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ARTICLE

Artificial intelligence and auditing in small- and medium-sized firms: Expectations and applications

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Abstract

Auditing is a field of expertise often mentioned as being ripe for automation using artificial intelligence methods at all levels of operations. Primarily, the application of artificial intelligence (AI) in the auditing profession is done by and for large organizations, leveraging large datasets. While AI approaches for big data are continually improving, methods for small data are scarce. Yet most firms in the world employ fewer than 50 people and can, therefore, rarely rely on big data for automation. In our study, we ask auditors, who mainly audit SMEs, about their expectations towards the impact of AI on the auditing profession and where they expect it to provide the most value when it comes to auditing SMEs. We find that these auditors expect significant improvements in their own efficiency on the job, that learning to use AI applications will not be a challenge for them, and that the use of AI in auditing firms will become mandatory in the future. They expect the performance of certain tasks to become AI-augmented, including risk assessment of individual transactions, conducting audit interviews, performing all manners of analysis, writing confirmation letters, performing the final verification of annual reports, and performing physical observations. Considering these results, we discuss the potential impact of these developments, such as how AI could make the auditing process more effective and efficient but also how AI could lead to an even higher concentration of the auditing service industry.

INTRODUCTION

Artificial intelligence is one of the essential pillars of the Fourth Industrial Revolution and is predicted to influence a wide range of jobs (Schwab, Davis, and Nadella 2018; Kokina and Davenport 2017). Although the foundations of artificial intelligence research are steadily becoming stronger, its application still requires a combination of technology, artistry, and intuition, not least when applying the latest, most experimental methods. From the perspective of industry application, artificial intelligence solutions are currently not “pure package products” but rather require the application of custom designs and installations that consider the specific needs of each project and firm. Integration with legacy systems is an additional source of complexity, which may vary widely between companies depending on their needs, goals, and existing infrastructure.

Auditing is the evaluation of the reliability and credibility of a companys financial and nonfinancial information as well as the systems and processes responsible for recording and summarizing that information. This involves conducting various tests of the company's financial transactions and processes, interviews with management, gathering of evidence to corroborate statements and account statuses, as well as physical verifications of asset values. An auditor is a person, or a firm, appointed by a company to execute such an audit. The purpose is to arrive at an opinion on whether the company's financial statements are free of material misstatements due to fraud or errors. This opinion is expressed in an auditor statement in the companys annual report. Currently, the auditing service market is valued at 215 billion USD and is expected to grow to 295 billion USD by 2028 (VMR 2021).

As forecast by several researchers, artificial intelligence is likely to make the work of auditors more efficient and cost-effective, as well as improve the quality of audits (ICAEW 2018; Kokina and Davenport 2017; Raphael 2015). Studies of technology acceptance of auditors and technology diffusion in auditing firms have been undertaken, but no studies have focused specifically on AI adoption amongst auditors. Many of the applications mentioned in the academic and popular press focus on specific AI technologies in the context of large data sets and big organizations used by specialists.

Small and midsize enterprises (SME)[1] are critical to economic growth and employment. In many economies, SMEs comprise over 90% of all firms and create most new jobs (Mohsin 2022). In many of these economies, SMEs thus constitute a relatively large portion of auditing firms customer portfolios. Recently, auditors have seen more requirements for quality control, compliance with the new standards, and more comprehensive oversight of auditors' work with SMEs. This evolution of the audit profession has made SME auditing more time-consuming and costly and as well as increased the audit risk (IFAC 2018). Coordination, standardization, and automation could, therefore, be a solution to achieve optimization of the auditors' work and lower costs in SME auditing (AICPA 2015; Basuony et al. 2017; Sutton, Holt, and Arnold 2016).

Fraud detection, based on available data and information, is one example of auditor focus when auditing SMEs. Available data for such work includes annual reports of organizations, bank transaction records, invoices, contracts, meeting minutes, and other available documentation of organizational activity. Mostly these are available in digital form, but many SMEs still rely solely on printed materials. The primary operations that could thus potentially be automated involve alphanumeric data, semantic reconstruction and interpretation of events, and contextual risk assessment in terms of organizational opportunities for, and probability of, fraud, serious mistakes, and gross negligence. Among the most resource-intensive activities of auditors, besides the acquisition and collation of necessary data, is the cross-validation of invoice statements with annual reports, finding anomalies (in various forms), and detecting inconsistencies in bookkeeping practices, to mention only a few. For improving auditors' ability, speed, and quality when doing anything from rudimentary surveys, more detailed comparisons, or deep-dive analyses, any automation that can assist in some way, by, for example, focusing auditors' available time on the most relevant data sets, time periods, target individuals, third-party collaborators, clients, and so forth, would be likely to increase auditor effectiveness and thus be extremely valuable.

Research on AI and auditing traditionally has focused on large firms and large data sets. It also tends to be primarily limited to methods based on machine learning and neural networks (Alles and Gray 2020; Kokina and Davenport 2017; Sun and Vasarhelyi 2017; Vasarhelyi, Sun, and Issa 2016). There has neither been an abundance of research focus on using AI in the context of SMEs nor on how auditors[2], who engage with SME clients, perceive AI in terms of opportunities and impacts. This paper explores the expectations of auditors towards AI and what AI applications could be most valuable in auditing SMEs. We address two main research questions: (i) What are the expectations of auditors towards the impact of AI on auditing work? (ii) What potential applications of AI are considered to create the most value in auditing SMEs?

Answering these questions is important for several reasons. First, as mentioned, SMEs comprise a large portion of the client portfolio of many audit firms. As SME auditing costs rise, auditing firms will look for applications to increase the efficiency and effectiveness of the auditing process. AI development is expensive, identifying what AI applications are deemed most relevant by these auditors can give guidance regarding future application development and implementation. Second, auditors have the social role of increasing trust in financial information and preventing fraud and misrepresentations. Understanding how AI could improve its role, and what changes could materialize in the coming years due to AI and automation, adds to our understanding of the link between technology and economics processes. Third, understanding how auditors see this emerging technology's potential in the coming years and decades adds to our understanding of how the technology might diffuse when it progresses along the development curve towards standardization and general deployment. Finally, identifying auditors' expectations towards the use of AI can also guide future researchers in identifying the variables affecting the use of coming AI applications.

The research reported here was conducted in Iceland, where 99% of all firms fall into the most common definition of SMEs. In Iceland, most of these SMEs are obligated by law to disclose an externally audited annual report and send it to a central firm registry. Using the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003), all certified public accountants working in this context were contacted to answer our first research question. To answer the second main research question, audit academics, audit practitioners, and AI academics were brought together, in a workshop-based process, to identify potentially valuable applications of AI in auditing SMEs. In-depth interviews were also conducted as part of the workshops.

The paper is structured as follows: The next section describes the understanding of AI applied in this research. "Artificial intelligence and auditing" describes prior research into AI and auditing and "Methodology" details the theoretical framework applied as well as the research methodology. "Findings: expectations of auditors towards AI" and "Findings: AI applications considered valuable in auditing SMEs" present the findings from the survey and workshops and in "Discussion and conclusions," we present our discussion of the findings and conclude the paper.

DEFINITION AND APPLICATIONS OF ARTIFICIAL INTELLIGENCE

Gartner (2018) states that the incorporation of applied artificial intelligence (AI) technologies into various jobs and processes is one of three main technology-driven transitions that will have the greatest impact on social development in the coming years. They point out that AI is a multi-use (general) technology used to improve and change the use of other technologies and processes. AI in this context is an umbrella term for technologies to collect, analyze, and control complex structured and unstructured data, to automate both digital and physical tasks and processes. AI technologies comprise tools and methods for visual perception, audio interpretation, various database types, probabilistic methods, and machine learning. The boundaries between artificial intelligence and "advanced automation" are not clear and are constantly shifting. Regardless of exactly where the boundaries are considered to lie, the impact of automation and related technologies on various fields, and its potential for improving processes, speeds, performance, and safety, is evident.

Given the AI field's breadth, there is no correct way to fully capture and express different applications, technologies, and domains. One way of illustrating the span of AI technologies is the map shown in Figure 1, based on Corea (2018). The figure gives an overview of some of the methods and technologies of AI development combined with AI's different applications (Corea 2018).

Combining the applications and technology domains gives us specific technologies such as (see Corea (2018) for more examples):

1. **Inductive language programming** that uses formal logic to represent a database of facts and formulate hypothesis deriving from those data.
2. **Robotic process automation (RPA)** that extracts the list of rules and actions to perform by watching the user doing certain tasks in the application user interface with the aim of achieving certain goals
3. **Expert systems** that have coded rules to emulate the human decision-making process for reasoning and to solve certain class of problems.
4. **Decision networks** include a set of variables and their probabilistic relationships that can deal with missing information to solve problems and improve decisions.
5. **Artificial neural networks** that can learn to improve performance without being explicitly instructed on how to do so with the aim of improving decision making, planning, and goal achieving.
6. **Autonomous systems** include the intersection between robotics and intelligent systems and applied, for example, in self-driving vehicles and manufacturing.

The above technologies can be combined with other technologies such as computer vision, which includes methods to acquire and make sense of digital images, and natural language processing, which is used for gathering and analyzing language-based data and communicating with AI applications.

Academic research of artificial intelligence in auditing evolves in conjunction with advances in technology. It seems that the definition of artificial intelligence is broader today than earlier. For example, the definition proposed by Sutton, Holt, and Arnold (2016) divides accounting-related AI into knowledge-based systems and machine learning, which only includes some of the technologies shown in Figure 1. In their overview, Issa, Sun, and Vasarhelyi (2017) only focus on expert systems and neural networks (Issa, Sun, and Vasarhelyi 2017). Given the rapid development of AI, academic research needs to respond accordingly and use flexible definitions and frameworks that fully encompass the variety of technologies under the "AI umbrella" (Gray et al. 2014; Sutton, Holt, and Arnold 2016).

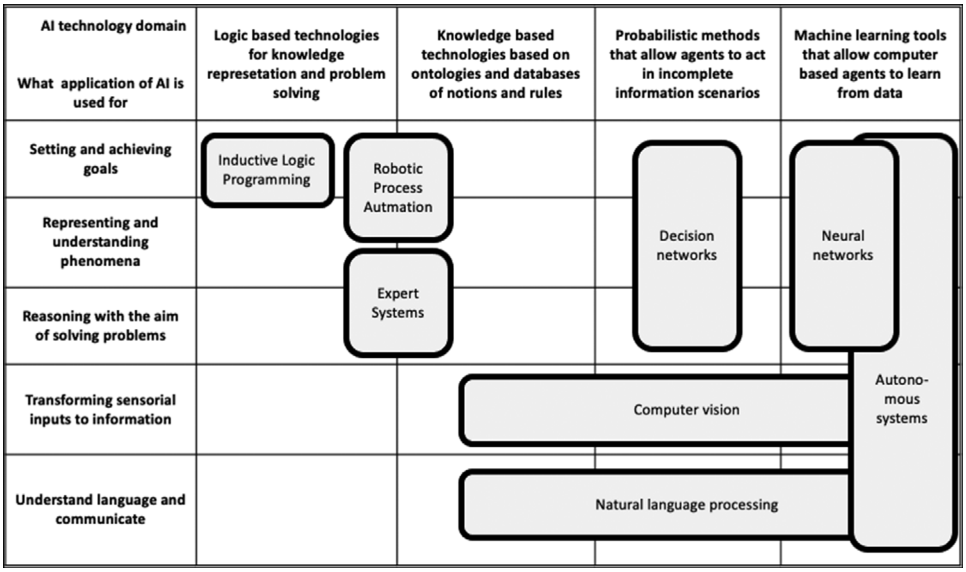

FIGURE 1 A map of AI technologies and applications based on AI technology domains and what the application of AI is being used for (based on Corea 2018)

ARTIFICIAL INTELLIGENCE AND AUDITING

Auditing is based on working with data and other types of information. As information technology evolves so does auditing. Auditors are no strangers to technological developments impacting their jobs. This has been the case with technologies such as the electronic calculators, computers, the database, spreadsheets, and ERP systems[3]. Auditors are, therefore, aware of some of the potential AI has for change, and its potential impacts on the jobs of auditors (Tiberius and Hirth 2019). A variety of forecasts has been made on what jobs will disappear, what jobs will change, and what new jobs will be created with the use and development of AI (WEF 2018). McKinsey reviewed more than 820 different occupations and found that fewer than 5% could be completely automated. However, more than 60% of these occupations were made up of tasks of which more than 30% could be automated (McKinsey Global Institute 2017). Therefore, when it comes to AI, job *change* is more likely to be prevalent soon than job *loss*. All in all, forecasts seem to indicate—some media stories to the contrary—that we are in for an evolutionary development rather than a revolutionary "big bang" (Ford 2016; McKinsey Global Institute 2017; Susskind 2020; WEF 2018). The impact of AI technologies on auditing could be expected to largely follow this.

In general, artificial intelligence can impact the auditing process in two ways. The first impact is that AI by itself is a source of risk as audit clients use AI in their operations. This can generate both operational and financial risk through for example data breaches, incorrect use of data, and reputational risk through AI biases. This vector of impact is the focus of some research, mainly from an internal auditing[4] perspective (Alina and Cerasela 2018; Applegate and Koenig 2019; Chan and Kim 2020), although to this date, those issues remain relatively unexplored in the literature from the perspective of external auditing. The second impact of AI—and the focus of this paper—is that AI can make the audit process more efficient and effective. This has been predicted by several scholars (AICPA 2015; Kokina and Davenport 2017; Sutton, Holt, and Arnold 2016; Vasarhelyi, Sun, and Issa 2016). Numerous articles suggest AI research ideas in this context, present conceptual frameworks, and predict how the impact of AI may happen in auditing (ICAEW 2018; Kokina and Davenport 2017; Omoteso 2012; Raschke et al. 2018; Sun 2019; Van den Bogaerd and Aerts 2011; Vasarhelyi, Sun, and Issa 2016). The audit process includes tasks where artificial intelligence and automation can potentially benefit the audit firms and their clients. Not by replacing the human auditor, but by automating specific tasks and augmenting the knowledge, skills, and competencies of the human auditor in performing others (Faggella 2020).

Looking at technology acceptance and AI, no studies have been done specifically on AI adoption and acceptance amongst auditors. However, there have been studies on technology acceptance of auditors and diffusion of other technologies, including, for example, the diffusion and acceptance of a computer-assisted audit application tools, audit automation tools, testing software, and spreadsheets (Rosli, Yeow, and Siew 2012). Research that specifically focuses on AI and auditing ranges from research showing how various AI technologies can benefit auditors to technical papers presenting designs of specific applications of AI in auditing. In a conceptual paper, Sun (2019) shows, for example, how deep learning can be used in conjunction with text analysis, audio analysis, videos, and images to generate outputs usable for judgment support as well as in various phases of the audit process. She concluded that the use of deep learning has the potential to change the amount and type of evidence considered in the audit as well as the nature and extent of auditor's professional judgment. In another conceptual paper, Raschke et al. (2018) looked at the potential for automating auditor inquiry. They proposed that machine learning can be used to evaluate responses from audit clients and natural language processing to automate the communication process. Based on an interesting study of a RPA pilot project in auditing, Huang and Vasarhelyi (2019: 9) concluded that: "Although the benefits of RPA have been documented in different industries and many audit tasks … applications of RPA in auditing remain relatively unexplored" indicating that research focus on RPA has been relatively limited. Finally, although not using a technology acceptance model, an interesting recent study by Commerford et al. (2021) examined if auditors react differently to evidence from AI algorithms versus human specialists. The results indicated that auditors place unwarranted trust in evidence from human specialists, indicating what the authors call "algorithm aversion" amongst auditors. This bias would be an important element to consider in implementing AI in auditing firms.

Summing up the previous sections, we may conclude that AI is expected to have significant impacts on the audit profession. Current research has focused either on broad technologies and their applications or specific technical designs and applications. Therefore, there is limited knowledge about auditors' expectations regarding AI in auditing and what factors will create the predicted impact. Thus, we do not know what AI applications auditors see as having the most impact on auditing in general and especially not when it comes to SME audits. Referring to the aims presented in the introduction, our research begins to fill these gaps.

METHODOLOGY

Information technology must be accepted and used before it can create benefits in an organization. User acceptance is a rather mature theoretical focus in information technology research, with several models being introduced in the past decades (Venkatesh et al. 2003; Venkatesh and Davis 2000). The red thread running through all these models is the measurement of user expectations of what will influence their use of information technology, how this affects

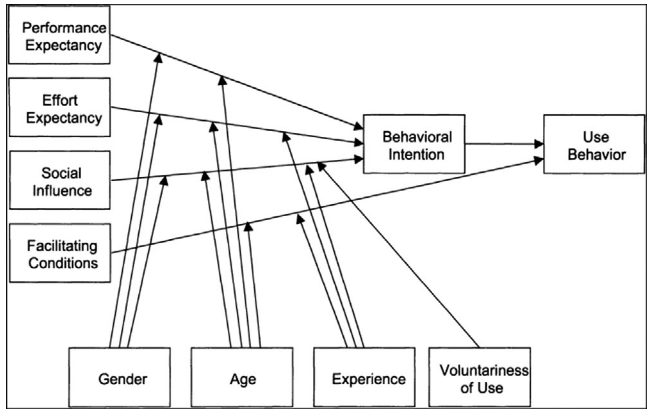

FIGURE 2 The United Technology Acceptance and Use of Technology model (Venkatesh et al. 2003)

their intentions to use this technology, and then comparing this to how actual use of the technology develops (Ibid).

Different models of technology acceptance have been integrated into the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003). Furthermore, Venkatesh et al. (2003) also present different scales used to measure the different variables and propose a unified approach to measuring them. Figure 2 presents the UTAUT model.

This model proposes that user expectation of (i) how the technology will improve his or her performance; (ii) what effort is expected by the user to acquire skills to use the technology; and (iii) social influence and the influence of intermediating variables such as gender, age, experience, and voluntariness—will determine the actual use of the technology.

Examining various technology model studies, some general conclusions can be drawn regarding performance expectations, effort expectancy, and social influence, respectively (Venkatesh et al. 2003):

1. Intention to use information technology is stronger for men compared to women, and younger workers compared to older, if they perceive that it will increase their performance.
2. Intention to use information technology is lower for women, older workers, and those with limited experience, if they perceive it will require a lot of effort to use the technology.
3. Intention to use information technology is stronger for women, older workers, and those with limited experience if they perceive that "significant others" (e.g., co-workers) will promote the use of the technology.

Applying UTAUT in an auditing context for an emerging technology like AI is challenging since few applications of AI are in use by auditors. In the context of this research, no AI applications have made their way to the arsenal of tools at the disposal of the participating auditors. Therefore, it becomes difficult to relate auditors' expectations to "Intention to use" and "actual use behavior" and to answer the second research questions asked in the introduction to this paper.

To overcome this challenge, we design a data collection strategy in two parts:

1. Drawing on UTAUT, we carried out a questionnaire survey of auditors to identify performance expectancy, effort expectancy, and expectations towards social influence regarding the potential use of AI in auditing. In short to measure the expectations of auditors regarding the impact of AI on auditing and their intentions to use this technology.
2. Using a sample of auditors we hosted a workshop, as well as conducted in-depth interviews with them individually, to identify what applications of AI could benefit SME auditing. These opportunities were then evaluated by AI experts and matched with available AI technologies to create an overview of potential AI applications relevant to auditing SMEs. Of course, this is not to say that auditors will use them if the applications are made available. But it gives an insight into what auditors see as important applications of AI in a SME context.

An electronic survey was sent to all 390 members (as per June 2019) of the Institute of Authorized Public Accountants in Iceland. These members include auditors working in auditing firms, in public organizations, and as private practitioners. Of all 390 members, 231 worked in auditing firms. The survey was launched in December 2019 and closed in March 2020 after two follow-up reminders.

The questionnaire was based on the questions and scales published in Venkatesh et al. (2003), which linked to each dimension of the UTAUT. The questionnaire contained the 21 questions shown in Table 1.

To recruit participants for the workshop, we sent an email to the same auditors as the survey went out to, explained the purpose of the workshop, and asked for interested auditors to contact us. We received 11 expressions of interest. From these, seven ended up participating with four from the Big 4[5], one from a smaller audit firm but in an international network, one from a smaller local auditing firm and one from a governmental audit entity charged with also auditing smaller governmental units. The aim was to create a broad base of audit experience and contexts for this part of the study. The participants from the auditing community, each had more than 10 years of audit work experience, were senior managers or partners, and had expressed an interest in applications of technology in auditing. Other participants in the workshop included the research team comprising an AI expert and two academics.

The workshop was held in late 2019. The agenda was communicated to the participants beforehand and included: (i) presentation of participants; (ii) presentation of the research project; (iii) overview of artificial intelligence as a technology; (iv) individual views on potential applications of AI in auditing of SMEs; (v) collective brainstorm to generate as many ideas as possible about where AI could be applied in auditing work with focus SMEs. Beforehand, the participants had received information about the project and the objectives of the workshop. The workshops lasted for 3 h. One member of the research team had the role of taking notes, writing the minutes in cooperation with the other members of the team, and distributing these to the participants afterwards for comments or corrections.

After the workshop, the research team conducted virtual live interviews (using Zoom.com) with each participant in early 2020 for following up on the ideas generated at the workshop in terms of specification of data needs, potential benefits, potential challenges, and potential impact on jobs of auditors and the auditing process. These should only be interpreted as those selected by the workshop participants as potentially creating the most value in auditing SMEs and not as the most valuable applications of AI in auditing overall.

FINDINGS: EXPECTATIONS OF AUDITORS TOWARDS AI

In all, 18% (n = 70) auditors responded to the survey, of which 91.4% (n = 64) are State Certified Auditors, and about 76% (n = 53) work in auditing firms. Tests showed no difference between early respondents and late respondents. Most of the respondents were between 35 and 54 years of age. Our sample was composed of 70% (n = 49) male and 30% (n = 21) females. In all, 53% (n = 37) worked at one of the Big 4 and 23% (n = 16) worked at a smaller auditing firm but in an international network. Of those, 39% (n = 27) were partners and 39% (n = 27) were team managers or similar. In assessing their knowledge of AI, 69% (n = 48) assessed their knowledge to be average or higher.

Regarding the perception toward AI, 94% (n = 66) stated that AI would have a positive impact on auditing, and about 97% (n = 68) answered that it would make the job of the auditors more interesting. About 94% (n = 66) claimed that AI would significantly impact their job, and almost 96% (n = 67) claimed that it would change the profession.

The respondents were also asked about the potential impact on the auditing process as shown in the relevant International Standards on Auditing and related

TABLE 1 Overview of questions and scales used in the questionnaire. Based on Venkatesh et al. (2003)

Variables measured	Number	Question content	Scales used
Gender, age, and experience	1.	Year of birth	Drop down with years
	2.	Gender	Male/Female/Other
	3.	Holder of current state authorization	Yes/No
	4.	Date of state authorization	Drop down with years
	5.	Type of current employment	Big 4/Other international audit firm/Other local firm/Solo practitioner/Not with an auditing firm/Other
	6.	Position in current employment	Partner/Team leader or similar/Other
	7.	Level of knowledge about AI	5-point Likert scale
Expected impact on audit process	8.	Assessment of AI impact on the risk assessment phase of the audit process	5-point Likert scale
	9.	Assessment of AI impact on the risk response phase of the audit process	5-point Likert scale
	10.	Assessment of AI impact on the reporting phase of the audit process	5-point Likert scale
Performance expectancy	11.	Expectations towards AI increasing your productivity as an auditor	5-point Likert scale
	12.	Expectations towards AI increasing the quality of your work as an auditor	5-point Likert scale
	13.	Expectations towards AI improving the performance of audit tasks	5-point Likert scale
Effort expectancy	14.	Expected effort in learning how to use AI applications	5-point Likert scale
Social influence/Voluntariness of use	15.	Likelihood that colleagues will motivate you to use AI in your work as an auditor	5-point Likert scale
	16.	Likelihood that your superiors will motivate you to use AI in your work as an auditor	5-point Likert scale
	17.	Expectations regarding AI impacting your career as an auditor	5-point Likert scale
Expectations towards general impact of AI	18.	Is the use of AI in auditing a positive or a negative development	5-point Likert scale
	19.	Expectations towards AI making the job of the auditor more interesting	5-point Likert scale
	20.	Expectations towards the level of impact AI will have on the job of auditors	5-point Likert scale
	21.	Expectations towards the level of impact AI will have on the job market in general	5-point Likert scale

TABLE 2 Expectations of auditors regarding AI impact on job performance, effort in learning how to use AI, and the social influence on auditor use of AI

UTAUT dimension	Percentage answering Very little or very low	Percentage answering Rather little or rather low	Percentage answering Average	Percentage answering Rather much or rather high	Percentage answering Very much or very high	n
Expectations towards AI increasing your productivity as an auditor	1%	2%	13%	36%	17%	69
Expectations towards AI increasing the quality of your work as an auditor	3%	0%	13%	31%	20%	67
Expectations towards AI improving the performance of audit tasks	0%	0%	11%	41%	16%	68
Expected difficulty in learning how to use AI applications	8%	28%	31%	5%	0%	70
Likelihood that colleagues will motivate you to use AI in your work as an auditor	1%	5%	18%	34%	10%	68
Likelihood that your superiors will motivate you to use AI in your work as an auditor	1%	4%	21%	34%	10%	68
Likelihood regarding AI impacting your career as an auditor	5%	12%	26%	16%	8%	67

guidance documents, for example, from The International Federation of Accountants in the context of small- and medium-sized enterprises (IFAC 2018). The respondent's view is that AI will have rather much or very significant impact on risk assessment (69%, $n = 42$) and on risk response (75.7%, $n = 53$). The view was that AI would have somewhat less impact on the reporting phase of the audit process (55%, $n = 39$).

Table 2 shows the responses to questions regarding performance expectancy, effort expectancy, and social influence.

There were some significant correlations in the answers that indicate that younger auditors perceive their knowledge of AI to be higher than older auditors in that there was a negative correlation between age and perceived knowledge $r\,(67) = -0.278$ and $p = 0.023$. There was also a significant correlation between the position of auditors in their firms and their perceived knowledge of AI with lower positions estimating their knowledge to be greater than higher position $r\,(57) = -0.280$ and $p = 0.035$. Younger auditors also estimate that it will be easier for them to learn how to use AI applications $r\,(67) = -0.253$ and $p = 0.039$. Lower-level employees also estimate their effort to learn how to use AI will be lower than higher-level employees $r\,(57) = -0.321$ and $p = 0.035$. Younger auditors also think that the impact of AI on the productivity of auditors will be greater than that estimated by older auditors $r\,(66) = -0.255$ and $p = 0.039$. Finally, younger auditors, more than older auditors, estimate that the impact of AI on their careers will be more significant $r\,(65) = -0.495$ and $p < 0.01$.

Apart from the age and current position, there were no other significant differences in the answers.

FINDINGS: AI APPLICATIONS CONSIDERED VALUABLE IN AUDITING SMES

As explained in "Methodology," the auditors participating in the workshop and interviews were asked to identify the potentially valuable application of AI in auditing SMEs, and where they would see the most benefit in applying. These ideas were then evaluated by the AI experts. The below describes these applications in terms of auditing problem solved, value created, key development issues, and key challenges.

AI-based risk assessment of individual transactions

The auditing problem addressed is how the validity, completeness, and accuracy of individual transactions can be automatically assessed. Today reconciliations and validity checks can be a laborious process and the risk of mistakes is always present—especially with SMEs. Using AI to perform these activities could result in substantial savings, reduce the risk of errors, thus improving the quality of the audit. The first application is to automatically identify and flag unusual transactions between, for example, unrelated accounts, to seldom used accounts or to accounts that did not fit the transaction. Second, to identify outliers that could indicate an erroneous or fraudulent transaction. Finally, to assess authorizations for transactions. Whether this would be done in real time or as a part of an audit was not addressed as such but in the context of SMEs, it would be more likely that this was carried out as a part of the audit.

From an AI development perspective, the key issue in developing the technology is teaching the AI the difference between what transactions are within given criteria and what transactions lie outside it. This is to ensure that the right transactions will be flagged and to minimize the number of false positives. To do this, a machine learning algorithm, such as a deep neural network or rule-learning system (or a combination), would have to be set up and trained. It would have to be trained on data that included correct and incorrect transactions within the parameters specified. Usually, the data volume for such training needs to be very large (on the order hundreds of thousands of data points) and uniform (having a small set of recurring structures). In an SME context, this gathering and composing an adequate set of transactional data and applying the desired criteria to train the system is a challenge. Using whole accounting data sets from many companies for several years to train the network could overcome this limitation. Another challenge lies in properly preparing this data, including verifying that it represents the desired content in the correct format—this can only be done programmatically as manual work would be too expensive. A third lies in ensuring that the application of the trained system is in accordance with the background assumptions underlying the training, which would mean an extensive control of the output of the network being trained. The time usually needed to train such a system depends on several factors but is typically counted in months rather than weeks.

AI-augmented audit interviews

In planning and carrying out an audit, auditors conduct several types of interviews and meetings. One type is management interviews for, for example, risk assessments, another type is meetings in the auditing team to plan the audit, and the third type is interviews to confirm practice or transactions, ask for clarifications, and deliver results. Today these interviews are seldom recorded, notes are in local repositories, and knowledge does not get transferred between audit teams. AI could be used to capture and automatically analyze client-related verbal interactions. The AI could create a repository of central knowledge about the client's risk profile, business operations, and related parties. It could propose planning of the audit in terms of what audit activities should be carried out to match the risk assessment as well as trigger advice based on specific words or phrases. This could increase the quality of the audit, ensure risk assessment, save resources, improve planning, and ensure better documentation of the audit.

To develop these applications, several technologies could be combined, including speech recognition, which has evolved extensively for the past years. Advanced models and software already exist for this task although an audit-specific vocabulary might need to be developed. Other components of such a system could be based on semantic Web standards and methods (e.g., RDF, OWL) could provide a needed framework for efficient human–machine collaboration on structuring the data. Designing the right combination of hardware (microphones), noise-rejecting speech recognition, end-user text and information-editing tools, and content-based search methods is necessary for such a technology to be worthwhile to the auditors. This is likely to take several iterations of design and deployment before an acceptable solution is found, each counting several months and dozens of people.

AI-augmented analysis

An important source of substantive evidence is external data. Such data can be analyzed and compared to firm-reported data to assess the validity and indicate over- or underestimation of amounts or other firm-reported information. This can then lead to validation or further investigations by the auditor. The work involved in getting such evidence can be substantial, however, leading to other types of evidence being collected instead. There is an opportunity in that new sources of data are now available in digital form, as well as new forms of data. Using AI to gather, process, and compare data to firm-reported data could lead to more efficient audits and reduce the risk of misrepresentation in annual reports. Such analysis could also potentially generate an additional revenue stream for the audit firm on its own.

The main automation technology applied would be like that described for "AI-Based Risk Assessment of Individual Transactions" above. In one approach, the AI might be trained beforehand to compare a new dataset to a set of targeted outside sources. In this case, the choice of outside sources would be still done by the auditor, based on the AI technologies at their disposal. The development of this technology is heavily dependent on the scope of the data and the amount of the automation sought. As in all of these, the quality of the data is both a fundamental limiting factor of the result of such technology and the cost of development. There is little doubt that this area presents some good opportunities for efficient and effective automation using AI, but work needs to be done to further limit and define the scope and specific aims of the automation.

Automatic confirmation letters

As part of the audit process, auditors compose and send messages/letters/emails to third parties such as creditors, debtors, and customers to confirm transactions and statuses on the account. These communications are mostly standardized but require time and attention. Given that this is mostly in electronic form, there could be an opportunity to automate this correspondence. This would save time and resources as well as ensure that this part of the substantive evidence chain is secured.

Examples are requests for verification of account balances from customers and suppliers. An AI could select the accounts and the balance that need to be verified, compose the correspondence, email the confirmation request, read the response, and update the confirmation status. A potential technology use would be RPA given that this task is repetitive, and rule-based (see Figure 1). The RPA application could encompass the entire portfolio of SMEs in the audit firm or be set up for each individual firm. The RPA would open the files containing third-party details, select from confirmation letter templates, enter the account balances that need to be confirmed, send an e-mail, receive a response, read the response as either positive or negative, if positive mark the balance as confirmed. If negative, then an alert is created for the human auditor. RPA technology is maturing into standardized solutions and use cases for confirmation letters already exist from vendors such as altexsoft.com. The challenges would lie in the cost of such solutions for an audit firm, setting up the solution to reflect the SME portfolio, ensuring correct contact information for third parties.

Automating the final "tick & tie"

Before releasing the annual report for signatures, the numbers and the text in such a report goes through a final check to ensure that the audit has produced evidence of the validity, accuracy, and completeness of the numbers reported. This documentation is in the form of working documents, journals, and references to the corresponding relevant transactions in the client's systems. The process is manual and very time-consuming. There is an opportunity to develop an AI that can go through the numbers in different clients' annual reports and automatically check the relevant corresponding data for validation.

When the audit is done, the annual report is ready in draft form, usually in an electronic format. The AI compares the text and numbers to the corresponding documentation available in a central repository. The AI needs to be trained in each of the components of the annual report and the type and scope of the necessary documentation. It produces a "tick & tie" score for the human auditor to follow up on in case of low scores.

One possible approach is to use a combination of RPA and machine learning. Deep learning is now well versed in recognizing a variety of handwriting and images, as well as text and numbers. This could be used to recognize and process different document formats, whereas RPA would be used to integrate such operations into the auditing process workflow. Among the larger challenges is the design and implementation needed for coordinating and integrating automatic operations into the workflow, which can vary greatly depending on the type of firm and department being audited.

AI augmenting physical observations

During an audit, auditors can have to verify the existence, state, and valuations of assets through physical observations. A common one is an inventory audit, where the auditor counts samples of inventory and compares them to firm registrations. Gathering such evidence is manual, time-consuming, involves few skills, and prone to errors. Using AI to augment such audits would save time and increase the quality of results as well as augment the audit results in some cases.

One example is the counting of physical inventory in the form of product components, raw materials, and ingredients where the AI could assess number and state of these in a controlled setting such as a warehouse. The second is to have the AI augment the counting of stock in other environments such as crops in a field or livestock. The third is to have the AI that also assesses the quality and value of the above in conjunction with the counting. This could include evaluating the financial value of a crop on a field before it is harvested taking its maturity, quality, and market value into account.

The main technologies applied are visual recognition and machine learning combined with drone technology. Drone technology is rapidly maturing with various firms selling drones for visual observations in agricultural and manufacturing settings. Examples of such vendors are Precision Hawk and Flytware. There are also various firms developing and selling AI for analyzing and assessing the visual data in terms of counting and quality. Examples include Mobidev and Scopito. Although this technology is becoming standardized and broadly accessible, there are still challenges to be addressed in an auditing context. Many of the solutions on the market are focused on one context with specialized applications in, for example, agriculture or surface mining. An auditing firm might have to develop solutions that encompass a variety of context depending on the client portfolio.

DISCUSSION AND CONCLUSIONS

The research questions we asked in the beginning were: (i) What are the expectations of auditors towards the impact of AI on auditing work? (ii) What potential applications of AI are considered to create the most value in auditing SMEs?

Using the UTAUT model to answer the first question, the adoption of AI technology is seen as positive by the responding auditors and will add value in terms of lower costs and increased audit quality. Contrary to predictions of the UTAUT literature, there is no gender difference in the responses at all. Male and female auditors have the same expectation towards the impact of AI on productivity and auditors' jobs. The homogenous educational background and positions of the responding auditors could explain this to a degree. As predicted by the UTAUT literature, however, there were age-related differences in the responses regarding the expected impact on career advancement, effort in learning how to use the technology and the knowledge about AI. In general, younger auditors in lower-level positions expect AI to have more impact on their work than older auditors in higher-level positions. This makes sense considering the speed of AI development and how long younger employees can expect to stay on the job market.

The answer to the second question is the applications pointed towards by the interviewed auditors as creating the most value. These were applications that augment auditors in risk assessing individual transactions; conducting interviews; performing analysis; writing confirmation letters, performing the final verification of the annual report, and performing physical observations.

The responding auditors expect that AI use will lead to improved performance and make their jobs more interesting and that the use of AI will become mandatory in auditing firms. The responding auditors do not seem worried about AI replacing auditors as has been predicted and referred to earlier. The nature of auditing services might change but the fundamental product—that is, trust and assurance—remains the same. Although auditing will be augmented by AI, there is a role for human agency. However, it is noticeable that the larger audit firms are focusing on and investing in AI (Faggella 2020). This is also the case in our study. This could mean that as AI develops, mainly larger auditing firms will have the resources necessary to implement AI-augmented

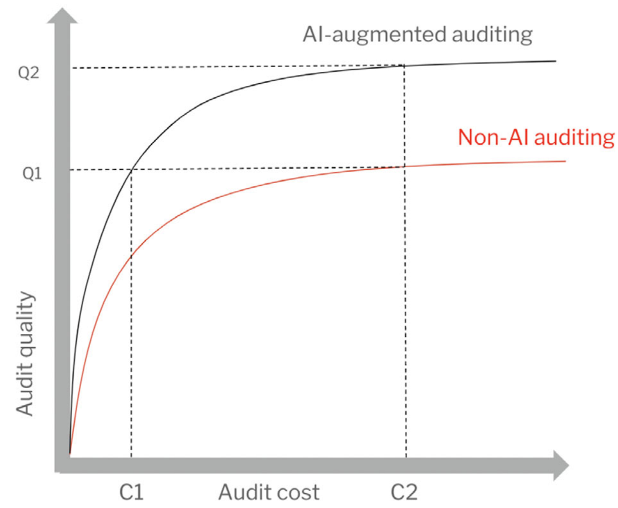

FIGURE 3 The costs and quality relationship between non-AI auditing and AI-augmented auditing

auditing. If audit customers come to see AI-augmented auditing as creating more trust (Alles and Gray 2020) with audit stakeholders than non-AI auditing services, this will increase the demand for AI applications in auditing. Given that AI-augmented audits will deliver higher quality at lower cost following the law of diminishing returns, this could produce a divide between AI augmented auditing and non-AI auditing as illustrated in Figure 3.

Auditors not using AI may not be able to match the quality nor the price of AI-augmented auditors. This could lead to an even more pronounced concentration of the audit industry with a few very large firms dominating the market. Smaller auditing firms could risk facing insurmountable investment and entry barriers into AI-augmented auditing. This is analogous to what has already happened in some other industries. This would be an interesting research subject as the adoption and applications of AI in auditing mature.

Another question is if AI development has the potential to disrupt the 295 billion USD a year auditing industry by enabling other types of firms to enter as competitors. Audits are currently required by law and governed by standards and various regulations. If the use of AI shifts trust from the auditing firm to AI augmented audits, then this could open a way for firms in other sectors such as technology, accreditation, law, and engineering, to acquire a part of that market. Examples could be firms offering new ways of physical observations through AIs and drones, new analysis of third-party data to support audit evidence, and firms offering new audit support services such as smart contract reviews. Such change in the audit ecosystem with new providers of services replacing the services offered by auditing firms or taking bites out of the revenue streams could leave auditing firm managers facing the same challenges as managers of brick-and-mortar bookstores, videotape rentals, and film developers. In general, managers in auditing firms will need to decide on how to develop and apply AI. It means in general staying abreast of technological developments, experimenting with AI, and participating in AI development ecosystems through, for example, universities or innovation accelerators.

To respond to these pressures, auditing managers would need to consider paths of innovation and the challenges faced by in-house innovation processes in large companies. Fundamentally, it means answering three key questions on how to develop AI in an auditing firm:

1. Do we embed AI into existing core or business line solutions to increase automatization and worker sentience of processes and activities?
2. Do we invest in the competencies and capabilities necessary to build our own AI solutions?
3. Do we invest in start-up firms developing AI technologies that are relevant to meeting our business challenges?

The development of how audit firms innovate and adopt AI would be an interesting research topic in the future.

Finally, the emergence of an AI-augmented auditor also raises issues regarding auditor education. As the use of AI in auditing develops, auditing educators would need to revise their curricula and keep abreast of AI-related developments and impacts. Auditing educators should explore teaching, for example, AI package interactions, AI quality assurance, AI setup, professional judgement, interdisciplinary team management, ethical thinking, and consultative skills. Moreover, they should put less emphasis on, for example, sampling, inventory evaluation, and bookkeeping. Making these changes would require an interdisciplinary approach to developing the auditing education of the future.

Although not without limitations, our study sheds light on what auditors engaging with SMEs deem the most valuable AI applications to develop and apply. It also shows that the expected acceptance of AI by these auditors will be high. Our study points towards several potential future developments in terms of industry effects and impacts on audit education that merit further attention.

ENDNOTES

[1] We use the EU definition of an SME as an organization with less than 250 employees, a revenue of under EUR 50 million and a balance sheet total of under EUR 43 million. https://ec.europa.eu/growth/smes/sme-definition_en.

[2] We use the term auditors in this paper to mean the auditing professionals who do not have any special AI knowledge but will apply the technology when it becomes available through the audit firm internal technology portfolio or through the audit firm's technology purchases.

[3] Enterprise Resource Planning systems are the software many companies use to manage day to day business activities such as sales, procurement, accounting, production, materials management, and human resource management.

[4] Internal auditing is performed by internal auditors who, contrary to external auditors, are employed by the organization they audit. Their job is to help the organization accomplish its objectives by bringing a systematic, disciplined approach to the evaluation and improvement of risk management, internal controls, and governance processes.

[5] The term "Big 4" denotes the four largest auditing companies that dominate the global auditing market: Deloitte, PwC, KPMG, and EY.

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CONFLICT OF INTEREST

The authors declare that there is no conflict.

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