TECHNOLOGY AND THE FUTURE OF THE PROFESSION

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TABLE OF CONTENTS

1. INTRODUCTION

We live in an age of unprecedented technological change which has triggered an explosion in information and knowledge. While the pace and scale of change has increased, thus far the accounting profession has largely kept pace with technological progress.[1] The purpose of this report is to review current technological changes and chart a path that enables accounting professionals to continue to thrive in the face of these developments.

1.1 The Technologies:

We focus on three technologies that have been put forward as potential game-changers for the accounting profession:

1. Robotic Process Automation (RPA)

2. Blockchain

3. Artificial Intelligence & Data Analytics (AI&DA)

Each of these technologies embodies both threats and opportunities for accounting professionals as the technologies impact the nature of the work carried out by accountants and auditors. The scope of the technologies varies greatly. For example, RPA can carry out some tasks typically undertaken by entry-level staff providing more opportunities for firms to engage junior staff with more value-added tasks earlier in their careers. In contrast, blockchain technology provides for security and integrity of data and thus can shift the focus of work away from some of the data processing considerations. Finally, AI&DA encompasses a broad range of different technologies for finding patterns in data, and thus demands higher degrees of accounting expertise and experience to make sense of the patterns and their implications for business decision-making.

1.2 A Framework for Evaluation:

As a matter of history, accountants are the original business data professionals. From a data perspective, accounting work can conceptually be broken into three broad yet distinct categories of activities: DATA ACQUISITION & PREPARATION, DATA PROCESSING & ANALYSIS, and INTERPRETATION & DECISION-MAKING. Table 1 below provides illustrative examples of accounting tasks for each of these categories.

Each of the three categories of activities presents a range of issues to be addressed by accountants. The impact of the technologies discussed in this report can be evaluated by considering how the technology alters the role of the accountant in addressing these issues. Table 2 provides details of the range of issues under each activity and serves as our framework for evaluating the impact of the three focal technologies on the professional work of accountants.

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[1] The Australian Bureau of Statistics (2018) forecasts a 4.6% growth in accounting/auditing jobs over the next five years (2023), and that is without recognising the broader opportunities for accountants in other occupational roles.

TABLE 1:
ILLUSTRATIVE EXAMPLES OF ACCOUNTING TASKS BY ACTIVITY CATEGORY & PRACTICE AREA

ACTIVITY CATEGORY	AREA OF ACCOUNTING PRACTICE		
	Financial Accounting	Management Accounting	Audit & Assurance
DATA ACQUISITION & PREPARATION	Determine how changes in accounting standards will impact firm processes and data requirements Determine how much/which metadata to capture De-identify and clean transaction data Research market for fair value inputs	Determine the desirable granularity of data for internal decision-making Identify cost drivers of each firm activity Determine relevant non-financial data Identify appropriate (industry) standards/KPIs for benchmarking purposes	Determine scope and manner of transaction data collection based on auditing standards and scope of the assurance engagement Request third-party confirmations Collect sample of transactions for testing Client site visits to collect data and discuss contextual information
DATA PROCESSING & ANALYSIS	Complete consolidations for intercompany transactions Aggregate costs and revenues into appropriate categories Analyse and identify trends in financial statements	Cost-volume-profit analysis for a new product/service Variance analysis to determine underlying causes Analyse and identify trends in operational reports	Trace a transaction from accounting record to source document and vice versa Compare current year revenues and expenses with prior year results Perform cut-off tests for sales and receivables
INTERPRETATION & DECISION-MAKING	Internally discuss financial results Determine how to contextualise and present firm's financial position to creditors and investors Determine voluntary disclosures for financial statements Prepare a forecast	Assess the impact of an outsourcing decision for labour or goods Determine appropriate pricing for a new product or service Evaluate performance of current firm strategy Produce a flexible budget	Communicate any audit issues with client Prepare relevant notes and summary of audit for next year Render going concern decision Communicate with successor auditor

TABLE 2:
EVALUATION FRAMEWORK

ACTIVITY CATEGORY	Data Acquisition & Preparation	Sourcing data
		Evaluating data reliability
		Evaluating data relevance
		Determining data scope
		Determining data content
	Data Processing & Analysis	Classifying and aggregating data
		Ensuring data integrity
		Ensuring data security
		Maintaining an audit trail/transparency
		Modelling with data
	Interpretation & Decision-Making	Collaborating with other professionals
		Communicating and reporting information
		Contextualising reported information
		Providing guidance and insight
		Planning and control

2. ROBOTIC PROCESS AUTOMATION

That many see a bright future for Robotic Process Automation (RPA) (Gartner, 2018; PwC, 2016) is evident in the valuation of one of the major players in Robotic Process Automation – UiPath. In April 2017, UiPath was valued at US$110 million, at its most recent funding round (April 2019) it was valued at US$7 billion (Lunden, 2019). The other major players in the market (Automation Anywhere and BluePrism) have likewise grown dramatically in value.[2] For a technology that is targeted at bringing automation to repetitive and mundane tasks normally performed by human users of systems, this implies a significant market for the potential efficiency gains offered by RPA. Indeed, Deloitte's global RPA survey suggests that RPA can improve not just efficiency but also compliance and quality (Deloitte, 2018). While some fear that this may lead to a decline in employment opportunities, a more positive perspective is that automation software like RPA can be used to "amplify and augment distinctive human strengths, enabling large economic gains and more satisfying work" (Lacity and Willcocks 2016, p.41). We explore below what RPA is, and how it may impact the work of professional accountants.

2.1 What is it and how does it work?

While the term Robot conjures up images of a physical machine, an RPA robot is a piece of software just like any other software application (whether it be Excel or SAP). In this regard, fears of RPA replacing workers are as unfounded as earlier concerns that computerised spreadsheets would replace accountants. These "bots" employ scripts and rules to carry out routine operations that otherwise would have to be carried out by human users. A simplistic view would be that they are akin to an Excel macro on steroids. However, this analogy understates their capabilities. Somewhat akin to workflow automation tools they can work across a range of different systems. The bots essentially interact with the various screens displayed by applications in much the same way as a human user would (e.g., opening an e-mail with an attached invoice, and cutting and pasting relevant data into the accounting system).

As a result, they sit on top of existing organisational systems (e.g., ERP systems, MYOB, email systems) rather than being integrated into those systems.

RPA software platforms provide the capabilities for developing and managing bots. This includes capabilities that allow the bot to read text on a screen and enter data into on-screen forms in the same manner that a human user might. From the perspective of the underlying organisational systems the bot thus is no different from a human user. Amusingly, this means that bots are often given names and assigned formal employee credentials (and have even inadvertently been invited to staff meetings and the like) (Carey, 2019; CFB-Bots, 2018).

The RPA platforms also provide for the management of the bots. This is critical as unlike end-user developed solutions (e.g., Excel macros), bots are developed by programmers and their development is a formally planned and managed activity. This means that bots are not only more transparent in their operation and that their use can be monitored by the platform (providing information to management on use and efficiency), but also that their activities are more readily auditable (since they are formally managed rather than ad hoc).

RPA can also entail some elements of artificial intelligence, in which case the term Intelligent Process Automation may be used. At its simplest, this can entail coding domain expertise into the rules that are part of a bot's script. At a more advanced level there are efforts to integrate machine learning based approaches with RPA, rendering them a far more powerful tool. However, with greater power comes greater risk as the bot is given more autonomy to learn and act – possibly in completely unanticipated ways. It also potentially entails greater risk if careful consideration is not given as to how the bot and machine learning are integrated, and whether the task context is appropriate for such automation.

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[2] Blue Prism was valued at GBP 48.5 million at its IPO in March 2016 and by June 2019 had reached a market capitalisation of GBP 1.46 billion (source: Bloomberg). Automation Anywhere was valued at US$2.6 billion at its last funding round (Wiggers, 2018).

2.2 Applications

As a highly-structured form of automation, RPA is best suited to applications with well-defined, high volume, mature tasks (Moffitt, Rozario, & Vasarhelyi, 2018). These tasks tend to be operational and routine in nature, but also consequently subject to refinement and change, particularly as the underlying systems on top of which RPA operates change. Obvious possibilities include payroll, accounts payable and accounts receivable related tasks as they are routine and repetitive. Importantly, applications of RPA are not about outsourcing jobs to a bot, but rather about enhancing productivity at tasks. Consequently, bots can free up staff time to focus on more value-added or strategic activities. Below we provide some illustrative examples of the types of tasks to which RPA is applied.

Consider the routine processing of supplier invoices. These may be routinely received by accounts payable functions as a PDF attachment to an e-mail. Without RPA, a manual process is required to open the PDF and extract the relevant data and enter it into the firm's accounting system. This can be a time consuming and repetitive task that could be largely automated. How easy this is to automate with RPA is dependent on the structure of the invoices. Since all invoices typically label the relevant information (invoice #, date, amount due, due date), a bot can readily extract this information.

As the supplier invoicing example suggests, the more structured and consistent the labelling of the input data sources is, the more likely RPA is able to carry out the task. Consider for example a routine accounting task like a bank reconciliation. While this is a multi-step process, it is one in which the steps and the underlying data sources (e.g., the bank statement) are well-known and hence lends itself to the application of RPA. Applying RPA to tasks that work with internal data and systems, as opposed to external data and systems, is even simpler and easier than the supplier invoice example. With internal data and systems, the structuring and labelling of the input data source (e.g., a PDF form, Excel spreadsheet, or system generated report) is well known in advance and so it is easy to build the script for the bot to handle the activity. More broadly, RPA is very useful in routine data manipulation tasks: transferring data from one system to another, merging data from two systems, or sorting, organizing and routing data. Any sufficiently structured task offers an opportunity for the application of RPA.

Despite these potential applications, and the benefits they would bring, a Deloitte (2017) survey found that although 53% of organisations have begun implementing RPA, only 3% have reached a scale of 50 or more bots (i.e., 50 or more process or tasks handled by bots). While this suggests that RPA has yet to reach scale, it likely understates the impact of RPA. As the tasks for which RPA is used are naturally highly repetitive, the value in applying RPA may not just be evident from the number of bots deployed, but rather from the volume of the tasks undertaken by those bots. Once the payoff from initial forays into RPA become evident the number of bots is likely to increase.

2.3 Considerations

Business and accounting applications of RPA are often driven by a desire for cost reduction, and greater speed and efficiency in the execution of tasks (e.g., Carey, 2019). RPA can also be used in sales and marketing. For example, an electricity company could have a customer provide a PDF copy of their current bill from which a bot could extract information to generate a competitive quote or direct the customer to the most appropriate offering (of course this can be problematic if the company's standard offerings are not competitive, and negotiation with human sales agent would be warranted). RPA also lends itself to ensuring consistency in the tasks it carries out, and a clearer audit trail for activities that would have otherwise been handled through manual means (Deloitte, 2018b). Nonetheless, there are a number of important considerations to be taken into account in the use of RPA. We outline these considerations below.

Development and control: Impetus for automating tasks needs to be led by business unit staff but should ideally have some involvement of an organisation's IT function (EY, 2016). RPA is about automating tasks, not entire processes or fully automated systems. Consequently, those with a business operations perspective are going to be in the best position to identify the needs which will often take the form of filling a gap between existing systems that are not integrated and for which full integration would be expensive overkill or remain a long-term vision. Involving the IT function in RPA implementation decisions can ensure timely consideration of the impact of updates or planned changes in underlying systems that may have implications for the proper functioning of bots. While the RPA platforms can enable end-users to develop bots, it is important that there be appropriate oversight and control over development and deployment: given the high-volume nature of tasks that bots perform, any errors can have sizable impacts very quickly. IT function staff, working in concert with business operations staff can help ensure an appropriately managed development process. Bot development, however, should always be driven by the business, and the development approach should be lean, lest the "gap-filling" benefits of bots be lost.

Human and Intellectual Capital: The prospect of automation often brings with it a fear from employees that they will lose their jobs, lose aspects of their role they enjoy, or have to retrain to undertake new tasks. Care needs to be taken in introducing RPA to ensure that staff understand that bots are task-oriented not job-oriented. Introducing RPA is not just about productivity gains and lowering costs. In an RPA enhanced work environment, the human worker has greater capacity to carry out higher value tasks that are less structured, require human judgment or have uncertain outcomes. In this regard RPA can actually enrich the work of those for whom it performs tasks - assuming of course they have the willingness and capability to undertake such higher value tasks. It is also important for the organisation to maintain the operational knowledge of the tasks carried out by the bot – lest the firm lose intellectual capital and become dependent on the bots. This is particularly concerning with RPA because even minor changes in an organisation's operational processes and systems can lead to a bot failing. For example, something as simple as a minor labelling change on a screen (e.g., accounts to account) could cause a bot to fail if it is relying on that label to identify a data source or data entry location on screen.

Monitoring: Bots are not static. They require ongoing performance monitoring to ensure they are working effectively and efficiently (Deloitte, 2018b). This is an important control consideration. The underlying systems RPA bots sit on top off, and the data sources (especially external data sources) which they make use of, can change – necessitating change to the scripts employed by bots. As noted above, this requires staff who work with bots to retain the capability to carry out the task should a bot fail. Indeed, such knowledge is essential for monitoring and identifying causes of any failures.

2.4 The Impact on the Profession

The primary impact of RPA on the accounting profession is in the automation of routine data manipulation tasks. Table 3 highlights the accounting activities in which RPA is most likely to have the greatest impact. This assessment considers the current state of RPA technology and does not include the integration of machine learning capabilities (i.e., sophisticated Intelligent Process Automation). Such sophisticated intelligent process automation is very much in its infancy and is a qualitatively different technology.

As the above example applications of RPA suggest, one of the major impacts is in sourcing data. RPA can enhance the efficiency of routine tasks for getting data into the accounting system. Because RPA bots consistently follow a script, they can also help ensure the accuracy of data acquired and thus provide assurance evidence in regards to evaluating data reliability. Of course, this is contingent on each bot's script being correct for the given input data source. For example, if a bot is processing supplier invoices but the format of a supplier's invoice changes, the bot may no longer correctly extract the data. Hence, accountants need to be prepared for ongoing monitoring of bot behaviour and performance. Similar problems may also arise with changes to internal systems. However, implementing appropriate RPA management practices should provide some forewarning of those issues. If problems do occur, they are traceable because the bot's script provides ready transparency into any DATA ACQUISITION or DATA PROCESSING activity.

As RPA excels at routine data manipulation tasks it can make operations like sorting, classifying and aggregating data more efficient. Moreover, the consistency of the script not only provides an audit trail of any processing but also helps reduce inadvertent errors in the data processing. This greatly assists with ensuring data integrity. However, to the extent any data processing and analysis is not pre-structured and thus requires human judgment, RPA is not readily applicable.

RPA is not a replacement for human judgment. Consequently, it has little impact in helping in activities of INTERPRETATION AND DECISION-MAKING. The one notable exception is that RPA can facilitate communicating and reporting information via bots that provide new standardised reports or visualisations (charts and graphs, etc.).

At a macro level, RPA may lead to changes in the nature of the work conducted by entry-level and junior accountants. Importantly, as RPA is task rather than job-focused, it means that entry-level and junior accountants will likely be carrying out tasks that require more judgment at an earlier stage of their career than has historically been the case. For accountants in leadership or executive roles RPA poses some managerial challenges rather than role changes. Specifically, recruiting and developing capabilities of the staff they lead and manage will be more challenging as junior accounts will require enhanced professional judgment skills.

TABLE 3:
IMPACTS OF ROBOTIC PROCESS AUTOMATION

ACTIVITY CATEGORY		
Data Acquisition & Preparation	**Sourcing data**	
	Evaluating data reliability	
	Evaluating data relevance	
	Determining data scope	
	Determining data content	
Data Processing & Analysis	**Classifying and aggregating data**	
	Ensuring data integrity	
	Ensuring data security	
	Maintaining an audit trail/transparency	
	Modelling with data	
Interpretation & Decision-Making	Collaborating with other professionals	
	Communicating and reporting information	
	Contextualising reported information	
	Providing guidance and insight	
	Planning and control	

Blue shaded areas indicate activities impacted by robotic process automation

2.5 Practical Questions

Is RPA only suited to organisations of a certain size? NO.

RPA is applicable in both small and large organisations where there are tasks that are high volume, repetitive and well structured. For small organisations, this can enable professionals to focus much more on value adding activities rather than routine processing if they have that capability and interest. For large organisations, RPA might be used more as means to fill gaps in the integration of larger otherwise siloed systems.

Must we hire programmers rather than accountants to exploit RPA? NO.

RPA platforms can learn scripts from observation of a human user. A tech savvy accountant, even without programming skills, will be more useful for modest forays into RPA than will a dedicated programmer. Larger initiatives might entail a small team with a portfolio of skills (including a programmer), but RPA initiatives should be driven by business operations, not technology.

A client uses RPA - does this affect my audit? YES.

RPA automates manual data manipulation tasks. From an audit perspective, if the manual task needs to be documented then the auditor needs to ensure the bot's activities were appropriately documented. Auditing of the results of data processing done by a bot will be a little different as the bot is consistent in its process (unlike a human). However, some assurance may be required as to the bot's script and to who has the ability and authority to control and/or edit a bot's script.

Can I use RPA in conducting an audit? YES.

For any data manipulation task that is repetitive and well-structured RPA can be of assistance. This may open up scope for larger scale sampling (or even work on a population of transactions). As with a client's use of RPA appropriate documentation of the bot's script in the audit working papers is an important part of the audit evidence.

3. BLOCKCHAIN

Blockchain is one of the most hyped technologies of the last decade. Proponents of blockchain have touted its potential to revolutionise accounting and assurance, as well as enabling efficiency in supply chains, transacting via cryptocurrencies and managing workflow (Dai & Vasarhelyi, 2017; Kokina, Mancha, & Pachamanova, 2017). Fundamentally, blockchain is a technology for providing a secure, unalterable recording of digital data (Deloitte, 2018a; Schmitz & Leoni, 2019; Tan & Low, 2019). There has been sizable investment in blockchain (Woodside, Augustine Jr, & Giberson, 2017) and major universities around the globe have established blockchain research centres. However, recently there has been increasing scepticism that the reality of blockchain will not live up to the hype (Irrera & McCrank, 2019; Orlowski, 2018). What then is blockchain and what are its implications for the accounting profession?

3.1 What is it and how does it work?

As a technology, blockchain enables secure digital interactions (transactions, contracts, communications) in which integrity mechanisms for verifying the data are part of the core design of the technology (Deloitte, 2018a). At its heart, it is a digital ledger. Like a ledger, it contains data entries, in chronological order, called "blocks". The blocks are chained together such that each block contains a "digital fingerprint" that also provides a link to the previous block in the chain. The size of a block can vary, so the data contained within the block can potentially be multiple transactions or other pieces of information.

The digital fingerprint is generated by a hash function – essentially a complex computational coding that summarises the data. The computer algorithm for determining the hash or digital fingerprint is a one-way coding mechanism. The data cannot be reverse engineered from the hash. The hash is also mathematically dependent on the entirety of the data, meaning any manipulation of the data would be evident as the hash would be wrong. As each block contains the hash of the previous block in the chain, the hash protects against both alteration

of the data in a given block and attempts to remove or insert a block in the middle of the chain. In essence, it is like the digital ledger of the blockchain is written in indelible ink. This is a key integrity mechanism built into the core of the blockchain's workings.

Another integrity mechanism of the blockchain is that the digital ledger is "distributed". Each part in a blockchain network maintains a copy of the blockchain ledger. Depending on the application, the blockchain network might be public (e.g., digital currency), or private (e.g., closed-supply chains, or blockchain consortia). In either case, the data is protected by encryption. Validity in the blockchain is established by consensus among the parties who maintain the different copies through what is essentially a voting mechanism. Interfering with data in a blockchain record thus would require changes to a majority of the copies of the chain distributed around the network. This decentralisation of authority is a critical integrity feature of blockchain and sometimes referred to as one of the pillars of blockchain.

The use of a distributed ledger and consensus validation to maintain data integrity can be problematic in practice with performance issues arising, particular at scale. Indeed, a recent study of three major blockchain platforms (Ethereum, Parity and Hyperledger) noted that "blockchains perform poorly at data processing tasks currently handled by database systems" (Dinh et al., 2018, p. 1382). To help address the scale issue some blockchain setups employ a hybrid model where certain pre-defined sites in a network have voting rights to validate the blockchain. This is particularly the case in blockchain consortia where both allies and competitors work together to use blockchain as infrastructure for market interactions.

To add a new block to the blockchain (i.e., add new data to the ledger) requires calculating the digital fingerprint for the block. The digital fingerprint has specific computable properties it needs to satisfy (e.g., randomness). The other parties in the distributed network can computationally validate the digital fingerprint and then, through consensus validation and voting, the new block gets added to the distributed copies of the ledger.

The result of the design of blockchain is the ability to construct a data record that is secure and relatively easy to validate. The data record is "immutable" and "irreversible": it cannot easily be altered, manipulated, or deleted (Dai & Vasarhelyi, 2017; Yermack, 2017). The validity or authenticity of the data record is robustly determined without reference to a central authority. Validity is determined by consensus in the network and thus much harder to manipulate maliciously.

3.2 Applications

Applications of blockchain typically aim to utilise its most significant feature - immutability. Below we provide some illustrative examples of current and potential applications of blockchain technology.

Cryptocurrencies: Bitcoin, and cryptocurrencies in general are the blockchain applications that have attracted the most public attention (Eyal, 2017). Banks and other corporations have invested into cryptocurrency services to allow customers to make purchases using the most common cryptocurrencies such as Bitcoin and Ethereum (de la Merced & Popper, 2019; Waters, 2016). Blockchain facilitates record keeping related to storage and transactions in a secure but transparent fashion which appeals to currency users. However, cryptocurrencies have also been at the centre of the biggest blockchain controversies. In one case human error and bugs in the virtual wallet service for the Ether cryptocurrency led to a $300 million loss (Hern, 2017). The immutable and irreversible blockchain record may be difficult to hack, but the virtual wallets and other systems that interact with the blockchain can be hacked or introduce human error. Blockchain's secure design still requires proper policies and controls in its use if similar financial disasters are to be avoided. In short, one can expect plenty of action in the cryptocurrency space as even Facebook has announced it is pursuing its own cryptocurrency (Libra) (Morse, 2019). However, the current volatility of cryptocurrencies makes it clear that their long-term role in the market place is far from settled.

Smart Contracts: One of the most promising applications of blockchain is the notion of smart contracts (Iansiti & Lakhani, 2019). Blockchain enables the creation of smart contracts where the terms of a contract are autonomously verified, enforced, and executed. Terms of the contract are embedded in the blockchain to be automatically triggered by the relevant criteria. The immutable and decentralised nature of blockchain means that smart contracts are able to reduce contracting costs, including risk of a contract not being fulfilled. Some organisations are trialling this possibility. For example, insurance company Axa has launched flight delay insurance using blockchain under which reimbursement is tied to flight and air traffic databases that trigger automatic payment once a pre-specified condition has occurred.

Settlement and Payment: Systems for payment and transfer of financial securities are also a potential application area for blockchain under exploration by securities exchanges. Blockchain has also been commercially tested for payment transactions in the health insurance industry, with Change Healthcare reporting that they ran 50 million transactions a day through a blockchain based system (Hyperledger, 2019). The value proposition of blockchain for settlement and payment lies in leveraging the security and integrity offered by blockchain, and the ability to automate the execution of transactions, as is the case with smart contracts.

Accounting Systems and Supply Chains: Given that a blockchain is, at its core, a distributed ledger system, an obvious question for accountants is whether existing accounting systems will transition to blockchain technology (Tan & Low, 2019). Again, blockchain's inherent capability to maintain a secure and immutable record is an important and valuable feature. What particularly stands out here, however, is that this capability can potentially operate between transacting organisations - providing a secure mechanism for sharing and verifying data, enabling collaboration across the supply chain. This sharing and verification of data may ultimately result in enhanced reliability of financial reporting. Going further, some have touted the potential for blockchain-based systems to support continuous reporting and continuous auditing. Of course, all these potential options open up new challenges for accountants and auditors, challenges that may not be outweighed by the potential benefits.

3.3 Considerations

There are a number of practical considerations and important limitations in the deployment of blockchain technology that need to be considered. As the discussion below reveals, there is good reason to have reservations about whether blockchain will indeed lead to a revolution in accounting as has been suggested by some.

Input Data Validity, Accuracy and Completeness: The blockchain distributed ledger provides for the security and integrity of data. However, as a source of truth it faces the same fundamental problem as any ledger system with respect to the input data. Specifically, it fails to address the issue of whether the data entered validly, accurately and completely reflect the economic reality of the transaction being recorded -- issues of human error and fraud remain (Tan & Low, 2019). "Lies encoded into the blockchain are still lies. They're just immutable lies" (Bradbury, 2015). Consider the simple example of receiving goods at a retailer. Even if the shipping documents and invoice are securely communicated via blockchain, the existence of the inventory, the completeness of the shipment, and the quality of the product may in reality be different from what is represented in the data. The situation is obviously even more complicated when matters of valuation or accounting judgment come into play – the data record may be secure and its integrity maintained but it can still be wrong. Of course, this means any reporting and decision-making made on the basis of blockchain data may similarly be wrong.

Automation Risks: While innovative applications of blockchain such as smart contracts offer significant potential efficiencies, the automated triggering of contract terms and resulting autonomous actions are not without risk (CPA-Canada & AICPA, 2017). The potential for errors in triggers or contract terms have potentially significant economic consequences for both the contracting parties and the markets in which they operate. The risk here is in some respects greater than that posed by RPA as problems arising with blockchain have potentially greater economic consequences for an organisation. Moreover, those consequences may extend beyond the boundary of the organisation and impact the organisation's interactions with other parties in the marketplace.

Resource intensity: Blockchain is not efficient in its use of computational resources (Fairley, 2017). The security and integrity of blockchain technology is tied to the complexity of the computation of the digital fingerprint and the size of the network (e.g., how many systems the ledger is distributed across and vote on the consensus truth). While computing resources having historically been declining in price, the costs at scale can be non-trivial. At the extreme, consider the initial application of blockchain – Bitcoin. Estimates in 2018 indicated that the computer servers in the Bitcoin blockchain network were consuming 22.7 Terawatt hours of electricity p.a. (i.e., nearly as much as the entire nation of Ireland and around four times as much as Google's worldwide consumption) (The Economist, 2018). The Bitcoin ledger is comparatively large, and consequently with smaller networks and ledgers the resource intensity is lower but with current integrity mechanisms, smaller networks are also inherently less trustworthy.

3.4 The Impact on the Profession

Table 4 highlights the different accounting data activities on which blockchain is most likely to have the greatest impact. Unsurprisingly, given blockchain's key features are with respect to ensuring data integrity and ensuring data security, much of the impact is in DATA PROCESSING AND ANALYSIS, while there is no major impact on INTERPRETATION AND DECISION-MAKING activities. Blockchain does open new possibilities for sourcing data (e.g., from external organisations), and provides some assurance in evaluating data reliability of these new data sources (e.g., by virtue of the distributed ledger and consensus authentication of the blockchain). However, the above noted issues around input data validity mean that claims for radical changes in DATA ACQUISITION AND PREPARATION are potentially overstated. The immutability and irreversibility of the blockchain ledger and its distributed nature contribute strongly to maintaining an audit trail/transparency in data processing. However, when it comes to activities that require a greater degree of professional judgment (i.e., analysis-oriented data processing tasks), blockchain adds little value.

More broadly, accountants have good reason to be somewhat sceptical about the potential wide-ranging and fundamental changes arising from blockchain's deployment. Much of blockchain's impact is on activities that are not high value adding activities in the data work of accounting professionals. In short, while blockchain will make inroads into some very specific application areas (cryptocurrencies, smart contracts), its impact on the value-adding activities of accounting professionals has likely been over-hyped (Irrera & McCrank, 2019).

TABLE 4:
IMPACTS OF BLOCKCHAIN

ACTIVITY CATEGORY	Data Acquisition & Preparation	**Sourcing data**
		Evaluating data reliability
		Evaluating data relevance
		Determining data scope
		Determining data content
	Data Processing & Analysis	Classifying and aggregating data
		Ensuring data integrity
		Ensuring data security
		Maintaining an audit trail/transparency
		Modelling with data
	Interpretation & Decision-Making	Collaborating with other professionals
		Communicating and reporting information
		Contextualising reported information
		Providing guidance and insight
		Planning and control

Blue shaded areas indicate activities impacted by blockchain

3.5 Practical Questions

Can small organisations use blockchain? YES.

While only large organisations will likely develop their own blockchain applications, small organisations will be able to make use of blockchain technology developed and supported by external organisations (e.g., Hyperledger, Ethereum). Smaller organisations thus may participate in blockchain-enabled applications but it is unlikely that they will drive the development of such applications.

A client uses blockchain - does this affect my audit? YES

However, only in regards to very specific applications; hence, the concerns vary greatly with the application. For example, if an audit client holds cryptocurrencies, confirmation of holdings can typically be obtained by the cryptocurrency exchange through which the client holds the funds. However, the volatility of the currency may pose risks. For cryptocurrencies the issues are less about the technology. By contrast, smart contracts, payment and settlement systems, and the use of blockchain in a supply chain context require deeper consideration of the data stored in the blockchain and how it is used (e.g., triggers for smart contracts).

As an accountant, do I need a deep technical knowledge of blockchain? NO

However, a functional understanding in regards to very specific applications will be needed. When confronted in an audit or accounting setting with a blockchain application what is essential is sufficient functional understanding to properly consider the accounting and business risks and implications (e.g., the limits of data reliability/integrity under blockchain – such as input validity issues). Accounting professionals will rarely need to know the technical, computer science aspects of blockchain (e.g., exactly how the hashing function is computed).

4. ARTIFICIAL INTELLIGENCE AND DATA ANALYTICS

Artificial Intelligence and Data Analytics (AI&DA) refer to a collection of tools and techniques that are fundamentally concerned with patterns in data that ultimately can be translated into actions (Mitchell, 1999). Neither are in substance new, although the terms data analytics and data science are new labels[3] (Hurwitz & Kirsch, 2018). However, several changes in the broader environment have brought AI&DA to the forefront of business practice: increased processing power, the pervasive availability of data, the connectedness of technology and markets, and the speed of activity (decision-making and data generation). This has made computationally and data intensive approaches that have previously been more in the domain of research now feasible in a broad range of practical applications.

In assessing the implications for the accounting profession of the broadening of the application of AI&DA it is important to recognise not just the relevant aspects of the environment that have changed, but also what has not changed or indeed has become more problematic. While data availability has exploded, the quality or veracity of data has never been more in question. Furthermore, while the technological ability to analyse and process data has expanded exponentially, what has not changed is the human capability to interpret and provide meaning to the patterns in data found by computational methods.

4.1 What is it and how does it work?

AI&DA can take either a machine learning (computer science) or a statistical approach to extracting patterns from data[4] (Jordan & Mitchell, 2015). Indeed, it is a commonly known aphorism that a data scientist is a statistician with programming skills or a programmer with statistical skills. As a result, many statisticians and computer programmers have relabelled themselves as data scientists.

Statistical approaches employ traditional techniques such a linear regression (to find a line of best fit, such as for forecasting purposes), probit regression and logistic regression (for classification of data, e.g., risk of a customer defaulting), clustering techniques (e.g., for identifying market segments based on customer demographics or purchasing behaviour). What is new here is the ready availability of powerful tools to conduct such analyses. For example, while tools like SAS and SPSS both began as statistical analysis packages (SAS was an acronym for Statistical Analysis System, SPSS was an acronym for Statistical Package for the Social Sciences) running on large mainframe computers, they are now pitched as analytics platforms (SPSS has been owned by IBM since 2009). These tools turn statistical analyses into point-and-click activities, which can dramatically expand the user base and thus the potential applications. Similarly, the availability of tools to visualise data and the results of data analysis in multiple ways have also made more complex analyses readily accessible. At the somewhat less user-friendly end, there are even very powerful free options for data analytics in the likes of the open source R statistical software (r-project.org, 2019).

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[3] Historically, Artificial Intelligence has its roots in the cognitive revolution of the 1950s and the development of digital computers. This excludes rule-based expert systems that were introduced in the 1970s and were popular in the 1980s and 1990s but which have fallen to the wayside because of the difficulty in extracting the knowledge from domain experts to encode into the set of rules (an issue exacerbated in changing environments where the "rules" may need to change over time).

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Machine learning approaches rely on training data (i.e., historical data) to which one of a variety of computational approaches are applied to detect patterns in the training data. While traditional statistical approaches can be applied to relatively small data sets (e.g., hundreds of observations), machine learning approaches typically require large data sets (i.e., at least tens of thousands). In broad terms, there are two machine-learning approaches – supervised learning and unsupervised learning. Supervised learning requires training data that has both inputs (predictors) and outputs (results) from which to learn. Typical applications may include credit risk analysis, customer profitability analysis, market forecasts and the identification of fraud/ errors in transactions. Unsupervised learning requires training data only to have inputs, not outputs. This type of learning is used to identify different patterns within a data set, such as customer segments, or to identify anomalous transactions (i.e., transaction that are in some way atypical).

Another key difference between machine learning approaches and statistical approaches is that some machine learning approaches (e.g., neural networks, deep learning) are inherently opaque in how they identify patterns in the data or make predictions (Adadi & Berrada, 2018; Guidotti et al., 2018; Kokina & Davenport, 2017). In other words, while the historical accuracy of such techniques may be assessed, it is impossible to know how the results were arrived at or even how much weight was given to a particular piece of data in reaching a conclusion. By contrast, traditional statistical approaches (e.g., linear regression) are by nature transparent (e.g., the weighting of factors is evident from the coefficients of the terms in the regression equation). However, statistical approaches require some form of pre-specified model; machine learning merely requires plentiful training data.

4.2 Applications:

AI&DA has potentially a broad range of applications in accounting and business, provided the requisite data is readily available and of sufficient volume (Brynjolfsson & Mitchell, 2017; Kokina & Davenport, 2017). AI&DA applications can be distinguished by the nature of output they produce. Below, we focus on three major types of application (classification, clustering and prediction/estimation).

Classification: AI&DA is proficient at analysing patterns in data and the identified patterns can be used in classification tasks. A classic example here is fraud detection, in which, based on historical data, a machine-learning algorithm can be trained to differentiate between fraudulent and non-fraudulent transactions, such as in the context of credit card purchases. This sort of classification requires identifying the differences in data patterns for fraudulent vs. non-fraudulent transactions. It is an example of supervised learning, and as such requires a history of both fraudulent and non-fraudulent transactions as training data from which to learn. As a supervised learning technique, the different classes (fraudulent vs. non-fraudulent) are predetermined, and the algorithm is learning into which class a given observation is most likely to fit.

Clustering: A classic example of a clustering application is in retailing, where clustering algorithms are used to identify baskets of goods commonly sold together or where clustering algorithms group like customers into segments. Clustering is unsupervised learning and so the interpretation and labelling of clusters identified (e.g., customer segments) is something done by the business professional after the machine learning algorithm has identified the clusters. In an auditing context, clustering can be used to identify transactions that are anomalous and do not fit the pattern of usual transactions. However, just because a transaction has been identified as anomalous does not mean it is fraudulent or erroneous. Rather, clustering merely highlights a transaction that may warrant further investigation or consideration by the auditor. False positives, anomalous transactions that are not an audit concern, can be a major challenge here. This is particularly the case when a clustering algorithm is applied across different contexts: e.g., different geographical locations of an organisation; different market conditions or varying seasonality.

Prediction/Estimation: Example applications of machine learning in prediction and estimation include sales forecasting, predicting the likelihood of a credit customer defaulting, or the likelihood that a customer may respond to a particular targeted promotion. Each of these different types of application imply different sets of AI&DA analytical method, tool or approach. Importantly however, the choice of analytical approach is both a function of the technical aspects of the computational/statistical method (each with its various assumptions and limitations), and the business requirements. For example, consider the case of a credit customer defaulting. Depending on the business requirements a classification approach (defaulter/non-defaulter) may be appropriate or a prediction approach (likelihood of default). If it is a decision about the granting of credit a classification might be appropriate. If it is about estimating a provision for doubtful debts a likelihood approach might be more appropriate. As discussed below there are other important practical considerations involved in applying AI&DA.

4.3 Considerations

While AI&DA is the most mature and widely used of the three technologies covered in this report, it is not without limitations. Accountants should be keenly aware of the following practical considerations:

Data: The quality of AI&DA results are contingent on the quality of the underlying data. In the big data world in which we now live access to data has exploded exponentially. While this has led to greater variety and velocity of data (i.e., the speed at which data is generated), it has also led to a decline in the veracity, or in accounting terms, the representational faithfulness of the data. The new data sources, while providing more timely information, are less likely to be from formal systems with established controls and subject to some sort of assurance. For example, Orbital Insight processes satellite images of retailer Walmart's parking lots to count the cars as a means of capturing data about customer volume to inform investors and other stakeholders (Vance, 2019).

Secondary use of data: In the big data world, it is increasingly common for data to be used for analysis and decision-making purposes that were not the primary purpose for which the data was collected (Someh, Davern, Breidbach, & Shanks, 2019). As a result, the fitness for purpose of this secondary use of data may be questionable. The use of social media data is a classic example here – what does it actually mean (represent) when people are tweeting about a firm's product or service? At the same time as this data explosion is occurring, markets and the economy at large have become more global, more complex, and more dynamic. The patterns in data can thus be changing more rapidly. As a result, the actionable insights obtained from AI&DA may potentially have shorter and shorter half-lives.

Training: Moving beyond concerns about the data itself, a number of issues arise around how the data is analysed, or how "the machine" learns, i.e. machine learning. The patterns that are of real interest are patterns that reflect the causal factors that are driving the historical results. However, neither statistical approaches nor machine learning approaches actually understand causes (Hurwitz & Kirsch, 2018). They merely report correlations or associations between different data items. As a simplistic example, consider the relationships between cost, volume and profit. AI&DA tools may be able to establish mathematically what the relationship is, but that does not mean the machine understands the concepts of fixed versus variable costs, or the relevant range for costs – all of which are critical to interpreting the pattern in the data. The term Artificial Intelligence should not be misconstrued as implying understanding – a matter of substantial debate amongst philosophers and proponents of AI.

A problem with any computational or statistical approach looking for patterns in historical data is overfitting the pattern to the historical data. The patterns learnt from the historical data are specific to the historical data and are not predictive of the pattern in the future. This can be somewhat remedied by testing the patterns found with a hold-out sample, and also by weighting recent data more heavily than older data in the analysis. However, there is no hard and fast rule for the weighting or the requirements for the holdout sample – this is part of the art of the application of AI&DA and as a result there is subjectivity introduced into the results. Contrary to popular misconception, AI&DA is not entirely objective.

While the available tools for AI&DA have grown in both power and usability these improvements come with significant risks. The availability of point-and-click tools to carry out computational or statistical analysis means users of these tools do not need to be as skilled in the computational approaches employed. Of course, this means that AI&DA can very easily be misapplied by those unaware of the specific underlying mathematical assumptions and limitations of the approaches. By the same token, those proficient in the computational or statistical approaches often lack the relevant business domain knowledge to understand what the data actually represents – leading to misuse of analytical approaches. By way of simple example, consider the typical non-accountant's lack of understanding of the differences between accrual accounting and cash accounting – and the consequent opportunity for misinterpretation of what figures like profit, assets, and even revenue mean.

Transparency: Much of the work of accountants requires an audit trail or a basis for justifying a decision. The ability of AI&DA tools to discover interesting patterns in data is not matched by its ability to explain how such patterns were identified or to justify a particular prediction or recommended course of action (Adadi & Berrada, 2018; Guidotti et al., 2018). Indeed, some machine learning techniques (e.g., so-called deep learning), are inherently opaque – they are "black boxes" and because of the way the technique works it is simply not technically possible to provide a meaningful explanation of the results. This obviously limits the application of these opaque tools and techniques to situations that do not require an audit trail or justification. For example, sales forecasting might be a suitable application area, but deciding whether to approve a loan would not, as a justification is typically necessary.

This lack of transparency problem is exacerbated by the underlying complexity of the computational and statistical approaches. Consequently, even where a justification, explanation or audit trail can technically be generated, the operations of the AI&DA may effectively remain a black box to the decision maker using the analytics (Davern, Gondowijoyo, & Murphy, 2019). Whether inherently or practically opaque, the potential consequences are concerning. Naive reliance on AI&DA opens up the opportunity for unobservable bias (including illegal discrimination) in decision-making with these tools. It also can lead to a loss of intellectual capital within a firm as decision makers become dependent on the tools and are unable to learn from the tools to build their own domain expertise. Unsurprisingly, a recent survey found that 84% of CEOs agreed that trusting AI decisions required that they be explainable (PwC, 2019).

Ethicality and Legality: The availability of advanced AI&DA tools, and the associated massive data collection activities, also raises legal and ethical considerations (Someh et al., 2019). In addition to the bias and discrimination that can result, there is the inherent loss of privacy. There are now effectively secondary markets for data and the trading of data. There are also significant legal issues to consider around data use and privacy. For example, the European Union's General Data Protection Regulation impacts any organisation interacting with EU citizens, and its sanctions can be heavy (up to 4% of global revenues) (European Union, 2016). While the sanctions under Australian regulations may not be as extreme, the requirements to notify of data breaches (Ismail, 2018), at the very least increases reputational risk. While in the social media age privacy is arguably dead, a question that risk managers, chief data officers and even boards are now asking is just because we can exploit data in a particular way, should we? What this then means for the accounting profession's ethical requirements in the 21st century is a question yet to be resolved. Indeed, it presents an opportunity for the accounting profession to engage in developing governance frameworks for the deployment of AI&DA (Goh, Pan, Seow, Lee, & Yong, 2019; Unsworth, 2019).

4.4 The Impact on the Profession

The major impacts of AI&DA on accounting activities are highlighted in Table 5. In contrast to RPA and blockchain, AI&DA has a broader impact across the full range of activities. As discussed below, this impact also encroaches somewhat more into areas of human judgment – but as the discussion of example applications highlights, there is still plenty of need for human judgment.

While AI&DA typically requires large data sets and as a technology does not aid in DATA ACQUISITION, the pattern learning capabilities can assist accountants in evaluating data reliability and evaluating data relevance. In the case of data reliability, consider the above-mentioned example application of identifying anomalous transactions: while the detection of anomalies is informative, it is not conclusive evidence in an assessment of data reliability. Similarly, identifying factors that influence sales, define a customer segment, or classify a debtor as a potential defaulter can assist in determining what data is relevant. However, when it comes to making predictions or classifications (and determining what managerial levers may be used to alter outcomes), human judgment is required to ensure the factors identified as influence are indeed causal as opposed to spurious correlations.

As a technology for establishing patterns in data, AI&DA can excel at classifying and aggregating data (e.g., aggregating data about customer behaviour to classify them into segments based on profitability). More broadly, AI&DA are tools for modelling with data. In the case of many machine learning techniques the pre-specification of a model is not even required; only the identification of the data to be used in developing a model is required. However, the impacts of AI&DA on DATA PROCESSING AND ANALYSIS are not all positive. As noted above, some techniques are inherently opaque, while others by virtue of their complexity, are practically opaque black boxes. This opacity severely compromises maintaining an audit trail/

transparency in justification or explanation of decisions made using such techniques.

AI&DA are also useful in providing guidance and insight as part of INTERPRETATION AND DECISION-MAKING activities. However, this guidance and insight is incomplete without the business professional to interpret it and give it meaning. Take the examples of clustering discussed above – AI&DA can identify customer segments or baskets of goods but interpreting their economic significance and meaning requires human judgment. For example, an often recounted (but possibly apocryphal) basket of goods analysis in a US supermarket context was that beer and nappies occurred together with economically significant regularity. The question that arises is whether such a result is purely a spurious correlation that should be ignored or a causally driven pattern that should be considered in planning and control decisions such as pricing and sales incentives?

TABLE 5:
IMPACTS OF ARTIFICIAL INTELLIGENCE AND DATA ANALYTICS

ACTIVITY CATEGORY		
Data Acquisition & Preparation	Sourcing data
	Evaluating data reliability
	Evaluating data relevance
	Determining data scope
	Determining data content
Data Processing & Analysis	**Classifying and aggregating data**
	Ensuring data integrity
	Ensuring data security
	Maintaining an audit trail/transparency
	Modelling with data
Interpretation & Decision-Making	Collaborating with other professionals
	Communicating and reporting information
	Contextualising reported information
	Providing guidance and insight
	Planning and control

Blue shaded areas indicate activities impacted by artificial intelligence and data analytics

4.5 Practical Questions

Is AI&DA only suited to organisations of a certain size? NO.

The potential to apply AI&DA is driven not by the size of an organisation but rather the availability of relevant data for analysis. To truly be available for AI&DA, the data needs to be in machine readable form and appropriately prepared (cleaned, structured and formatted). This can be a major challenge for both large and small organisations (e.g., the data may be trapped in silos, inconsistently labelled, and/or poorly formatted).

Should we be hiring data scientists rather than accountants to exploit AI&DA? NO.

Data scientists will not replace accountants. Rather, what is ideally required are accountants who have some data analytics skills (a growing component of university accounting programs). This allows accountants to utilise the less technically demanding tools, or to communicate effectively with data scientists when more technologically sophisticated analytical approaches are required.

A client uses AI&DA, does this affect my audit? YES.

AI&DA applications can lack an audit trail or explanation of their outputs. Obtaining reasonable assurance about black box or opaque analytics is thus extremely challenging.

Can I use AI&DA in conducting an audit? YES.

There is a large scope for using AI&DA in auditing. A major advantage of AI&DA in audit is that it can be used to efficiently analyse entire populations of transactions and negate the need for sampling. However, there are important caveats to the use of AI&DA in auditing. Specifically, when AI&DA techniques are opaque, they cannot be used in and of themselves as audit evidence. Rather, in such cases AI&DA is useful for identifying transactions that warrant further audit investigation and analysis (which can yield relevant audit evidence).

5. SUMMARY CONCLUSIONS

For accountants, as true business data professionals, information technology will always play an integral role in their work. Keeping abreast of developments in information technology is thus an essential for ongoing success in the profession. However, this does not mean that accountants will be replaced by technologists, nor do they need to become technologists; rather, they need to engage with technology and technologists while focusing on solving the business and accounting problems that is the core of their expertise as accountants and business advisors.

The potential impacts of the three technologies discussed in this report are highlighted in Table 6. Across these technologies the greatest impact is where technology has a long-established role: routine DATA PROCESSING AND ANALYSIS activities. The least impact is in the high-value, human judgment and expertise driven activities of INTERPRETATION AND DECISION-MAKING. This is consistent with technology as a complement to the expertise of accountants and serving as a tool for facilitating their professional work, as opposed to outright replacing them.

At a broad level, the big challenge that these technological advancements pose is that at the outset of their careers accountants will be involved to a greater degree in tasks requiring the exercise of professional judgment. The opportunities for young accountants consequently require a broader and deeper knowledge/skill base. While this means the roles will be more demanding and challenging, the roles will also be more interesting and rewarding. The challenge for both entry-level accountants and those in leadership roles will be crafting new career pathways to build future leaders (CPA Australia & L+D, 2019). These pathways must appropriately develop professional judgment and an expert understanding of the lower-level tasks that will be increasingly executed by technology. The ability of accountants to oversee and leverage these technologies in their decision-making and actions will be critical for their career and professional development.

In short, while technological change continues, and the profession must continually adapt, the changes brought about by the technologies discussed in this report demand that the business skills and expertise of accountants will become even more critical and valuable. It is change that will make for a more exciting and rewarding career for accounting professionals.

TABLE 6:
THE IMPACTS OF THE THREE TECHNOLOGIES

		RPA	Blockchain	AI&DA
DATA ACQUISITION & PREPARATION	Sourcing data	� (shaded)	(shaded)	
	Evaluating data reliability	(shaded)	(shaded)	(shaded)
	Evaluating data relevance			(shaded)
	Determining data scope			
	Determining data content			
DATA PROCESSING & ANALYSIS	Classifying and aggregating data	(shaded)		(shaded)
	Ensuring data integrity	(shaded)	(shaded)	
	Ensuring data security		(shaded)	
	Maintaining an audit trail/transparency		(shaded)	(shaded)
	Modelling with data			(shaded)
INTERPRETATION & DECISION-MAKING	Collaborating with other professionals			
	Communicating and reporting information	(shaded)		
	Contextualising reported information			
	Providing guidance and insight			(shaded)
	Planning and control			(shaded)

Blue shaded areas indicate activities impacted by the relevant technology

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Professor Michael Davern, BCom (Hons.), PhD, CPA is the Chair of Accounting and Business Information Systems at The University of Melbourne where he holds appointments in business and in engineering. For over 25 years, both in Australia and overseas, he has led industry engaged research projects in accounting, business and information technology. With a focus on decision making, his work has covered a diverse range of topics including business analytics, ethics, financial reporting, data driven transformation, business process design, investment analysis, risk management and revenue management. He serves on boards in both the not-for-profit and private sector. Michael's industry focused work has included research and executive education with, among others, EY, Microsoft, NAB, PETRONAS, and CUA, among others.

DR. MARTIN WEISNER
BSBA, MBA, PHD

Dr. Martin Weisner, BSBA, MBA, PhD is a Senior Lecturer at The University of Melbourne. Prior to his academic career, Martin worked as an auditor and business consultant in the United States. As a Nevada licensed CPA (currently inactive), he gained significant experience in casino auditing and performing internal audits within this industry. His research has been published in leading international journals and has examined topics such as the role of technology in accounting, auditors' reliance on specialists, and risk management.

NICOLE FRASER
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Nicole Fraser, BCom, is an Industry Research Assistant/Senior Tutor at The University of Melbourne where she teaches enterprise performance management. Nicole is currently pursuing honours in accounting, with a focus on the role of analytics in a budgeting context. With prior industry experience with EY and GM Holden in audit and aftersales roles, Nicole will be joining Deloitte Private in 2020.