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Adoption of AI in the Auditing Practice: A Case study of a Big Four Accounting Firm

Jiaqi Yang
Macquarie University, jiaqi.yang@hdr.mq.edu.au

Yvette Blount
Macquarie University, yvette.blount@mq.edu.au

Alireza Amrollahi
Macquarie University, ali.amrollahi@mq.edu.au

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Full research paper

Jiaqi Yang
Macquarie Business School
Macquarie University
Sydney, Australia
Email: jiaqi.yang@hdr.mq.edu.au

Yvette Blount
Macquarie Business School
Macquarie University
Sydney, Australia
Email: Yvette.blount@mq.edu.au

Alireza Amrollahi
Macquarie Business School
Macquarie University
Sydney, Australia
Email: ali.amrollahi@mq.edu.au

Abstract

This paper explores and explains key factors influencing the adoption of Artificial Intelligence (AI) in the auditing practice by a Big Four accounting firm, through the lens of the technology-organisation-environment (TOE) framework. Using the case study method, we conducted semi-structured interviews with decision-makers of the firm, complemented by secondary data. The findings showed that the firm's adoption process was influenced by technology affordance, technology barriers, communication process, linking agents, firm scope and readiness, regulatory environment, and predicted industrial changes. This study will contribute to the literature by providing a better understanding of AI adoption at the firm level. It may strengthen the theories that underpin our understanding of the technology adoption, elaborating the TOE framework with more empirical evidence. The practical contribution to the auditing profession is that firms can use the knowledge to evaluate whether the functionality of AI fits into their firm's context and external environment.

Keywords Artificial Intelligence; Auditing; TOE framework

1 Introduction

Digital technologies drive the reinvention of our work lives. From lawyers to truck drivers, professions of all kinds are upended by emerging technologies such as Artificial intelligence (AI) and automation (Brynjolfsson and McAfee 2014). The audit profession is not an exception. AI has been increasingly adopted by auditing firms to facilitate the auditing procedures at different levels (Issa et al. 2016; Kokina and Davenport 2017). For example, AI-enabled auditing tools using machine learning can perform a range of auditing tasks such as bad debt recognition and bankruptcy prediction (Omoteso 2012). These tools can potentially free auditors from repetitive and low-judgment tasks and enable them to focus on risky areas that require a high level of professional judgment. To date, the Big Four accounting firms (the four most prestigious accounting firms worldwide) have made significant investments in AI for auditing practice (Issa et al. 2016), but the research on the adoption process is limited.

Scholars have consolidated the recent findings and provided a clear research agenda for future research on AI and auditing. In an editorial, Issa et al. (2016) raised 23 research questions aiming to study the application of AI in audit. However, few of these questions have been examined thoroughly. The gaps and limitations of extant research are twofold. The first gap is the neglect of the factors that affect the adoption process of AI-enabled auditing tools. Extant research has mainly focused on the impact of adopting AI on the auditing practice (Seethamraju and Hecimovic 2020), without a good understanding of what drove, facilitated and inhibited their study objects' journey towards adoption. The second gap is that researchers have often focused on the adoption decision rather than the adoption process when studying the adoption of new technology. Previous studies describe firms as adopters vs non-adopters (Siew et al. 2020). This binary approach may not provide in-depth insights for the AI adoption process in auditing. Moreover, the existing literature has only examined the 'technological' aspect of AI-enabled auditing. For example, prior research examined the potential applications of Intelligent Process Automation (IPA) in inventory audits (Zhang 2019). Nevertheless, the affordance of the AI technology alone may not explain why AI is adopted at the firm level (Oliveira and Martins 2011). The adoption of AI in audit practice needs to be examined thoroughly from different aspects (Issa et al. 2016).

This study will contribute to the literature by providing a better understanding of the adoption process of AI-enabled auditing tools by one of the Australian Big Four accounting firms. It will elaborate and extend the adoption theories in the context of emerging technology. The study included two other case studies, a mid-tier firm and a small firm that will be reported in subsequent publications. The results of case analysis revealed substantially different adoption process between Big Four accounting firms and the second tiers/boutique firms in terms of AI technology adopted and the development process. To present the findings with sufficient detail and depth, this paper reports the findings of the Big Four case firm (pseudonymised as PEYG). The study focuses on the functionality of AI in the context of the firm's characteristics and external environment. Specifically, this study aims to answer the research question:

RQ: How does the interplay of technological, organisational, and environmental factors affect the AI adoption process at the Big Four accounting firms?

The following section provides the literature review. The remainder of the paper discusses the research design and methodology, case analysis and findings, and contributions.

2 Literature Review

2.1 AI and Audit

The boundary between AI and other intelligent technology is not always clear; therefore, there is no agreed definition in the literature (Tiberius and Hirth 2019). The "Artificial Intelligence Tree" by Sutton et al. (2016) informed this study by taking a broad lens in considering the contemporary technologies in the AI realm. The term "AI" used in this paper is an umbrella of a series of supervised and unsupervised machine learning technologies such as neural network and nearest neighbour (Sutton et al. 2016). In the auditing field, the idea of using AI and automation can be traced back to the 1950s (Keenoy 1958), but it was not until the 2010s when this field witnessed some substantial advancements. Researchers have conceptualised the transformation of each of the seven distinct audit phases, from the pre-planning to the audit report (Issa et al. 2016). For instance, machine learning tools can perform bad debt recognition (Omoteso 2012); IPA tools can automate the substantive test of inventory (Zhang 2019). These studies established a conceptual ground for examining the technical aspects of AI-enabled audits.

AI-enabled tools have broad use in audit process. AI tools demonstrate different intelligent levels when performing auditing tasks, ranging from basic human support like character recognition to context awareness and learning like natural language processing (Kokina and Davenport 2017). However, many researchers have not considered the intrinsic differences among AI tools (Seethamraju and Hecimovic 2020). To better understand the AI adoption process by PEYG, an “adoption spectrum” was used, which include the typology of AI, adoption process, task coverage, development process and integration level (Kokina and Davenport 2017; Munoko et al. 2020; Poba-Nzaou and Raymond 2011).

2.2 Adoption Theories

Considering the exploratory nature of this study and the evolving nature of the AI-auditing context, we developed a theoretical perspective for abductive analysis of our data. The abductive approach is the ‘systematic combining’ where theoretical framework, empirical fieldwork, and case analysis evolve simultaneously (Dubois and Gadde 2002). It enabled us to use an explorative approach at the same time with using theoretical basis in the adoption literature. In extant literature, the Technology-Organisation-Environment (TOE) framework (Tornatzky et al. 1990) has a broad application in examining the technology adoption at the firm level. The TOE framework explains three different categories of factors influencing the adoption of new technology. These three categories are the technological context, the organisational context, and the environmental context (Baker 2012). The technological context includes the characteristics and availability of technology. The organisational context includes the firm’s formal and informal linking structures, communication processes, size, and resource slack. The environment context is the arena in which a firm conducts its business, including the industry characteristics and market structure, technology support infrastructure, and government regulation. The comprehensiveness of the TOE framework provides a good explanation about the firm’s technology adoption. In the auditing field, the TOE framework has been used to understand auditing firms’ adoption of new technologies, such as the adoption of the Generalised Auditing Software (Widuri et al. 2016) and Computer Assisted Auditing Tools (Siew et al. 2020).

3 Research Design and Methodology

The study used the qualitative case study method. The data were collected using semi-structured interviews with decision-makers of Australian accounting firms, complemented by secondary data. The coding techniques by Corbin et al. (2008) informed the case data analysis. Abductive reasoning was used as the guiding principle to connect data with the theories that underpin this study. Examining the adoption of AI by auditing firms requires an in-depth and comprehensive understanding of the context of the firm. This understanding is best obtained by using the case study method, which is an empirical inquiry that investigates a contemporary phenomenon within its dynamic context, especially when the boundaries between phenomenon and context are not clearly evident (Yin 2018). The case study data were collected from multiple sources of evidence to be able to triangulate the data.

3.1 Case Selection

The selection of cases was informed by prior research that firms with different TOE factors could be grouped by the firm size, reflecting differences in the organisational resource slack, client segments, competitive environment and other factors (Lowe et al. 2018). In the literature, using three different categories of cases met the replication logic of the multiple-case study (Yin 2018). The number of cases selected for this study was similar to the convention of case study research in IS adoption and auditing areas (Widuri et al. 2016). The selection of cases was purposive, driven by the research interest to deeply understand the adoption process, not simply the adoption decision. Thus, the key criteria for case selection were that firms should have already finalised their decision-making on adoption and had launched some formal projects, witnessed by the approval of funds for either in-house development or external purchase. Among nine firms approached, six firms responded to the participation requests, and three firms from each of the Big 4, mid-tier and small/medium categories were selected. The understanding of the AI adoption in PEYG was first obtained from the publicly available information such as the firm’s public report, media release and news. Then the managing director was contacted to confirm the adoption status and request for participation.

3.2 Data Collection

Thirteen semi-structured interviews were conducted with three case firms, each lasting between 30 minutes to one hour. Interview data was complemented by secondary data, including the firms’ transparency reports and news releases. The selection of interviewees was purposive, aiming to obtain the understanding of the adoption process from the different perspective of decision-makers, users and developers. Thus, within three firms, the interviewees are from two categories: (i) people who led, participated in, or influenced AI adoption; and (ii) those who had extensive knowledge and experience of the adoption process, including engaging partners and IS/IT experts. After each interview, the snowballing method was adopted to locate the person who is in the best position to answer the questions that had not been fully addressed. Within PEYG, five interviews were conducted, including the assurance partner and transformation champion (A1), the director of assurance digital transformation (A2), two senior managers from the in-house development teams (A3, A4), and one data scientist (A5).

The interview guide was developed and refined in a way that was pertinent to the context of AI and auditing. It contained four sections, including the 24 questions about the spectrum of adoption (Munoko et al. 2020; Poba-Nzaou and Raymond 2011), technological factors (Oliveira and Martins 2011), organisational factors (Zhu et al. 2006), and environmental factors (Widuri et al. 2016). As research progressed, the themes contained in the interview guide were constantly compared with the data collected. The interview guide was reinforced in a way that is more pertinent to the context of AI-audit. For instance, the "IT infrastructure" was an adoption factor examined in prior literature (Oliveira and Martins 2011). However, the case data revealed that AI tools had requirement on data infrastructure rather than IT infrastructure. These findings informed some modification of the interview questions.

3.3 Mode of analysis

The coding techniques by Corbin et al. (2008) was used to analyse the case data. Using the abductive approach, the study considered the recommendations of Timmermans and Tavory (2012) to examine the fit between data and theory. Open coding enabled the labelling of the raw data according to different concepts and categories. Subsequently, axial coding was conducted to explore the relationship between the concepts and categories, during which process the themes began to emerge. Finally, the themes and existing theories were compared to evaluate whether anomalies or unexpected findings occur. When the anomalies suggested the changed circumstance or additional dimensions to the existing TOE framework, a tentative proposition was built on the abductive conceptualisation from the data. As this iterative and recursive process continued, the TOE framework was refined to suit the research context.

4 Case Study Analysis

The results of data analysis confirmed the impact of some factors in the extant TOE framework, while significant anomalies to existing theories emerged, revealing the specificity of the AI adoption process in auditing firms. This paper reports on findings from case firm PEYG. The adoption spectrum of the PEYG is shown in Table 1.

4.1 Technological Factors

4.1.1 Technology Affordance

Technology affordance significantly drove PEYG to adopt AI-enabled auditing tools. Technology affordance means the technology potential that comes from a goal-oriented behaviour turning into concrete actions (Strong et al. 2014). The first affordance was the improvement of audit quality by reducing audit risks. AI-enabled applications were instrumental in reducing the risks by standardising and automating the audit procedures. The following quote (A1) illustrates this point: "*Improvements in the quality of our auditing and our audit product. We know that we standardise and automate, we know that quality improves.*" Standardisation means that AI was trained on big data sets, assimilating the decision-making process of many auditors and mimicking their behaviours, where individual auditors' personal bias was expected to be reduced. Audit quality was also expected to be improved by automating repetitive, routine auditing tasks, where the AI-enabled tools outperform human auditors. A typical example of the quality enabler was the supersession of the traditional sampling method by AI-enabled full population scanning and tests, targeting at risks and bias in random selection.

Producing a better client experience was the second affordance of AI-enabled auditing tools. A1, A2 and A5 agreed on the benefits that clients can derive from the value-adding services enabled by AI tools, such as evaluating operational and quality effectiveness, business risks, business performance and compliance. The value-adding service was facilitated by the insights that AI tools obtained from the data pattern that was difficult to be identified by human auditors. In addition, PEYG perceived that the automation of the audit process enabled real-time response. This affordance removed the delays in the communication between auditors and clients by synchronising everyone to the same page when risks were detected, documents were requested, and further steps were planned.

Though AI-enabled tools can improve work efficiency, three out of five interviewees only perceived it as the third-order affordance. Instead of aiming at efficiency improvement, they believed that the benefit was related to the better work experience. The digital/human configuration improved staff experience so that the nature of the work shifted from repetitive, mundane tasks to something more productive, creative, critical, and managerial. For example, A2 noted: "*so, I wouldn't say that we're adopting AI and machine learning with a target of efficiency. There is a secondary benefit of people experience as well. So, if we can take away routine, mundane work from our people.*"

Adoption Timeframe	**Technology Ownership**	**Functions**	**Technological Underpinning**
• AI was first used for consulting services in the US branch in 2014 • The use of AI in audit started in 2017 in the global network • The Australian branch announced the adoption AI in audit in 2017 • Ongoing new applications development with 2-6-month development cycle	• Global tools are developed by Global Technology Centre • Global tools are a digitalised audit platform • Local tools are a joint investment among firms within the Asian-Pacific region • Local tools are a secure web-based portal	• Data analysis engine • Mathematical accuracy tests • Extract information from PDF and reformat • Automate the check of comparative numbers • Match the leger transactions to the supporting documents	• Rule-based Engine • Optical Character Recognition • Data Visualisation • Robotic Process Automation • Analysis and Scoring • Natural Language Processing • Computer Vision • Machine/Deep learning
Auditing Tasks Coverage	**Development Approach**	**System Integration**	**Design Concepts**
• Risk assessment • Risky transaction scanning • Preparing audit work papers • Full population testing • Account classification • Lease documents analysis • R&D capitalisation testing • Client communication	• Primarily In-house development • Heavily rely on open-source tools and Slack • External vendors and off-the-shelf software for less essential applications • Benchmark between vendors and in-house tools	• Tools were all microservices or a series of plugin modules • Must be able to integrate into the grand audit platform and interface with third-party tools • Allow advancements and swap out	• Focus on the practical value that the AI can add to the practice • Tools have simple functions but needed complex design • The Minimum Viable Product (MVP) approach was adopted for the development of most applications

Table 1. Adoption Spectrum

4.1.2 Technological Barriers

During the adoption process, PEYG experienced some technological barriers to adoption. Three out of five interviewees agreed that the 'black box problem' was a concern before adoption. The 'black box problem' refers to the explainability challenge of AI (Kim et al. 2020), where auditors cannot explain, interpret, or document how AI converts the input information into a report. The black box problem first created a trust issue between the users and AI-enabled applications, especially for those constructed on the neural network rather than rule-based engines. For example, some data analytical tools were designed to learn from patterns in the raw data flow through the network layer by layer. Because hidden layers were used in the network, auditors could not visualise the decision-making process of the applications that how they learned from the raw data and what triggered the flags of risky items. One interviewee (A3) noted: "*Bear in mind for all the designers or developers is everything should be explainable. But in reality, it is not the case. (If not explainable,) they don't trust and don't use it,*".

PEYG adopted a risk-based approach to address the explainability challenge. The in-house team always assessed the business risk and context of how AI should be used. In low-risk cases, the accuracy and the explainability was less of a concern. Examples include detecting tables in documents and optical character recognition, with fewer demands on the clarity of the machine's decision-making process but more on the efficiency of the task performance. In high-risk cases where machine learning produced unacceptable outcomes for a black-box decision, the developers would only use more explainable algorithms and visualise the machine's decision-making process. A good example was using rule-engine rather than deep learning in the risk filtering tools. Nevertheless, developers needed to trade-off between explainability and efficiency, as explained by A4. "*And then some of the time we might need to have to use some simple or explainable model to address that, making a sacrifice on accuracies and efficiency*."

The second technological barrier was the biases associated with AI technology. Interviewees A3 and A4 emphasised the issues of the training bias in AI development. Inevitably, biases were introduced by the people who participated in the development process and the data set used to train the AI. The algorithm generated in the development environment may not apply to the client case without biases. PEYG adopted the Minimum Viable Product (MVP) approach to managing the training bias and overcoming the constraints in development environment. After the initial launch of the application with the most critical functions, the in-house team worked in fortnightly sprints to receive feedback from users and iteratively improved the accuracy of the application in real-world settings.

The third technological barrier to AI adoption was the compatibility issues between the AI tools and clients' systems, noted by A2, A3 and A5. The diverse landscape of ERP and finance systems used by clients mean that it was nearly impossible to have a universal audit tool fitting all contexts. Quite often, AI-enabled audit tools cannot read and assimilate the processes, documents and outputs produced by clients' systems. As a result, auditors had to invest in additional manual effort to transform clients' data into the standard data format for the AI application. Though AI-enabled tools automated and sped up some audit processes, the data preparation process consumed extra time and reduced work efficiency.

4.2 Organisational Factors

4.2.1 Communication Process

The senior management had a critical role in embedding innovation into the firm's overall strategy, which drove the firms to use technology innovatively (Tushman and Nadler 1986). In PEYG, the strategy emphasised audit quality, digital transformation, and brand. The adoption of AI in audits was a result of the strategic shift from labour-intensive to technology-led, where technology was perceived as the key quality enabler, growth leverage, and brand builder.

The policies regarding innovation were twofold, consisting of policies fostering innovation and policies controlling quality. A pivotal policy to enforce the strategy was introducing KPIs to each service line, requiring staff to demonstrate how they were disrupting themselves and being innovative. Innovative performance was aligned with remuneration and promotion, which provided sufficient incentives for citizen-led, bottom-up innovation. Meanwhile, a top-down approach, called business-led innovation, guided the firmwide projects initiated at the senior level and scaled across the firm. The development team was granted sufficient authority and backed up by policies to request resources, including obtaining finance and assigning people from different departments to collaborate. In addition, while quality control policies reinforced the risk control side of innovation, they inhibited fast-track adoption. A2 believed that: *"I think our policies are not necessarily designed to drive adoption of AI. They are designed to govern and manage the risks associated with automation and AI."*

4.2.2 Linking agents

In addition to the linkage between strategy and policies, there were other forms of linking agents. The first one was the gatekeepers of innovation. In PEYG, strategic decision-makers only had a broad prospect of using AI in audits, without necessarily understanding how AI could be used to support the specific auditing tasks. The ideation of optimising the existing audit procedures usually resided with front line auditors. Thus, the gatekeeper of innovation was essential to enable ideas to flow up from the bottom. A1 explained that: "*We have citizen-led innovation, so that's from the grassroots up, where we encourage the innovation*." The gatekeepers of innovation were formally appointed senior managers to collect ideas and assess feasibility, as well as organise the internal discussion forum.

The second linking agents were the champions. A1 is the champion in PEYG who was appointed to lead the national project leveraging new technology and methodology in the audit department. A critical role as champion was to gain support from the senior leadership group by educating and increasing their awareness of AI technology. A1 also worked on the global liaison side to use the resources available in the firm's global network. The third role was to work alongside the engagement teams to diffuse the AI-enabled tools among auditors. In addition, PEYG has a strong in-house development team, which also acted as a champion. The development team had incentives to promote the applications to users and prove they were functional. As an example, A4 noted: *"Our goals are to try something new; we need to produce enough projects. My boss tried her own best to promote this to all (internal) clients."*

4.2.3 Firm resource and readiness

Two critical resources discussed by interviewees were financial resources and AI-human resources. Financial resources referred to the capital budget that the firm could spend on developing the AI-enabled auditing tools. The AI-human resources referred to the capacity of the in-house team to develop those tools. PEYG has a development centre (more than 300 employees) working on AI projects using open-source tools. It had less reliance on external vendors and off-the-shelf software. This adoption approach involved high development costs, but was preferred because of the emphasis on AI in PEYG's overall strategy and the resources allocated to the development team.

Regarding the firm's readiness to use AI-enabled tools, all interviewees agreed that no specific IT infrastructure was required since the existing computing power and the network were sufficient to operate those tools. However, A2 raised a point of the data infrastructure, which is the standard data format that can capture data from the client's system for input into the AI tools. This task requires a significant number of employees. In terms of the IT expertise of staff, A1, A2 and A5 agreed that the current skillset of auditors was not sufficient to leverage the AI-enabled auditing tools. Before and during the adoption, digital accelerators and repository centres had gradually taken off traditional auditing tasks, while auditors were required to learn data visualisation and Robotic Process Automation tools. However, the insufficiency of skills was not an inhibitor in both the adoption and roll-out phases. At the decision-making level, senior management believed that automation of auditing tasks created spare capacity for auditors to acquire digital skills through iterative training programs. Auditors were incentivised to upgrade their skills to be involved in more productive, critical, and managerial tasks.

Within PEYG, resistance to adopting AI-enabled auditing tools came from the senior level rather than the junior level. This was caused by the lack of executives' know-how (Zhu et al. 2006). Some audit partners were satisfied with the traditional approach and did not realise the necessity to shift to the digital-driven, AI-enabled approach. A key reason for that was the lack of AI literacy and awareness of the value that AI can bring to the practice. Some partners had experienced failures of previous attempts on innovations in auditing practice, which negatively impacted their perceptions of new technology.

4.2.4 Firm scope

Though PEYG is affiliated with a network of firms from more than 160 countries, the global network had limited input into its adoption process. PEYG had an in-house development team defined by A1 as: "*envy of the network*" and "*a desire to lead*". But the A1, A3 and A4 also agreed that other member firms contributed to the test-feedback loop, and the global team guided integration between the local tools and the global system. It also actively collaborated with other firms within the network, primarily through bilateral partnerships with the UK and the US firms.

All interviewees agreed that adopting AI in other service lines positively impacted the adoption in audits. The impact was permeated through three channels, being corporate capability, collaboration, and clients' readiness. Primarily, the greater use of AI and machine learning in other service lines increased the firm's overall capability. A2 noted: "*The greater use of AI and machine learning and other lines of service increases our organisation's overall capability, and that capability isn't necessarily siloed to individual lines of service.*" Secondarily, collaboration, communication and knowledge sharing among departments served as boundary spanners (Baker 2012). The diffusion of AI technology within the firm was driven by the earlier adopted departments and supported by each other. The tertiary mechanism was indirect, through clients' readiness to use AI. Once clients adopted AI/automation or received AI-powered services, they transited towards a more structured, AI-friendly information system. This, in turn, benefited the adoption of AI in the auditing practice. A2 gave an example: "*If our consulting businesses are working with clients to help them implement AI, then that has a potential to create an overall industry maturity uplift, then it's going to make it easier to use them in audits.*"

4.3 Environmental Factors

4.3.1 Regulatory Environment

The primary impact of regulation came from the Australian auditing standards. The standards were principle-based, meaning that they neither prescribed nor prohibited the use of AI in auditing practice. A1, A2 and A5 agreed that neutrality created obstacles to adoption. Using AI in audits was risk-taking, which challenged the longstanding tradition of the audit profession that is risk adverse. Without back-up from standards, auditors had concerns over the appropriateness of using AI to conduct the work. "*In* *order to do something different, you need some encouragement; you need some cover,*" A1 said. Nevertheless, the anticipated changes to the auditing standards and regulation facilitated PEGY to adopt AI. Decision-makers were aware of the importance of getting themselves ready for the upcoming regulatory change. A1 noted: *"(full population test) is a non-audit, non-assurance piece of work under the current regulations. But pretty soon, if the auditing standards catch up and if methodology moves on, that's going to be statuary audits are delivered."* Decision-makers were optimistic that the changes would be in favour of AI-enabled audit, witnessed by the growing discussion on this topic in roundtables brought together technology experts, professionals, and regulators (FRC 2019).

On the other hand, regulators' focus on audit quality drove the adoption of AI. In PEYG, embedding audit quality into the strategy resulted from the increased scrutiny from the regulators and the concerns from the public (ASIC 2017). ASIC required firms to remediate findings by obtaining the audit evidence necessary to form an opinion on the financial report. Because of the regulatory pressure to improve audit quality, PEYG relied on AI and technology to release the tension.

4.3.2 Industry and Competition

The findings showed that the influence from competitors was weak. A1, A2 and A5 pointed out that there was hype in the market that some firms mainly used AI-enabled auditing as a marketing tool to attract clients and build brand image. The actual use of AI by its competitors was unclear. A1 noted: *"I think all the firms have done enough to put a marketing story out there around what they have done. But who is actually using it in audits on a scaled basis now? I don't think that's happening at the moment."* Another reason for insignificant competitors' influence was that PEYG lacked an insight into competitors' use of AI. Because AI was still in its introductory phase in the audit industry, information regarding the adoption on the market was limited. A2, A3 and A4 admitted that they were not clear about the focus and maturity of the AI technology developed by other firms. It was also difficult for them to assess their position with competitors. *"So, I think the answer is, it probably doesn't influence our decision-making too much because we don't have too much visibility into it. The thing that does influence our decision-making more so is demand from the market and our clients,"* A2 noted.

The predicted changes to the auditing industry drove firms to adopt AI-enabled auditing tools. Decision-makers perceived that digital transformation of the audit was inevitable, and some changes will happen to the auditing industry in the near-medium future. *"When I talk about what's happening here (in audit industry), auditing and assurance services have moved from the backwards looking, point in time, sample based, in the past, and where technology allows us to go now is continuous auditing, real time, possibly predictive, and full population,"* said A1. Interviewees' prediction was also made based on the growing maturity of AI technology, wider acceptance among clients and regulators, and the more robust interface between audit tools and clients' systems.

4.3.3 Acceptance and Resistance of Clients

The role of clients in the adoption of AI was positive, as agreed by all the interviewees. A growing number of clients showed interest in the technological aspects of audit during the tendering process. Interviewees reported that clients had a desire to receive high-quality audit service and more valuable insights from AI-enabled audits. Some benefits to clients were straightforward and readily justifiable at this stage, including more business insights and speedup of the whole audit process. To support this finding, as an example, A2 noted: *"my observation has been overall positive. I think what we are seeing in the market is that clients are very open to us delivering a higher quality audit and more valuable insights. I don't think it's a difficult selling point to make.*" Nevertheless, clients also raised concerns over data security and sovereignty. Some clients were sensitive to using their data for machine learning, especially when the applications were acquired from external vendors rather than developed in-house by PEYG. Clients were aware that their data might be used beyond the objective of delivering the audit engagement, which may be used for training machines and even used for other audit engagement. They were reluctant to given consent for using their commercially sensitive data in a way that they are not directly benefited, as A1 noted: "*I don't think we have any resistance to using AI per se, but they are sensitive to sovereignty. It's becoming more complicated, and so it's harder to deal with that aspect.*"

Clients' resistance may also come from the auditors' request for additional data. The AI-enabled auditing tools required massive data volume, with high data quality and AI-readable data structure. This inevitably needed collaboration from clients, who had to allocate more staff, time and even financial resources to meet auditors' need for data. The engagement teams experienced some pushback when they requested more efforts from the clients, as explained by A2: "*What can become more of a difficult selling point is if we need to request additional data or integration to achieve that. So, some of the broader* *applications of AI in the audit requires to ingest and obtain far more data from our clients than we do today. So that is where we can see some pushback."*

5 Discussion

Within the technological dimension, the affordance of AI-enable auditing tools drove PEYG to adopt them. This finding was consistent with the prior research that the adoption of technology was driven by its affordance (Strong et al. 2014) and perceived benefit (Albawwat and Frijat 2021). However, the impact of technology affordance was not in a vacuum of the firm's organisational context and external environment. Rather, the technology affordance perceived by decision-makers was closely linked to some external factors (Kashi et al. 2016). The findings showed that the adoption of AI was primarily driven by the affordance to improve audit quality, as a result of increased scrutiny from the regulators. The second affordance was the better client experience, which is aligned with clients' desire to receive high-quality service and real-time response. The third affordance was better work experience of auditors, as a way to release the tension of talent acquisition. Findings also revealed the disruptive nature of AI technology, whose affordance is significantly different to the traditional auditing tools that focus more on the task fitness and interface with existing audit tools (Widuri et al. 2016).

On the other hand, the technological issues associated with AI technology hindered the adoption, which is in line with prior research (Venkatesh 2021). The issues can be classified into two groups. The first group were those specifically relating to the inherent design of AI technology, such as the black box problem (Kim et al. 2020) and the training bias (Mehrabi et al. 2019). PEYG developed policies to address these two issues, being the risk-based development approach and MVP approach. It is noteworthy that the MVP approach is usually for lean start-up of system development (Duc and Abrahamsson 2016), but the PEYG applied it as the solution to the training bias of AI. Extant literature examining AI bias mitigation has neglected that MVP approach could be used to overcome the constrains in development environment (Mehrabi et al. 2019). The second group was related to some more general issues using new technology, such as incompatibility. In line with prior research, the incompatibility reduced the scope of application and slowed down the adoption (Widuri et al. 2016).

Within the organisational dimension, the adoption of AI is driven and facilitated by the firm's communication process consisting of the strategy and policies emphasising audit quality, technology and brand (Tornatzky et al. 1990). However, the quality control policies inhibited fast track adoption. In addition, two forms of the linking agents were found in PEYG, including the gatekeepers of innovation and the champions (Baker 2012). Their role was critical in the ideation and diffusion of AI within the firm. The impact of the communication process and linking agents have not been sufficiently discussed in extant literature (Seethamraju and Hecimovic 2020).

Regarding firm readiness, the case data did not support existing literature that firms needed to have established IT infrastructure and IT expertise of staff before AI adoption (Oliveira and Martins 2011). Instead, senior managements' AI literacy was an important factor when assessing the firm readiness (Zhu et al. 2006). The lack of AI literacy among PEYG's senior management was a significant inhibitor to adoption. Moreover, the findings identified three mechanisms the firm scope facilitating innovation, adding to prior research (Oliveira and Martins 2011). The adoption of AI in audit was facilitated by the adoption of other service lines, through the improvement of overall capability, the knowledge sharing as boundary spanners (Baker 2012), and the improvement of clients' readiness (Damerji and Salimi 2021).

The environment dimension of the TOE model was where most anomalies from previous studies occurred. The findings did not support the binary conclusion of previous research that government regulation either inhibited or drove innovation (Kuan and Chau 2001). In the context of AI-enabled audits, the impact of the regulatory environment was complex. The neutrality of auditing standards hindered the adoption of AI (Seethamraju and Hecimovic 2020). The case data showed that the increased scrutiny on auditing quality and the predicted regulatory changes stimulated adoption. However, we were unable to find a discussion in the literature that addressed these issues.

The findings from the PAYG did not support prior research that a firm's adoption of innovation was under the institutional influence of its competitors' adoption (Teo et al. 2003), or support those claiming that the adoption is a direct result of extensive competitive pressure (Zhu et al. 2006). Instead, the impact of existing competition was less significant than the predicted industrial changes on how AI could disrupt the auditing practice (Tiberius and Hirth 2019). Case data did not support prior research that a firm's adoption of innovation was driven by its powerful customers (Iacovou et al. 1995). PEYG reported that clients were open but had increasing concerns over data security, sovereignty and compatibility issues, in line with prior research (Munoko et al. 2020). Therefore, the impact from clients depended on their overall response to the benefits vs costs of using AI-enabled auditing tools in their engagement. The findings of factors influencing the adoption process in PEYG are summarised in Table 2.

Dimension	Factors	Explanation
Technological	Technology Affordance	Technology affordance drives adoption, including better audit quality, client experience, and better work experience
	Technology Barriers	Technology barriers inhibits adoption, including black-box problem, training bias and compatibility with clients' systems
Organisational	Communication Process	Innovation strategy drives adoption, but quality control policies decelerate the adoption process
	Linking Agents	Gatekeepers and champions facilitate the adoption process
	Firm Readiness	Lack of AI literacy among senior management inhibits adoption
	Firm Scope	Using AI in other services facilitate the adoption in audits
Environmental	Regulatory Environment	Neutrality of auditing standards inhibits adoption, but regulators' focus of audit quality stimulates adoption
	Industry	The predicted changes to auditing industry stimulates adoption
	Clients	The impact from clients depends on their overall response to the AI-enabled tools

Table 2 Finding Summary

6 Conclusion

This paper primarily reports on findings from the Big Four case firm. The case analysis of other two case firms and the findings from cross-case analysis will be reported in future papers. This study contributes to the academic community and practice. It contributes to the literature by enhancing our understanding of AI's adoption at the firm level, thus filling the gaps in the extant research (Issa et al. 2016; Sutton et al. 2016). The study provides a theoretical contribution by extending the TOE framework to include influential adoption factors that are appropriate for understanding emerging technology adoption. This study contributes to practice by providing a conceptual framework and data to inform practitioners on the factors for assessing the adoption of AI in the auditing process. Firms that are committed to using AI might find this study insightful, as it provides details on the adoption spectrum and factors pertinent to the adoption process of PEYG, one of the best practices in the auditing industry. This study has some limitations. The primary limitation is that the scope of the study was conducted within the Australian context. The generalisability of the findings in this study may need to be verified by future research conducted in different contexts and countries. Second, the exploratory nature of the study and the qualitative methodology could be further explored with quantitative methods to confirm the findings.

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