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Charting the future of accountancy with AI

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Charting the Future of Accountancy with AI

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FOREWORD

Artificial intelligence (AI) has the potential to transform the finance function and the way organisations and professionals work.

AI has been identified as one of four frontier technologies to grow Singapore's economy. The Singapore government also launched AI Singapore (AISG), a national programme aimed at developing deep national capabilities in AI, thereby creating social and economic impacts, grow local talent and build an AI ecosystem.

While companies and employees alike are trying to grapple with the changes that AI brings, these developments should not be feared. Instead, organisations and individuals should leverage the new technologies and embrace the opportunities created in the years ahead.

Against this backdrop, CPA Australia and Singapore Management University School of Accountancy believe that there is merit in contributing to the eco-system by equipping finance professionals and corporate decision makers with insights to understand how to anticipate and respond to AI technologies.

This toolkit shares practical knowledge with accounting and finance professionals, directors and senior management in corporations and SMEs, as well as business advisors at large.

This endeavour brings together various stakeholders and subject matter experts from accounting, business and academia. We are grateful for the generosity of time and effort by our contributors from Accenture, Deloitte, EY, KPMG, PwC and SMU in providing their valuable insights in this publication. We also thank the staff of CPA Australia and SMU who have supported the production of this toolkit.

We hope you will find this resource on AI useful in increasing the knowledge of your organisations and finance teams in this fast-developing technology.

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July 2019

PROLOGUE

Artificial intelligence (AI) is transforming the accounting and finance sector. With the ability to learn and adapt, AI is poised to develop increasingly sophisticated capabilities that will allow it to execute a growing number of tasks that accountants perform today. Given its heavy reliance on numbers and data, the accounting and finance sector is well placed to reap the benefits that AI has to offer.

While there had initially been fears that AI would displace accountants, the emerging consensus is that AI will prove to be a boon for accountants because it will allow machines to execute repetitive, mundane accounting tasks while freeing human accountants up to perform higher level activities that will increase their overall productivity.

It is crucial that accounting professionals keep themselves abreast of key advancements in AI and how they can benefit from developments in this area.

As editors of this book, we have assembled authors with a diverse range of professional expertise to discuss important issues in the implementation of AI in the accounting and finance sector. In particular, we seek to answer several important questions: what is AI and what are emerging trends in this area? How can AI be implemented in the accounting and finance sector to solve problems? What are some practical steps that accountants can take to capitalise on AI?

It is our hope that the issues examined in this book will contribute to the professional literature on AI in accounting and finance. We also hope that it will bring forth meaningful discussion of how AI will reshape the accounting and finance sector in the coming years and how the profession can continue to thrive alongside AI.

This book is organised as follows:

Chapters 1 and 2 provides an overview of AI and how it is leading the way forward in the accounting and finance sectors. Chapter 1 investigates how AI can lead revolutionary change in the accounting and finance industry and reshape how accountants work while Chapter 2 discusses emerging AI trends in accounting and finance.

Chapters 3 to 6 examine how AI can be used to solve problems in a variety of areas in accounting and finance, including in forensic accounting and fraud detection (Chapter 3), internal audit (chapter 4), internal finance processes (Chapter 5), and in finance's interactions with external interfaces (Chapter 6).

Chapters 7 and 8 provide practical insights into how accountants can capitalise on AI. Chapter 7 focuses on how it is critical that ethical considerations are taken into account when implementing AI in accounting and finance while Chapter 8 examines how we can equip the future generations of accountants with skills that will allow them to thrive in the AI world of the future.

We are pleased to be part of this collaboration between CPA Australia and the School of Accountancy, Singapore Management University. We would like to record our immense gratitude to the contributing authors for supporting this project. Finally, we hope that you, the reader, will find this collection of articles a practical and useful resource.

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AI & ITS POTENTIAL TO REVOLUTIONISE THE ACCOUNTING INDUSTRY

Benjamin Lee, Clarence Goh,
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WHAT IS AI?

Artificial Intelligence (AI) is all around us; in our mobile phones, watches, cars, home appliances, in our dining and retail experiences, in our offices, in public services, throughout media and beyond. AI promises to fundamentally change our everyday living and seemingly abracadabra away our problems with the wave of the AI magic wand. The growing hype surrounding AI's advancement in recent years has led to several observers making damning claims about how AI will soon take over multitudes of jobs, rendering a big percentage of the current workforce jobless.

That may be somewhat of an overstatement because at present, the part of human intelligence that AI is, is actually only prediction. Prediction is a critical component of AI and is the reason why AI is so powerful today. While AI has not yet reached the level of replacing human intelligence completely, this could still be a possibility in the future as the capabilities of AI are being improved upon.

What we need now is to cut through the AI-hype by bringing across a clear definition of what AI is and how it will partner human intelligence in revolutionising businesses and industries.

DEFINING AI

Russell and Norvig[1] use AI as a term describing machines which mimic human cognitive functions like "learning" and "problem solving". Where the word AI is used, the term "machine learning (ML)" is likely to be found close by too. ML, a subfield of AI and the driver of most of AI's recent progress, is defined today as the use of techniques that enables computers to learn and continuously improve without being explicitly programmed. In essence, AI and ML (in their current form) consist of techniques which learn to recognise patterns in order to make predictions that facilitate decision-making.

Going deeper with AI and ML has also brought forth more sophisticated techniques like Natural Language Processing (NLP) which combines learning with linguistics, allowing for intelligent analysis of written languages. Advanced AI and ML systems have also allowed machines to produce more accurate results than humans, particularly for areas which involve repetitive work.

The growing hype of AI is therefore not without legitimacy. AI systems are promising and powerful decision tools for organisations across different industries to adopt. But before looking into how they can be implemented, it is important to identify the fundamental trends that allow for AI to be feasibly adopted.

TREND-ENABLERS OF AI

For AI to gain a strong foothold in today's world rather than fizzing out several times throughout the several decades before, it leans heavily on four trend-enablers: ABCD.

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1   Artificial Intelligence: A Modern Approach (Global Edition), 2018, Stuart Russell and Peter Norvig

Availability of affordable and powerful machines. Rapid technological advancement has opened the doors for exponential growth of computing power. This has been accompanied with tumbling costs of computing. While some technology observers claim that Moore's Law[2] is dead or will reach its limits by 2020, the phenomenon where higher computing power follows lowering computing costs is very much alive.

Back when the hype of AI manifested mainly in science fiction films and tv shows, the cost of large-scale implementation made it infeasible and impracticable. The IBM 3380, in 1980, was the first hard disk drive to have a storage capacity of 1 gigabyte (GB) and had to be housed in a cabinet, making the 250kg device almost as big as a refrigerator. Contrast that with the first commercially available 1-terabyte (TB) SD card (just slightly bigger than a $1 coin) released by Lexar in January 2019 and it is obvious how readily available storage space is. Even though the Lexar 1TB costs US$500, high by today's standards, that is less than 0.5% of the IBM 3380 which cost upwards of US$100,000.

Enhanced computing power also comes in the form of drastically improved processing speed. These days technology experts have noted that what might have taken weeks to process a decade ago, took just hours five years ago and can now be done in minutes. Affordability, portability and speed are why AI has now become readily available to businesses for implementation, adoption and use.

Better algorithms for use. Much like computing power, AI techniques and algorithms have also seen great improvement in recent times. With multitude of research poured into evolving and advancing the fundamental algorithms behind AI, there is now a whole suite of AI techniques which can be used to solve a variety of different problems. A growing community of developers continuously revise and refine these algorithms while also consolidating them into packages that are accessible for free through open-source programming languages like R and Python.

In the past, programming and coding was seen as extremely technical and even agonising to do. But today, R and Python's plethora of libraries and packages of AI and ML, coupled with developer communities such as GitHub and Stack Overflow (among many others) have opened the gates for businesses to pick and choose AI algorithms suited for their work.

Cloud-computing has given AI a platform to shine by providing improved accessibility that goes beyond hardware and device storage. Companies have begun migrating to cloud-based platforms so as to run operations directly from the cloud without being bogged down by physical limitations. Cloud providers like Google Cloud integrates AI and ML services into application programming interfaces (API) that allow for businesses to develop customised solutions to their problems or for their clients. Cloud platforms also make data storage, computing power and graphic processing units (GPU) scalable, thereby enabling AI and ML algorithms to work more efficiently without the restrictions of on-site hardware. Deep learning using Neural Networks have proven to work at least 10 times faster with cloud-based GPU acceleration as compared to the regular computer processing units (CPU).

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2   Cramming more components onto integrated circuits, Gordon E. Moore, 1965 https://drive.google.com/file/d/0By83v5TWkGjvQkpBcXJKT1I1TTA/view

Data is everywhere. Traditionally, data collected for analysis have primarily been numerical and structured. The boom and influx of Big Data, supplemented by the growing number of social media platforms has led to an unprecedented "hunger" for data of all sorts, including images, text and videos. These kinds of data are unstructured and was previously not thought of as usable for analytics or AI and ML. However, Big Data storage systems, whether physical or cloud-based, have now allowed for the storage of unstructured data as well as the processing of these data. A good example is Apache Hadoop, a powerful analytics engine for Big Data.

With these ABCD trend-enablers, AI is now well-positioned to completely revolutionise the accounting industry and change the way that accountants work.

SHOULD ACCOUNTANTS BE FEARFUL OF THE AI INVASION?

Back in 2013, a University of Oxford study by Frey and Osbourne suggested that the accounting profession is among the most at risk of being replaced by AI, largely because of the heavy task-based jobs accountants do. There is some truth in this because AI and ML systems will in the coming years begin to take over an increasing number of tasks from humans. Administrative tasks that are manual and arduous are most definitely going to be fully taken on by AI and ML simply because machines are faster and more efficient than people.

Instead of painting such a grim picture on the future of the accounting profession, this is actually a good thing! In fact, it has been a long time coming and accountants should look forward to this day when they are finally liberated of laborious and boring tasks allowing them to now focus fully on adding and delivering more value to businesses, which is at the core of what they do.

VISION FOR THE AI FUTURE OF ACCOUNTING

The automation capability of AI systems has led to a strong emphasis on the manual tasks they are able to complete in a speedier fashion. This intimidates many professionals including accountants and lawyers because a big part of their work is indeed manual. While these manual tasks are important, the professional aspect of their work involves adherence to codes of conduct, ethical and moral obligations as they apply professional judgement which they are legally bounded to. Instead of threatening their livelihoods, AI and ML have the capability of assisting accountants with a portion of their work so that they are freed up to focus on fulfilling the accounting profession's purpose.

Rather than replace human accountants, AI and ML become colleagues to their human counterparts and help to get the job done in the most effective and best way possible. The more pertinent question is how can AI partner human intelligence and work together?

PARTNERS AT WORK

With AI systems improving rapidly, the rush for everyone to adopt it is unprecedented. Its high accuracy and efficiency in calculations is way ahead of what humans are capable of. Yet, AI cannot replicate human intelligence completely. While AI and ML techniques can mimic the human cognitive ability of learning and recognising patterns, the human intuition combined with logical reasoning that can respond well to complexity and ambiguity have yet to be replicated. This is the reason why AI is unable to fully capture context and string together pieces of physical, visual, behavioural, psychological, emotional information and connect them all together like humans do so spontaneously.

Specifically, within the accounting profession, the approach to the partnership of accountants and AI accountants begins with knowing the strengths of AI and ML techniques. At present, they are able to reliably handle and process voluminous data while also ensuring that there is continuous monitoring so as to learn from new data and errors.

While AI and ML techniques are powerful, models trained on a specific dataset often run the risk of overfitting and hence not generalisable to new data. Even with the influx of Big Data, data quality can be a big problem leading to a "garbage in garbage out" scenario where poor-quality data leads to analysis results that are unusable. Most of these models are prediction-based ones meaning that their predictive performance and accuracy may vary. Accountants must also recognise that statistical models and mathematics formulae the foundation of AI and ML models and this in itself is a limitation because some business problems cannot be easily solved simply by mathematical computations.

Only after weighing the strengths and limitations of AI and ML are human accountants ready to work hand in hand with AI accountants.

IMPLEMENTING AI IN ACCOUNTING

Adopting AI systems will not be the first time in history that accountants have made use of technology to help them do a better job of providing financial information to users, which ultimately is their main objective. Using AI will help achieve this objective through data-driven decision making, data analytics to derive actionable insights and freeing up accountants to work on value-adding tasks rather than being swamped by tedious grunt work.

AI and ML can be implemented in accounting projects involving fraud detection, forecasting and prediction (of cash flows, inventory, revenue), rules identification to improve process automation, full-scale audits (without the need for sampling) and more.

TECHNOLOGY TRENDS IN ACCOUNTING AND FINANCE

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INTRODUCTION

We are witnessing the emergence of a "post-digital" era, in a new world that tailors itself to fit every moment. The foundational digital tools and concepts have eroded the competitive advantage as most companies are well on the way and near the tail end of their digital transformation journeys. Digital saturation is raising expectations, abilities and risks across industries and businesses are seeking new ways to differentiate themselves in the marketplace.

The new post-digital era focuses on a new set of rules, a new generation of technologies and innovations that businesses will need to apply to differentiate themselves in the marketplace. Not surprisingly 89% of businesses are already experimenting with these new generation of technologies and innovations to pave the way ahead[1].

As new technologies provide both the ability to understand individual consumers at a level never before possible and the agility to instantly tailor products and services to meet their needs, companies must reinvent their organisations to find and capture those opportunities to create "momentary markets", and shape them into individuals' "realities".

Finance is increasingly called upon as a strategic enabler and catalyst to help spearhead business imperative drives, broadening the traditional remits of CFOs towards value-led business partnering and digital evangelism to explore the immense potential data and technology "would bring to the table" and differentiate the enterprise in this disruptive marketplace.

ARTIFICIAL INTELLIGENCE X FINANCE

The impact of the post-digital era is so pervasive that incrementalism leads quickly to irrelevance. Corporate life expectancy of S&P500 companies is expected to last only 14 years by 2026, a far cry from the 61 years in the 1950s[2].

Finance is increasingly challenged to evolve and broaden its remit to fuel the "Finance for Enterprise" agenda, driven by the forces of the new value-led business model. Being brilliant at the basics of financial stewardship and governance of the organisation continues to be an implied expectation of the Finance, hence "Finance for Finance".

Even the most skeptical of Finance C-Suites are reshaping the finance agenda. 3 out of 4 CFOs surveyed in Accenture's Global CFO Research are heading up efforts to improve through[3] adoption of digital technology. 42 percent of Executives reported AI adoption in at least one business unit, including 18 percent who reported adoption across multiple business units[4]. As Finance repositions itself towards the front line, the function will be in for a radical facelift on how it manages service delivery, talent, data and technology.

1   Accenture Technology Vision 2019 | https://www.accenture.com/_acnmedia/PDF-85/Accenture-CFO-Research-Global.pdf#zoom=50
2   "Innosight, Corporate Longevity: Turbulence ahead for large organizations," Spring 2016
3   The CFO Reimagined: from driving value to building the digital enterprise | https://www.accenture.com/_acnmedia/PDF-85/Accenture-CFO-Research-Global.pdf
4   Accenture Technology Vision 2019 | https://www.accenture.com/_acnmedia/PDF-85/Accenture-CFO-Research-Global.pdf#zoom=50

FINANCE OF THE FUTURE

CFOs' radical repositioning of Finance has been focused on embedding AI and new technologies at the core of Finance to pivot to the new and can be characterised by three thematic initiatives:

1. Continuing the digital drive and transformation through AI: **Intelligent Finance**

2. Leading digitalisation efforts and innovation: **Digital Factory & Incubation**

3. **Developing future finance talent** to manage the post-digital Finance function

1. Intelligent Finance: Digitising Finance and Harnessing the Power of Data

CFOs continue to focus on the digital drive of establishing Intelligent Finance within their organisations as part of the digital transformation, embedding AI technologies to automate routine accounting, control and compliance tasks. They are increasing their focus on value creation as AI empowers them to shape strategy.

As a result, they can increasingly be relied upon for higher-level thinking, answering new questions in new ways and bringing the C-suite together to act on insights gleaned from data analysis.

The key focus areas of Intelligent Finance are:

• *Enabling touchless in-memory processing, reconciliation and allocation activities;*

• *Mechanising accelerated (and continuous) accounting, closing and compliance in real time through automation and machine learning*

• *Enabling smart financial reporting encouraging real-time self-service reporting and analytics;*

• *Performing rapid planning and predictive forecasting to drive real time insights and;*

• *Freeing up valuable talent resources to focus on value creation.*

Intelligent Finance provides the foundational capabilities stemming from AI, which Accenture perceives to constitute of a constellation of enabling technologies to enable intelligent functions, that can be applied within different finance areas to digitise, eliminate, automate and augment current Finance capabilities.

Figure 1: Artificial Intelligence and its applications in Intelligent Finance

AI DRIVERS

SENSE
Perceive the world by acquiring and processing images, sounds and speech.

COMPREHEND
Analyse and understand the information collected by adding meaning and insights.

ACT
Act in the physical world based on comprehension and understanding.

LEARN
Improve performance (quality, consistency, and accuracy) based on real world experiences.

WHAT ARE THE AI TECHNOLOGIES?

WHAT CAN BE TRANSFORMED BY AI?

MACHINE LEARNING
Using iterative algorithms to learn, performing and refining tasks from experience

- Cash reconciliation
- Intercompany reconciliation
- Performance forecasting
- Judgement-based journey entry validation
- Spend optimisation
- Payables/Receivables behavioural analysis
- Marketing spend analysis by SKU and channel

ROBOTIC PROCESS AUTOMATION (RPA)
Using software to automate computer-based processes

- Finance transactions processing
- Journal Entry Validation (see example)
- Cross-function workflow management
- Control and compliance workflow
- Revenue management

VIRTUAL AGENTS
Communicate in natural language with humans, enabling them to answer questions as a human would and perform business processes

- Payment Term Rationalisation for P2P and OTC
- Control/exceptions management (e.g. rejection resolution)
- Finance (internal/external) query management

COMPUTER VISION
Detecting and identifying objects in digital images

- Real-time Inventory Accounting
- Real-time Fixed Asset Maintenance/Adjustments
- Visual Search
- Contract and billing compliance

SPEECH
Detecting and identifying words and phrases in spoken language

- Finance Helpdesk

TEXT
Text analytics combines linguistic knowledge with statistical methods

- Automated Contract Management
- Purchase Order Management
- Reporting analysis generating (natural language generation for standard analytical reports
- Social Media

Artificial Intelligence Use Case 1 - Journal Entry Validation

Accenture worked with a major hospitality to implement an AI solution within the general accounting team to automate reduce the workload of full time employees while performing journal entries. The solution replaces the manual validation with a customised rule engine with 27 classification parameters to validate journal entries drawing data from multiple sources including vendor database, vendor websites and invoice OCR. Errors are forwarded to employees to perform manual checks. As a direct result of the solution, the client realised a 35% FTE reduction, reduced handling time from up to 6 hours to just 8 minutes as well as reduced error incidence rates at the same time.

Artificial Intelligence Use Case 2 – Intelligent Cash Reconciliation

Accenture developed an AI-powered reconciliation advisor tool which helps improve efficiency by performing continuous cash reconciliations to perform real-time oversight on cash balances and credit card reconciliations. The AI engine suggests different combinations of open line items and makes the best match based on the minimum variance and confidence score through contextualised or fuzzy matching that supports continuous machine learning, drawn from unstructured data. The open items are classified based on the predefined knowledge and continuous self-learning from user feedback.

This innovative solution has enabled the client's Finance team to lay the foundation for continuous reconciliation thereby enabling management to drive real time decisions on cash flow.

2. Digital Factory & Incubation: Leading Digitalisation Efforts and Innovation

CFOs play a critical role in the digitalisation of their enterprises, with most starting in their own departments. In a virtuous circle, the data capabilities CFOs develop can help them make decisions about investing in digital and technology across the enterprise based on economic value, which in turn empowers them to generate and combine even more useful data.

Future-minded CFOs and leaders know that they will need not only every digital tool in their current arsenal, and new ones to build intelligent and highly customised, in-the-moment experiences and differentiate themselves from the competition. Distributed ledger technology (DLT), Artificial intelligence (AI), extended reality (XR) and quantum computing—or, collectively, "DARQ." DARQ presents a first mover's advantage with 41 percent of Executives surveyed envisioning AI having the greatest impact on their organisations over the next three years[5].

More importantly, CFOs are leveraging their new-found expertise and are increasingly advocating incubation of digital factories or studios where cross-functional teams convene to collaborate and innovate on creating in-the-moment experiences for their customers to differentiate themselves in the marketplace.

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5   Accenture Technology Vision 2019 | https://www.accenture.com/_acnmedia/PDF-85/Accenture-CFO-Research-Global.pdf#zoom=50

Accenture is collaborating with a leading airport operator to develop the first digital factory in Asia Pacific for travel industry, bringing the right skills and technology capabilities to organise, invent, incubate and industrialise opportunities with agility.
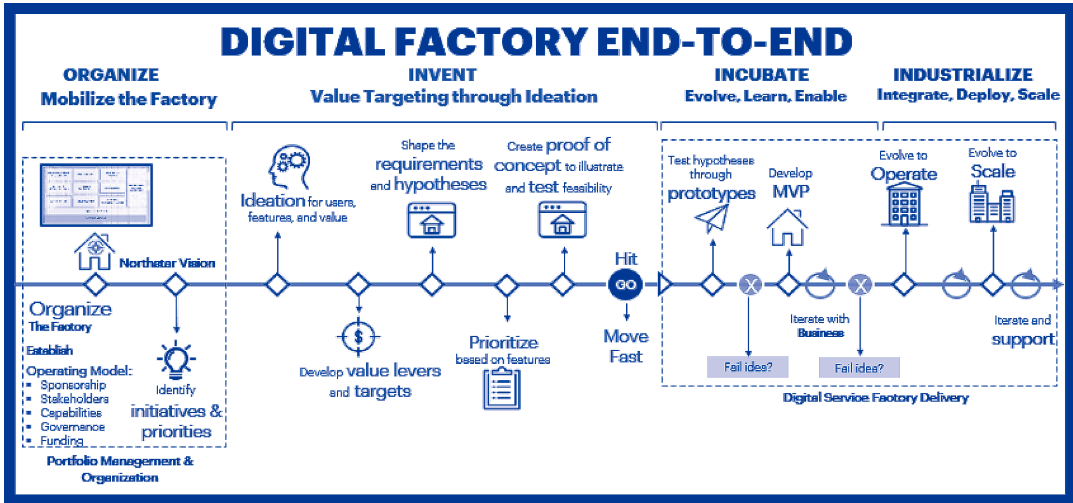
Figure 2: Digital Factory Production

3. Developing the Future Finance Talent

As AI becomes embedded in the fabric of the finance organisation, human talents are now freed up to focus on higher value-added activities and to manage the virtual talents with which they need to collaborate. CFOs need to shift their hiring and talent development criteria so the next generation of finance leaders — who will more than likely follow different career paths than previous generations — can flourish in this expanded role. Knowing how to collaborate and innovate are requisite traits of the new finance leader.

Striking the right balance in the future finance talent mix is also key in achieving the imperatives of Intelligent Finance as well as digitalisation. The post-AI impact on the Finance function trickles down and challenges the current assumptions of a human and functional-centric Finance talent strategy that would evolve towards a cross-function skills and capability-based talent strategy powered by AI. AI will work alongside humans in their organisations, as a co-worker, collaborator and trusted advisor, complementing their human counterparts as the function invests in strategic value creation.

Figure 3: Projected Evolution of Finance Staffing Levels Impacted by Artificial Intelligence

Accenture analysis projects aggregate staffing levels in the finance function for the median company to see a net reduction of 40 percent by 2025, dr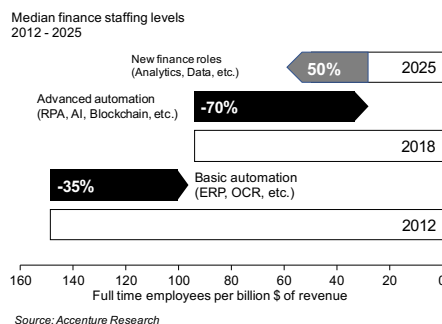iven by almost 70 percent reduction of transactional scope powered by advanced automation (RPA, AI, Blockchain, etc.), while new finance roles focus on cross-functional capabilities will represent of the new finance staffing levels, fueled by investments in higher value-added services.

Yet, today's finance talent is hired and evaluated based on the static yardstick of being concrete, reliable and detailed oriented, while the new expectations of a post-digital finance prize the ability to be outward focused, to collaborate and innovate, to manage virtual talents (e.g. AI and Robotics) as requisite traits of the Finance function. CFOs need to shift their talent strategy, hiring and talent development criteria as well as their continued investments on upskilling and education so the next generation of finance leaders, who will more than likely follow different career paths than previous generations to address the critical skills gap to march on towards the finance. As a causal effect, new Finance roles will emerge while the remit of traditional roles will evolve.

Figure 4: The new finance workforce

TRADITIONAL ROLES	HIRING NEEDS	MAIN IMPACTS
Financial Planning & Analysis	▲	The real work starts when you deliver the report or analysis: • Anticipating alternative scenarios, tracking their emergence and executing on contingency plans • Not just answering the "what happened" and "why did it happen" questions but also answering "what should we do" questions
Financial Controller	▼	• Focusing on preventive and real time control rather than relying on detective controls • Managing outcomes, not process
Accounts Payable Clerk	▼	• Focusing on exceptions as routine work is automated • Greater collaboration with other functions

EMERGING ROLES	HIRING NEEDS	NEW SKILLS AND REQUIREMENTS
Data Scientists	▲	• Ability to understand and manipulate massive volumes of data from internal and external sources • Detailed industry knowledge to pose the right questions of the data • Ability to combine market, operational and financial data into rich data sets • Technical Competencies: SQL, R, Python, Power BI/Visualisation
Scenario Planner	▲	• Ability to determine likely scenarios, the triggers for each scenario, and the business impact of each scenario • Ability to run several models simultaneously • Technical Competencies: Power BI/Visualisation, Python, TensorFlow

	Market Maker	▲	• Ability to analyse new business opportunities and ways the organisation can profit from them • Technical Competencies: TensorFlow, AppZen, Wolfram Alpha, IBM Watson, IPsoft
	Social/ behavioural scientist	▲	• Ability to model changes in customer and competitor behaviour and describe the financial implications • Technical Competencies: Power BI/Visualisation, Python, TensorFlow

CONCLUSION

CFOs are increasingly called upon to be a strategic enabler to keep pace and to drive value creation in times of pervasive disruption and change brought about by digital. Finance Leaders are embracing the digital agenda and have been increasing investments in AI and new technologies to achieve its new imperatives in the post-digital era, starting with Finance itself before broadening their remit.

CFOs' imperatives continue to spearhead Finance's transformation into an Intelligent function and advocate new digital technology adoptions and incubations to drive agility, value and insights creation. Talent remains integral to enable the transformation with new roles and continued investment in skills and capabilities to fuel new expectations as well as to manage the new talent mix powered by AI and Robotics.

It is no wonder our CFO Reimagined research showed 78 percent of more junior finance practitioners say that there has never been a more exciting time to be a finance professional.[6] Are you ready to be finance leaders of the future?

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6 The CFO Reimagined: from driving value to building the digital enterprise | https://www.accenture.com/_acnmedia/PDF-85/Accenture-CFO-Research-Global.pdf

CHAPTER 3

AI IN FORENSIC ACCOUNTING AND FRAUD DETECTION

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INTRODUCTION

The use of Artificial Intelligence (AI) and Machine Learning are still in their infancy in the practice of forensic accounting.

While there are increasing attempts to use AI and Machine Learning to detect fraud and misconduct, deploying such techniques in forensic accounting investigations have had mixed results. The complexity of the models also makes it challenging to explain how results were derived. Such models may take time to build, train and refine, hence may not be practical for time sensitive forensic accounting investigation.

AI and Machine Learning can however introduce significant advancement in automation and sophistication that will never be achieved in traditional forensic accounting procedures, involving manual review of accounting records and correspondences. Such techniques also help forensic investigators examine large volume of data expeditiously.

To leverage AI and Machine Learning, forensic investigators need to understand the model used, how the model is developed, and are able to assess the reliability of the model.

WHAT IS FORENSIC ACCOUNTING?

Forensic accounting is a practice area of accounting that engages in the investigation of an organisation's records for evidence of financial crime. Through careful analysis of quantitative and qualitative data from the organisation's books and records, forensic accountants are able to detect evidence of fraud, misconduct, and other regulatory violations.

While forensic investigators do go over bookkeeping records, similar to an auditor, the objectives and scope of a forensic investigation are vastly different and require a different form of training. Forensic investigators also examine non-financial records such as management records, minutes of meeting, or even the access records maintained at the guard house. Forensic investigations focus on a firm's system of internal controls but are also aimed at understanding their potential weaknesses to identify possible exploitation, usually in the form of sophisticated fraud schemes or other asset theft methods.

In addition, forensic accounting can also be used to assess a firm's regulatory compliance and overall organisational structure for managing both current and future risks. These advisory services often see forensic accountants providing expert opinions or advice to help the firm manage its risks. Forensic investigators often consider instances where the existing controls have broken down, or there is potential fraud, or where there are instances of non-compliance that the firm has never experienced. As regulations are constantly changing, firms require assistance in designing and implementing future-proof compliance frameworks, reviewing observance with ever-changing regulatory expectations, and remediating potential deficiencies.

Forensic accounting firms seek to provide a consistent global approach that can be tailored to clients' needs. These include employing a wide variety of professionals, ranging from auditors to law enforcement regulators and even technology specialists. These tools better equip organisations to effectively monitor and respond to potentially damaging situations, while reducing adverse financial, reputational, and operational impact.

TRADITIONAL METHODS OF FORENSIC ACCOUNTING

Forensic accounting involves reviewing large amounts of data to analyse trends and reveal anomalies. More companies are now using advanced technology and data analytics to help detect fraud.

Before the emergence of data analytics, forensic accounting relied heavily on manual processes to sieve out information and evidence to support investigations. In the early stages of forensic accounting, investigations were restricted to book records. These include meticulous reviews of the various accounting documents to identify suspicious transactions and records which deviate from the expected, and collection of supporting documents to obtain justification and evidence of legitimate transactions. All these processes were often conducted via retinal scanning of hardcopy documents.

With the lack of data visualisation tools and software, all records had to be manually reviewed and analysed before trends can be identified. Furthermore, while materiality is used as a threshold in audit, sample testing cannot be relied on in the forensic field. Even the most insignificant transaction could be evidence of fraud, emphasising the importance of all records to be reviewed. Consequently, a huge amount of time was spent on identifying trends before further analyses could take place, significantly reducing efficiency of investigations as compared to the use of detection software which can analyse the data and flag anomalies.

DIGITISATION OF ACCOUNTING

In recent years, firms have become increasingly reliant on technology. The accounting industry is no different, as firms have started digitising a large majority of their financial data. The digitisation movement has led to an explosion of data, and forensic investigators have to pick up new skills to be able to sift through gigabytes and sometimes terabytes of data to find anomalies.

For a forensic investigator, this trend provides more data points that may constitute evidence, hence more opportunities to detect instances of fraud, misconduct and non-compliance. Investigation techniques and approaches have changed along with the digitisation of the environment we live in. Forensic data analytics allow forensic investigators to examine large volume of datasets expeditiously to detect anomalies, patterns, and trends that are traditionally indicative of fraud or other misconduct.

Increasingly, forensic investigators are also deploying forensic data analytics as a continuous compliance mechanism to innately prevent, proactively detect and swiftly respond to instances of potential fraud and misconduct. These include:

– Fraudulent financial reporting
– Procurement fraud
– Payroll fraud
– Abuse of entertainment and expense reimbursements
– Bribery and corruption
– Financial crime such as money laundering

USE OF AI AND MACHINE LEARNING IN FORENSIC ACCOUNTING

Forensic accounting procedures usually consist of reviewing of accounting records (e.g. payment vouchers, sales invoices, goods receipt), reviewing of correspondences (e.g. emails, instant messaging) and performing corporate intelligence (e.g. corporate registry searches, public news). A forensic investigator can leverage data analytics to more effectively and efficiently accomplish forensic accounting procedures in three major ways - analysis of structured data, analysis of unstructured data, and network analyses.

1. Analysis of structured data

The traditional way: Rule-based analyses

Prior to the proliferation of AI and Machine Learning, rule-based analyses were (and still are) the common form of data analytics techniques used in forensic accounting procedures. Rule-based systems involve human-crafted rule sets. These analyses require coding to uncover instances with specific characteristics. The common forms of rule-based analyses are duplicate transaction checks, odd-hours transactions check, accounts with common traits (e.g. same bank account, same address) and surge in transaction volume. Therefore, these rule-based analyses help to identify abnormal transactions or data, drawing attention to these instances for further investigation to be conducted.

These analyses are easier to code compared to Machine Learning and are sometimes embedded into organisations' fraud detection platform as a form of continuous fraud or financial crime monitoring tool. However, since such techniques are highly specific and targeted at revealing certain instances, these techniques are generally threshold based and are rigid. They take into account solely the rules set and draw conclusions based on the limited factors taken into consideration in the codes.

The effectiveness of such analyses is also highly dependent on the creator of the code. Therefore, its effectiveness is limited by the forensic knowledge of the coder. If a certain critical factor is overlooked by the coder, the rule-based analysis tool would lose its effectiveness and the results generated would not be as reliable. As a result, many false results are picked up by such analyses.

Therefore, for such rule-based systems to be used as a continuous monitoring tool, analyses have to be regularly calibrated to ensure they are updated and relevant so as to enable a certain level of reliance on such analyses.

Going forward: Artificial intelligence and Machine Learning in statistical data analyses

With the advancement of technology, there are increasing attempts to use AI and Machine Learning to aid the detection of fraud.

However, forensic accounting investigations often have a narrow scope, targeted at specific areas, and are time sensitive with tight deadlines, making rule-based analyses more suitable since they are easier to code and are more targeted. Forensic data analysts generally rely on carefully crafted scenarios based on their past experience, along with the details of the specific case.

Attempts to deploy supervised Machine Learning often have mixed results. Supervised Machine Learning requires the use of training data consisting of labelled data. Machine learning uses an algorithm to build a mathematical model from the data containing inputs and desired outputs. Using generalisation, the trained machine would be able to perform predictions on a new set of data to identify anomalies. However, in most forensic accounting investigations, there is a lack of fraud cases to train a supervised Machine Learning model. Without known past cases to train the model, a basis for patterns of fraud cannot be obtained.

Unsupervised Machine Learning methods are more commonly deployed for forensic accounting investigation. Unsupervised learning algorithms use only data inputs and learn from the data, which are not labelled, by identifying common features in them. Clustering and anomaly detection are two common unsupervised Machine Learning technique

Anomaly detection

Anomaly detection identifies data that deviates from the majority of the data. This flags out outliers and is especially useful for detection of fraudulent transactions which often differ from the normal operational transactions. Unsupervised anomaly detection techniques identify instances in unlabeled test data based on the assumption that most of the data is normal.
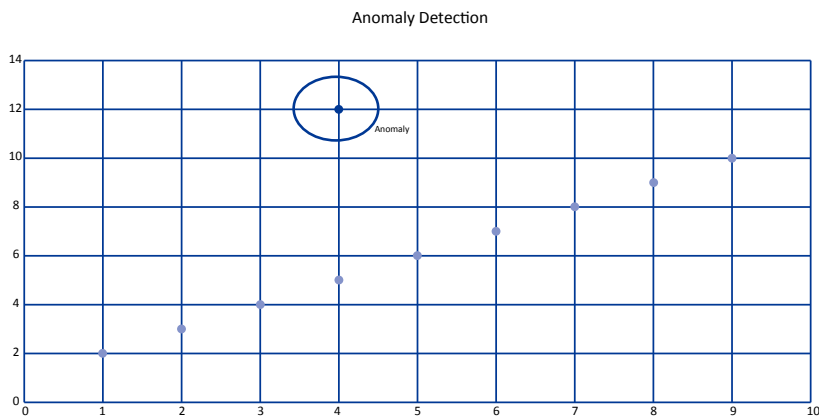
Anomaly Detection

However, anomaly detection may identify multiple transactions which deviate from the normal data as outliers although they may merely be due to bursts in activity. Therefore, a cluster analysis may be able to identify such patterns consisting of micro-cluster

Clustering

Cluster analysis groups similar entities into subsets based on observations that are common within each cluster. Data in different groups have low inter-cluster similarity. Similarity is determined based on one or more predetermined criteria. The most common methods of clustering include K-nearest neighbor, the Naïve Bayes technique and self-organising map

Clustering
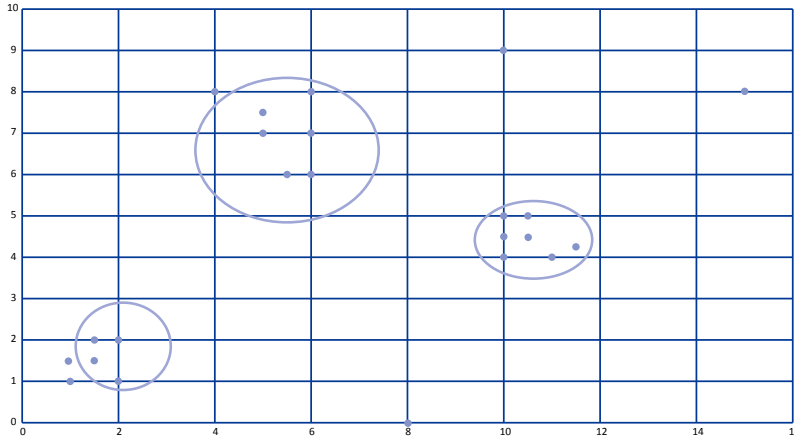
In cases where there are known past cases of fraud to be used as a basis, forensic accountants face a different issue. Fraud cases form a very small percentage of the population, which can skew accuracy scores if used as basis for fraudulent pattern detection through Machine Learning.

The "confusion matrix" below indicates the four possible scenarios arising from data analysis procedures. Ideally, we only want to identify the true positive and true negative results, as the false negative and false positive scenarios could cause misclassification and subsequent incorrect courses of action. Such errors in data identification could potentially lead to the firm suffering substantial financial losses and long-term consequences.

	Actual = Yes	Actual = No
Predicted = Yes	True Positive	False Positive
Predicted = No	False Negative	True Negative

There are several performance metrics that we can examine in our analysis:

Accuracy – This refers to proportion of correctly labeled items in the entire population.

Precision – Also known as positive predictive value. This refers to the number of items which are correctly labeled, out of the total number of positively identified items.

Recall – Also known as sensitivity or true positive rate. This refers to the proportion of actual positive items that are correctly identified as such.

F1 – This measure considers the balance between precision and recall. F1 ranges from 1 to 0, with 1 indicating perfect precision and recall and 0 indicating extreme imbalance. Each measure should not be improved at the expense of the other.

Let's take the example of detecting fraud in a dataset of 1000 entries with 10(1%) fraudulent entries.

If a very simplistic model predicts that all entries are non-fraudulent, the resulting confusion matrix will be as follows:

Using this example, it is apparent that using accuracy as a performance metric is not ideal when the data set is highly imbalanced, as even the most simplistic model will be able to achieve 99% accuracy. This will be a great statistic to put on market materials, but a very misleading one. It is

	Actual = Yes	Actual = No
Predicted = Yes	TP 0	FP 0
Predicted =No	FN 10	TN 990

$$Accuracy = \frac{990}{1000} = 99\%$$

$$Precision = 0\%$$

$$Recall = 0\%$$

$$F1 = 0\%$$

recommended that other metrics be used, such as F1 score, which balances between precision and recall.

2. Unstructured data analysis

The traditional way: Keyword search

In addition to analysing structured data as mentioned above, forensic accountants also review unstructured data such as emails and instant messaging in computers or smartphones using keywords that they deem relevant to their forensic work. Keyword searches can be incredibly powerful tools, if given the right keywords. Although a suspect might have deleted or hidden files, a keyword search is able to go through all the data to identify documents which match its basis.

Once again, the downside of these techniques are that they are rigid and highly dependent on the keywords used. This limitation may result in extensive amounts being unnecessarily reviewed, but more importantly, missing out relevant information due to the specific scope of each keyword.

Going forward: Natural Language Processing

Machine Learning is constantly developing; forensic accountants can potentially make use of natural language processing (NLP) when reviewing unstructured data such as emails to produce results with greater efficiency and accuracy. NLP refers to the use of artificial intelligence in analysing and understanding human language through the use of algorithms.

NLP is inherently difficult for machines to learn and handle due to the rules of human language that are not always clear. While artificial intelligence might easily understand simple rules such as plurality, other less straightforward rules such as sarcasm or the use of puns could prove difficult due to their versatility. Understanding language is a two part process, as both the literal word meaning and the intention of the message must be understood together. Human language lacks consistency and specificity by nature, making natural language processing difficult to implement with reliable success.

The biggest difference in using NLP over a standard keyword search is that the artificial intelligence is able to make sense and understand words in a manner that can not only streamline the scope of textual data analysis, but also extend it to relevant data that might not be directly covered by the exact keyword.

An example of this would be the NLP technique of named entity recognition. This technique is able to extract and classify entities from textual data into predefined categories such as "individuals", "companies", "places", "organisations", "cities", "dates", and "products". While a traditional keyword search might return all documents containing the word 'Apple' (fruit), such NLP models are able to recognise the word's reference to the company 'Apple' and return documents that are relevant to the term but might not be covered by the exact search word.

While NLP techniques are still not perfectly capable of understanding the semantics of unstructured human language, this area of data science is making rapid progress and may be able to accurately

identify relationships between entities and other various linguistic objects in the near future.

3. Corporate Intelligence

The traditional way: Manual mapping of relationships

Forensic accountants make use of link analysis to identify relationships between entities such as organisations, companies, individuals and transactions. This enables the forensic investigators to view and keep track of connections between entities, which is especially useful in complex cases with a huge number of suspects involved or where collusion is suspected such as insider trading.

However, without advanced tools, forensic investigators had to painstakingly obtain information regarding every entity from a spread of different sources. For example, corporate information could be gathered from the Accounting and Corporate Regulatory Authority of Singapore (ACRA), individual information could be obtained from government organisations such as Housing and Development Board (HDB) and Singapore Land Authority (SLA), public records, general search engines to obtain background information about involved entities. Due to the vast amount of information to be collected from various sources, forensic investigators engage in many hours of background searches and corporate investigation work. This information would then be manually pieced together to form a web of connections and relationships between entities, based on the information gathered. However, due to the heavy reliance on manual searches, relationships between certain parties may be overlooked. This would significantly slow down the investigation especially if these relationships are critical connections which are key to solving the case.

Going forward: Use of AI in network analyses

With AI, network graphs can be automatically built from data, instead of manually sourcing for background information from the various sources. Data can be gathered from open source intelligence (OSINT) tools which make use of AI to obtain data regarding an entity. This enables more relevant data about a target to be gathered within a much shorter period of time, making the investigation more efficient.

CHALLENGES IN THE USE OF AI AND MACHINE LEARNING

The use of Artificial Intelligence and Machine Learning involves extensive use of algorithms and statistical models to build a mathematical model which makes predictions to help fraud detection. It acts as a tool to extract and identify financial data to find evidence of fraud from the data processed.

Machine Learning results are harder to explain

Although AI and Machine Learning are capable of generating results to identify and detect fraudulent transactions, the complexity of the models pose a barrier to the explanation of how results were obtained. It is difficult to explain how the results were derived without understanding the rationale of each algorithm put in place. Especially from the receiving end, the results obtained may be hard to interpret without fully understanding how the Machine Learning was developed and implemented, from the 'training' to the processing of data. This may result in doubts about the reliability of results generated using Machine Learning.

Machine Learning models require a longer amount of time to build and refine

In investigations, time is always of the essence. Rules-based analyses are faster to implement and easier to explain compared to building, training and refining a Machine Learning model for the particular problem statement.

CASE STUDY

To leverage AI and Machine Learning, forensic investigators need to understand the model used, how the model is developed, and are able to assess the reliability of the model.

KPMG in Singapore has investigated and researched the use of AI and Machine Learning in forensic accounting since 2012.

Using anomaly detection and text clustering to identify fraudulent vendors

The team used a procurement dataset with known fraud cases to develop and validate a vendor anomaly detection model.

Using NLP, the descriptions in the procurement data were used to cluster vendors selling similar products and services together. After which, each vendor was given an anomaly score using anomaly detection models that calculate how far a vendor was from the other vendors based on a set of hand crafted features.

The dataset contained over 1,000 vendors, and the results generated found that the top 10% of vendors based on overall anomaly score contained all known fraudulent vendors. This was done without indicating to the unsupervised model which were the proven fraud cases.

This example is a strong indicator of the effectiveness of unsupervised Machine Learning in fraud detection and that such approach can also be applied to detect fraudulent financial reporting, payroll fraud, bribery and corruption, employee misconduct or non-compliance activities.

INTERNAL AUDIT FUNCTION OF THE FUTURE

SEIZING THE ARTIFICIAL INTELLIGENCE OPPORTUNITY

Greg Unsworth, Digital Business Leader
PwC Singapore

INTRODUCTION

As business leaders prepare for the future of their organisations in the new digital world, they have their sights firmly trained on Artificial Intelligence (AI), a technology that holds the key to surviving, thriving and leading the digital revolution.

If the internet has changed the way we live, work and play, AI is inspiring us to reimagine the possible, propelling innovation to create better people experiences, boosting productivity and powering business growth. From chat bots to mobile phones to most of our financial transactions, AI increasingly will be everywhere.

According to PwC's 22nd Annual Global CEO Survey, AI will add US$15.7 trillion to global GDP by 2030, which is more than the current output of China and India combined. Business leaders know that those who take the lead now will get the biggest share of this prize. Nearly 3 out of 5 Global CEOs believe AI will have a larger impact on the world than the internet revolution, according to our latest Global CEO Survey (*Exhibit 1*).

Exhibit 1

Impact of AI

Artificial Intelligence (AI)	Global CEOs	Asia Pacific CEOs	ASEAN CEOs
Will displace more jobs than it creates	49%	60%	62%
Will eliminate human bias like gender bias	48%	61%	56%
Is good for society	79%	85%	73%
Will become as smart as humans	45%	58%	51%
AI based decisions need to be explainable in order to be trusted	84%	88%	90%
Will have larger impact on the world than the internet revolution	62%	72%	72%
Governments should play a critical and integral role in AI development	68%	79%	79%

PwC's 22nd Annual Global CEO Survey

Source: PwC, 22nd Annual Global CEO Survey, 2019

But, even as businesses reap the rewards of AI en route their digital transformation journeys, questions remain unanswered over the risks associated with AI and some concerns remain. For example, in our CEO Survey launched this year, 84% of the Global CEOs feel that AI-based decisions need to be explainable in order to be trusted. This is one reason causing some to be slower in adoption of AI (*Exhibit 2*).

Exhibit 2

Data and analytics fuel AI adoption

ASEAN CEOs

72% Believe AI will be bigger than internet revolution.

Yet

36% Have no plans to pursue AI now,

as

53% Struggle with poor data reliability & lack of analytical talent.
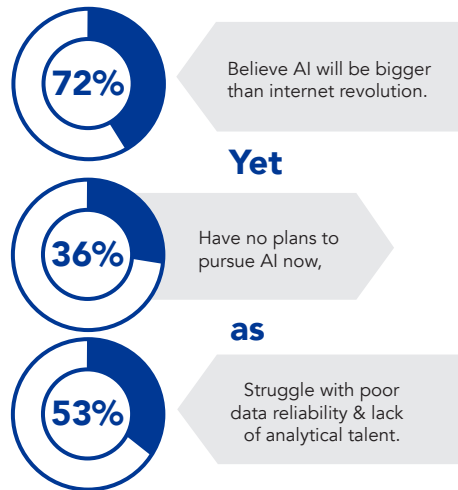
PwC's 22nd Annual Global CEO Survey

Source: PwC, 22nd Annual Global CEO Survey, 2019

Although we see AI being deployed across business functions including human resources, finance, sales, marketing, logistics and customer relationship management, strategic corporate functions like internal audit and risk management have so far just dipped a toe into new technologies like AI.

In future, we expect that it will be critical for the internal audit and risk management functions to adopt AI, not only from the perspective of boosting the function in itself, but also to keep a check on AI use across the organisation.

Presently there is limited use of predictive analytics in the internal audit functions with financial and risk assessments often performed on excel spreadsheets, and automation of team activities has not progressed in a meaningful way. This is fast changing with AI creating many possibilities for organisations. We believe the widespread adoption of AI in internal audit and risk management functions will gradually gain more momentum.

However, effective deployment requires willingness among stakeholders to invest, besides commitment to embrace change and even reconsider career models for future internal audit and risk professionals. To support this, leadership and tone from the top as well as development of programmes to digitally upskill internal audit and risk assessment professionals will be essentia

ROLE OF AI IN INTERNAL AUDIT AND RISK ASSESSMENT

A number of organisations are taking the lead in this change and the future internal audit functions are likely to look very different. Robotics Process Automation (RPA) is being deployed to improve the efficiency of testing, new technology tools are being used to enable real time auditing and monitoring, while predictive analytics is powering risk assessment and developing more effective, tailored internal audit procedures.

This will generate a number of benefits including better quality risk assessment, timelier reporting and importantly, monitoring, providing increased assurance for the organisation. These changes will also often generate better business insights for the organisation from the work of internal audit.

According to PwC's 2019 Global Risk, Internal Audit and Compliance Survey, successful internal audit functions need: (1) the dexterity to pivot quickly and to keep up with the fast-changing pace of digital business developments, and (2) have the knowledge and skills to provide relevant advice and strategic assurance in this new digital world.

Internal audit functions that increase their own levels of digital fitness will be far more effective at meeting these twin challenges. By harnessing digital capabilities, including the power of AI technologies, internal audit functions will be better placed to keep pace with changing risks and also help predict changing future risk profiles.

Leading organisations are developing a clear vision of the digital future for internal audit functions, and asking critical questions such as "what is the specific role for AI?" and "how can organisations benefit in practice?" We will further explore these topics and, in particular, address the following[1]:

1. The opportunities to enhance the role of internal audit and risk assessment through the use of AI technologies; and

2. The increased role for internal audit functions to provide assurance around organisational wide AI programs;

3. The key challenges and success factors for deployment of AI and to enable internal audit professionals for the future

> *"AI is no longer about a machine playing chess. AI is on the streets driving our cars, call centres talking to customers, drafting and reviewing legal documents with immaculate precision, it is even trading using indices derived from satellite imagery"*
>
> *– World Economic Forum (WEF) Annual Meeting 2017*

1   For examples of key considerations for AI solutions, refer to the special edition of the IIA global perspectives and insights publication, "Artificial Intelligence – Considerations for the Profession of Internal Auditing" (https://na.theiia.org/periodicals/Public%20Documents/GPI-Artificial-Intelligence.pdf)

OPPORTUNITIES TO ENHANCE THE ROLE OF INTERNAL AUDIT AND RISK ASSESSMENT THROUGH AI

As internal audit functions develop, there will be increasing use of technology tools; more automation of activities and the power of AI may also help address future needs. In evaluating the potential use of AI for any internal audit function, it is worth considering some of the pros and cons at the outset. In particular, AI can:

• Simulate human behaviour and cognitive processes

• Capture and preserve human expertise

• Enable fast response to business problems

• Provide the ability to comprehend large amounts of data quickly

All of this can enable better business insights, enhanced decision-making and improve efficiency of work performed.

However, there are also challenges to consider, including the following:

• AI has no "common sense" in the same ways that humans do – the effectiveness of its "intelligence" is entirely reliant on the algorithms developed.

• AI needs fixed rules to operate consistently and may not be able to analyse all relevant data sources required for fully nuanced decision-making, without re-configuring the algorithms and data feeds

• AI often has high development costs

• AI can raise legal and ethical concerns – there are important considerations for the potential impact on the future workforce and society as machines take on greater "decision making" roles

Considering these factors, each organisation should evaluate the potential uses of AI in the context of their business needs and strive for an effective balance of dynamics combined the capabilities of humans and machines. Whilst extensive deployment of AI technologies in internal audit and risk assessment functions is still not common, some companies are moving ahead quickly. In fact, many small automation projects that use RPA and basic AI can often only require a few weeks to automate processes for quick wins. These small-scale projects put these technologies into action quickly, generating immediate benefits across a number of activities. Common areas for deployment include fraud detection and compliance reviews as well as establishing predictive analytics for risk monitoring.

Importantly, anomaly detection and machine learning can also help analyse new kinds of transactions and scan more comprehensively. This opens up possibilities to enable greater coverage for testing, until eventually the audit will scan complete populations of transactions – rather than sampling.

In the longer term, AI technologies will also help enable the prospect of continuous audit to provide real-time assurance and transactions verification, rather than a historical assessment. Real-time assurance provides input on key judgements as decisions are made, enabling organisations to continuously monitor and visualise enterprise risks in real time and propose actions.

"As you would expect, the risk of human error is high with manual processes. Additionally, you don't always achieve the same level of transparency you would like. Many finance departments in Singapore are still working on Excel spreadsheets – even basic automation would significantly improve controls and transparency."

– Daniel Berenbaum, VP Finance, Asia Pacific CFO Global Foundries

In recent years, most of the advances in use of AI in the risk assessment and internal audit areas have been in the field of machine-learning, in particular deep-learning and reinforcement of learning.

To illustrate, the hospitality industry is one industry that uses AI and data analytics extensively. Hotel chains operate globally and deal with millions of customer records and transactions. To protect customer data, such organisations are looking to AI and data analytics technologies to continuously scan their systems and to ensure they minimise threats and keep their systems up to date.

Another risk in this sector is in food and beverage operations, which are particularly susceptible to frauds. Continuous monitoring allows patterns such as applications of discounts, void transactions and splitting of cheques to be identified and investigated early. As AI is further deployed, more proactive follow-up without human intervention will take place for anomalies.

The banking sector is also a key target for fraud. Credit card providers have long been using analytics to detect and follow up on suspicious transactions, e.g. large value of overseas transactions. However detection often only happens after the transaction has occurred. Contemporary methods based on predictive analytics are now able to generate alerts and block suspicious transactions in real time. Machine learning algorithms have taken on a more preventive and proactive role in helping credit card institutions detect unknown types of fraud by analysing wider data sets (*Exhibit 3*).

Banks' second line of defence leverages AI

United Overseas Bank (UOB) applies analytics in their compliance function to enhance its Anti-Money Laundering (AML) surveillance.

The use of advanced data analytics within UOB's AML framework has enabled the bank to identify risks that may arise from triggers such as new sanctions faster and more accurately.

The bank is also using advanced analytics such as statistical programming languages and visual analytics to determine targeted risk areas to better prioritise business reviews on potential high risk clients or transactions. Transactions of concern that are identified from these reviews are fed back into the AI-driven data analytics solutions to improve the way in which it identifies risks.

UOB plans to deepen the way in which it is using AI in compliance, such as exploring deep learning to provide contextual analysis on news articles. These automated and intelligent searches can then feed into the risk profiles of customers to enhance the Know Your Customer (KYC) process.

Source: United Overseas Bank

Exhibit 3

Source: PwC Singapore, ACCA and INSEAD,
Re-inventing Internal Controls in the Digital Age, 2019

Increasingly, internal audit functions will look to understand their unique industry needs and embrace AI technologies directly to help provide the assurance their stakeholders are seeking.

INCREASED ROLE FOR INTERNAL AUDIT FUNCTIONS TO PROVIDE ASSURANCE AROUND ORGANISATIONAL WIDE AI PROGRAMMES

Beyond an effective tool used by internal audit functions, it is also likely that AI will be implemented in different ways across organisations. Therefore in the internal audit plan, there should always be considerations made to address risks that are unique to AI technology. The beauty of AI is that as algorithms process increasingly larger amounts of data over time, the machine decision-making becomes smarter and more effective leading to better outcomes. On the flip side, there are risks where this goes wrong, particularly, if criteria for algorithms are not well-defined or if data used for processing is erroneous or incomplete. Hence, where AI programmes do "go wrong", the speed and pervasiveness of the impact for any organisation can be devastating due to the efficiency of AI to execute programmed actions.

Accordingly, there is a significant need for effective assurance to address the following risks for any organisation:

- The need to maintain effective governance structures, processes and procedures

- The risk of unintended human biases and logic errors in the AI programme

- The risk of AI outcomes causing harm, or undesirable outcomes

- Data protection, quality and effectiveness

- The performance and overall cost/benefit analysis of AI programmes

As more organisations deploy organisation-wide AI programmes, there is a key role for internal audit to provide assurance that risks are being well-managed, and that AI programmes are delivering their intended outcomes for the organisation. Important questions to address for internal audit teams include the following:

A. Is the AI initiative well-defined, governed and monitored against expected business outcomes?

B. Are all ethical, moral and safety considerations fully addressed in any responsible AI programme?

C. Are criteria well-defined and algorithms developed effectively?

D. Are the relevant criteria appropriately tailored for the business?

E. Are algorithms subject to continuing review and monitoring for their continued relevance and effectiveness?

F. Is data subject to processing being completely and accurately captured?

G. How is data security, privacy and protection maintained?

H. In what circumstances should human override be applied where things do go wrong and how is this controlled and monitored?

Internal audit should be involved at the outset during the development stage of AI programmes to ensure that they comply with relevant laws and policies and are free from risk of bias. Internal auditors should also test for the reliability, accuracy and completeness of data sources for AI programmes and perform tests over the overall design of AI programmes and related controls.

As AI programmes are implemented they should also be regularly tested for effectiveness against intended outcomes, including assessing the operational effectiveness of key controls around significant risk areas. As AI programmes evolve, new procedures, policies and controls will logically evolve and be developed. These should be subject to regular review and testing by internal audit teams to provide the necessary assurance to stakeholders that changes are being well-managed.

Effective procedures should also be developed to address other key related objectives such as addressing data privacy and security risks. These steps should be built into any well-developed internal audit programme of work.

THE WAY FORWARD FOR INTERNAL AUDIT PRACTITIONERS

When looking to the future, internal audit function and risk management professionals will increasingly embrace AI technologies. For Internal Audit and Risk Assessment Practitioners, what's key to seizing the AI opportunities?

- Data is the fuel for AI. Design a robust Internal Audit and risk management strategy aligned with the corporate data strategy.
- Build digitally-fit risk functions by:
  i) Identifying the knowledge and capabilities required
  ii) Having in place the right skills and competencies to strategically advise stakeholders on risks
  iii) Changing the risk functions' processes, tools and services to become more data driven and digitally enabled, thus anticipating and responding to risk events at the required pace and scale for the future.
- Create the governance and trust framework for your Internal Audit and risk management function and ensure data security within this framework.

CONCLUSION

Digitally-fit internal audit and risk functions will be better prepared to roll out AI successfully and enhance assurance provided to stakeholders. Embracing AI effectively will help enable many organisations to develop an internal audit function that is fit for the future.

USING INTELLIGENT AUTOMATION TO TRANSFORM THE FINANCE FUNCTION

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INTRODUCTION

An estimated 20%-40% of professional occupations are at risk of automation by smart technologies in the coming years. Roles within the internal finance function are no exception. Clearly, intelligent automation represents a major challenge, and a huge opportunity, that CFOs need to prepare themselves for right now.

In this chapter we will first give a practical definition of intelligent automation for the finance professional and outline the main technologies it incorporates before looking at the value proposition for the CFO. We will then identify the automation hotspots across the finance value-chain and review a real-life case study, before identifying some of the common risks and implementation pitfalls. Finally, we will look at how these technologies are enabling a major change in the role of finance and organisations can do to ease that transition for its people.

THE KEY TECHNOLOGIES

The first problem finance leaders face when addressing this challenge is one of definition. At EY, we believe the most practical definition for today's CFO is to think of intelligent automation as an umbrella term for a range of automation technologies, from relatively simple robotic process automation software to highly specialised artificial intelligence (AI) tools that can mimic, or even out-perform, human intelligence in some specific cases.

Artificial Intelligence Solutions

► Deep Learning & Decision Making
► Machine Reading & Machine Vision
► Natural Language Processing & Generation (Chatbots)

Cognitive Automation Solutions

► Machine Learning
► Unstructured data processing
► Human-in-the-loop

Robotic Process Automation Solutions (RPA)

► Rules-based automation
► Structured data processing
► Unattended automation

Figure 1: The key technologies

ROBOTIC PROCESS AUTOMATION (RPA) SOLUTIONS

For many organisations, RPA can be a first step to adopting automation, due to the relative simplicity of the technology combined with the opportunity to make significant improvements in operational efficiency. It is an enterprise-class software that, once set up, can run unattended. However, unlike a pre-configured, out-the-box system, RPA needs to be programmed specifically for the processes and actively managed by a combination of business and technology specialists.

RPA robots (bots) work best when activities are structured and repetitive – data entry, reconciliations and reporting are prime examples. The technology sits on top of legacy systems and does not require deep integration, so implementation timelines are relatively short – typically measured in weeks rather than months for a simple process. The technology can be developed with multiple, transferable bots performing a range of tasks so, at scale, RPA acts like a virtual workforce within the organisation.

Cognitive automation solutions

Not all processes can be captured by a simple set of rules. To address these use cases, RPA must be augmented with cognitive automation – a solution that leverages machine learning to enable it to "learn" an unstructured process and adapt to changing business logic by continually observing human co-workers.

This ability allows cognitive automation to address larger and more complex processes than RPA, for example, teaching a robot to recognise and extract data from a range of unstructured documents. As such, these solutions typically result in more transformative outcomes. It is important to recognise, however, that implementation timelines are longer and the costs are typically higher than a pure-RPA project, due to the need to train the robot for the specific task using a large amount of historical data or real-time examples.

Artificial intelligence (AI) solutions

Even more complex processes will require something approaching human intelligence. AI solutions use algorithms, which are built to function similar to human brains to solve complex problems. Developing these solutions requires a huge amount of data and significant computational power, in addition to the expertise needed to codify the problem statement and train the bot. Typically, therefore, they are complex to develop, although many AI solutions can be procured "pre-trained" and integrated with other automation tools.

In practical terms for the CFO, these artificial intelligence solutions fall broadly into two categories. Firstly, those that support insight and decision-making, such as data analytics and visualisation tools. And, secondly, those that automate highly complex processes or human interactions such as machine vision and natural language processing.

BENEFITS OF INTELLIGENT AUTOMATION

The largest benefits of intelligent automation are unlocked through a combination of the above technologies, enabling end-to-end processes to be automated. These benefits fall generally into three categories: increased efficiency; improved decision-making; and enhanced control environment.

Figure 2: Benefits of intelligent automation

While efficiency is not always the primary driver, most organisations look for financial savings to "fund" the qualitative benefits of an intelligent automation implementation. The efficiency savings potential in the finance function varies, depending on the maturity of the current processes and systems, but targets typically range 15%-30% once the end-state is achieved.

AUTOMATION HOTSPOTS

There are many automation opportunities in the finance function due to its relatively high proportion of rules-based processes in comparison with other business functions. Some of the key hotspots, where the benefits are typically highest, are illustrated in figure 3 below.
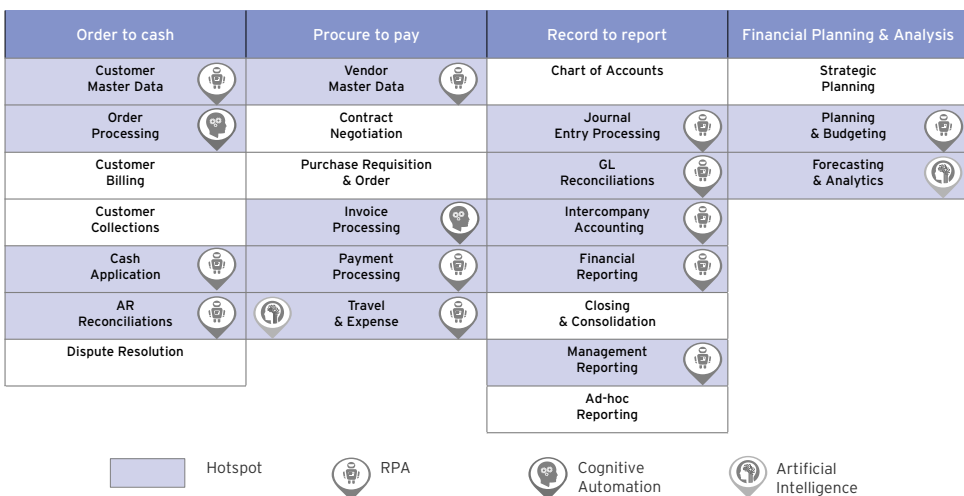

Figure 3: Automation hotspots in the finance function

Order to cash or accounts receivable

Typical hotspots in the order to cash process include:

- Customer master data: RPA bots collect information from emails, forms or workflows, validate for completeness, route for approval and update systems

- Order processing: Cognitive automation bots are taught to extract and process order data from unstructured sources including forms, spreadsheets and emails

- Cash application: RPA bots download bank files, enter or upload data, match payments against remittances and summarise outstanding items

- AR reconciliations: RPA bots are deployed to validate and reconcile data across multiple billing systems or between billing, customer relationship management (CRM) and enterprise resource planning (ERP) systems

Procure to pay or accounts payable

Typical hotspots in the procure to pay process include:

- Vendor master data: RPA bots collect information from emails, forms or workflows, validate for completeness, route for approval and update systems

- Invoice processing: Cognitive automation bots are taught to extract and process invoice data from unstructured sources including forms, spreadsheets and emails

- Payment processing: RPA bots create and edit payment proposals, check for duplicated payments and send payment notice to vendors

- Travel and expense: AI analytics tools identify fraud risk upfront, while RPA bots allow for 100% sample checking of receipts

Record to report or general accounting

Typical hotspots in the record to report process include:

- Journal entry processing: RPA bots check for information completeness (e.g., cost centre), automate preparation and post or park to ERP system

- General ledger reconciliations: RPA bots download statements from bank portals, reconcile transactions to ERP, and create balancing entries to handle discrepancies

- Intercompany accounting: RPA bots check and reconcile counterparty balances and create exception reports

- Financial reporting: RPA bots automate data extraction, aggregation, preliminary analysis and exception identification for review

- Management reporting: RPA bots download ledgers, enrich with other sources (e.g., headcount data), then create initial trend and variance reports for review

Financial planning and analysis

Typical hotspots in financial planning and analysis include:

- Planning and budgeting: RPA bots distribute templates and collate data, perform basic completeness checks, and create initial variance analysis for review
- Forecasting and analytics: AI analytics tools generate new insights into costing, pricing, sales, revenue and cash-flow by analysing historical relationships between internal and external drivers (e.g., product portfolio, competitor behaviour, natural events, macroeconomics, historical performance). Data visualisation enables self-service querying and reporting.

CASE STUDY: AUTOMATING AN END-TO-END ORDER MANAGEMENT PROCESS

The issue

The company wanted to digitise their end-to-end order management process, which involves over 100 human resources. The process was massive, manual and relied on human checking of millions of non-standardised documents each year, including over 70 unique document types, over 150 unique data points to check and extract, and over 800 different possible business rules to be executed.

The solution

The solution utilises a combination of optical character recognition, cognitive automation and RPA to automate the end-to-end process as illustrated in Figure 4 below.
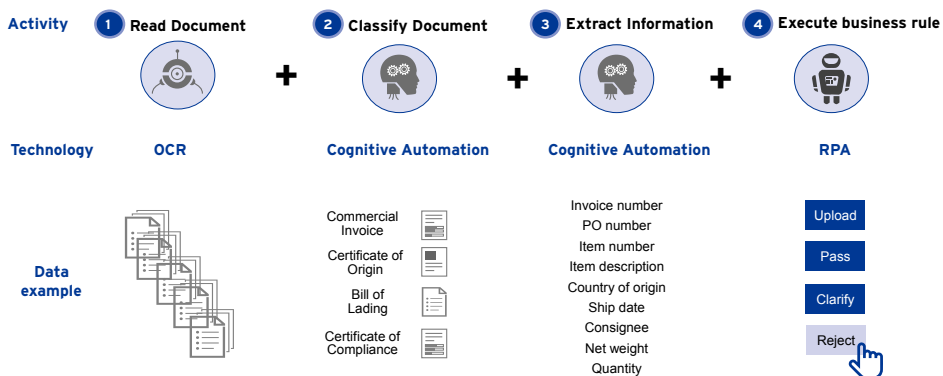
Figure 4: An end-to-end automation process

- Automation software observed human processors tagging data points over a period of months to build its own process model, enabling it to recognise over 70 non-standard document types and extract up to 150 data points from each document.
- RPA developers then coded over 800 business rules to process the orders, verify discrepancies, invoice customers and report KPIs.
- The process operates with a human "in-the-loop": unrecognised documents are routed to a person and the bot observes the outcome, continually learning the process.

Outcome

The solution automated over 40% of end-to-end transactions from customers that were onboarded. In addition, millions of data points that were previously restricted to paper documents are now available for the company to analyse and improve future business performance.

IMPLEMENTING INTELLIGENT AUTOMATION EFFECTIVELY

These technologies are powerful tools for transforming business processes. However, when automation programs are not correctly managed, they can become costly exercises that do not deliver the required results. The common pitfalls include lack of a clear RACI (Responsible, Accountable, Consulted, and Informed) framework, getting the execution wrong and lack of ongoing bot management, detailed in Figure 5 below.

Lack of a clear RACI	RPA is a hammer, but not everything is a nail	Getting the execution wrong	Lack of ongoing bot management	Managing Change
▸ Weak business and IT collaboration ▸ Roles and responsibilities unclear ▸ Squeaky wheels get the oil	▸ Poor process selection ▸ Lack of focus on benefits	▸ Not Agile ▸ Too much focus on technology ▸ Ignoring process reengineering	▸ Inadequate training / skills / capacity ▸ Poor transition ▸ Not planning for on-going support	▸ Inability to build a shared vision ▸ Not managing expectations / stakeholders

Figure 5: Common pitfalls in intelligent automation

To avoid these pitfalls, companies should focus on these three guiding principles:

1) Automating a bad process is bad process automation

Process re-engineering accounts for 20%-50% of effort in successful implementations. Standardising, simplifying and eliminating activities before they are automated not only reduces the overall implementation effort but also improves the resilience and ease of maintenance of the final, digitised process.

2) Manage your bots like any other recruit

Strong governance, with clear roles and responsibilities, must be embedded throughout the automation lifecycle – most importantly after the digital workforce goes live. Intelligent automation solutions are different from out-the-box systems in that they are typically developed bespoke for the organisation. So, they must be actively managed, measured, trained and improved over time.

3) People before technology

Ultimately, technology is just an enabler for the outcomes that organisations want to achieve. Even the smartest AI systems currently only outperform humans in very specific activities. We are probably decades away from a general AI that can be as flexible and intuitive as a well-trained human colleague. In the next section, we'll look at what these technologies mean for the people in the finance functions.

INTELLIGENT AUTOMATION AND THE FINANCE ORGANISATION

Managed well, smart technologies can be transformative for the finance function, moving it up the value chain within the organisation. This is not a new objective but there are now new tools that can help the CFO to achieve this goal by simultaneously automating transactional accounting activities while enabling finance with new analytical capabilities.
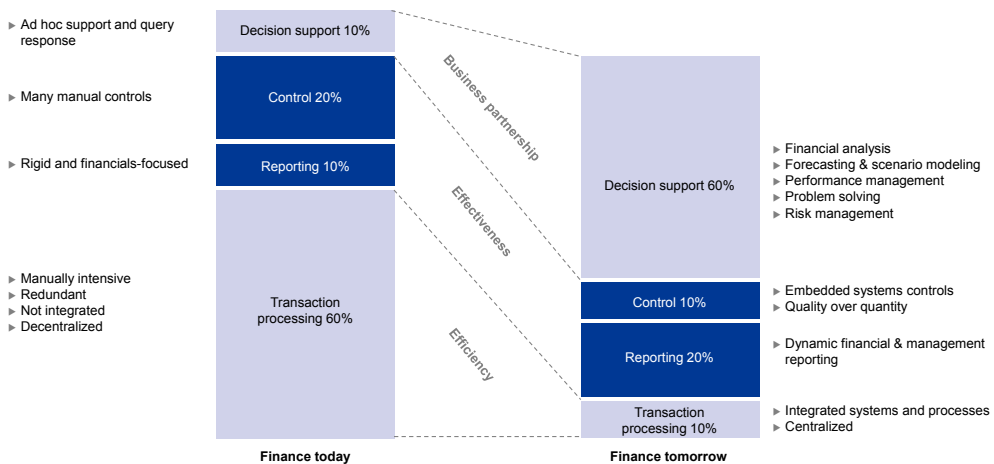
Figure 6: A vision of the finance function tomorrow

Technology alone will not make this vision of finance a reality. Having a coherent workforce transition strategy is key and can be executed at three levels:

Individual

• Overcoming "automation anxiety" – enhancing the brand perception of automation and addressing job uncertainty

• Enabling new ways of working – redefining measures of success and closing knowledge gaps where needed

Organisational

• Designing the future organisation – redesigning roles and responsibilities, redeploying and reskilling

• Developing future finance leaders – developing executives who can embrace change and manage both virtual and physical teams

Strategic
- Embracing the new role of finance – transforming finance as an example to the rest of the business
- Creating a new work culture – updating the strategic narrative and building a future-focused ethos

CONCLUSION

The most practical way for the CFO to understand intelligent automation is as an umbrella term for a range of smart technologies. These technologies can automate both simple, rules-based activities, such as creating a standard management report, and more complex, unstructured processes, such as capturing data from a non-standard invoice. Moreover, some sophisticated AI tools can mimic near-human activities and outperform people in performing complex analytical problems and delivering insight.

These technologies can be thought of as a digital workforce and should be managed as such. There are many common pitfalls that can result in suboptimal implementation or performance if not addressed properly, and the human impact should be of primary concern. Nevertheless, automation is certain to bring a range of benefits across the finance function – increased efficiency, improved decision making and an enhanced control environment. Embracing this opportunity should be a key objective for any finance professional or aspiring CFO today.

USING AI TO TRANSFORM EXTERNAL FINANCE PROCESSES

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BACKGROUND

The role of the CFO and finance professions is constantly under greater scrutiny, internally and externally. Finance functions face pressure to cut costs, grow revenue and ensure control. Economic uncertainty, increased regulatory requirements, financial restatements and increased investor scrutiny have forced them into the spotlight.
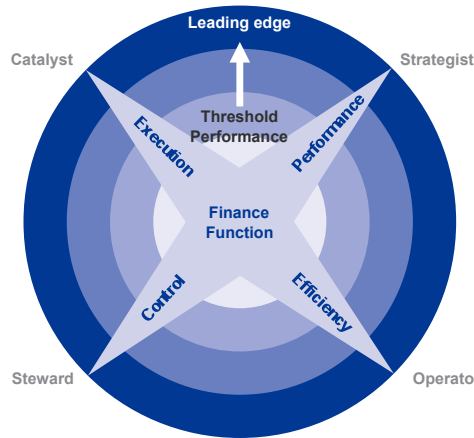
Exhibit 1: Deloitte's Four Faces of the CFO framework

Today's finance functions are expected to play four diverse and challenging roles (Exhibit 1). The two traditional roles in this framework are: Steward - preserving the assets of the organisation by minimising risk and getting the books right, and Operator - running a tight finance operation that is efficient and effective. Finance functions also aim to be Strategists - helping to shape overall strategy and direction, and Catalysts - instilling a financial approach and mind set throughout the organisation to help other parts of the business perform better. In Southeast Asia (SEA), we have seen most finance functions spend 70 to 80% of the time on the lower half roles (i.e. Steward and Operator), with limited capacity to focus on the Strategist and Catalysts. Most aspire to move at least 15-20% more time towards the top half. What is your mix of time spent on bottom half vs top half currently?

More recently, in a poll conducted by Deloitte, over 90% of CFOs identified the following 3 trends *(Exhibit 2)* that will have most significant impact on the finance function.

Poll Results: Top 3 Trends Impacting Finance	% of response
Data	91%
The Role of Finance	56%
The Finance Factory	51%

Exhibit 2: Top 3 Trends Impacting Finance (as ranked by CFOs)

Technology advancements in the past decade have transformed how work is performed by both humans and machines. AI presents an opportunity for finance functions to overcome the 3 key trends to better make sense of data, increase the value-added role of finance, and move towards a "touchless" finance function.

UNDERSTANDING THE CAPABILITIES OF AI

AI is the simulation of human intelligence by machines. A typical AI process involves learning data and decision-making rules, rationalising and defining conclusions, and self-corrections. These processes are enabled by pattern recognition technologies to draw conclusions based on data trends and decision rules. As data patterns and rules evolve over time, AI machines can also learn the new patterns and rules for updated decisions to be made.
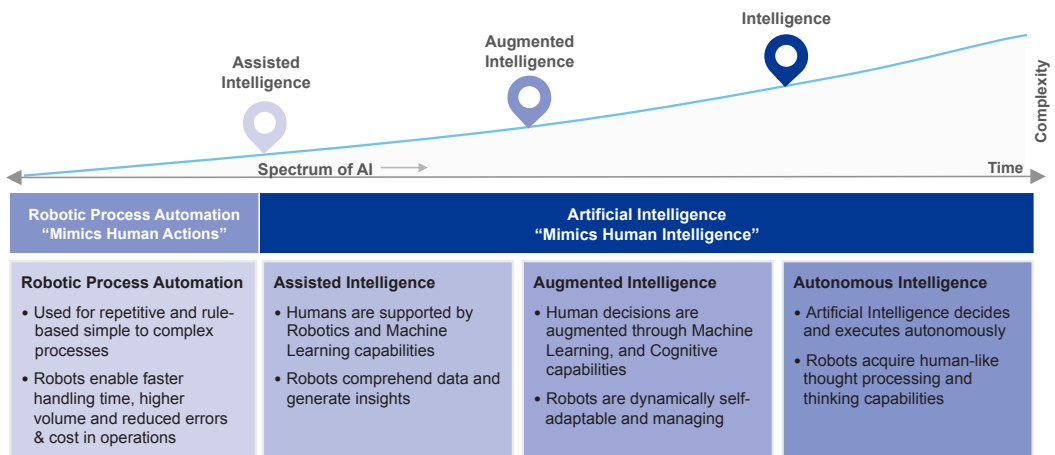
Exhibit 3: The Automation Spectrum

Initial development of AI largely revolved around big data and science-based logic to assist humans in deriving logical decisions. Today, AI leverages the capabilities of Machine Learning (ML) for the augmentation of human analytical competencies and will soon be fully integrated into operations and granted autonomous authority to automate processes through an amalgam of powerful machines, bots and systems *(Exhibit 3)*.

RE-SHAPING FINANCE WITH AI

AI integration offers opportunities for finance functions to perform better in each role:

- **Steward and Operator:** Automation of governance or other rule-based finance processes, report generation by machines, and intelligent identification of risks / issues reduces manual processes and enhances stringent governance

- **Catalyst and Strategist:** Deep learning of data patterns and analysis of business trends provide ideas for strategic direction and execution

MAXIMISING THE POTENTIAL OF AI

To realise the full potential of AI, organisations need to look beyond improving internal operations and explore AI for interactions with external interfaces. AI can be applied at varying degrees for different types of external interfaces as illustrated in *Exhibit 4*.

Customers

Improve overall credit limit management based on trends and external data, and responding more quickly to changes

Manage risks in order processing by identifying anomalies and automated approval

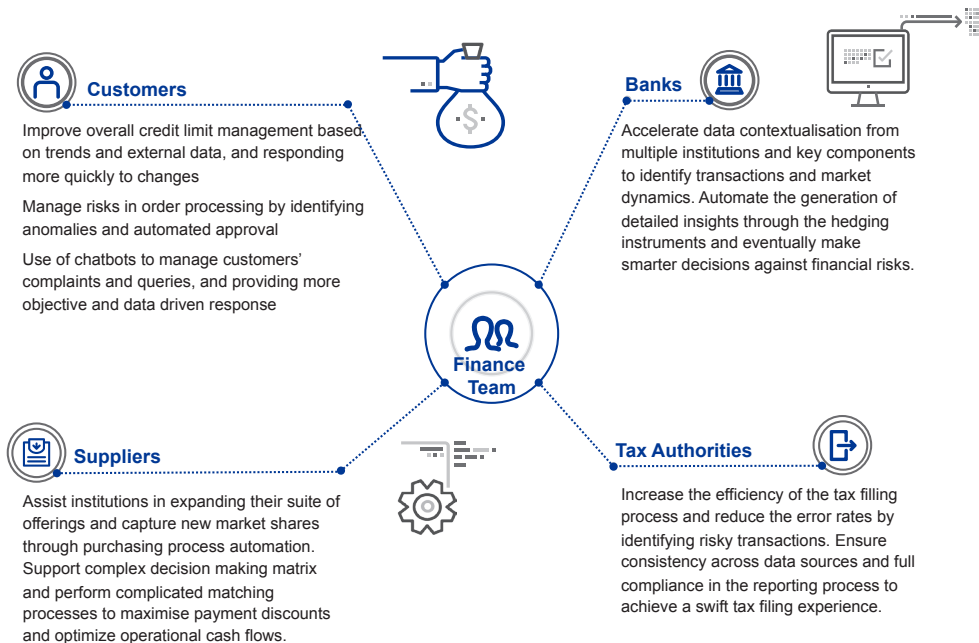Use of chatbots to manage customers' complaints and queries, and providing more objective and data driven response

Banks

Accelerate data contextualisation from multiple institutions and key components to identify transactions and market dynamics. Automate the generation of detailed insights through the hedging instruments and eventually make smarter decisions against financial risks.

Finance Team

Suppliers

Assist institutions in expanding their suite of offerings and capture new market shares through purchasing process automation. Support complex decision making matrix and perform complicated matching processes to maximise payment discounts and optimize operational cash flows.

Tax Authorities

Increase the efficiency of the tax filing process and reduce the error rates by identifying risky transactions. Ensure consistency across data sources and full compliance in the reporting process to achieve a swift tax filing experience.

Exhibit 4: Impact on External Interactions

Customers

Credit analysis and management

In the *assisted* intelligence stage, AI assists to identify data trends and relationships to reflect potential debtors' credit limit. With *augmented* intelligence, trend identification methods are enhanced to predict potential changes to debtors' credit limit. In the *autonomous* intelligence stage, AI aims to eliminate human intervention by actively scouring the web for data, analyse and offer insights such as the optimal credit limit for clients by predicting their ability to pay, and also identify sales opportunities in the process.

Order processing and invoicing

The *assisted* intelligence engine leverages on OCR to recognise order items and flags out multiple orders requiring separate processing or duplicates for manual exception handling. With *augmented* intelligence, anomalies in invoicing such as an unusual amount ordered or purchase behaviour by established customers can be identified. In the *autonomous* intelligence stage, approvals are automated using digital signatures based on a set of predefined criteria to maximise efficiency in the order to cash process.

Queries, complaints and return/refund

Assisted AI leverages on Natural Language Processing (NLP) - where machines are able to comprehend and relay output in human languages, to mine unstructured customer complaint and refund request data. Term-Frequency-Inverse-Document-Frequency (TF-IDF), Latent Dirichlet Allocation (LDA) and Support Vector Machines (SVM) are examples of models that support topic classification, keyword identification and evaluation, so that machines can interpret and handle customer complaints and refund requests more efficiently. With *augmented* intelligence, AI identifies trends and advices the sales and finance function by learning the historical records. In the *autonomous* intelligence stage, the AI bot analyses return patterns and manages the automatic refund process based on a set of thresholds defined by the business users.

Banks

Hedging on interest or exchange rate fluctuation

With *assisted* intelligence capabilities, AI helps to identify internal data trends and relationships between the organisation and market environment that may result in foreign exchange or interest rate flux. In the *augmented* intelligence stage, identification features are enhanced by incorporating predictive capabilities to forecast events and send finance function alerts and warnings. In the *autonomous* intelligence stage, AI evolves as a trusted partner to manage hedging instruments and make decisions through active monitoring and assessment of transactions, organisation and market dynamics; and eventually weighing up the risk vs cost of different permutation of instruments and determining the optimal risk coverage at most efficient cost and transacting with the respective banks.

Tax Authorities

Tax validation, forecasting and payment

In the *assisted* intelligence stage, AI supports human tasks by enabling the scanning of expenditure items and extraction of key information for proper classification of documents. Such capabilities also facilitate the scanning of GL and payroll files to determine the appropriateness of payroll tax. With *augmented* intelligence, AI bots are further equipped with the capabilities to highlight key areas of concerns that may contravene tax laws. This is especially useful when operating in multiple jurisdiction. Finally, with *autonomous* intelligence, AI transforms the process by assisting humans in tax filling through identification of at-risk transactions, expenditure classification, and applicability of tax treaties and tax law/notice compliance.

Suppliers

Vendors in Account Payables (AP)

AI bots with *assisted* intelligence scans details in invoices, purchase and delivery orders, and prompts system users to process them. With *augmented* intelligence, AI captures and analyses vendor invoice details to suggest payment dates to maximise discounts. Finally, in the *autonomous* intelligence stage, AI bots are empowered to handle the payment process and are capable of suggesting optimal payment dates and amounts to maximise payment discounts and optimise operational cash flows.

INTEGRATING AI INTO THE WORKPLACE

Challenges and change inertia are bound to occur with the introduction of new technologies and many early adopters often struggle with the basics. Based on a Deloitte survey conducted across 1,110 IT and line-of-business executives on the adoption and benefits from cognitive computing/ AI, respondents had cited key challenges in implementation, integration and data issues *(Exhibit 5)*.

(Ranked 1-3, where 1 is greatest challenge):

	Ranked 1	Ranked 2	Ranked 3	Ranked top three
Implementation challenges	13%	14%	12%	**39%**
Integrating AI into the organisation's roles and functions	14%	13%	12%	**39%**
Data issues (e.g. data privacy, accessing and integrating data)	16%	13%	10%	**39%**
Cost of AI technologies / solution development	13%	12%	11%	36%
Lack of skills	11%	10%	10%	31%
Challenges in measuring and proving business value	10%	11%	9%	30%

Source: Deloitte State of AI in the Enterprise, 2nd Edition, 2018

Exhibit 5: Top Challenges for AI initiatives

To mitigate these challenges, Finance functions should adopt a balanced approach, considering people, business, and technology readiness in deploying AI programmes across the finance function. The following are key considerations to assimilate AI into the ecosystem:

Partnerships with External Interfaces

For AI with external interfaces to work, collaboration between finance function and the external parties is essential. Different functions in the ecosystem need to share data and abide by processes and governing policies. For example, prescriptive regulations preventing data sharing is currently one of the limiting factors in the advancement of AI in the finance function. To mitigate these issues, the finance function has to work closely as a collaborative unit with all external interfaces to align and achieve the common goal.

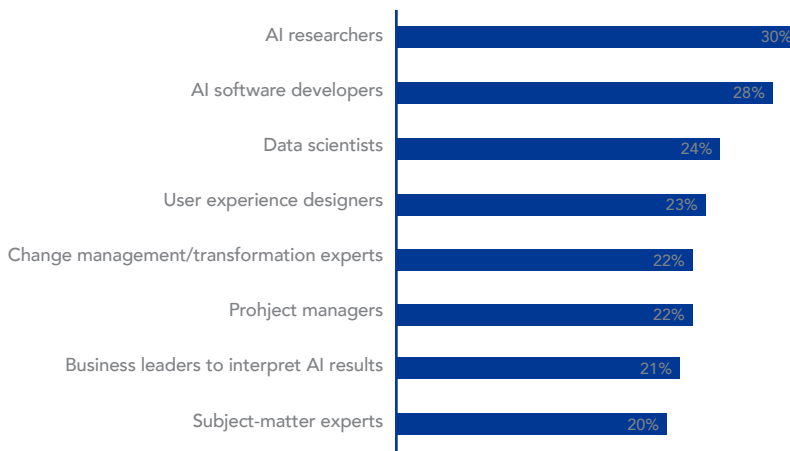## Data Management, Security and Ethics

Data is the single most fundamental and important ingredient of AI, but is often a struggle to deploy effectively in AI applications due to common issues such as fragmentation in data quality, lack of data digitisation and insufficient breadth and depth of data. One major issue is that the AI algorithms and data that fuels these algorithms are vulnerable to attacks like the falsification of images, bots that create "fake news" and the hacking of fully autonomous machines.

Ethics and discrimination are common issues linked with data security and regulatory risks. Currently, AI algorithms can help to make important decisions like granting credits and detecting crimes but biasness in human data input, development models and AI's post-trainings may result in discrimination. A bigger problem for biasness is that it will be difficult to detect and explain the output once the factors are compounded. To mitigate such risks, organisations need to align ethics and data governance, and ensure transparency in AI decision making. It is also vital to create calibrating mechanisms for algorithms models to be consistent so that unconscious bias can be eliminated.

Organisational and Cultural Changes

AI-researchers, software developers and data scientists form the core technical team that will bring the aspiring organisation to the next level. From a human resource perspective, acquiring and managing these talents, as well as training existing staff to equip them with the right skills are key imperatives to build a sustainable and successful AI-enhanced workforce *(Exhibit 6)*.

Respondents rating the top-2 needed skill to fill their organisation's AI skills gap:

Skill	Percentage
AI researchers	30%
AI software developers	28%
Data scientists	24%
User experience designers	23%
Change management/transformation experts	22%
Prohject managers	22%
Business leaders to interpret AI results	21%
Subject-matter experts	20%

Source: Deloitte State of AI in the Enterprise, 2ⁿᵈ Edition, 2018

Exhibit 6

TOWARD THE NEXT FRONTIER

AI technologies will propel the next wave of growth and organisations need to ride on this wave to remain competitive. In our engagement with clients, Finance is often seen to be a slow adopter, maybe in part due to our risk adversity and lack of understanding of the rapid changes. Deloitte has launched the "Crunch Time" series, to help finance functions better appreciate the impact of digital. Ultimately, AI will present Finance functions with an opportunity to redefine their role and be a catalyst for change to create an AI-fuelled finance organisation.

1. https://www2.deloitte.com/sg/en/pages/finance-transformation/articles/finance-digital-transformation-for-cfos.html.

BUILDING ETHICAL ARTIFICIAL INTELLIGENCE

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In a recent study conducted by researchers at the University of Bologna, two artificial intelligence (AI) algorithms were allowed to compete against each other in a setting where they could simultaneously set prices and reap profits accordingly. Before long, the researchers found that the algorithms had taught themselves to collude, with prices rising to levels that a monopolist would choose, to the detriment of consumers.

That these AI algorithms could, independent of any human intervention or oversight, take actions which compromise human well-being illustrates the ethical challenges that designers face in building autonomous AI systems.

Certainly, with rapid developments in AI technology, autonomous AI systems capable of performing increasingly complex tasks have become commonplace in many domain areas. To ensure that these autonomous AI systems take decisions or actions that do not cause harm to people, it is important for us to include ethical considerations when implementing AI.

ETHICAL CONSIDERATIONS WHEN IMPLEMENTING AI

In the field of ethics, moral agents are entities which are able to monitor and regulate their behaviour in light of the harm that their actions cause or the duties that they may neglect. A good moral agent is one that can detect the possibility of harm or neglect of duty, and take appropriate steps to avoid or minimise such undesirable outcomes.

While autonomous AI systems may never develop to become moral agents in the traditional sense that the term is understood (as human beings are understood to be moral agents), the challenge for designers is to get them to act as if they were moral agents.

In developing autonomous AI systems which can also act as good moral agents, a designer can consider two possible approaches. First, a designer can attempt to anticipate the possible courses of actions that an autonomous AI system might possibly take and deliberately design rules that bound the system to taking only ethically acceptable ones.

Second, a designer could develop technologies to build a more open-ended AI system that is capable of gathering information, predicting the consequences of its actions, and customising an ethically acceptable response to the challenge. Such systems should be designed to be dynamic and be capable of independently developing novel or creative solutions to ethical challenges (that may even surprise its designers).

But on what basis do we decide which actions or decisions are ethical? Indeed, while there may not be a clear consensus on what might or might not be deemed to be ethical, the widespread use of autonomous systems that rely on AI makes it important for designers to consider the ethical values these systems can and should promote.

Traditionally, the field of computer ethics has largely focused on promoting human safety and well-being, as well as other specific issues such as maintaining personal privacy, protecting property and civil rights, and inhibiting hacking, viruses, and other abuses of technology. As new ethical values emerge and gain prominence with the development of AI technology, the field of computer ethics will certainly also have to expand to consider how it can cover them.

Regardless, with the growing complexity of autonomous AI systems, addressing conflicts between ethical values threatens to pose a serious problem to designers. Consider the case of Allen. Allen recently drove from Singapore to Bangkok for the first time. It was only when he reached the city of Kuala Lumpur that he decided to use a particular credit card at a petrol station to refuel his car. When he tried to use the credit card at the station, it was rejected. Thinking that there was a problem with the pumps at the station, he drove to another station and tried to use the same card again. His card was again rejected. It was only upon calling his credit card company did he learn that the company's autonomous system had evaluated his use of the credit card more than 350 kilometres from his home city as being suspicious, and had automatically blocked his transactions. Upon hearing his explanation, the human agent at the credit card company was eventually able to override the autonomous system and remove the block on Allen's credit card.

In this particular instance, the autonomous AI system did not necessarily use any ethical judgment. However, the ethical significance of the actions taken by the autonomous AI system to block Allen's credit card transactions stemmed from rules that had been programmed into it.

On one hand, the ethical values designed into the system sought to protect the credit card company and credit card holder from the inconvenience and losses that might have resulted from potentially fraudulent charges. On the other hand, however, if Allen had urgently needed fuel for his car because of an emergency (and had suffered negative consequences because of the delay), the actions of the autonomous system might reasonably have be viewed as being less ethically justified.

This example highlights the increasing need for autonomous AI systems to weigh risks against ethical values when making decisions. As AI technology develops, it may eventually be possible to build explicit ethical reasoning into AI systems, giving it the capacity to evaluate and decide when the ethical thing to do would be to allow credit card transactions to go through even though the analysis may suggest a higher risk of fraudulent charges.

HOW AI CAN DEVELOP ETHICAL CAPACITIES

In their book, Moral Machines: Teaching Robots Right from Wrong, Wendell Wallach and Colin Allen introduce a framework for understanding how autonomous AI systems can develop ethical capacities.[1] The framework consists of two independent dimensions: autonomy and ethical sensitivity.

1   Moral machines: Teaching robots right from wrong, Wendell Wallach and Colin Allen, 2009
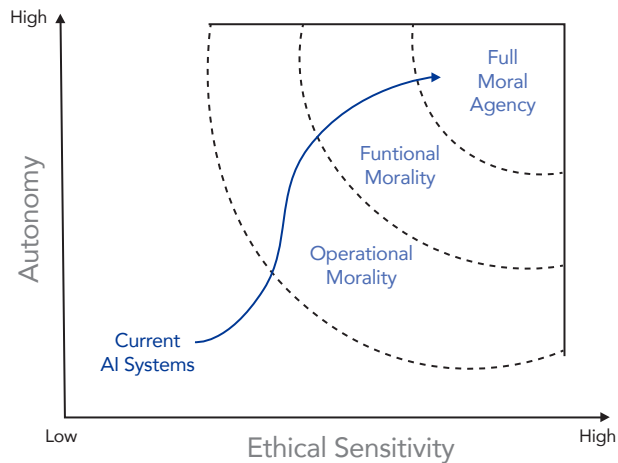
Figure 1: Framework for the Development of AI Systems

The simplest tools today have little autonomy and sensitivity to ethical values. For example, hammers do not hammer nails on their own (a human is required to pick up the hammer and do the job). By themselves, hammers are also not sensitive to any ethical issues related to the tasks they perform.

As we progress up the autonomy and ethical sensitivity axes, we encounter tools which can exhibit some form of "operational morality," where the ethical values of the designers are imparted to the tools. For example, while a gun with a safety mechanism lacks any appreciable autonomy and sensitivity to ethical values, its design embodies the designers' values of seeking to protect the safety and welfare of the public. In exhibiting "operational morality," the morality displayed by a tool or system is entirely within the control of its designers or users.

Moving further up the axes brings us to the realm of "functional morality". Many autonomous systems that rely on artificial intelligence today exhibit some form of "functional morality". Such systems typically display some level of autonomy and sensitivity to ethical values. For example, auto-pilot systems are trusted to autonomously fly aircrafts in a wide variety of situations, with minimal human supervision. These systems also display some ethical sensitivity in its design which protects passengers' safety and comfort by setting certain limits to the manoeuvres that the aircraft is able to undertake in any situation.

As we move even further up the scales of autonomy and sensitivity to ethical values, we enter the realm of "full moral agency", a region for which the technology for such artificial systems, to a large extent, does not yet exist. Certainly, the development of AI in the coming years will incorporate some form of increased autonomy and increased sensitivity to ethical values in autonomous AI systems. Increased autonomy for artificial systems is a process that will continue to develop rapidly. At the same time, a key challenge for designers of autonomous systems is how to simultaneously move up along the axis specified by ethical sensitivity.

MOVING UP THE ETHICAL SENSITIVITY AXIS

In discussing the sensitivity of artificial intelligence systems to ethical issues, it might sometimes seem like there is clear consensus on what might be considered to be ethical actions or behaviour. In truth, there is a great deal of disagreement among people about ethical matters. For example, while truthfulness may be an ethical virtue which most people would instinctively value over dishonesty, some people might accept (or even applaud) the telling of a white lie if it could lead to a net benefit. Such possible disagreements about the ethicality of various actions or behaviour of AI systems underline the difficulties that designers face in determining criteria for ascribing morality to the actions or behaviour of artificial systems.

In this regard, the authors Wendell Wallach and Colin Allen highlight the top-down and bottom-up approaches to the design of ethical AI systems. The top-down approach takes a specified ethical theory (or theories) and analyses its computational requirements in guiding the design of algorithms and sub-systems capable of implementing the theory.

At the same time, given the complex intuitions that people have about right and wrong, it should be acknowledged that it is perhaps close to impossible to turn existing ethical theories into a set of logically consistent principles or laws that can be used to design ethical decision algorithms for artificial intelligence systems.

Nor do people necessarily want AI systems to replicate the abstract concepts laid out by ethical theories: people do not make everyday decisions based on ethical theories. Instead, abstract ethical theories are perhaps more suited for representing ideals against which actions (by humans or machines) are to be evaluated rather than for representing the basis for decision making by an autonomous system.

A more practical implementation of the top-down approach to designing ethical AI systems may then be to broaden the moral considerations that impinge on a particular situation and in addition to ethical theories, to also factor in appropriate human intuitions, social practices, and norms when designing the computation rules that an AI system uses when evaluating possible actions or behaviour choices.

In the bottom-up approach to designing ethical AI systems, ethical theories are not explicitly employed. Instead, the emphasis is placed on creating an environment where an autonomous AI system is able to explore various courses of action and learn when it is rewarded for behaviour or actions that are deemed to be ethical. The development of AI has been closely connected with the field of machine learning which has developed many learning models that could be adopted for building ethical AI systems using the bottom-up approach.

Despite rapid technological developments in recent year, it should be acknowledged that although the bottom-up strategy holds great promise for giving rise to great leaps in the development of dynamic ethical AI systems, such technologies are, in fact, extremely difficult to evolve or develop.

In practice, designers are instead likely to employ a combination of the top-down and bottom-up approaches in developing ethical AI systems: part of the AI system might rely on rules specified by a top-down approach while bottom-up self-organising techniques are employed to complement or fine-tune actions or behaviour specified by these rules.

MOVING FORWARD WITH AI ETHICALLY IN SINGAPORE

In January 2019, the Personal Data Protection Commission of Singapore released the first edition of *A Proposed Model AI Governance Framework* which seeks to translate ethical principles into practical measures that can be implemented by organisations deploying AI solutions at scale.[2] Being the first of its kind to be launched in Asia, the model framework aims to promote AI adoption while building consumer confidence and trust in providing their personal data for AI.

In his foreword to the model framework, Mr S. Iswaran, Singapore's Minister for Communication and Information, highlighted that the model framework "aims to frame the discussions around the challenges and possible solutions to harnessing AI in a responsible way" and that it also "aims to collect a set of principles, organise them around key unifying themes, and compile them into an easily understandable and applicable structure."

The model framework is based on two high-level guiding principles that promote trust in AI and the understanding of the use of AI technologies. Specifically, the first principle specifies that decisions made by AI should be explainable, transparent, and fair. While acknowledging that perfect explainability, transparency, and fairness are impossible to attain, the principle highlights that organisations should nonetheless strive to ensure that their use or application of AI is undertaken in a manner that reflects the objectives of these principles in order to help build trust and confidence in AI.

The second principle specifies that AI systems should be human-centric. In particular, as AI is used to amplify human capabilities, the protection of the interests of human beings - including their well-being and safety - should be the primary consideration in the design, development, and deployment of AI.

The model framework also provides guidance on measures promoting the responsible use of AI that organisations should adopt in the following four key areas:

Internal Governance Structures and Measures: Adapting existing or setting up internal governance structure and measures to incorporate values, risks, and responsibilities relating to algorithmic decision-making.

Determining AI Decision-Making Model: A methodology to aid organisations in setting its risk appetite for use of AI, i.e. determining acceptable risks and identifying an appropriate decision-making model for implementing AI.

Operations Management: Issues to be considered when developing, selecting, and maintaining AI models, including data management.

Customer Relationship Management: Strategies for communicating to consumers and customers, and the management of relationships with them.

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2. A proposed model artificial intelligence governance framework, Personal Data Protection Commission Singapore, 2019.

CONCLUSION

In examining ethics in the field of AI, we extend ethical considerations in the field of computer ethics from a concern for what people do with their computers to concerns about what machines do by themselves. Indeed, the AI systems that we have today are quickly approaching a level of complexity that will require the systems themselves to make ethical decisions.

While we cannot be certain about how autonomous AI systems will develop in the future, it is important to include ethical considerations when framing the task of developing new generations of AI systems. In particular, considerations around safety and societal benefits should be at the forefront of our decision making when designing such systems.

GROOMING THE NEXT GENERATION OF ACCOUNTING PROFESSIONALS FOR THE AGE OF AI

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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Artificial Intelligence (AI) is going to transform every economic sector, including accounting industry. As accounting functions rely more and more on machines to calculate, reconcile and respond to inquiries from other departments or clients about balances and verifying info, accountants can now better deliver efficiency and create higher value for their organisations. This transformation means that repetitive, manual and tedious tasks are handled by machines while accountants focus their attention on higher-level, more sophisticated tasks that involve professional judgement and interpretation.

Broadly speaking, AI technology may be categorised into machine learning (ML), deep learning, machine reasoning, and natural language processing. Among these sub-categories, ML has the largest array of applications and functionalities that can most support the work of an accountant. It is known that major accounting practices have applied and are continuing to adopt ML techniques to streamline their operations in order to achieve time and cost reduction, increased productivity and improved accuracy. For instance, one of the Big Four accounting firms has deployed a system that could evaluate credit information related to a bank's commercial loan book, including unstructured data from social media. In this application, ML technology is deployed to establish forecasting models that, based on data from the past, generate predictions on identifying 'problematic' loan transactions.

With ML, computers can recognise and apply patterns, derive their own algorithms based on those patterns, and refine those algorithms based on feedback. Similar to human-beings, ML algorithms need to be trained at its infancy phase, which come in the form of data. With more training examples, the more they learn, the better they get and the more accurate their predictions will be. ML's models are perceived to be consistent decision-makers as they do not exhibit human biases. Conversely, human's strength lies with its ability to interpret novel situations quickly and handle them effectively.

For ML to work effectively, it is important to ensure data sets that are used to "teach" machine learning algorithms, do not have inherent biases. Success of these ML models also depends on having sufficient data of the right quality. While ML has several benefits, it does bring about certain level of associated risks. As such, considerations will have to be taken in evaluating design and effectiveness of internal controls over ML risks.

MACHINE LEARNING IN ACCOUNTING APPLICATIONS

Increasingly, ML techniques have been applied in accounting applications. For instance, by going through the source data of historical transactions, ML is able to predict classification of additional accounting transactions as they are recorded.

In audit, ML is able to learn a company's expense policy, read receipts and audit expense claims to ensure compliance and forward questionable claims to humans for approval. ML can also facilitate risk assessment mapping by pulling data from every project a company has ever completed, to compare it to a proposed project. Such comprehensive assessment may be impossible for humans to do on a large scale and under a similar timeline.

Another area where ML can be applied, is in spend analytics. Expenditure data can be analysed to help procurement departments make better purchasing decisions and improve compliance monitoring. Clustering methods may help to classify items with similar properties together, hence allowing better categorisation of spending patterns. For instance, applying clustering techniques to procurement of services may enable ML to classify cleaning, painting and pest control services under the umbrella of "maintenance services". This can be extended to the "service provider level" based on the logic that similar service providers are likely to provide similar types of services. This will be useful for relevant departments to monitor spending within a category as well as across categories.

The most common ML application for anomaly and fraud detection is unsupervised learning task of clustering. Unsupervised cluster analysis aims to learn patterns from within the data without predicting an outcome. In fraud detection, clustering helps to identify transactions that differ significantly from others (i.e. outliers) and appear suspicious. This is used when there is no prior knowledge of fraud within dataset. Suppose there is another dataset that already has cases of fraud, other ML techniques can be used to identify features that constitute fraud and these same features can be used in a predictive tool that can detect new cases of fraud.

Probabalistic ML methods (incorporating probability theory in making predictions) will always have an element of error in their results but this could be minimised by using larger datasets to train the models. Textual analysis and web crawling could also be adopted to derive information from textual data. The information is then analysed using natural language processing, which further improves the ML model's "vocabulary bank" and better understands context, conditions that are essential to spend analytics.

MACHINE LEARNING KNOWLEDGE AND SKILLSET

Organisations will need access to right technology knowledge and skillsets. Clearly, this starts with technical expertise in ML. But these technical skills will need to be complemented by deep understanding of the business context that surrounds the data and the insight required. Some roles will continue to emphasise technical accounting expertise and human judgement to deal with difficult and novel cases. Other roles may expand to increase collaboration and partnering with other parts of the organisation to help them derive the right meaning from data and models. There will also be new jobs. For example, accountants will need to be involved in training or testing models, or auditing algorithms which may require deep knowledge of ML techniques. In other roles, accountants may just need a more superficial knowledge of ML to be able to have informed conversations with experts and other parts of the business.

Increasingly, more and more accounting work is now done by machines that rely on algorithms to make certain judgement or classification. Going forward, auditors will be engaged to understand algorithms and to provide algorithms assurance services to ensure ML algorithms remain robust and accurate.

With ML, both machine and employee can perform the task at the same time. He or she can have oversight of the operations and achieve greater efficiency at work. Sometimes what we find is that ML algorithms can be great at picking up pervasive but subtle patterns that many people, even experts, gloss over. ML also makes it much easier for professionals to analyse unstructured data such as the text of documents, including contracts, legal documents, accounting filings, press releases, news articles, emails, etc.

For accountants, this does not mean that jobs are getting more difficult; it's simply that what is needed is changing. It is therefore necessary to pick up programming languages for statistical analysis, such as R or Python, SQL for data query, and Spark and Hadoop for big data analytics. For instance, if an accountant needs to prepare a weekly report, where he or she collects data from the same sources and combine the data in the same way each time, this process can be automated in Python or R, such that one command is run and all data work is done.

As ML technology continues to expand in accounting practices, it is important to note the exposure of accounting students to ML will become increasingly urgent. Accounting faculty should move towards integrating ML topics into the accounting curriculum, so that students can start learning about ML before they encounter it in the workplace.

As the Accounting industry begins to realise that education is the key to closing the widening skills gap, there is growing momentum in the upskilling of those currently working in the accounting sector, as well as in the training and hiring of the next generation of accounting professionals. It is hoped that a sustainable talent pool of technologically-adept accounting and financial professionals will certainly emerge.

CASE STUDY: SMU SCHOOL OF ACCOUNTANCY TAKES THE LEAD TO BRIDGE THE TECHNOLOGY SKILLS GAP

The Singapore Management University School of Accountancy (SMU-SOA) aims to develop versatile accounting professionals and business leaders through holistic education, thought leadership, and collaboration with businesses and society. To this end, SMU-SOA places a strong emphasis on the industry-responsiveness of our accountancy curriculum. The majority of the practitioners agreed that data analytics and ML have a vital role to play in the future of accounting. Yet, data scientists often lack domain knowledge in accounting areas, while those with domain knowledge in accounting or business areas lack the technological know-how. The key challenge they faced was to recruit talent who have knowledge in both disciplines.

Therefore, it becomes apparent that educators should take the lead to groom the right talent to meet the current and future demands of the Accounting sector. In August 2018, SMU-SOA launched a suite of accounting data analytics and ML curriculum designed to groom a sustainable talent pool of technologically-adept accounting and financial professionals. In the process of designing its data analytics curriculum, the school consulted its industry partners and placed emphasis on the applicability and currency of their content. Below are three course samples that cover ML knowledge in the accounting data and analytics curriculum.

Course Content Illustration I: Statistical Programming

In this statistical programming course, students acquire knowledge in applying statistical theory for analysing data that is crucial to all four stages of analytics (descriptive, diagnostic, predictive and prescriptive). One of the tools students will learn is R programming.

R is an established open-source statistical programming language containing data analysis packages used in transforming, mapping and visualising data to facilitate advanced analytics techniques such as ML. With accountants handling data that is growing in volume and variety, it is essential for them to harness the power of R in analysing their data as they help organisations make better business decisions. For example, the "financial statements in R (finstr)" package allows for the creation of reproducible financial statement analysis enabling users to store, share, reuse and reproduce results from their analytical work. This helps management accountants to better handle data that are customised to corporate strategy through improved financial reporting.

The "budgeting in R (budgetr)" package also helps users to create budgets easily so as to support the company's finance function. The created budgets and schedules can be replicated and updated using R scripts for automation to ensure that the arduous tasks of doing so can be handled by a machine, thereby freeing up accountants to focus on interpretation of analyses and the application of the results to management action.

Lastly, Activity-Based Costing can also be improved through the use of ML techniques in R to more efficiently trace overheads and assign them appropriately. Optimisation algorithms will be faster at calculating costing ratios and hence enhance costs distribution. The accountant's role then becomes one of interpreting the ML outputs and designing implementation measures for management while also evaluating the ML performance. This will ensure that ML is continually monitored and improved.

Several topics that are covered in this course include basic ML concepts; supervised and unsupervised learning; predictive and prescriptive analytics; unsupervised learning using clustering - optimal clusters, clustering concepts; extending clustering to anomaly detection - point anomalies, cluster anomalies, contextual anomalies and finding outliers.

Course Content Illustration II: Forecasting and Forensic Analytics

In this course, students will gain exposure to techniques to explore how financial and non-financial data are used to forecast events, detect financial discrepancies and frauds, predict corporate default, optimise operations, and determine business strategy. Programming and data visualisation skills will be required to draw insights from large volumes of data. Advanced analytics methods such as text analytics, ML, neural networks and deep learning will also be introduced. This course has been designed to equip students with an analytical mind-set to develop advanced analytics strategies and make better business decisions.

Several topics that are covered in this course include ML and other recent advances in analytics. ML and other analytical models are explored in contexts such as forecasting sales and financial statements; identifying red flags for contracting; predicting default and bankruptcy; and fraud detection.

Course Content Illustration III: Accounting Analytics Capstone Course

The accounting analytics capstone course is a hands-on capstone project represents an opportunity for students to apply what they have learnt in the accounting data and analytics curriculum in a real-world setting. Building on the foundations of statistical models, students adapt them to fit the project cases they are tasked to solve, taking on the role of consultant teams working with their clients to develop forecasting models for inventory, production and product sales planning.

The capstone course operates on a partnership model, where companies can collaborate with SMU school of Accountancy faculty to mentor students in data analytics and ML projects aim to help to solve complex financial analytical problems in a real-world setting.

An example of an accounting analytics capstone project is as follows: a Small and Medium Enterprise (SME) from the food manufacturing industry commissioned a team of five accounting students from the Accounting Analytics Capstone course in January 2018, to build a financial predictive model with both analytical and predictive capabilities. The SME was keen to venture into new and different markets, but lacked sufficient information to proceed, such as operating costs and return-on-investment. With the help of predictive analytics using ML techniques, the company could then calculate the likelihood of success when introducing a new product in a new market, such as identifying the countries with market potential for the specific food item consumption; calculate the start-up costs; the sales volume that would enable the company to break even; the return-on-investment; and even the expected profit following five years of operations. Throughout the project, as consultants to the SME, the student team brainstormed on possible actionable insights and recommendations using the financial model they had developed.

The food manufacturer had been keeping track of more than 40 varieties of food products in different packaging designs and weight. In addition to the various retail packaging formats were the customisations for private labelling, again in different packaging, weight and quantity for different customers, hence resulting in too many SKUs to manage, and also the problem of holding too much raw materials and packaging materials.

Another issue for the food manufacturer was that ideas of venturing into new and different markets had surfaced before, but they did not materialise. The big deterrence to further global expansion was the absence of important supporting information, such as operating costs, return-on-investment, production quantity, and so on. This information was a must to assess the potential risk of investing in different foreign markets, and its absence ultimately determined the overall expansion strategy. Thus a key value proposition of data analytics was that it could help the company to visualise what the future holds, and hence in justifying decisions made.

With the company's historical sales data, the analytical findings revealed seasonal buying patterns by local consumers. It also showed the products which were most responsive during those periods. For instance, a spike in consumer demand was reported during the festive months of December to February every year, which coincided with Christmas, New Year and Chinese New Year celebrations; and which were the most popular food items bought by Singaporeans during this time.

Acting on these patterns, the food manufacturer could now manage the supply chain process more efficiently during the festive period by adjusting the procurement of raw materials, and managing production, marketing, distribution and warehousing suitably to cater to the increased demand.

Using predictive analytics with ML techniques, the company could calculate the likelihood of success when introducing a new product in a new market. The predictive model suggested a few countries that had market potential for the specific food item consumption, and based on the preferred manufacturing quantity, it would also calculate the start-up costs, the sales volume that would enable the company to breakeven, the return-on-investment and the expected profit following five years of operations. The predictive model also helped to quantify the potential reduction in revenue of well-established products upon market introduction of a new product variant under the same family brand.

Projects completed in the Accounting Analytics Capstone course include: developing Excel/Tableau dashboards for financial performance evaluation, inventory planning, and payment and collection cycles reviews; using ML to construct revenue and cash flow predictive modelling; conducting simulation of business scenarios on customer demand and inventory control; developing a balanced scored card encompassing both financial and non-financial performance metrics; exploring impacts of ML and other AI technologies on the effectiveness of audit design process.

CONCLUSION

The accounting industry needs to recognise that AI technologies such as ML, are enabling tools rather than adversaries out to steal jobs. After all, accountants are not mere bean counters susceptible to automation but professionals who provide actionable insights and their professional skepticism is not something a machine can replicate. The growing prevalence of advanced analytical tools and technologies allows business executives to seek timely and relevant data, which enables them to make better business decisions, grow revenue, improve efficiencies, and better manage risk and compliance.

Given the nature of the changing landscape, there is a need for universities to develop teaching pedagogy and learning approach that will prepare students for future economy. The new approach should be student-centred, industry aligned and turn students into active learners that learn how to learn. In order to remain competitive, universities must therefore find ways to attract, engage and sustain relationships with their students by enhancing their learning experience at the university.

The next generation of accounting professionals are expected to possess sound accounting knowledge underscored by a strong proficiency in accounting technologies, and be skilled in communication to be able to interpret and communicate the data effectively to their management and clients. This is the skill set which the SMU-SOA curriculum is designed to groom in our students.

The silver lining behind the 2019 Finance & Accounting Salary Guide by Robert Half was the anticipated surge in remuneration for job candidates who are technologically-adept, demonstrating a strong potential in the accounting sector. Contrary to a common misconception that automation will lead to a decline in the accounting profession, automation and digitalisation will instead lead to growth potential in the accounting sector locally and regionally. This echoed the report by the Committee on the Future Economy (CFE) for Singapore's Working Group on Legal and Accounting Services[1] released in April 2017, which identified accounting as a growth sector for Singapore. The CFE recommended that Singapore should aim to capture international demand for legal and accounting services and become a go-to location for international commercial transactions. This presents tremendous career development opportunities for the accounting professional with the right skill set and mindset towards continuous learning.

1   CFE Singapore. (2017, April 6). Report of the Working Group on Legal and Accounting Services (Rep.). Retrieved https://www.mlaw.gov.sg/content/dam/minlaw/corp/Seminar/CFE-Report of the Working Group on Legal and Accounting Services-Apr2017.pdf

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