous monitoring (CM), continuous auditing (CA) and continuous assurance (CAS), as conceptually illustrated in Figure 1 (Coderre 2005). These known concepts, including their variants hereinafter referred to as audit techniques, can change the audit paradigm by positioning the auditor as a continuous data examiner rather than a seasonal data collector.

1.2. Use of audit techniques

Audit techniques have in general the potential to support the auditor by detecting any irregularity in an early stage. From a functional perspective, they capture data continuously without customer intervention, allowing for direct processing with two main advantages. The first relates to widening the scope of audits to include all transactions and moving toward integrated control (Weins et al. 2017). The second advantage pertains to having the data available in advance, reducing the timelines needed by auditors to provide assurance. The idea behind audit techniques involves using information systems to automate the audit process, striving for (near) real-time assurance (Jans and Hosseinpour 2019).

Over the years, advances in enterprise resource planning (ERP) systems, packaged software solutions for governance, risk and compliance (GRC), data modeling and data analytics, and other valuable tools have been introduced to tackle the challenges that auditors face in a digitalized world (Rikhardsson and Dull 2016; Tarek et al. 2016; Eulerich and Kalinichenko 2018). However, research has indicated that although the benefits of audit techniques are becoming clear, their actual implementation level by practitioners is still in an early stage, mainly due to limited guidance about practicalities (Hardy and Laslett 2015; Weins et al. 2017; Vasarhelyi et al. 2018).

For instance, CA approaches often assume that all data are stored in a structured manner and that data collection is a fully automated process. However, large quantities of organizational data remain traditionally analogous (Byrnes et al. 2018). This reality poses challenges in the timeliness of the data (i.e., slow batchwise data processing) and audit execution, as the data structures are not consistently optimized to perform automated audits. Moreover, auditors are dependent on the validity of data coming out of diverse internal and external data sources. This situation still makes it difficult to benefit from the advantages of audit techniques requiring direct data access digitally.

1.3. Research Question

The aforementioned shortcomings triggered the idea of exploring the possibilities of audit techniques enabled these days by modern technological advancements that collect data directly, accurately and completely without the customer intervening in the process. Therefore, we proposed the following research question:

> "How can the application of a machine learning solution in audit techniques contribute to providing (near) real-time assurance?"

Our research process followed a case study design method with solely a focus on the invoicing process that tracks the revenue flowing into the organization from different sources (Yin 2017). To this extent, the paper fills a gap in research and practice, i.e., the need to develop and explore innovative technological tools to better support audits in the future.

1.4. Layout

The structure of the paper is as follows. In the following section, the theoretical background of digitalized audit techniques is described. In the third section, we explain our research design and elaborate on the technical components of the research object. The fourth section presents our results and findings, followed by a discussion in the fifth section. It indicates the implications for further research after which the final remarks are expounded in the sixth section. The paper holds two appendices that respectively contain an overview of the research methodology and a list of abbreviations.

2. Audit techniques

The rationale behind audit techniques has been relevant in the audit domain for more than three decades (Kogan et al. 1990; Weins et al. 2017; Gonzales and Hoffman 2018). The first studies appeared in the 1970s with the emergence of the electronic data processing (EDP) auditing field when the focus was on computer-assisted testing of internal controls. After its conception, the audit domain concentrated on technologies such as enterprise database audits in the eighties and network audits in the nineties (Vasarhelyi et al. 2002). Since the 2000s, an increase in IT audit related publications has been observed in practical and academic literature (Eulerich and Kalinichenko 2018). Additionally, massive corporate fraud and related bankruptcies occurred in the early 2000s (e.g., Enron and Parmalat), resulting in widespread concern about improved internal controls, more transparent and timely corporate reporting, and expansion of assurance activities, particularly in the area of IT controls over financial reporting (Kuhn et al. 2014).

Over the years, research about audit techniques has evolved from a theoretical pursuit to an area of audit practice. However, there is still an ongoing ambiguity about the features of and the differences between the audit techniques mentioned above (Hardy and Laslett 2015). Confusingly, the literature has sometimes used the terms ''continuous monitoring'', ''continuous auditing'' and ''continuous assurance'' interchangeably. Although there are similarities, the relationships among these audit techniques vary subtly between studies (Gonzales and Hofmann 2018). These variations are briefly explained in the following sections to bring more clarity.

2.1. Continuous Monitoring (CM)

It is important to understand first that continuous monitoring (CM) is management's responsibility. This concept assists in meeting fiduciary responsibilities, provides the possibility to measure the effectiveness of the organization's internal controls (Hardy and Laslett 2015; Appelbaum et al. 2016; Gonzalez and Hoffman 2018), and improves the ability to manage risks and opportunities. CM is defined as follows (AICPA 2015):

> ''A process by which online and real-time systems are used to manage the performance of corporate processes, on (or close to) a real-time basis. CM typically results in a timely detection of significant variances from expected performance with resulting rapid intervention and corrective action.''

The commonly held view is that CM is a subset of continuous auditing (CA) since monitoring information can be automatically assessed against predetermined criteria to enable CA (Rikhardsson and Dull 2016; Gonzalez and Hoffman 2018). The latter concept is explained next in more detail.

2.2. Continuous Auditing (CA)

A CA approach allows internal auditors to fully understand critical control points, rules, and exceptions. With automated, frequent analyses of data, the ability to perform control and risk assessments in real time or near real time becomes feasible.

Traditionally, independent testing of controls has been performed on a retrospective and cyclical basis, often many months after business activities have occurred (Coderre 2005). Fraud and errors remained uncaught until after the event and sometimes long after the possibility of financial recovery. By monitoring and auditing transactions continuously, organizations can reduce the financial loss from these risks.

"A methodology that enables independent auditors to provide written assurance on a subject matter using a series of auditors' reports issued simultaneously with, or a short time after, the occurrence of events underlying the subject matter" (Coderre 2005).

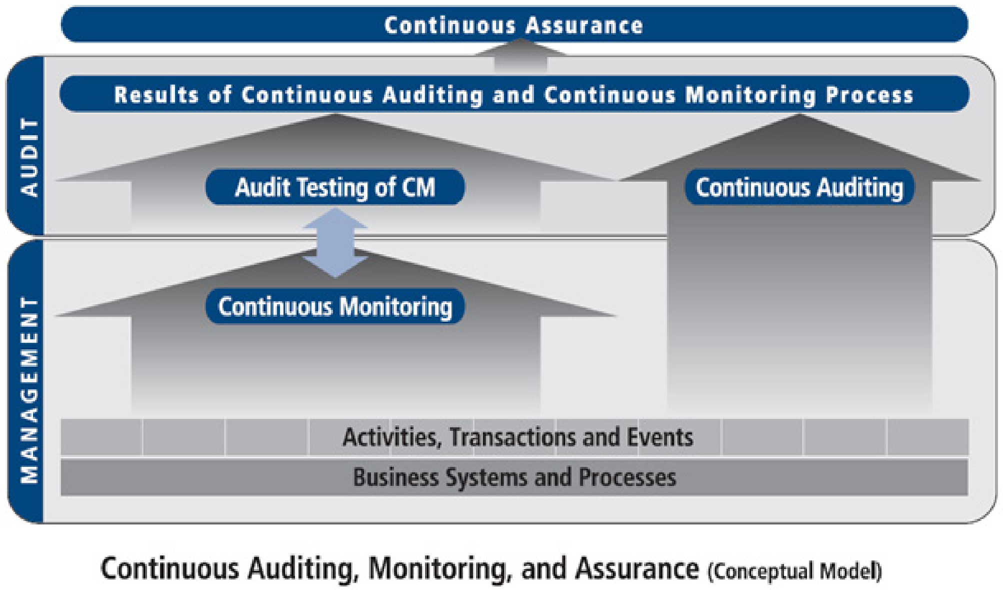

Figure 1: Relation between three auditing techniques (Coderre 2005)

Continuous audits are usually designed to automate error checking, management by exception and data verification in real time; hence, CA relies heavily on technology (Coderre 2005; Flowerday et al. 2006; Jans and Hosseinpour 2019). This technique increases the coverage and frequency of analysis of an organization's activities or "business process view" and is typically implemented by internal auditors with an explicit focus on CM (Gonzalez and Hoffman 2018; Jans and Hosseinpour 2019). An oftencited CA definition is as follows:

It is important to add to this definition that CA is a (nearly) real-time IT-enabled system that continuously and automatically audits clearly defined "audit objects" based on predetermined criteria (Gonzalez and Hoffman 2018). It identifies exceptions and/or deviations from a defined standard or benchmark and reports them to the auditor. With this continuous approach, the audit takes place within the shortest possible time immediately after the occurrence of an event (Eulerich and Kalinichenko 2018). To achieve its goal of reducing the latency between the occurrence of the business transaction and the provision of assurance on that transaction, CA relies strongly on IT solutions and technological advancements such as an ERP system, data analytics and business intelligence software, web application server technology, web scripting facilities and ubiquitous database management systems with standard connectivity (Vasarhelyi et al. 2012).

It is important to understand that originally, the ultimate goal of the described CA process was to bring the external audit closer to the everyday internal processes of the auditee and further away from the historical annual (financial) audit. Over time, however, CA and CM approaches have hardly been championed by external auditors in practice (Appelbaum et al. 2016).

Nevertheless, regardless of the subtle differences in terminology between CA and CM, at its core, as indicated above, CA involves continuously comparing actual observations to established benchmarks. The latter are "rule sets," the design and creation of which are crucial for implementing a CA system. When a transaction violates a rule in the predetermined rule set, this deviation triggers an alert to the internal auditor (Gonzalez and Hoffman 2018). From this background, we can learn that ownership is one of the key differences between CM and CA. The latter audit technique is owned by the audit to indicate control failures and is thus relevant to audit stakeholders. CM is intended for management to ensure that the business runs effectively and efficiently.

2.3. Continuous Assurance (CAS)

To remain "in control", top management continuously needs assurance on the operation, the risk management system, internal control and periodic financial information. In general, CAS is simply interpreted as the combination of CM and CA (NBA 2015). Real-time assurance is then delivered only if supporting technological advancements are properly deployed (Flowerday et al. 2006). CAS can support the external auditor with a more comprehensive, efficient and effective audit technique. This amenity is clearly provided through automated testing of the full population of transactions for specific audit areas rather than evaluating only smaller samples because of time constraints or manual processing (Kuhn et al. 2014). A common definition of CAS is as follows:

"Continuous assurance (CAS) is defined as a set of services that using technology and data transactions produces audit results immediately or within a short period of time after the occurrence of relevant events" (Marques et al. 2015).

Although research has claimed that continuous assurance can be attained by combining CM by management with CA auditing of data streams and the effectiveness of internal controls by an external auditor, research also acknowledges that the existing literature lacks an explanation for the final step to CAS. It is not explained how the results of CM and CA need to be combined to provide assurance (Kocken and Hulstijn 2017).

Auditors are facing the challenges of working with large, instantly accessible data generated continuously and automatically by the organization's IT systems. The massive use of IT in daily operations results in a continuously increasing amount of (transaction) data and therefore the necessity to use new approaches to analyze and audit this business asset (Eulerich and Kalinichenko 2018).

Although audit techniques differ in certain aspects, the technical implementations of CA, CM, and CAS are comparable. Based on (near) real-time information, these concepts should cover all of the company's transactions and thus eliminate sampling errors and produce test results simultaneously or soon after the occurrence of an event (Eulerich and Kalinichenko 2018).

3. Research Design

To structure the research, a gradual and case-based approach is applied that comprises six stages, each of which is described in Appendix 1 in more detail (Yin 2017). In this chapter, we focus on three aspects of the research design: (1) the research need, (2) the research object and (3) the technological components, including Optical Character Recognition (OCR), heuristics and machine learning.

3.1. Need

As stated above, this study intends to bring more clarity to the application of audit techniques in the provision of (near) real-time assurance, obtaining evidence directly by the auditor with no direct interference by the auditee, also visualized in Figure 2.

environment. Dai and Vasarhelyi (2020) discuss that this transformation of the audit profession largely increases the demand for technology-based assurance. In addition, the authors state that although auditors are increasingly aware of the value of intelligent technologies, the adoption and use of technology are substantially below expectation (Appelbaum et al. 2016; Dai and Vasarhelyi 2020; Lois et al. 2020). Research should discover opportunities and solutions on how to improve the adoption of audit techniques to achieve real-time technology-based assurance. This research contributes to this reoccurring call for action.

3.2. Object

The object of this research encompasses the

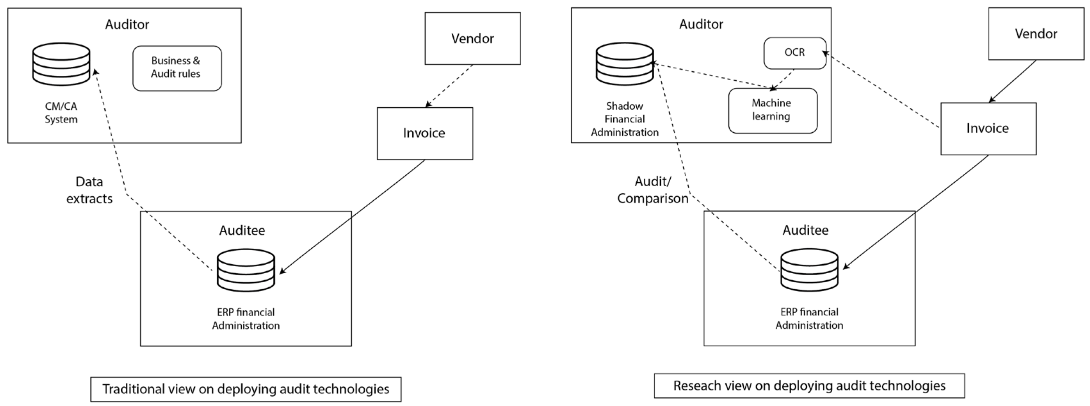

Figure 2: Visualization deploying audit technologies between traditional and research view

With this central argument, we contribute to an emerging debate in the recent literature. Central to this debate is the major transition of the audit profession toward a tech-savvy

assurance of the invoicing process using an early-stage machine learning audit technology developed by BDO Digital researchers.
The invoicing process is considered a key

organizational process that relies mainly on traditional data carriers (i.e., paper invoices). The early-stage machine learning solution is built to automatically extract audit relevant information from (paper) invoices. Invoices are diverse in their layout. Although there are legal requirements for the content of an invoice, there are none for its structure and formatting. This diversity in presentation complicates the automated processing and interpretation of an invoice. The amount of information, location, and wording may vary. A specific algorithm for invoices is therefore developed to detect specific parts of information independently of the invoice template and to structure these data for usage in business processes and audits. The constructed algorithm can detect the following so-called key values from an invoice (i.e., relevant fields of information):

- Invoice number.
- Invoice date.
- Total invoice amount.
- Value-Added Tax (VAT) number.
- Bank account.
- Company registration number.

The algorithm processes invoices in three stages. First, OCR is used to digitalize images of handwritten or printed text. Second, heuristics are used to detect common patterns of data. Finally, a machine learning model is used to detect deviant patterns. We further explain these technological components in the following section.

3.3. Technological components

This white paper recognizes the need to develop and explore technology-driven tools to support CAS in the future. To analyze the possibilities of CM, CA and CAS in a context where the auditor is responsible for data collection, we focused on an invoice processing algorithm that was developed in combination the three afore mentioned technologies.

3.3.1. Optical Character Recognition (OCR)

Optical character recognition (OCR) is a process of classifying optical patterns contained in a digital image corresponding to alphanumeric or other characters. It is an ancient dream to develop machines that replicate human functions such as reading documents (Chaudhuri et al. 2017). For example, OCR technology allows text to be extracted from image files, PDF files or paper scans, together with their location in the document. The combination of information and location is eventually used by an algorithm to classify the relevant fields of information from the invoice.
In this research, OCR technology is used to automate the processing of paper invoices. The aim is to test the accuracy of OCR technology and to clarify whether it can be used to provide (near) real-time assurance. The difficulty involved in doing this lies in the ability to distinguish similarlooking characters, such as zeros and the letter 'O'. This difficulty may result in occasional errors in interpretation. The OCR quality depends on various factors, such as image resolution, scan quality, font type, and the OCR engine. The algorithm used in this study utilizes multiple OCR engines in parallel to improve data extraction, resulting in a more complete and more reliable dataset.

3.3.2. Heuristics

After the OCR has digitalized the contents of an invoice, the algorithm is trained to use heuristics to systematically identify the relevant information from digital text based on standard structures. Compared to an algorithm, which is a step-by-step procedure for solving a specific problem resulting in a predictable and reproducible output, a heuristic is more of an educated guess that serves as a guide for subsequent explorations. Information on an invoice is most often positioned following a keyvalue structure. This means that a label (key) is positioned on the invoice ('invoice number') followed by the actual value ('202104113'). The algorithm starts by scanning the text for relevant labels and tries to estimate for each word the likelihood that it is a relevant key. For each key, starting at the highest score, a corresponding value is searched that is based on location and proximity.
For most keyvalue pairs, the task is relatively straightforward, as the number of potential keys is small and the corresponding values follow strict patterns. For example, the Invoice Date key is usually labeled 'date', followed by a value consisting of numbers and dashes (xx-xx-xxxx). We count on the high accuracy of these structured labels.
We expected challenges in scanning invoices when applying OCR and heuristics. The most complicated keyvalue pair to detect is theoretically the invoice number, as there are no generic rules or structures behind an invoice number. When labeling the potential values for the invoice number, a rather generic rule is applied: all words contain at least three consecutive num-bers. Thus, the number of potential values is large, leaving room for potential mis-matching.

3.3.3. Machine Learning

To ensure the detection of information structures on invoices, the algorithm uses a machine learning model to increase the quality of processing. A machine learning model can recognize certain types of patterns in data that cannot be described explicitly. During development, the model was presented with many correctly labeled key-value pairs from invoices. The model was trained to label keyvalue pairs based on these examples, considering the structure, content and position of the data on the invoice. Machine learning models can, after training, be used on data that have not been seen before. The algorithm applied to this dataset attempts to extract the remainder of the keyvalue pairs and thereby increase the quality of detection.

4. Results

We tested the accuracy of the algorithm by correctly labeling the invoice characteristics using OCR technology. The results are compared against the manually extracted baseline of 214 invoices, as we explain in our methods; see also Appendix I. It is important to understand that the set baseline did not contain 214 records for each field because some invoices did not contain all fields in scope. Missing values in the baseline are excluded from the comparison. The results of the model are explained in the following section. For an overview of the results, also see Figure 3.

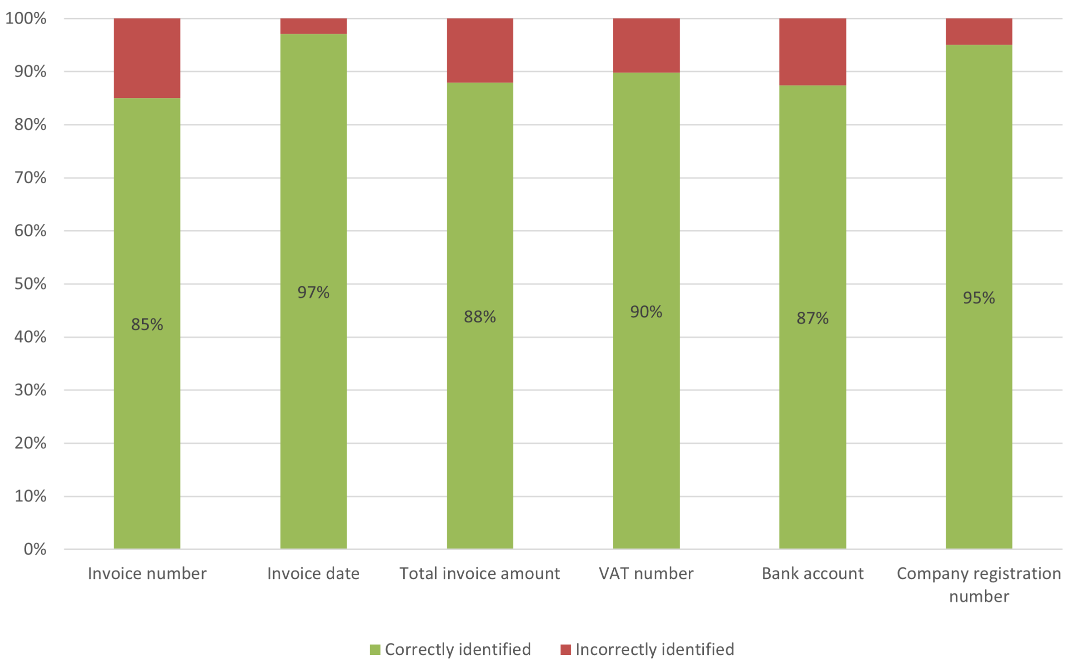

Figure 3: Comparison of automated OCR results and manual results

4.1. Findings

The detection percentage of the invoice number is the lowest, namely, 85%. We expected the invoice number to be challenging for accurate detection. An invoice number is a unique and sequential number on an invoice. The purpose of the invoice number is to enable organizations to invoice quickly and easily. A unique invoice number is one of the invoice requirements of the tax authorities. However, the layout of the invoice number is not standardized, so each invoice has its own formatting of the invoice number. It is evident that the algorithm had a lower detection rate in fields that do not have a standardized structure.

The invoice date has the highest detection rate of 97%. The invoice date is defined as a mandatory field by the Dutch Tax Authority and shows the date when an invoice is created and sent. For instance, the characteristics of the field that presents the date are limited. In Dutch, for example, 14 March 2021 is most common, and the abbreviated notation gets dashes or dots: 14-04-2011, 14.04.2011. This structure seems easily recognizable for OCR technology.

The correctly identified total invoice amount has a detection score of 88%. Additionally, the total invoice amount is a nonstandardized number. We discovered that the algorithm had difficulties detecting the correct total number, likely because it lacks a standardized label and is sometimes mistaken for a subtotal or individual line item.

An interesting finding is the relatively low score (90%) of the correct identification of the VAT number, while this is a standardized, unique number. The Dutch VAT identification number appears as follows: the country code NL, 9 (random) digits, the letter 'B', and a check digit of 2 digits. An example of a VAT identification number is as follows: NL 123456789B01. Although this is a unique number, the VAT number also used a combination of digits and letters, which might have caused the algorithm to mix fields.

The same argument applies to bank accounts. This correct identification rate scored even lower than the VAT number (87%). Bank account numbers use the standard Single Euro Payments Area (SEPA) structure, based on digits and letters. This composition gives more proof that the algorithm had difficulties detecting the combination of letters and numbers within the same string.

The aforementioned argument became even more obvious when the company registration number scored second highest at 95%. The registration number consists of only digits, making it potentially more unique than bank accounts and VAT numbers.

4.2. Summary

The results are factually presented after testing the algorithm in checking invoices and are matched with a manually prepared dataset. The accuracy of detecting the correct invoice label lies between 85 and 97% (see Figure 3). The key challenge for audit technology to correctly identify labels lies in the lack of standard formatting and in the combination of letters and numbers in the same label. In the following sections, we discuss the implications of the results in answering our research question: How can the application of a machine learning solution in audit techniques contribute to providing (near) real-time assurance?

5. Discussion

The algorithm tested in this study is an example of an early-stage audit technology that aims to automate part of the auditing process related to invoicing. The goal is to understand whether applying this technology can contribute to providing (near) real-time assurance.

In addition, this deployment brings the opportunity that the data are collected directly by the auditor without the interference of the auditee and are stored with an audit objective in mind. In this section, the research question is answered by individually discussing and evaluating the three aforementioned audit techniques (i.e., CM, CA, and CAS). Finally, the implications for further developments in the audit domain for research and practice are explored before we conclude the paper.

5.1. Continuous Monitoring (CM)

As explained above, continuous monitoring functions as the basis for insight in (or close to) a real-time status of controls in a more timely and ongoing assurance way of working (Tank Klein and Hilo 2016). Earlystage machine learning audit technology can be positioned as the missing link because plain text can be extracted and parsed straight from the source. The applicability of audit technology to provide support in continuously monitoring business processes shows obvious emerging potential.

The technological solution can help tackle the problem of a lack of CM implementations (Hardy and Laslett 2015; Weins et al. 2017; Vasarhelyi et al. 2018). It was previously mentioned that data are still often not stored in a structured manner, and data collection is not in all cases a fully automated process (Byrnes et al. 2018). From this perspective, early-stage audit technology can thus support CM solutions.

As our results show, the automated extraction of key values from an invoice demonstrates significant levels of accuracy (≥85%). However, the results varied depending on the type of data to be extracted. Key values are more suitable for automated extraction when they have unique characteristics.

More complex keys, such as bank accounts, invoice numbers and invoice amounts, have a lower detection rate. This outcome makes these examples less suitable for automated extraction.

One suggestion is to address these limitations in the CM context by adding additional business rules to correct recurring errors. For example, setting thresholds for certain numeric values reduces the likelihood of error. Additionally, some keys (e.g., IBANs) contain checksum functionality or control digits that add an additional validation opportunity.

A notable limitation of these types of automated invoice extractions is inherited from the limitations in underlying OCR technology. Practically, scan quality and font types have a strong impact on the quality of digitalized images and therefore automated extraction possibilities. This limitation is strengthened by the lack of contextual information available on an invoice body compared to a full text information carrier. Less context requires the algorithm to be more accurate, as it cannot infer information from surrounding text.
On the level of CM in an auditing context, it is concluded that there is potential to use early-stage audit technology to support CM purposes where data are gathered without the need for manual intervention.

5.2. Continuous Auditing (CA)

In supporting CA, the tested audit technology requires automated error checking against predefined criteria. It is particularly relevant to see if audit technology can support the invoicing process. Invoices with missing information or discrepancies at the end cannot be processed, which can have impact on business processes.

The average key detection score that we found of over 90% is a good result for monitoring purposes but poses data quality challenges in the audit domain.

Automation of the invoice detection process can substantially increase the quality of data for auditing purposes. In potential, the early-stage machine learning solution is likely to set off the limitations in extraction accuracy. Additionally, CA implementations can cover a wider scope – in terms of the processed volume of transactions, as well as the timeframe – of audit samples. Last, this audit technique simplifies the sample extraction for performing manual audits when needed.

In addition to advantages of CA for the auditing domain, continuous auditing within the invoice process enables automation of several (internal) auditing and control activities that may reduce organizational risk. Extracted fields can be compared to whitelist and flag potential fraudulent invoices, for example, an automated check of IBAN to known bank accounts or the automated provision of a supplier credit score using the Company Registration number (KVK). Although the insights and results of the tested audit technology are promising for the use of CA auditing, there are also required CA elements that we did not cover in this study. For example, real-time auditing demands a continuous auditing process embedded into the operation. In other words, CA relies heavily on IT solutions and technological advancements such as an ERP system (Vasarhelyi et al. 2012). However, we did not test the accuracy of the OCR potential in an operational setting to measure any interaction in an invoice process. In this way, we did not test whether audit technology identifies anomalies in a real-time operational setting. This limitation of the study is important since our theoretical framework explains that CA is about identifying errors during the process and not after the fact.

In summary, the potential of the early-stage machine learning solution lies in the automated checking of invoicing accuracy by OCR technology against an algorithmic rule set. With this technology, invoices can be checked continuously, and when a transaction violates a rule in the predetermined rule set, this deviation triggers an alert to the internal auditor (Gonzalez and Hoffman, 2018). In addition to the CA potential of the solution, we also addressed the limitations.

5.3. Continuous Assurance (CAS)

To continuously provide assurance, an audit solution relies on the maturity of underlying CM and CA solutions. The sum of these automated systems within an organization determines whether CAS can be attained.

The scope of this study covers early-stage audit technology in a standalone situation. The results indicate that there are opportunities for CM and CA purposes. However, the step from CA to CAS requires an evolution in scalability, as well as technical improvements in accuracy.

Attaining CAS from a scalability perspective requires a substantial percentage of the organization's transactions to be covered. CM and CA tooling should ideally be deployed across various business processes to give a full spectrum of controls.

From an accuracy perspective, there is a gap to be closed to attain CAS. An accuracy of 90% over the scope of the invoice process is insufficient to provide assurance within accounting standard practices. Technological advancements, data qua ons for the level of assurance needed. The organization's data source is in general more reliable (as the organization could not have tampered with the data); therefore, a lower threshold might be acceptable. It is therefore important that the profession facilitates further research on the audit techniques empowered by technology.

5.4. Research implications

In the previous section, it is discussed how the algorithm can contribute to the different stages of CM, CA and CAS solutions. In this section, we consider the research implications on a more general level. They are are shared as the key takeaways, contributions, limitations and suggestions for further research. In doing so, the idea is to improve and support the need to implement new audit approaches to keep pace with the changing and modern business environments (Eulerich and Kalinichenko 2018).

5.4.1. Computerization versus digitalization

This research contributes to the necessity of adopting digital technologies for auditors in deploying automated tooling to conduct the planned audit faster, more efficiently, more accurately and in more depth. To this extent, the tested audit technology provides insights into the challenges that are present in achieving (near) real-time assurance. Reflecting on our research, we found that an important restriction crept in the design of the research. This limitation addresses how we distinguish between computerization and digitalization. In short, computerization is considered the automatic execution of repetitive tasks to assist operations and activities of organizations (i.e., IT is supportive of business processes, hence secondary). Digitalization refers to fundamentally remodeling operations and activities so that they are fully executed by modern technologies without (human) interference (IT transforms business processes). For example, creating a design with computer software and having it printed by a 3D printer that directly makes the design. In other words, computerization such as putting a design in a fast moving machine to complete an assembly line does not structurally transform the business process, digitalization does.

In relation to the conducted research, we argue that the initial design of the audit technology is built as a solution that focuses on automating a manual check in the invoicing process. The tool is not positioned as an embedded check within a fully digitalized process. For example, if the invoicing process is fully digitized, an electronic invoice (e-invoice) can function as a structured, digital file (not a PDF) in which all data are in a fixed place in the file and have a specific meaning and definition. Because of the structured invoice format, the source is more accurate and complete. Checking elements, such as the translation of the received invoice to processing in an ERP system, are no longer necessary. Additionally, the scanning of invoice labels with OCR technology becomes obsolete.

However, this research makes a significant contribution to today's audit profession. Currently, 33% of invoicing only occurs in fully digitalized matter in the Netherlands . The machine learning solution presented in this paper can bridge the gap between the analog and digital world and accordingly provide valuable insights into how to provide real-time assurance with audit technologies.

5.4.2. Directly accessing data sources

Another contribution lies in the central argument of this paper, namely, that machine learning solutions are positioned to obtain direct information without auditee interference. In practice, auditors experience challenges about data quality and audit evidence. Well-known scandals illustrated that it is insufficient to rely only on documents, receipts, or management representations. Rather, the auditor must go beyond the façade and question the truth of any information received. However, relying heavily on the human factor of the auditor does not seem to be the way forward in a highly digitized world. Audit quality directly depends on correctly evaluating the probative value of the evidence, which is indispensable for a correct reconstruction of the "reality" (Gronewold 2006). This research shows that audit technologies can therefore support the audit profession to get close to this "reality" of the evidence and to provide a reasonable basis for rendering an audit opinion and providing real-time assurance.

5.4.3. Skills in using audit technologies

To improve and support implementing new audit approaches, the importance of skills that are required in using audit technology must also be acknowledged. During the research, we found that deep knowledge of the tested audit technology and underlining machine learning was required. This finding underlines a challenge often highlighted in research with regard to the adoption of audit technologies. The main reason why the adoption and use of audit technology are substantially below expectations is because of the lack of skilled and experienced auditors in using these technologies (Appelbaum et al. 2016). Auditors that are new to using audit technologies may not be able to create effective models, which could lead to failure of misstatement detection or overwhelming false alerts (Dai and Vasarhelyi 2020). Therefore, this research provides insight into the necessity for auditors to develop a skill set that is fit for the digital era.

5.4.4. Digital technologies in audit

Finally, this study contributes to emerging research on smart technologies in the audit and accounting profession (Dai and Vasarhelyi 2020; Lamboglia et al. 2020). To date, researchers have explored different topics, such as acceptance and use of audit technologies, focused on the use of technologies to avoid business risks or studied the analysis of auditors' professional skills and knowledge (Lamboglia et al. 2020). However, limited papers are present that analyze new technologies, such as big data analytics, machine learning and the Internet of Things. Our research contributes to addressing this research gap by providing insights into OCR- and machine learning based technology. For successful deployment of CA techniques at scale, close organization auditor collaboration is needed to overcome the technological challenges related to organization specific IT landscapes. External auditors may develop their own CA tooling that ensures flexibility in data collection to maximize reusability at various auditees. Flexibility will likely be at odds with quality criteria such as accuracy. However, standardization, technological advancements and scale can potentially support the external auditor in this task. In the end, working toward an audit data lake containing CM and CA output is a plausible way toward CAS. This separate audit data source, managed by the auditor, contains a set of audit data of the required quality, which can be employed to considerably increase the quality of the audit. To create this effect, it is essential to include the audit objective in any business process digitalization. Auditors play a key role in ensuring that this valuable topic lands on any organization's agenda.

6. Final remarks

This study started with the notion of irreversible digital transformation and its relation to the audit profession. In the digital business climate, the need to implement new audit approaches to keep pace with the changing and modern business environments is stronger than ever before (Eulerich and Kalinichenko 2018). Although the benefits of audit technologies are becoming clear, their actual implementation level by practitioners is still in an early stage. (Hardy and Las-lett 2015; Weins et al. 2017; Vasarhelyi et al. 2018). This study addresses this research gap and provides guidance about the practicalities of audit technologies.

6.1. Value

In the particular research design, we aimed to understand how an early-stage machine learning solution can contribute to providing (near) real-time assurance. An early-stage machine learning algorithm, in combination with OCR technology, was tested in the specific scope of an invoicing process. Our results provided promising insights into accuracy levels, and we found that audit technology contributes to enhancing CM and CA solutions. However, because of the isolated setting of the technology, we did not find evidence for providing near real-time assurance.

In our view, the research does shed fresh light on the way forward with regard to the use and implementation of audit technologies. Further research should at least consider differences in computerization and digitalization, the required skills of the auditor and direct audit access.

6.2. Acknowledgments

This study is one of the first to be conducted on behalf of the technology lab (TechLab) of the IT Audit, Compliance and Advisory (ITACA) program at the Vrije Universiteit (VU) Amsterdam. With TechLab, we hope to make impactful contributions to a world where business, society and technology are closely related and interact at an increasingly global scale. We want to thank all those involved in building the TechLab and participating in related projects.

Our special thanks go to the BDO Digital researchers who participated in the study. Without their ideas, knowledge and, most importantly, the development of the researched technology, the results would not have been achieved.

6.3. Further developments

The research presented in this paper is based on an early-stage machine learning algorithm developed by BDO Digital. As with all digital technologies, developments are fast paced. This is also the case with the technology used in this paper. BDO Digital has further developed this technology and is currently investigating on how this technology can be used to create a 'Digital Twin' of the financial processes of the organization. Continuously collecting and analyzing data with data pipelines and using machine learning techniques and artificial intelligence creates endless possibilities. The BDO and VU researchers will further investigate the opportunities arising from these techniques in a next research paper.

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Appendix 1: Methodology

To structure the research, a gradual and case-based approach was applied that comprised six stages, each of which is described below (Yin 2017).

Stage 1, the "Plan" phase, had the character of an inventory. The planning stage focused on drafting the research questions and defining the research problem. We created a detailed research plan to determine and define the research questions. A literature search was conducted to shape the research objectives and to empathize with the target audience. This preparation was the basis for defining the research question:
How can an early-stage machine learning solution contribute to providing for (near) real-time assurance?

Stage 2, the "Design" phase, defined the object of analysis. The design stage concerned defining the unit of analysis and the likely cases to be studied. The unit of analysis defines what the case is, for example, an event, a process, or an organization. The scope of this research encompasses the assurance of the invoicing process using the algorithm developed by BDO Digital researchers. In this study, invoicing was considered a key organizational process that relies mainly on traditional data carriers (i.e., paper invoices). To validate the possibilities for near real-time assurance in the invoicing domain, an empirical study was needed to assess the quality of the abovementioned technology. For collecting the relevant data (i.e., invoices), a randomized set of various types of invoices was necessary. They required an independent transcription of key fields in a separate database, which can be compared to automated extraction.

In **Stage 3**, "Prepare", the researchers were equipped to conduct the study. The preparation stage concentrated on activities such as developing skills, training for a specific case study, developing a case study protocol, and seeking any relevant approvals. For this study, the research team was prepared via a demo that was provided by BDO of the OCR technology and underlying algorithm. We checked if there were any relevant issues in the case study design before starting the data collection. We also gained a deeper understanding of the common body of knowledge about audit techniques, as it was important to be familiar with the main concepts and theoretical issues relevant to the study (see Figure 2). In addition, an extensive literature review was conducted using wellknown scientific databases (e.g., Web of Science).

Stage 4, "Collect", involved gathering data from multiple sources and creating a study database. We collected a set of 250 invoices. The dataset was consciously composed of a diverse set of sales and purchase invoices to test the algorithm as best and unbiased as possible. The invoices were heterogeneous in terms of layout, content and structure. Subsequently, a baseline of invoice fields (i.e., invoice number, invoice value, VAT number, etc.) was independently extracted from the invoices. For each invoice, a mixed team of researchers supported by OCR software manually extracted 6 key fields. This dataset was next validated to ensure an uncontested baseline. The manual labeling process clearly contained errors caused by mislabeling and misreading. To resolve this issue, the manual labeling process was updated. Instead of a fully manual process, extraction was automated using OCR and subsequently validated by humans. Some exceptional invoices (e.g., a double VAT number or double company registration number) were excluded from the baseline set, as these exceptions were classified by the researchers as nonstandard. The final dataset of 214 invoices delivered a standardized baseline to test the algorithm.

Stage 5, the "Analyze" phase, was used to interpret the evidence collected and to draft the results. During this stage, the findings were documented, and several feedback sessions were organized within the research team.

Stage 6, "Share", the final phase, was aimed at defining the audience and composing publishable material. The last stage resulted in this white paper targeted for a broad field of academics and practitioners in audit and assurance.

Appendix 2: List of abbreviations

An overview of the abbreviations used in this white paper is presented below:

API	Application Programming Interface
CA	Continuous Auditing
CAS	Continuous Assurance
CM	Continuous Monitoring
EDP	Electronic Data Processing
ERP	Enterprise Resource Planning
GRC	Governance, Risk and Compliance
IBAN	International Bank Account Number
IT	Information Technology
ITACA	IT Audit, Compliance and Advisory
OCR	Optical Character Recognition
SEPA	Single Euro Payments Area
TechLab	Technology Lab
VAT	Value-Added Tax
VU	Vrije Universiteit

TECHLAB

At IT Audit, Compliance and Advisory Program

About TechLab

TechLab is a research line founded in 2020 by the IT Audit, Compliance and Advisory (ITACA) program at the School of Business and Economics of the Vrije Universiteit (VU) Amsterdam, and encompasses multiple themes. This academic base is broadly centered on the impact of technology and related subjects on the audit profession, and studies these topics with own personnel or in conjunction with students and market parties. TechLab publications and meetings offer deeper insights and provide beneficial recommendations aimed at better equipping auditors to audit technological solutions or deploy them in auditing activities. It is strived to effectively identify risks that may have been missed in the past, and accordingly make a modest contribution to more successful audit teams. A higher quality audit can hence be enabled that drives value for all stakeholders.

Feedback and contact

Ideas and suggestions are gladly welcomed to advance what TechLab stands for and attempts to achieve. These inputs can be sent to the following email address: edp.sbe@vu.nl.

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