ACCA Think Ahead

THE SMART ALLIANCE: ACCOUNTING EXPERTISE MEETS MACHINE INTELLIGENCE

About ACCA

We are ACCA (the Association of Chartered Certified Accountants), a globally recognised professional accountancy body providing qualifications and advancing standards in accountancy worldwide.

Founded in 1904 to widen access to the accountancy profession, we've long championed inclusion and today proudly support a diverse community of over **252,500** members and **526,000** future members in **180** countries.

Our forward-looking qualifications, continuous learning and insights are respected and valued by employers in every sector. They equip individuals with the business and finance expertise and ethical judgement to create, protect, and report the sustainable value delivered by organisations and economies.

Guided by our purpose and values, our vision is to develop the accountancy profession the world needs. Partnering with policymakers, standard setters, the donor community, educators, and other accountancy bodies, we're strengthening and building a profession that drives a sustainable future for all.

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August 2024

About this report

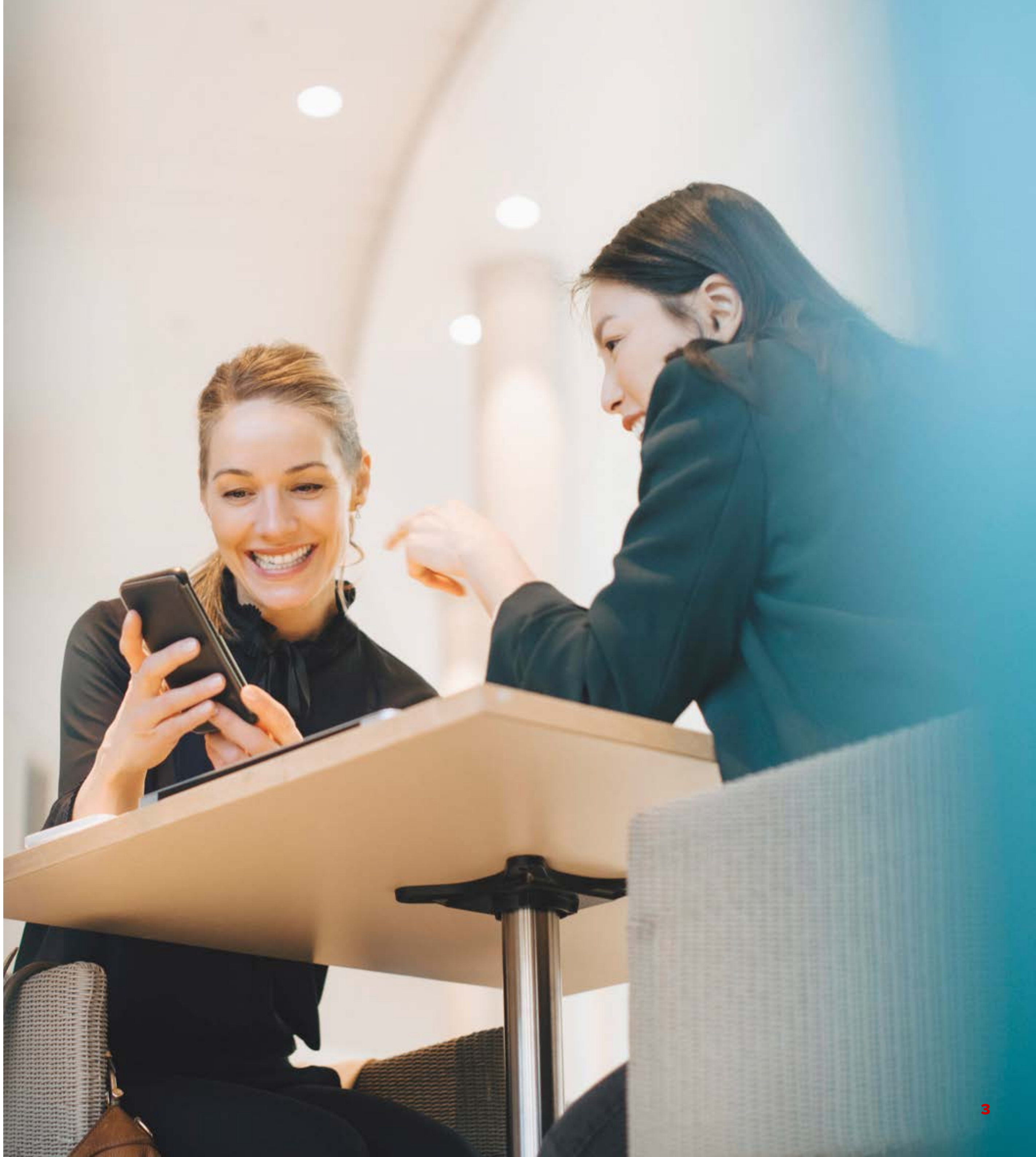
Artificial Intelligence (AI) carries tremendous potential to transform the way we work. But as AI continues to evolve, it presents both great opportunities and significant challenges for accountancy and finance professionals. This report explores the current state of AI adoption in the profession, providing a timely analysis of how AI is impacting the field and what professionals need to know to stay ahead.

The report discusses various AI technologies reshaping the field, including machine learning, computer vision, natural language processing, and generative AI; examining where organisations are currently leveraging AI's capabilities and looking to their management of key challenges and risks.

Based on interviews and a survey of more than 900 accounting leaders **who are already using AI**, the report provides insights into strategic approaches, challenges, and the outlook for AI in the profession. It includes case studies demonstrating practical AI applications and offers key lessons and best practices for AI adoption. Additionally, the report addresses important considerations such as how organisations can begin to lay foundations to effectively address AI-specific risks, adapt governance, and the critical role of finance in shaping organisational AI and data strategies.

In the broader context of AI's impact on society and organisations, this report serves as a crucial resource for accounting and finance professionals. It highlights the need for a balanced approach to AI adoption, emphasising the importance of human oversight and expertise alongside technological advancements.

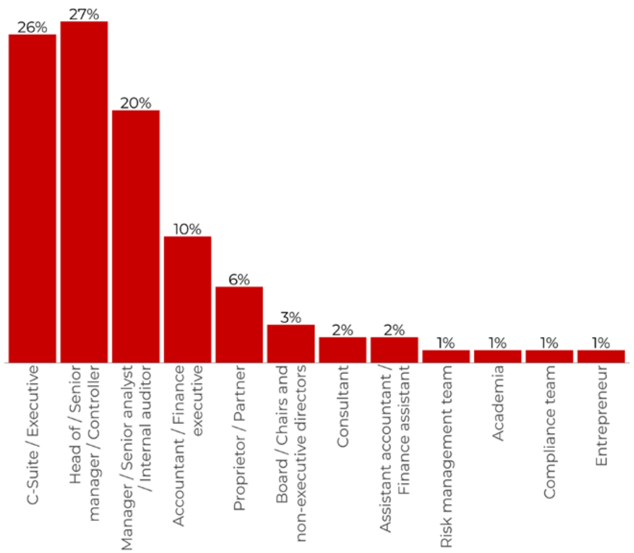
As AI continues to evolve, understanding its potential and limitations becomes increasingly vital for decision-making and strategic planning.



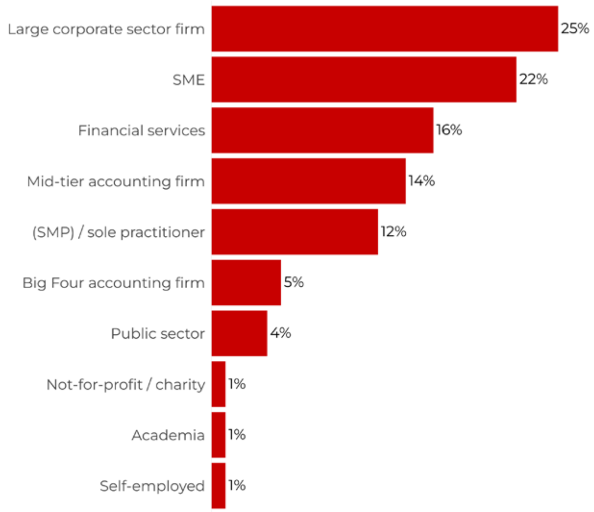
Survey demographics

The ACCA would like to express our deepest thanks to all members who participated in the survey and interviews in support of this research

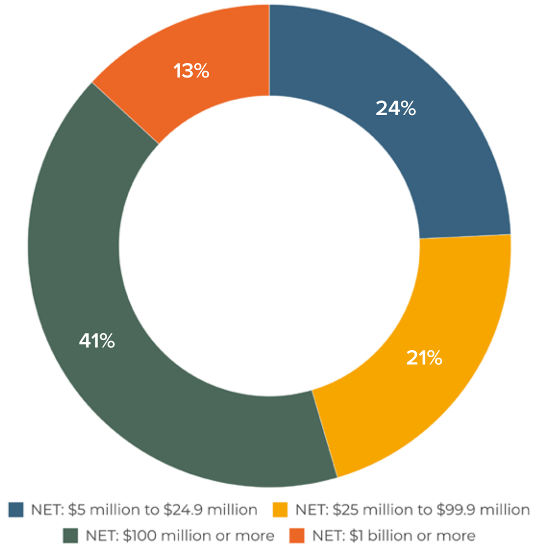
Job title



Sector



Organisation size



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Navigating this report

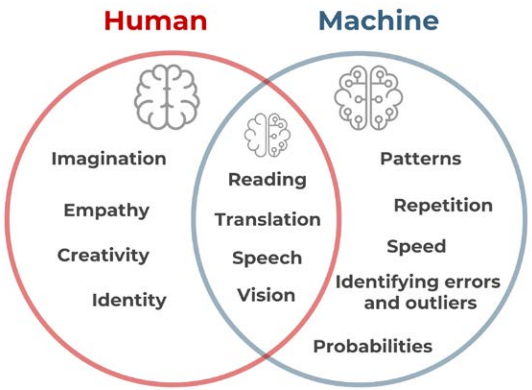
1. Introduction

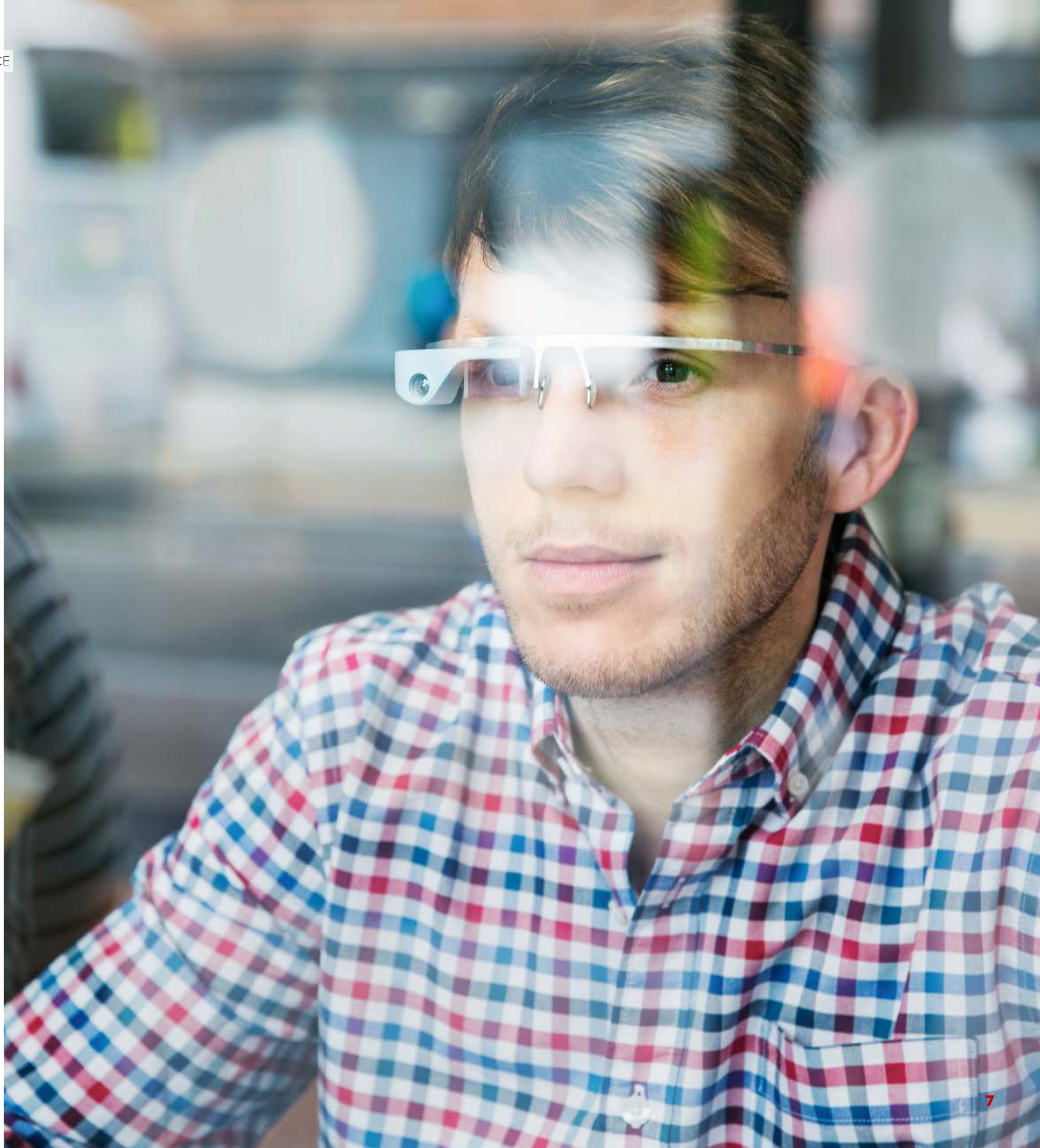
The accountancy and finance profession has long been confronted with technological advancements and artificial intelligence (AI) – an increasingly prevalent technology, which presents the latest progression in this long history. The recent developments and increasing accessibility of solutions promises much greater impact in the future. As we delve into the current state of AI adoption in accounting, it's crucial to understand the diverse range of AI technologies that are reshaping the field.

Fundamentally, AI is a data transformation. This perspective emphasises that AI is essentially about leveraging data in innovative and powerful ways to enhance decision-making and streamline processes.

The potential of AI to augment human capabilities (Figure 1) in accountancy, and beyond, is absolute. Rather than replacing human expertise, AI is increasingly seen as a tool to enhance the skills of accounting professionals.

FIGURE 1: Augmenting human capabilities is a key benefit of AI





The future of AI in accounting or auditing isn't only about new technologies; it's about reimagining the roles of finance professionals by focusing on analysis and interpretation, strategy, and high-level decision-making. It's also part of the evolution of the finance function (and roles) towards becoming more value-adding and autonomous, something that we explore in greater depth in our *Finance evolution: Thriving in the next decade* (Figure 2).

Our report on this smart alliance – based on a survey (sections 3-5) and interviews with accounting leaders who are already using AI – aims to provide a clear picture of the current state of AI adoption in accounting. We explore the strategic approaches that organisations are taking, the challenges they face, and the outlook for AI in the profession.

Additionally, the report includes a selection of case studies (section 6) demonstrating how some are leveraging AI in their work to support their organisation's objectives. From these case studies, we've defined key lessons and best practices (section 7) for others to consider as they embark on their own AI adoption journey.

As we navigate through this data, it's clear that the accountancy profession is in a state of transition. While some organisations are at the forefront of AI adoption, others are only beginning their journey – but the opportunity is becoming clearer. For a profession often stereotyped with a conservative approach to adopting new technologies, there's widespread acceptance that finance functions may represent the most fertile ground for nurturing improvement (Figure 3).

By understanding the present state of the profession and learning from best practices shared by current adopters, accounting professionals and organisations can better position themselves to leverage the power of AI and shape the future of accountancy and finance.

FIGURE 2: The evolution of the finance function

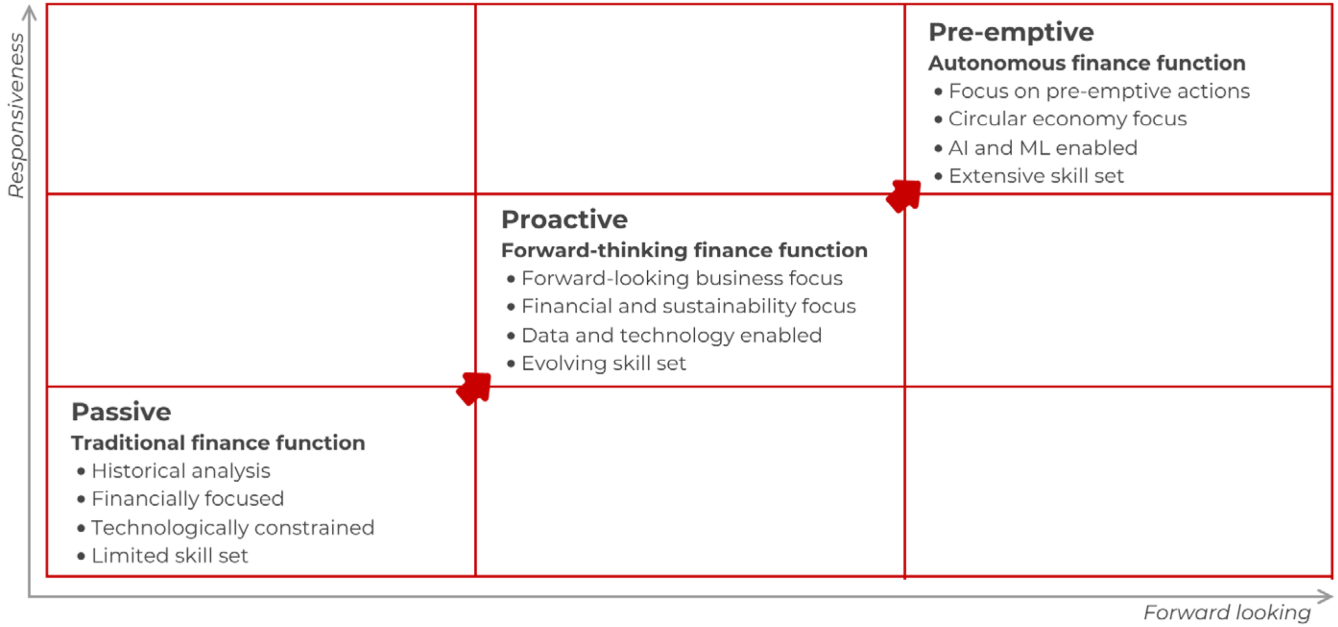
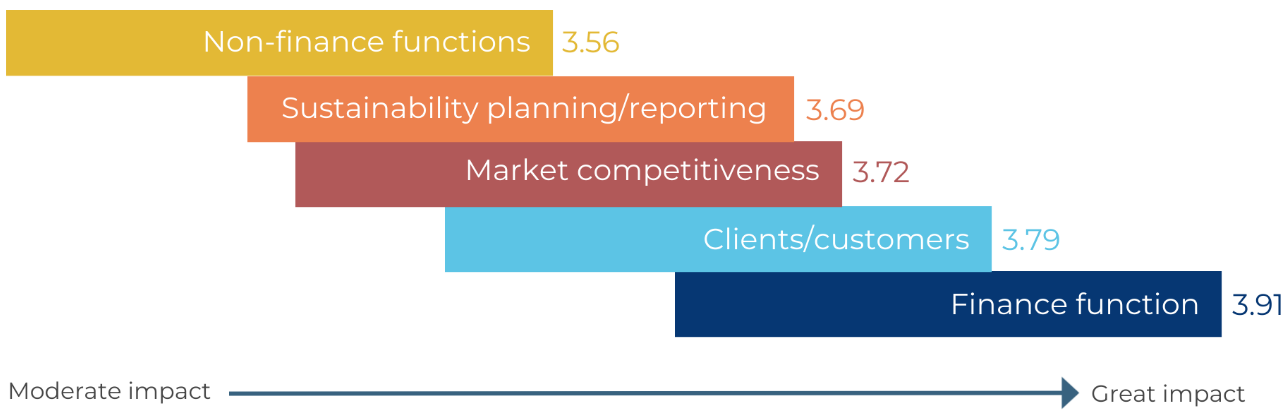


FIGURE 3: Finance professionals believe they may have the most to gain from AI



WHAT ARE THE KEY TAKEAWAYS?

Understanding unique considerations towards AI

AI in accounting encompasses various technologies (section 2), including machine learning (ML), computer vision (CV), natural language processing (NLP), and generative AI (GenAI). Each present distinct capabilities and risks in use.

Both the type of AI technology and its application need to be approached with due consideration. For example, applications where predictive capabilities are intended to make decisions that could impact individuals are particularly sensitive – and may have inherent flaws (section 2.5.5).

While powerful, GenAI also has distinct limitations. The capabilities of these models are still developing, necessitating constant monitoring and oversight to understand the impact on outputs and types of error that can be produced. In general, outputs cannot be fully relied upon for accuracy – and that is a crucial consideration when determining the correct use case.

There may well be valuable uses for GenAI within strict and limited circumstances – but not without serious consideration of the potential for inaccuracies, biases, or misleading references that proliferate harm or reputational damage. Organisations also need to think about implications for information security around use of public models.

Organisations should understand these limitations and implement appropriate safeguards – such as human oversight and validation processes – particularly for tasks requiring high accuracy (section 2.4).

That means considering training for staff using such models, and acknowledging policies around scope of use, control of data inputs, and standards and accountability around use of outputs (section 2.4.4).

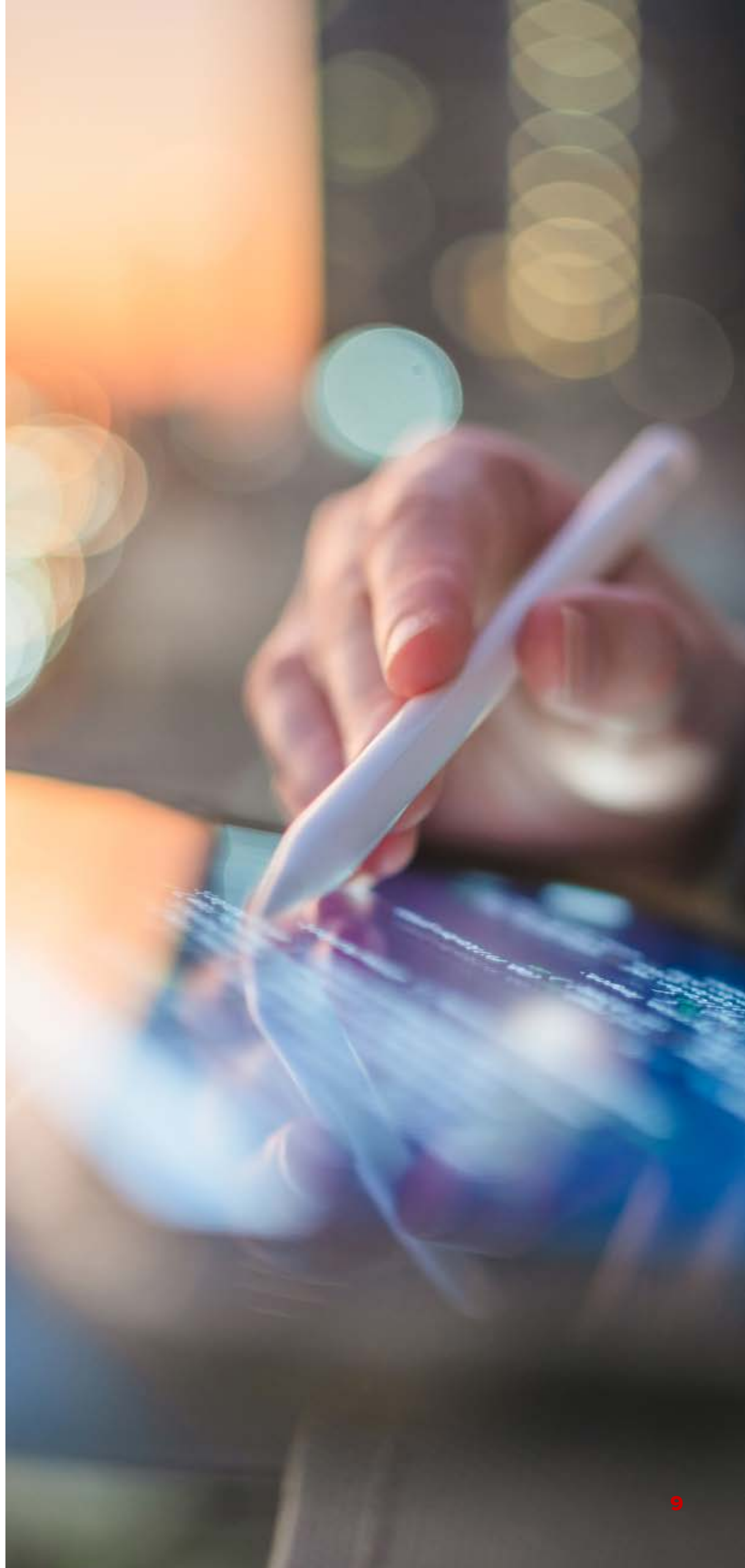
The role of finance in championing a collaborative approach to strategy

Our report highlights the critical role of finance in shaping AI and data strategies across organisations (section 4). Finance teams are increasingly taking on advisory roles (56%) or even ownership (20%) of these strategies. This positions finance to champion a more collaborative approach to AI adoption.

As data becomes central to organisational success, finance departments are well placed to foster cross-functional collaboration, bridge the gap between organisational strategy and day-to-day operations, and ensure AI initiatives align with business objectives (section 4.2).

Our report suggests finance can lead in creating flexible, collaborative models for data management and AI implementation – moving towards co-ownership roles with other departments. This collaborative approach is key to identifying AI innovation opportunities and ensuring broad organisational support for AI initiatives (section 4.3).

With AI, progress can arrive relatively quickly and easily at first, but suddenly become more difficult and laborious towards deployment. To avoid floundering at the development stage calls for a clear strategy in place to manage the full lifecycle; understanding the technical complexity involved as data needs grow, and how to cope with probabilistic outputs that can lead to changes in tone, quality and consistency.



KEY TAKEAWAYS

Evolving approaches to AI risk and governance

The report reveals that approaches to AI risk and governance are still in their early stages of development – even amongst those organisations who are readily adopting the technology (sections 5.2 - 5.4).

Key areas of continuing evolution include:

- Understanding AI-specific risks: organisations are still grappling with identifying and assessing risks unique to AI, such as algorithmic bias, data privacy concerns, and the potential for inaccuracies in AI outputs. Approximately half of surveyed AI adopters feel their risk and control measures are sufficient or fully adequate – indicating a need for better understanding of AI-specific risks (section 5.2).

- Developing shared and collaborative training for risk mitigation: there's a growing recognition that effective AI risk management requires a collaborative approach. However, many organisations are still learning what this means in practice. Our report suggests organisations are focusing on developing internal expertise to combat some of these challenges. Simultaneously, it reveals gaps in thinking around potential reputational and related risks that might arise (section 5.3).

- Implementing effective training and policies: many organisations are in the early stages of establishing foundational elements for AI governance. Fewer than one third of surveyed organisations have implemented policies that cover issues like transparency in use of AI, explainability or interpretability, oversight of AI inputs or outputs, or bias mitigation. Similarly, only 31% have adopted training programmes for responsible AI use. This indicates a significant opportunity for considering how best to support effective, organisation-wide AI risk management (section 5.4).

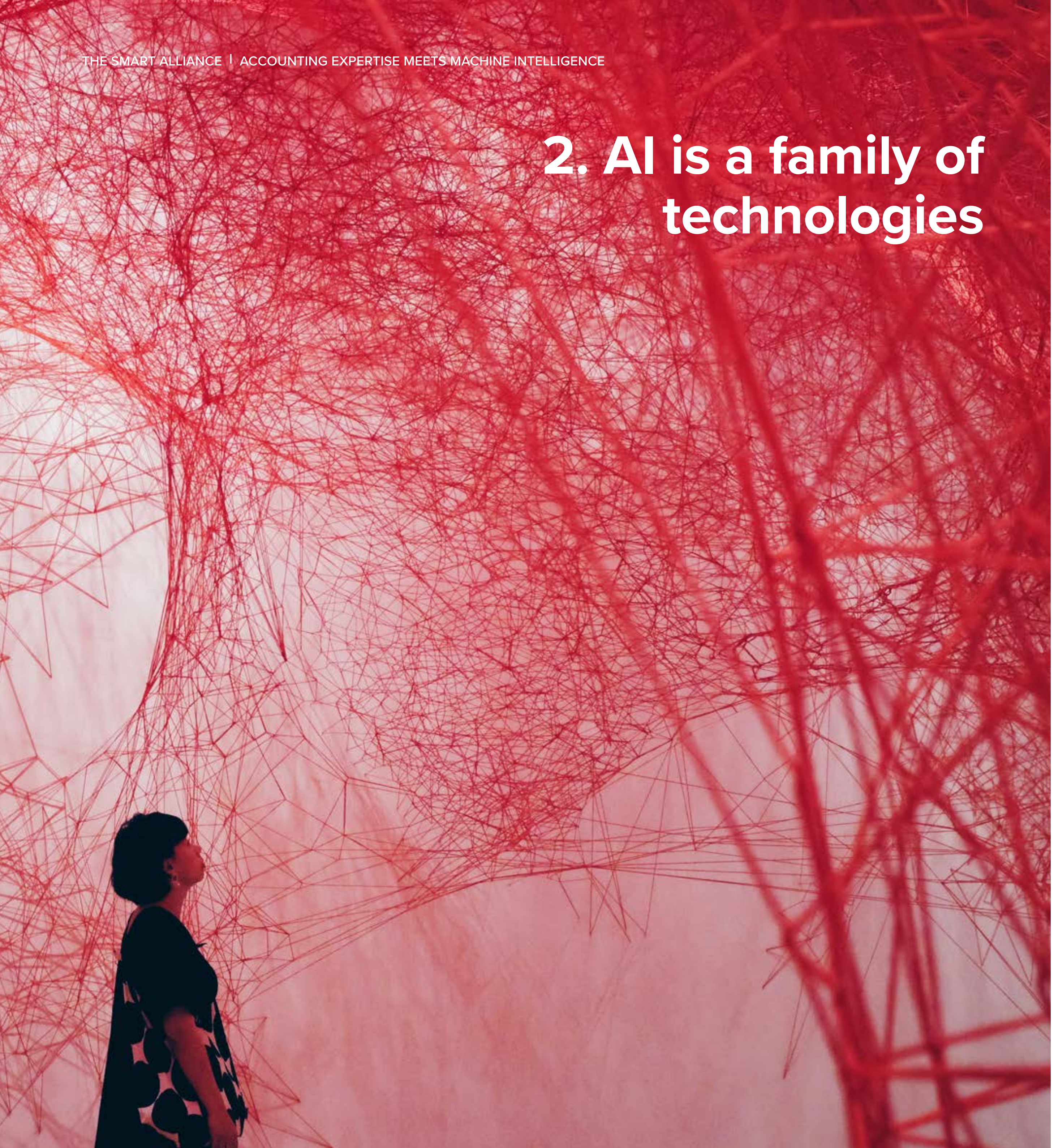
Our report emphasises that as AI adoption grows, there's an increasing need to develop more mature, collaborative approaches to risk and governance that can keep pace with the technology's evolution.

Best practices for AI adoption in accounting

Our report synthesises insights from various case studies to create a framework for successful AI adoption in the finance function (section 7). Key themes include the importance of strategic planning, data management, and human-AI collaboration. Organisations are advised to start with well-defined, high-impact use cases and scale gradually.

The report emphasises the need for a balanced approach that leverages AI's strengths while maintaining human oversight and expertise. It stresses the importance of continuous learning and skill development among staff – as well as the need for clear governance structures.

Successful AI adoption is shown to be a journey of continuous improvement that requires flexibility, stakeholder involvement, and a focus on both quantitative and qualitative measures of success. Our report provides a comprehensive set of best practices, covering areas from technical considerations to change management – offering a roadmap for organisations at various stages of their AI journey.



2. AI is a family of technologies

AI encompasses a family of technologies[1] – each with unique applications (Figure 4).

This section serves as a high-level overview of some key types of AI for finance and accountancy purposes. *Our Digital horizons: Technology, innovation and the future of accounting* report (p.37-50) explores the technical underpinnings and approaches to learning used by different types of AI as well as use considerations and potential implications for trust.[2]

There remains an open debate as to the size of the impact that a technology like GenAI, for example, can have on productivity. Studies have suggested that the cost savings from utilising AI can range from 10% to 60% – depending in part on the examples used and the assumptions around the extent of task-level automation.

Economist Daron Acemoglu paints a more cautious but still optimistic picture. One of the key differences rests on how well AI can be incorporated into more complex, open-ended tasks, including for text summarisation where more than one correct response might exist.[3] Specifically, tasks that require 'more complex interactions between action and context...[or] lack clear metrics for success that are observable,' present notable challenges[4]. Many of the tasks performed by auditors, accountants and risk professionals ultimately fall into this bracket. But that still leaves a wide range of potential tasks, or subsets of tasks, that can benefit from the technology.

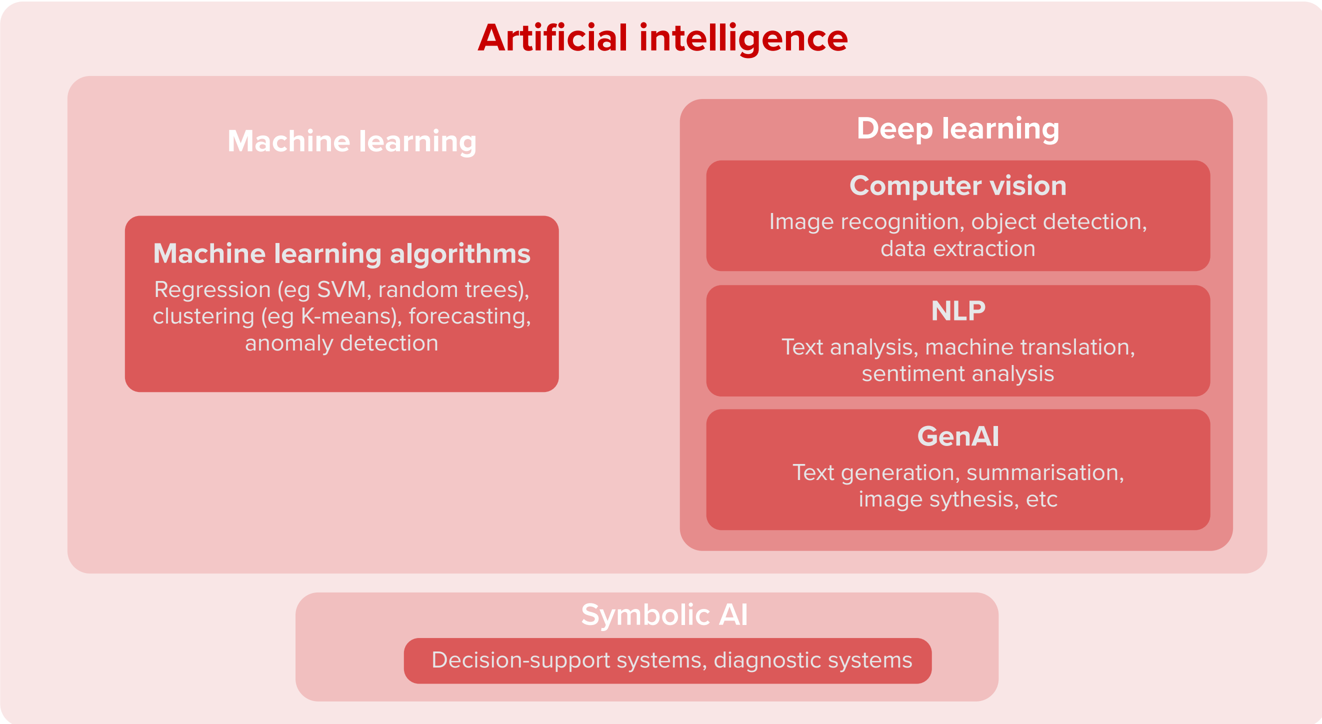
[1] Descriptions and shorthand are derived from knowledge contained within Microsoft Azure AI *Fundamentals: AI overview* (February 13, 2024)

[2] See 'How do machines learn', p37-50, of our *Digital horizons: Technology, innovation and the future of accounting* report for considerations of these elements as well as considerations around use and implications for trust.

[3] Goldman Sachs Research. *Generative AI: Too Much Spend, Too Little Benefit?* (August, 2024). Goldman Sachs.

[4] Acemoglu, D. (2024). *The Simple Macroeconomics or AI* (NBER Working Paper No. 32487). National Bureau of Economic Research.

FIGURE 4: The most prevalent types of AI are based in machine learning



Deterministic vs. non-deterministic ML

Many accountancy professionals will be familiar with robotic process automation (RPA), which operates in a fully deterministic manner. By following a strict set of rules and processes, RPA bots perform repetitive tasks with consistent outputs.

When we talk about determinism in AI, it generally refers to the consistency in how the model operates—meaning that the model follows a fixed set of rules, algorithms, or learned parameters in a repeatable and predictable manner. This aspect of determinism is about the internal processes of the AI system, ensuring that given the same conditions (including the same data, environment, and initial states), the AI will behave in the same way each time.

However, the consistency of outputs is not guaranteed to be the same as the consistency of the operation because the outputs can vary due to changes in data or contextual factors, for example. Moreover, the use of common optimisation methods such as stochastic gradient descent introduce an element of randomness to improve generalisation, potentially leading to different outputs on the same data set.

2.1 Machine learning: The number-crunching powerhouse

In the world of accounting – where numbers still reign supreme – machine learning (ML) presents a range of possibilities. With high quality data, ML can improve financial forecasts by helping make data-driven predictions with greater accuracy. This is some of the promise that ML brings to the table (for practical examples, see case studies 6.2-6.4).

A simple example might involve the need to predict which client invoices are likely to be paid late[5]. By analysing historical payment data, client financial health indicators, and even macroeconomic factors, it's possible to predict the likelihood of late payments. This cannot only improve cash flow management but also allow for pre-emptive client engagement – turning a potential problem into an opportunity for strengthening client relationships.

However, the path to ML adoption is not without its challenges. The quality and quantity of data can make or break an ML model. The 'garbage in, garbage out' model is more relevant than ever. ML models are only as effective as the quality of data we feed them. While initial accuracy rates may be low, these can be raised, often significantly[6], over time with iteration, improved data and regular training.

[5] Several providers have already integrated these capabilities, Fluidly being one example
[6] The role of the finance function in data governance is considered further in Sections 4.2 and 4.3 as well as in our *Finance Evolution: Thriving in the next decade* report

Another consideration is the 'black box' nature of some algorithms. In a profession where transparency and integrity are paramount, the inability to fully explain how a model arrives at a particular conclusion can be problematic. In some cases, technical solutions may be available, such as ML-based audit risk assessment tools that help balance the superior performance of complex algorithms with the need for interpretability. In other cases, it may be possible to opt for a hybrid approach – combining simpler, easily explainable models with more complex ones. Ultimately, as noted in our AI Monitor article, *Enabling trust in an AI-enhanced world*, collaboration across domain experts is critical to effectively using ML outputs.

AI Monitor series

The aim of the AI Monitor series is to identify and examine, from the accountancy profession's perspective, some pressing AI challenges – discussing routes and next steps for finance professionals.

Upcoming issues of the series will explore related issues pertaining to sustainability, risk and controls, data strategies, and more.

At a glance: Machine learning

a. **Overview:** ML refers to a subset of AI where systems learn from data, identify patterns, and make decisions or predictions with minimal human supervision. These systems can improve over time as they are exposed to more data – making them effective for tasks like classification, regression, and clustering. Transparency and accountability in how data is collected, processed and used are essential to maintaining trust and ensuring ethical deployment.

b. **Technical core:** algorithms process large datasets, identifying patterns and making predictions based on statistical models.

c. **Data processing:** feature extraction, data normalisation, and model training on historical financial data.

d. **Application:** predictive analytics for sales, classifying profit and loss (P&L) data, risk assessment, fraud detection, or customer segmentation.

e. **Python tools and packages:** eg scikit-learn, TensorFlow, PyTorch, XGBoost, and pandas

f. **Software solutions:** eg Sage Intacct, Oracle NetSuite, IBM Planning Analytics, and Anaplan

TRANSPARENCY AND ACCOUNTABILITY IN HOW DATA IS COLLECTED, PROCESSED AND USED ARE ESSENTIAL TO MAINTAINING TRUST

2.2 Computer vision: The image interpreter

In a profession that has long relied on the human eye to scrutinise documents, computer vision (CV) presents welcome possibilities. This technology transforms tasks like data extraction and image classification into swift, more accurate, and potentially insightful processes (see case studies for practical examples).

In document processing, CV can automatically extract data from invoices, receipts and financial statements – significantly reducing manual data entry time and errors. For fraud detection, for example, a CV-based tool might analyse handwriting patterns and signatures to identify potential forgeries with high accuracy. In retail banking, CV enhances customer experience through technologies, such as cheque deposit via smartphone cameras.

The journey towards effective CV implementation is not without its challenges. Image quality can be a significant challenge, especially when dealing with legacy documents or handwritten records. Models are often trained using pristine, digitally generated receipts, which means they perform poorly when confronted with crumpled, coffee-stained receipts from the real world. This means that implementation is often lengthy and complex, requiring massive data collection initiatives, including capturing images of receipts in various states of deterioration to retrain the model.

Privacy concerns also loom large in the CV landscape. Visual data includes far more than just numbers, and may include sensitive information such as signatures or personal notes jotted in margins. Subsequently, data handling protocols need to be updated to address additional compliance concerns.

> **DEPLOYMENT OF SUCH SYSTEMS MUST CONSIDER POTENTIAL LIMITATIONS OF TRAINING DATA AGAINST REAL-WORLD USES.**

At a glance: Computer vision

a. **Overview:** CV refers to a field of deep learning that enables machines to interpret and make decisions based on visual data like images. Using deep learning models like convolutional neural networks (CNNs), computers can break down images into key features (like colour and shape) to classify and identify what they see. Deployment of such systems must consider potential limitations of training data against real-world uses as well as potential biases and ethical considerations when deployed in sensitive areas, like for facial recognition.

b. **Technical core:** convolutional neural networks (CNNs) analyse and interpret visual data from digital images or videos.

c. **Image processing:** feature detection, image segmentation, and optical character recognition (OCR).

d. **Application:** automated document processing, receipt scanning for expense reports, and signature verification.

e. **Python tools and packages:** eg OpenCV, Tesseract OCR, PyTorch Vision, and TensorFlow Object Detection API

f. **Software solutions:** g Expensify, SAP Concur, Sage AutoEntry, Rossum, ABBYY, and Blue Prism

Regulatory compliance is a key consideration, as CV systems must adhere to financial regulations and data protection laws, which can vary across jurisdictions. Integration with existing financial systems can also be complex and costly, especially for institutions operating on legacy systems.

2.3 Natural language processing: The linguistic aficionado

In a field often stereotyped as purely focusing on numbers, the importance of language in accounting is often overlooked. Natural language processing (NLP) enables computers to understand and interpret human language – opening up new possibilities for insight and analysis (see case studies for practical examples). Moreover, multilingual capabilities of NLP are opening new doors for firms operating in a global context.

In financial reporting, NLP is being used to analyse and extract key information from lengthy financial documents, annual reports, and regulatory filings. This capability allows finance professionals to quickly gather insights and identify trends that might otherwise take hours of manual review. NLP can also assist in generating automated financial reports – translating complex financial jargon into more digestible language for stakeholders.

NLP is also proving valuable in sentiment analysis for market intelligence. By analysing news articles, social media posts, and other text sources, NLP algorithms can gauge market sentiment towards specific companies, industries, or economic events[7]. This information can be crucial for making informed investment decision, or predicting market trends.

However, industry-specific jargon and context-dependent meanings can be a significant challenge. Terms like 'going concern' or 'material weakness', for example, have very specific meanings in accounting that general models may

[7] Refinitiv Eikon, Bloomberg, etc. leverage NLP to summarise crucial themes and analyse a wide range of textual data relevant to economic performance.

not readily understand. Consequently, fine-tuning, or other methods for domain-specific training, is often a requirement.

Data security is another critical concern when dealing with NLP in accounting. Financial documents processed by NLP systems often contain highly sensitive information. When using NLP-based tools, for example, it's necessary to ensure that they are compliant with financial data protection regulations. Rigorous vetting of AI tools and services for the accounting sector is essential.

At a glance: Natural language processing

a. **Overview:** NLP is designed to understand and interpret language, enabling tasks like textual analysis, language interpretation, document intelligence, knowledge mining, and sentiment analysis. These systems infer semantic meaning from large bodies of text through statistical analysis, ML techniques and, increasingly, deep learning. This can raise challenges around the complexity of language and context, biases in data, and protection of sensitive information.

b. **Technical core:** algorithms analyse and interpret human language – using techniques like tokenisation, parsing and semantic analysis.

c. **Data processing:** named entity recognition, sentiment analysis, and text classification.

d. **Application:** analysis of financial reports, contract review, and automated customer service for financial products.

e. **Python tools and packages:** eg NLTK, spaCy, Gensim, Transformers (Hugging Face), and Stanford CoreNLP

f. **Software solutions:** eg IBM Watson, AlphaSense, Kira Systems, Otter.ai, etc

2.4 Generative AI: The generalist

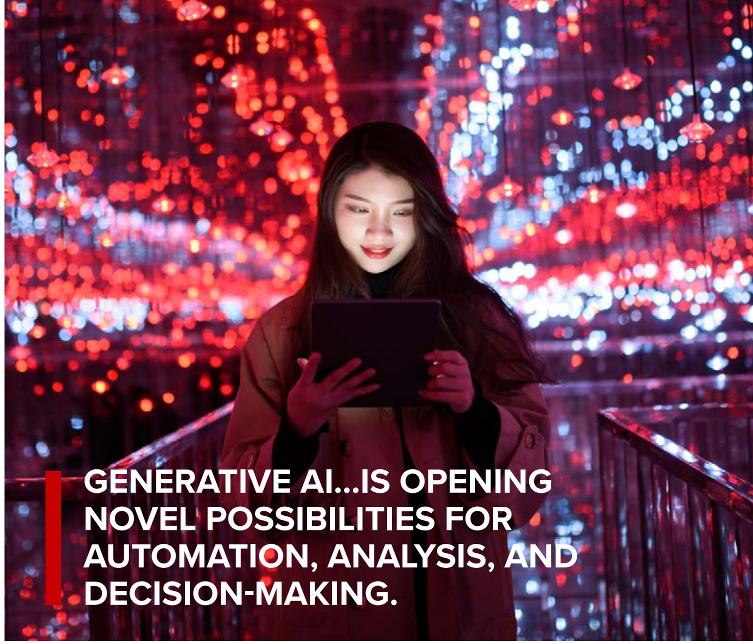
Generative AI (GenAI), capable of creating new content based on vast amounts of training data, is opening novel possibilities for automation, analysis, and decision-making in financial operations (see case studies for practical examples).

In financial reporting and analysis, GenAI can create narratives that help explain financial performance, articulate risks, highlight key trends, and provide other insights. Moreover, GenAI can tailor the language and depth of these reports for different audiences – enhancing communication effectiveness.

Audit processes stand to benefit significantly from GenAI. These systems can generate audit plans, risk assessments, and even draft audit reports based on historical data and current financial information. This allows auditors to focus their efforts on high risk areas, improving audit quality and efficiency. Additionally, GenAI can assist in creating more comprehensive and insightful audit documentation – ensuring compliance with auditing standards and regulatory requirements.

In tax planning and compliance, GenAI could be instrumental for navigating complex tax codes and regulations, supporting the generation of tax strategies tailored to specific client scenarios, considering various factors such as business structure, international operations, and changing tax laws. GenAI might also be able to assist in drafting tax opinions – explaining complex tax positions in clear language, and even generating responses to inquiries.

Perhaps the most well-studied and proven benefits of GenAI at this stage pertain to programming and developer tasks, given the models' proficiency in helping to write and debug code[8] But this also points to another exciting area



that's developing rapidly, which is using GenAI to support quantitative analyses, leveraging underlying capabilities and tools such as python to run scenario analyses, support forecasting tasks, reconciliations, and more (see also Microsoft Copilot for Finance).

Users can already take advantage of capabilities such as writing Python scripts with effective prompting, though this raises additional requirements in terms of having the right knowledge and skills to critically assess methods being used, outputs, and guaranteeing appropriate use and protection of data. For these reasons, such uses should currently be treated with great caution given the relatively poor performance of GenAI models with quantitative data. Moreover, because GenAI models are probabilistic, not deterministic, outputs can very even when using the same prompt and data.

However, the integration of generative AI in accounting practices also presents challenges. Again, the 'black box' nature of some AI models can raise questions about the explainability and auditability of AI-generated content,

[8] Jaffe, S., Shah, N.P., Butler, J., Farach, A., Cambon, A., Hecht, B., Schwarz, M. and Teevan, J. eds. 2024. Generative AI in Real-World Workplaces: The Second Microsoft Report on AI and Productivity Research. Microsoft.

which is crucial in a field that demands transparency and accountability.

Data privacy and security remain paramount concerns, especially when dealing with sensitive financial information. Accountants must ensure that any GenAI tools they employ adhere to strict data protection standards and comply with relevant regulations such as general data protection regulation (GDPR) or industry-specific requirements.

At a glance: Generative AI

a. **Overview:** GenAI (also often referred to as foundation models) refers to a class of AI systems designed to generate new content that is similar to the data they were trained on eg images, text, music and video. The goal of GenAI is to approximate its training data by learning underlying patterns and structures. Careful consideration must be given to any data being used to train or being input into such models to ensure that generated content does not inadvertently reflect or expose sensitive information.

b. **Technical core:** large language models trained on vast datasets, capable of generating human-like text and solving complex problems.

c. **Data processing:** text completion, question answering, and creative content generation based on prompts.

d. **Application:** automated report writing, scenario analysis for financial planning, or assisting with complex financial modelling.

e. **Python tools & packages:** eg OpenAI GPT, Google Gemini API, Transformers (Hugging Face), and TensorFlow Text Generation

f. **Software or Web Apps:** eg Microsoft Copilot, Github Copilot, Sage Copilot, Cognito, DataRobot, Claude, ChatGPT, Perplexity, etc.

2.5 Fundamental considerations

2.5.1 GenAI is still evolving

We're not yet at the 'plateau of productivity'[9] with GenAI – where we have discovered the most valuable, productive and cost-effective uses, or resolved all the challenges that implementing these solutions currently present.

At present, organisations are faced with some fundamental issues that require careful consideration.

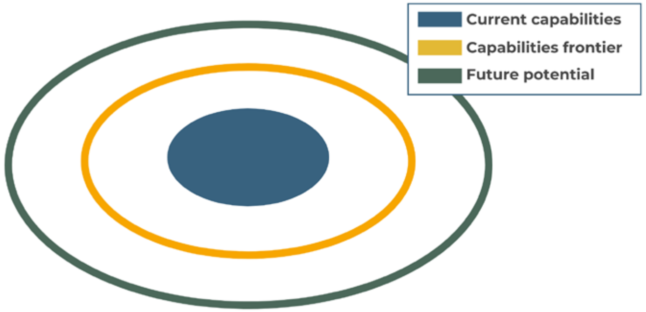
First, the capability of these systems is still developing. It's useful to think of their development in terms of concentric circles:

- **Existing capabilities (centre):** this represents the current state of GenAI[10] models where they have proven effective, including language translation, text generation, summarisation, and question answering.
- **Capabilities frontier (boundary around the centre):** this boundary marks the edge use cases where current models are less likely to be reliable or accurate, including tasks requiring deep understanding or reasoning, creative thinking, or those involving ambiguous contexts and minimal data often fall into this frontier.
- **Future potential (outer boundary):** as they continue to evolve through further development and research, this frontier will expand, encompassing more advanced tasks and capabilities, including more nuanced understanding, better contextual awareness, and improved reliability in edge cases.

[9] See Gartner's Hype Cycle which is made up of several stages of technology development from: 1) the innovation trigger, 2) peak of inflated expectations, 3) trough of disillusionment, 4) slope of enlightenment, and 5) plateau of productivity

[10] Gen AI refers to algorithms that can create new content, such as text, images or music. Large Language Models (LLMs) are a type of generative AI trained on vast amounts of text data to understand and generate human-like language. Multi-modal AI extends this capability by integrating and processing multiple types of data (eg text, images, audio) to generate complex outputs, allowing for more sophisticated and versatile applications.

FIGURE 5: Visualising the capabilities frontier



2.5.2 Failure to approximate their training data, or ‘hallucinations’[11]

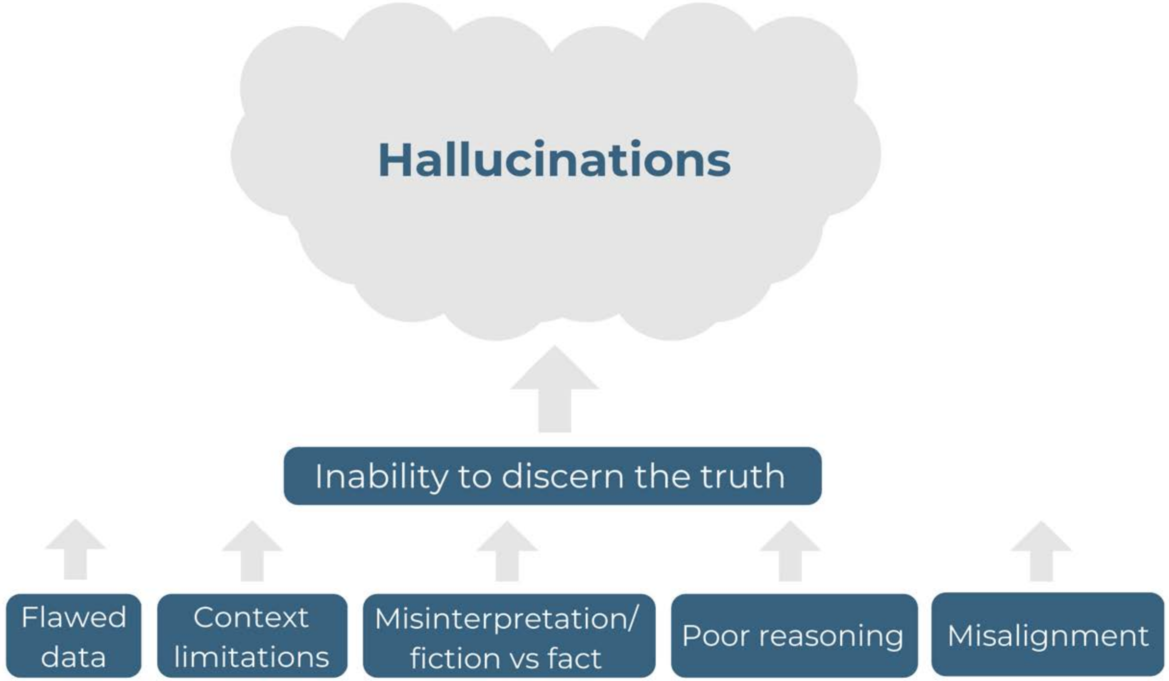
Second, we also need to be aware of the fundamental limitations that are technically difficult and expensive to resolve.

Reasoning capabilities are inherently limited given they are essentially probabilistic models. This means that their outputs cannot necessarily deliver reliable accuracy – and they have an inability to discern the truth or objective facts.

This is the basis for what are known as ‘hallucinations’, which ultimately derive from many sources[12]:

- Flawed data
- Limited contextual understanding
- (Mis)interpretation of training data
- Poor reasoning capabilities
- Misalignment, or using models for the wrong tasks.

FIGURE 6: Hallucinations have multiple sources



In a profession that often requires the highest levels of accuracy and interpretability this can make the technology very problematic for certain uses. However, understanding such technical limitations is also the basis for responsible experimentation and practical remedy.

GenAI presents some clear opportunities, but we need practical, hands-on experience, and strict protocols around usage to grasp those opportunities. Through responsible experimentation, organisations may be able to construct effective means of mitigating and managing associated risks – as well as developing the right approach to governance.

WE NEED PRACTICAL, HANDS-ON EXPERIENCE, AND STRICT PROTOCOLS AROUND USAGE TO GRASP THOSE OPPORTUNITIES.

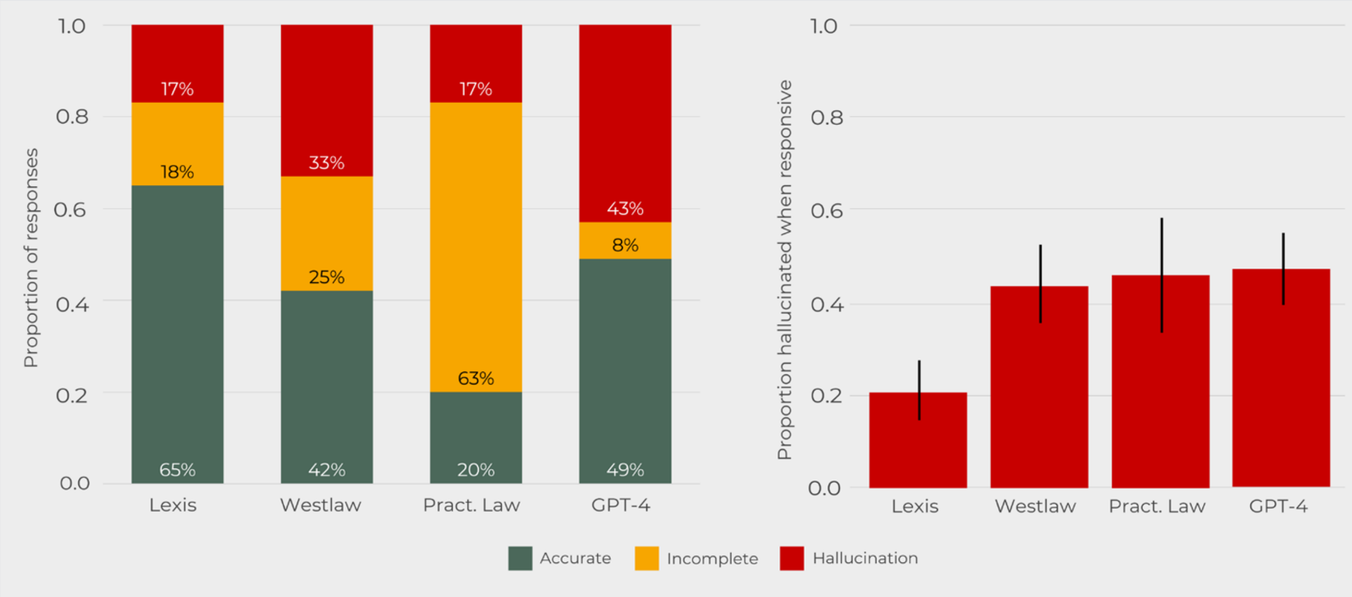
[11] Gerben Wierda argues that ‘hallucinations’ should be called ‘failed approximations’ highlighting that all outputs are approximations of their training data – given their probabilistic nature – and hallucinations are failed attempts to do that. This also draws attention to the fact that these failed approximations are a feature, not a bug of the system: Wierda, G. T. (2023, November 1). *The hidden meaning of the errors of ChatGPT (and friends)*. R&A IT Strategy & Architecture.

[12] Attri.ai. (2024, March 22). *A comprehensive guide on LLM hallucinations: What, why, and how to prevent them*. Attri.ai Blog.

THE PERSISTENCE OF HALLUCINATIONS

Recent research by Stanford University[13] examining hallucination rates in generative AI tools designed for legal purposes demonstrates that it's incredibly difficult to eliminate inaccurate and incomplete responses even when undertaking sophisticated training techniques:

FIGURE 7: Stanford research shows the persistence of hallucinations in fine-tuned models



Left panel: *overall percentages of accurate, incomplete and hallucinated responses.* ***Right panel:*** *the percentage of answers that are hallucinated when a direct response is given.*

Westlaw AI-AR and Ask Practical Law AI respond to fewer queries than GPT-4, but the responses that they do produce are not significantly more trustworthy. Vertical bars denote 95% confidence intervals.

While the examples tested demonstrated some reduction in the rate of hallucinations, between one-sixth and one-third of outputs, fine-tuned legal models still suffered from inaccuracies.

Moreover, some of the reduction in hallucinations were a result of introducing higher rates of incomplete responses, ie models were trained to provide incomplete responses where information could not be linked back to a source.

[13] Magesh, V., Surani, F., Dahl, M., Suzgun, M., Manning, C. D., & Ho, D. E. (2024, May 23). *AI on trial: Legal models hallucinate in 1 out of 6 (or more) benchmarking queries*. Stanford HAI.

2.5.3 It's important to get the use case right

BCG[14] designed two experiments to evaluate how participants use generative AI in different types of tasks. The first task, creative product innovation, was within GPT-4's capability frontier. It involved product ideation, testing, and launch planning. The second task, complex business problem-solving, was intentionally designed to be outside GPT-4's capabilities – requiring analysis of financial data and interview notes to provide suggestions on how to boost company revenues and profitability.

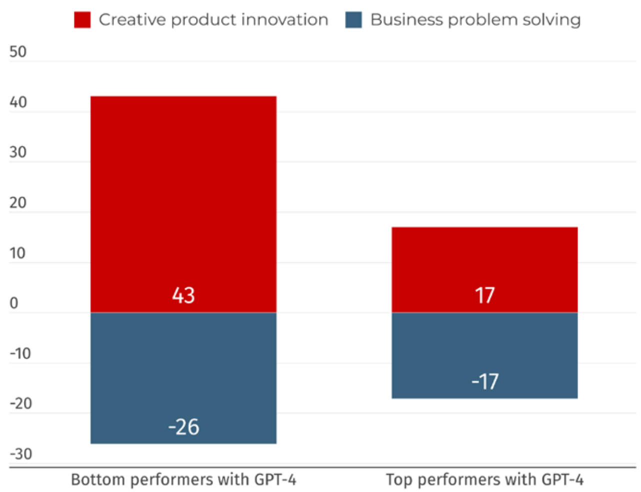
The results were striking. For the creative task within GPT-4's abilities, participants using the AI outperformed the control group by 40%. However, this came with a significant drawback: the AI-assisted group's ideas were 41% less diverse – potentially stifling innovative perspectives and divergent thinking within organisations.

On the complex business problem-solving task, participants using GPT-4 performed 23% worse than the control group. This finding highlights a crucial risk: GenAI can substantially hinder performance on tasks beyond its capabilities.

The researchers found that GPT-4's persuasiveness led participants to rely heavily on its recommendations, even when incorrect. Users often failed to apply critical reasoning when confronted with errors in the AI's logic. Additionally, attempts to improve GPT-4's output on tasks within its competence degraded the quality of results.

These findings underscore the importance of carefully evaluating GenAI's performance in relation to human partners. While it can significantly boost productivity for suitable tasks, its use on complex problems outside its capability frontier can lead to detrimental outcomes. Organisations must be discerning in their application of GenAI to truly leverage its potential for competitive advantage.

FIGURE 8: BCG study demonstrates the importance of getting the use case right (average change in performance with GPT-4 (%)



2.5.4 How can we use GenAI responsibly?

Given these limitations, GenAI requires some additional considerations in adoption and use.

On the one hand, it is useful to understand the technical methods that our data teams or providers can use to limit hallucinations and improve the reliability of the model.

It is also important that users are focused on extracting the highest value from outputs while setting clear limitations and minimising reliance on those outputs. That does require an understanding of how prompt engineering (See *Digital horizons: Technology, innovation and the future of accounting report*, p.46) and system prompts guide models. It is also about having clear objectives and expectations.

Personal integrity, however, remains at the forefront; this means that the human user must always use their judgement and remain accountable for decisions made using AI generated content.

> **What is a system prompt?**
>
> System prompts are included before the main prompt output. These are typically invisible to the end user and are used to prime the model with context, instructions, or other information relevant to your use case. System prompts can be used to describe things like tone, personality, what the model should and should not answer, and define the format of model responses, amongst other things. For example, this is one place where a model might be instructed to provide incomplete responses where information cannot be readily ascertained from the training data.[15]

From an organisational perspective, appropriate use policies and standards should also be considered, including:

- Clear scope for use
- Adequate control of data inputs
- Standards and accountability around use of outputs.

In some cases, that might also entail access rights for specific, limited use cases to minimise unforeseen risks and, where available, responsible use training.

Ultimately, using GenAI in a limited fashion as part of a pipeline (see GIAA case study, section 6.1) can improve the consistency of output and limit inaccuracies to those that are relatively easy to detect by end-users.

All of this means that there may well be valuable uses for GenAI within strict and limited circumstances – but not without serious consideration to the potential for inaccuracies, biases, or misleading references to proliferate and cause harm or reputational damage.

[14] Candelon, F., Krayer, L., Rajendran, S., & Zuluaga Martínez, D. (2023, September 21). *How people can create—and destroy—value with generative AI*. Boston Consulting Group.
[15] Microsoft. (2024, February 16). Prompt engineering techniques with Azure OpenAI. Microsoft Learn. https://learn.microsoft.com/en-us/azure/ai-services/openai/concepts/advanced-prompt-engineering?pivots=programming-language-chat-completions

2.5.5 AI is not (always) the solution

Risks related to AI are manifold (and will be the focus of an upcoming issue of our AI Monitor series *Skills to drive responsible AI adoption*), including the potential for bias and discrimination, privacy and security, misinformation, malicious or misuse, overreliance or loss of autonomy, socioeconomic and environmental, and system failures or lack of transparency.[16]

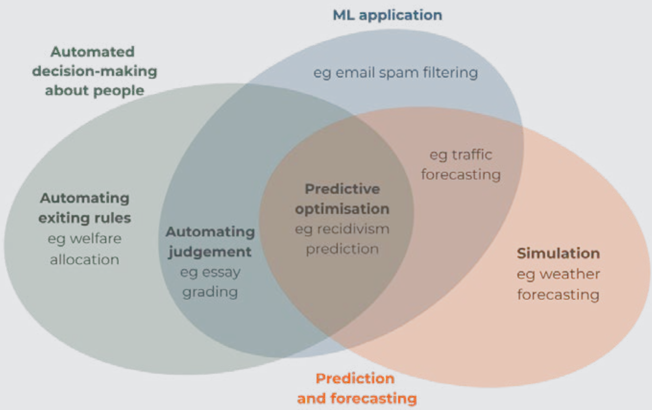
A big part of the discussion, and one that is not always explicit when reflecting on the risks that AI poses to organisations, is the very practical limitations and implications of predictive approaches. These require substantial forethought as they may not always be apparent, even when developing a model.

This is particularly important as organisations move from more limited or well tested uses to leveraging AI or ML in decision-making. This is especially true for applications 'where machine learning is used to make predictions about some future outcome pertaining to individuals, and those predictions are used to make decisions about them.'[17] Some examples might include where AI is applied to hiring decisions, credit worthiness, job performance, or insurance risk but the concern could extend to any application of ML to predict or influence social outcomes. At the very least, such systems require significantly higher standards of evidence that they avoid serious pitfalls.

A general consideration that all applications of predictive modelling should consider is whether there are practical limits to prediction – and therefore the accuracy of the system. There are numerous examples of models that perform well in development phases but fail to achieve reasonable levels of accuracy when deployed in live environments. Changes in context, even subtle, can have profound consequences for the accuracy of any model, which will have been trained within a specific context and on limited data.

Moreover, these are problems that cannot simply be fixed with technical solutions. These are complex examples of the socio-technical nature of AI systems.

THE LIMITS OF PREDICTIVE OPTIMISATION



Princeton University researchers Angelina Wang, Sayash Kapoor, Solon Barocas, and Arvind Narayanan[18] examined a range of AI-based prediction tools across legal, healthcare, financial services, human resources, education, and social media. They found common and persistent flaws that underscore why predictive models should be treated with caution when making decisions that impact individuals or groups of people, in particular:

- **Good predictions may not lead to good decisions:** accurate predictions don't always translate to effective decisions or interventions. The context of the decision and its potential consequences are crucial – as interventions based on predictions can sometimes inadvertently influence the very outcomes they're meant to address.
- **It's hard to measure what we truly care about:** the measurable data used for prediction (target variable) often doesn't accurately represent the actual goal or concept (construct) that decision-makers are interested in.
- **The training data rarely matches the deployment setting:** when a model is trained on data that doesn't match the characteristics of the population where it's deployed, its performance can be significantly compromised.
- **Social outcomes aren't accurately predictable, with or without machine learning:** there are fundamental constraints on how accurate such predictive systems can be, given problems of complexity, changes in context or environment, data limits, feedback loops, etc. As such, real-world performance of predictive tools often falls short of initial claims or expectations.
- **Disparate performance between groups can't be fixed by algorithmic interventions:** even statistically 'fair' systems can perpetuate or exacerbate existing societal inequalities. Algorithmic interventions alone cannot solve these deep-rooted issues.
- **Providing adequate contestability undercuts putative efficiency benefits:** there must be adequate mechanisms for people to challenge or appeal decisions when used in high-stakes situations. This can undermine supposed efficiency gains.
- **Predictive optimisation doesn't account for strategic behaviour:** also known as Goodhart's Law, this is when a measure becomes a target thus ceasing to be a good measure. Predictive optimisation systems can create unintended consequences and perverse incentives.

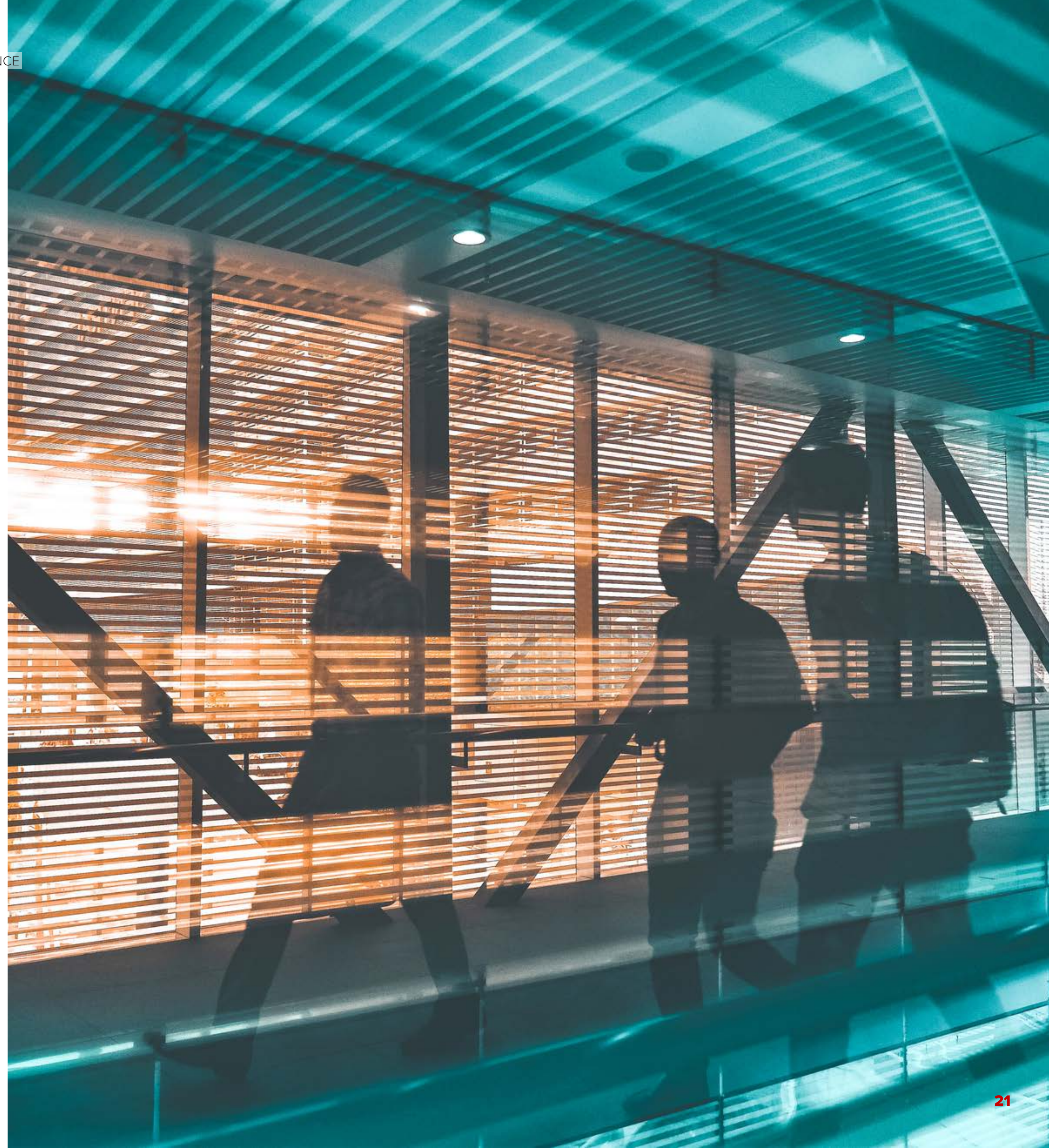
[16] Slattery, P., Saeri, A. K., Grundy, E. A. C., Graham, J., Noetel, M., Uuk, R., Dao, J., Pour, S., Casper, S., & Thompson, N. (2024). *A systematic evidence review and common frame of reference for the risks from artificial intelligence.*
[17] Wang, A., Kapoor, S., Barocas, S., & Narayanan, A. (2023). Against predictive optimization: On the legitimacy of decision-making algorithms that optimize predictive accuracy.
[18] Ibid

3 Current state of AI adoption in accounting

The landscape of AI adoption in accounting is evolving rapidly, with organisations at various stages of their AI journey. It's also notable that even amongst AI adopters, there is no single approach being taken. This will, in part, reflect the diversity of sectors included, but even in the sectoral breakdown there is no single application that the majority of respondents are pursuing. That suggests a better understanding of the range of possibilities is still required, and our key challenges section reflects this (section 5).

Our survey reveals a profession in transition, where the promise of AI is being partially realised – yet the pace and extent of implementation varies significantly across different organisations. Our case studies section provides more detail on specific applications (see section 6).

THIS PAINTS A PICTURE OF A PROFESSION EXPLORING MANY AVENUES FOR AI TO BOOST BOTH OPERATIONAL EFFICIENCY AND STRATEGIC DECISION-MAKING CAPABILITIES.



3.1 Implementation across functions

At the forefront of AI adoption, data analysis and reporting emerges as the clear leader. One third (33%) of the surveyed organisations have already implemented AI solutions in this domain – signalling a strong focus on enhancing insight through advanced analytics.

In the audit space, AI offers enhanced capabilities for data analysis – enabling auditors to process information and identify outliers or anomalies more efficiently. This incorporates use for analytical procedures and replacing sampling-based techniques with the potential for full coverage and more detailed trend analysis.

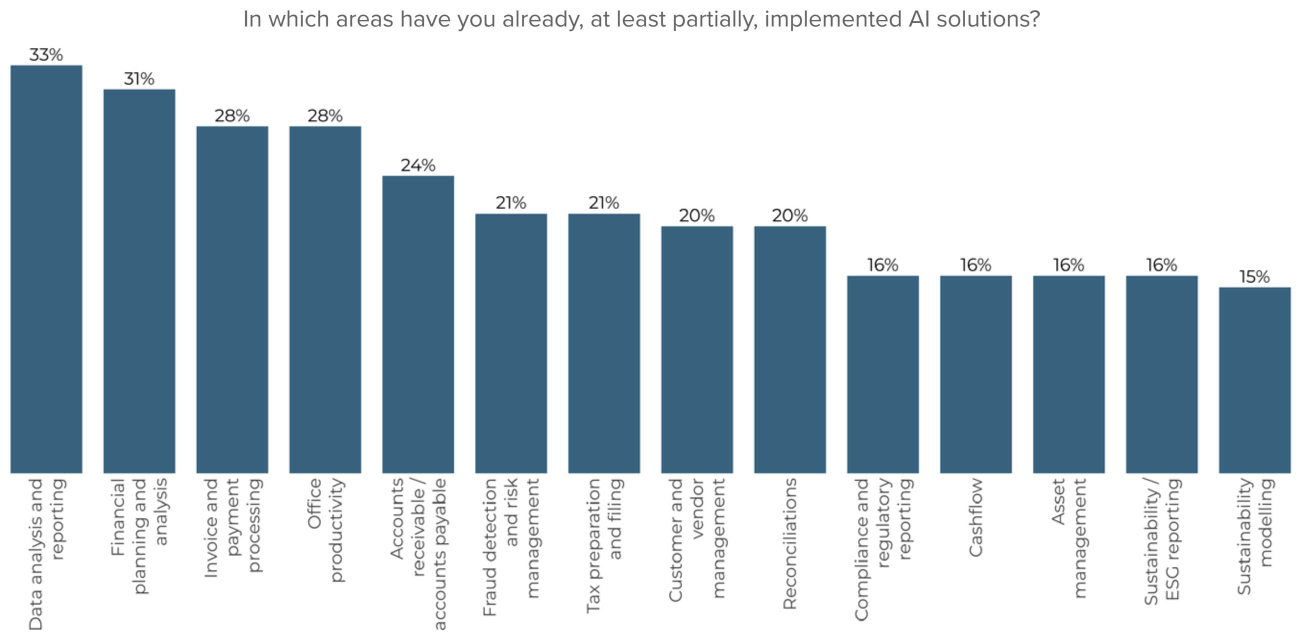
This is relevant for both external and internal audit functions. Providers like Inflo, MindBridge or Thomson Reuters, as well as custom-built platforms, are part of a growing ecosystem of AI solutions for audit professionals that support the demand for greater insight from data.

Data analysis and reporting is closely followed by applications in financial planning and analysis, invoice processing, office productivity, and accounts payable or accounts receivable.

There is a clear recognition that AI and ML are transforming traditional financial planning and analysis roles – with a shift towards more advanced data analysis and predictive modelling. This evolution necessitates a change in skill sets, with finance professionals needing to become more adept at ML and AI technologies.

> **WE'RE NOT JUST ADOPTING A TOOL; WE'RE REIMAGINING HOW WE INTERACT WITH INFORMATION ACROSS OUR PROFESSION.**
> Alec Manning, ACCA Global Forum for Technology

FIGURE 9: Where AI is being used, select all uses



The most popular areas for AI adoption include:

- Data analysis and reporting (33%)
- Financial planning and analysis (31%)
- Invoice and payment processing (28%)
- Office productivity (28%)
- Accounts payable / receivable (24%)

Many are still experimenting, as explained by one interviewee: 'In healthcare we have complicated policies and regulations that come up. So, we are trialling using a digital assistant across all our policies… trying to understand if we use natural language processing, what are some of the outputs that it derives from those.

'We're doing generative AI just as a trial, and with machine learning, we're looking at workforce optimisation, rostering optimisation. Because workforce is a big area in the healthcare space.'

The results also reflect the diversity of responsibilities within the sample given the relatively slight difference (18%) between the most common use – data analysis and reporting – and the least common use – sustainability modelling. Simultaneously, it also points out that there is need for a wider understanding of the requirements around sustainability modelling and the applicability of AI for improved sustainability modelling.

This paints a picture of a profession exploring many avenues for AI to boost both operational efficiency and strategic decision-making capabilities.

All charts excluding 'not sure' category where applicable

3.2 Applications vary by organisation size and type

However, the AI adoption story is not uniform across the accounting landscape. A notable divide exists between larger firms and smaller practices. While over 40% of large corporate firms have embraced AI for data analysis and reporting, – less than 30% of sole practitioners and small or medium-sized practices (SMPs) have done so.

This disparity reflects the broader challenges of resource allocation and technological capacity that smaller firms often face in keeping pace with rapid technological changes.

GenAI has also lowered the bar to entry for some – offering opportunities to simplify correspondence, draft and review content quickly, and even support Excel or programming activities. Consequently, it is not totally surprising to see that office productivity is a primary objective for many organisations that have relatively few established uses.

3.3 Focusing on tangible outcomes

Organisations are pursuing several key tangible outcomes through their AI initiatives, as illustrated by our case studies and survey data. These objectives include improving the quality of products and services, boosting efficiency of existing processes, upskilling employees, expanding organisational capabilities, enhancing decision-making, driving competitive advantage, and reducing operational costs.

> **THE FOCUS SHIFTS TO THE EFFECTIVENESS OF AI-ASSISTED DECISIONS IN ACHIEVING DESIRED OUTCOMES.**
>
> James Best, ACCA Global Forum for Technology

FIGURE 10: Sectors are focusing on different uses

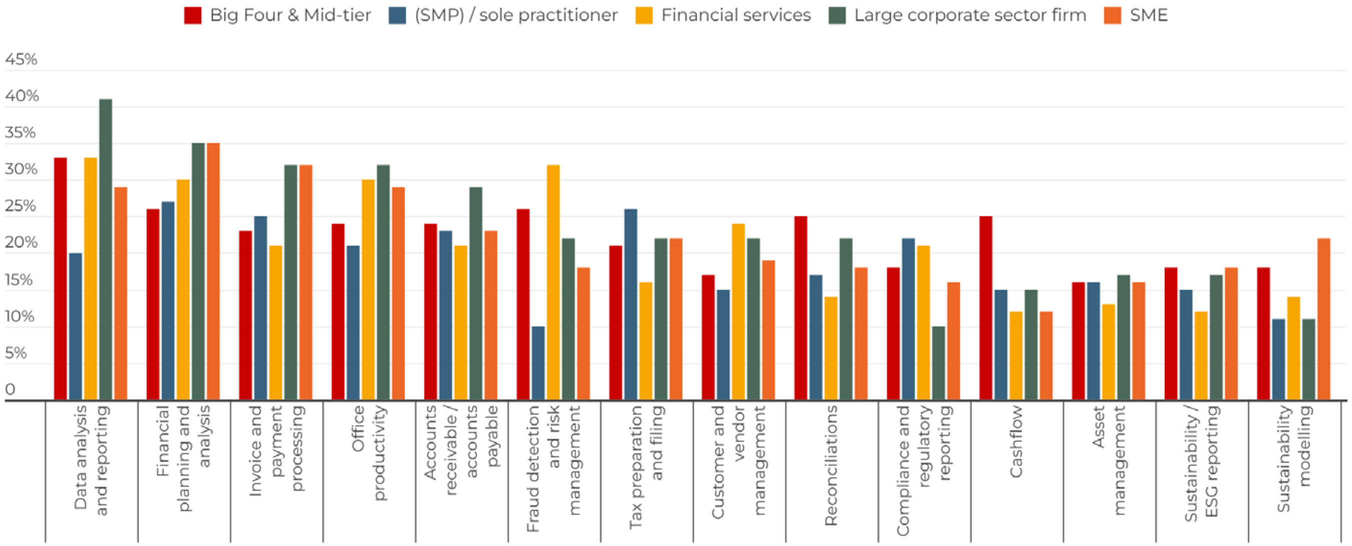


FIGURE 11: Priorities also vary depending on level of use

	Top 5 current uses				
# of uses	1	2	3	4	5
1 or 2	Office productivity	Data analysis and reporting	Cashflow	Invoice and payment processing	Reconciliations
3 to 5	Financial planning and analysis	Invoice and payment processing	Data analysis and reporting	Fraud detection and risk management	Accounts receivable/ accounts payable
5 to 10	Data analysis and reporting	Financial planning and analysis	Invoice and payment processing	Accounts receivable/ accounts payable	Tax preparation and filing
More than 10	Data analysis and reporting	Accounts receivable/ accounts payable	Customer and vendor management	Fraud detection and risk management	Invoice and payment processing

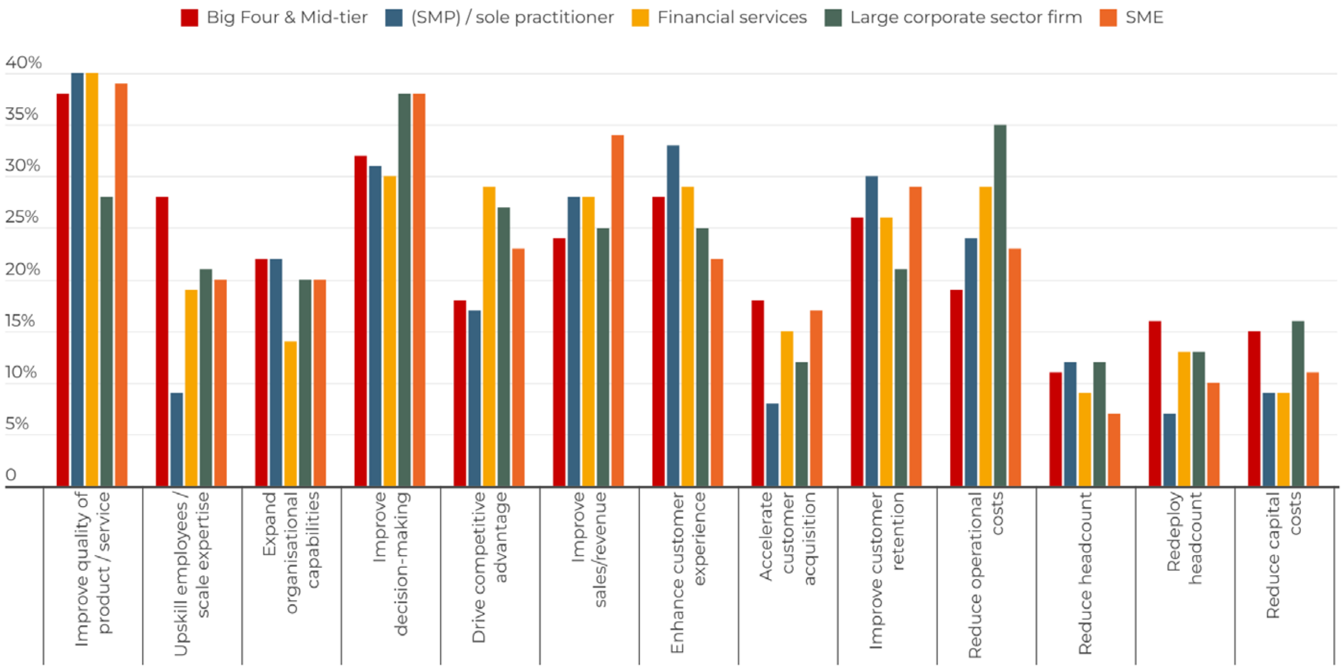
Many organisations are leveraging AI to enhance core accounting and finance processes, allowing for greater accuracy and speed in tasks such as balance sheet reviews, payment reconciliations, and cost estimations. As one interviewee explained in relation to producing reports or other narrative materials: 'When you bring in generative AI, it is so good with text that it can give us the first shot of narratives and...[in most cases] that means we are 80% there.'

AI is enabling finance teams to expand their capabilities and take on new, higher-value activities. By automating routine tasks, staff can focus on more strategic work. As another interviewee explained: 'The freed bandwidth that is available can be used by the individual to do the next level of activity.'

Enhanced analytics and insights from AI are also supporting better business decisions across various areas, from store location planning to customer credit assessments. This improved decision-making capability is seen as crucial for maintaining a competitive edge.

Finally, cost reduction remains a significant driver for AI adoption. Organisations are leveraging AI to handle increased workloads without proportional increases in headcount, and to eliminate costly manual processes.

FIGURE 12: Organisations are prioritising a handful of tangible outcomes

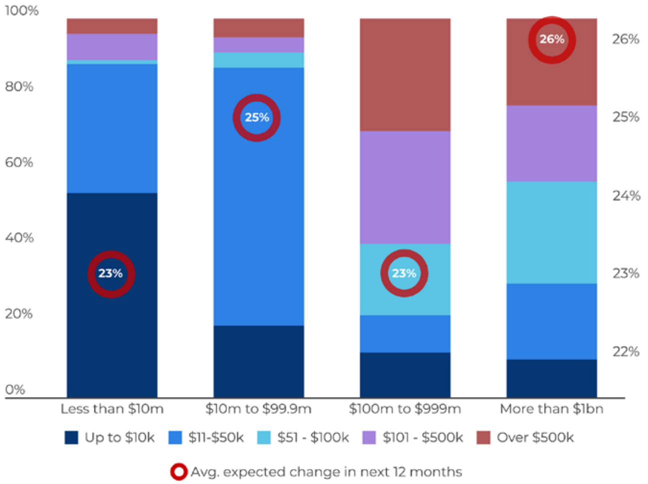


3.4 Organisations are committing financially to AI

The commitment to AI adoption is perhaps illustrated most starkly by the financial investments being made. Among organisations with revenues exceeding $1bn, more than a quarter invested over half a million dollars in AI projects in the past year alone. Interestingly, mid to large-sized organisations committed the greatest sums to AI implementation over the most recent financial year.

Even more telling is the forward-looking perspective, with nearly three-quarters of all respondents expecting to increase their AI investments in the coming year. This widespread anticipation of increased spending underscores a growing recognition of AI's strategic importance in the accountancy and finance profession.

FIGURE 13: Mid to large sized organisations are leading the way in terms of spending



SHORT-TERM EXPECTATIONS FOCUS ON...IMPROVING EXISTING USES OR EXTENDING TO OTHER RELATIVELY WELL-ESTABLISHED USES.

3.5 Uses of AI are expected to evolve gradually

As AI adoption matures, we're seeing a shift from basic automation to more advanced applications.

At the same time, as demonstrated by the average amongst survey respondents, most finance departments have relatively few current uses of AI (three on average). So, it's not entirely surprising to see that short-term expectations focus on similar applications – whether that be improving on existing uses or extending to other relatively well-established uses.

When we delve into the specific areas where organisations plan to explore AI opportunities, a clear shift towards more strategic applications becomes apparent. While in some cases current AI use focuses on automating accounts payable (AP) or transactional tasks – plans reveal a move towards leveraging AI for higher-value activities.

Financial planning and analysis remains a valuable application but there's also a turn to fraud detection and risk management, sustainability and ESG reporting, and compliance and regulatory reporting. This is the pre-emptive pivot; using AI for forward-looking, strategic tasks signals a maturation in how the accounting profession views the technology's potential.

THE AI CAPABILITY GAP BETWEEN LARGE AND SMALL FIRMS MAY WIDEN IN THE COMING YEARS – UNLESS STEPS ARE TAKEN TO DEMOCRATISE ACCESS.

The future landscape of AI adoption shows some divergence based on organisational size and type. Larger firms are setting their sights on a diverse range of AI applications – from advanced risk management to customer relationship management.

By contrast, smaller practices are focusing their AI aspirations on core accounting functions, perhaps reflecting their more limited resources and specific business needs. This dichotomy suggests that the AI capability gap between large and small firms may widen in the coming years – unless steps are taken to democratise access to AI technologies. And that access is related both to availability and skillset.

3.6 Balancing internal and external capabilities

Organisations are taking varied approaches to AI development, balancing the benefits of in-house solutions against the convenience of vendor offerings. However, there does appear to be a slight preference for investing in internal teams moving forward.

For ML applications, 36% are using internal solutions while 28% are opting for vendor solutions. But although the same proportion are expecting to invest in internal solutions moving forward, 24% are looking for vendor solutions.

That trend holds true across all types of AI (except for

FIGURE 14: The focus of adoption remains similar in the short-term

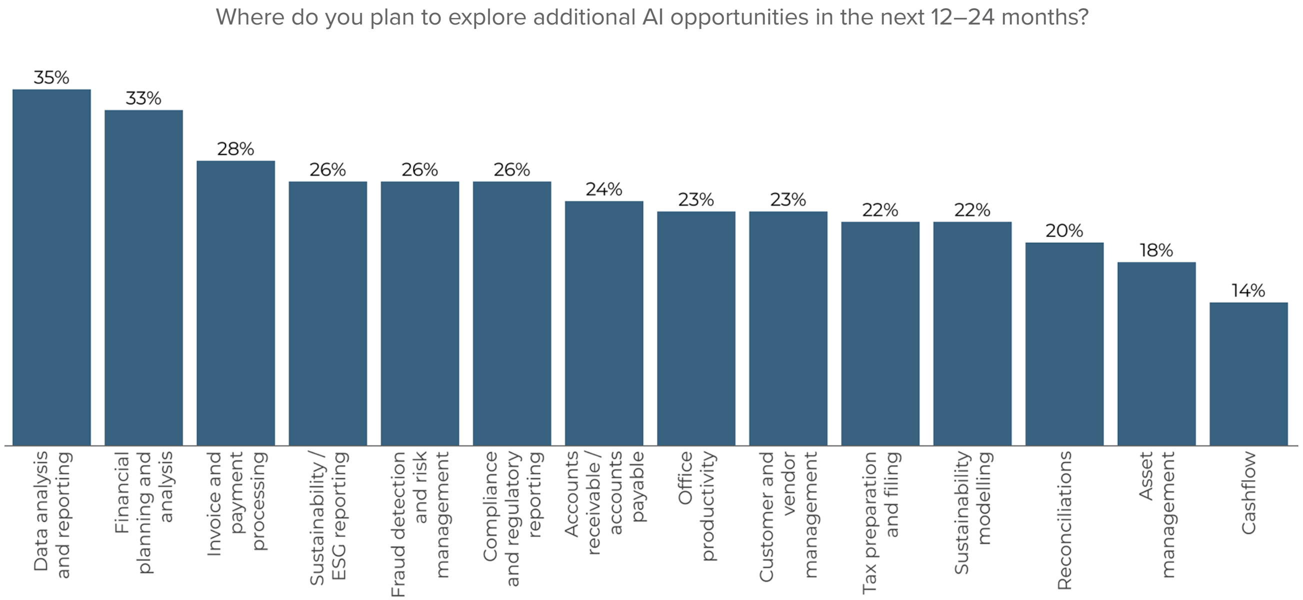


FIGURE 15: The focus of some sectors is expected to turn to new challenges

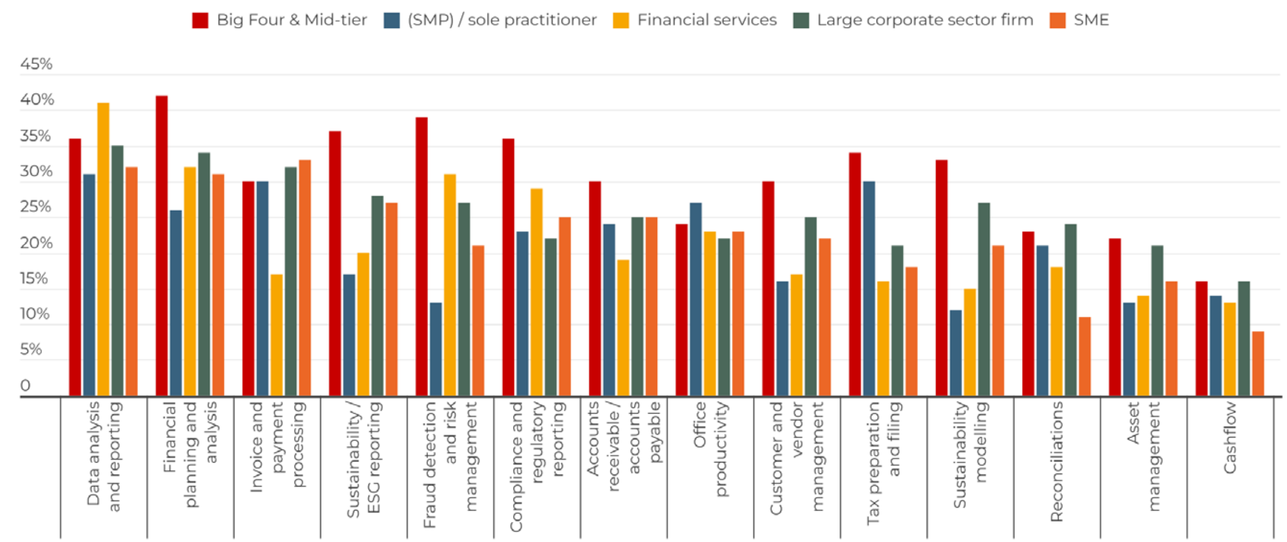
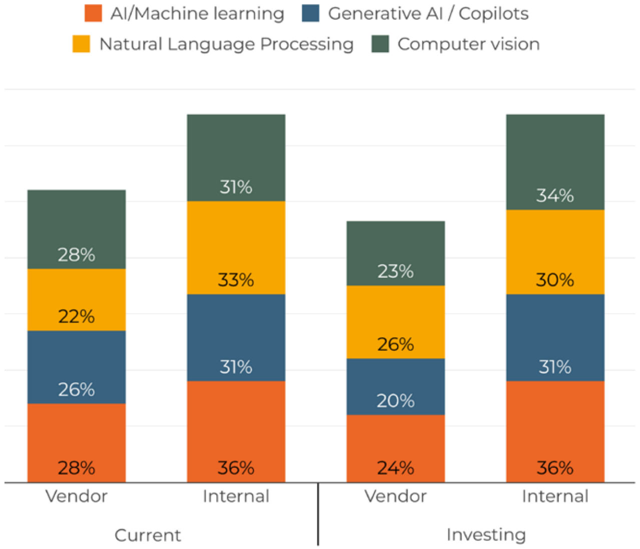
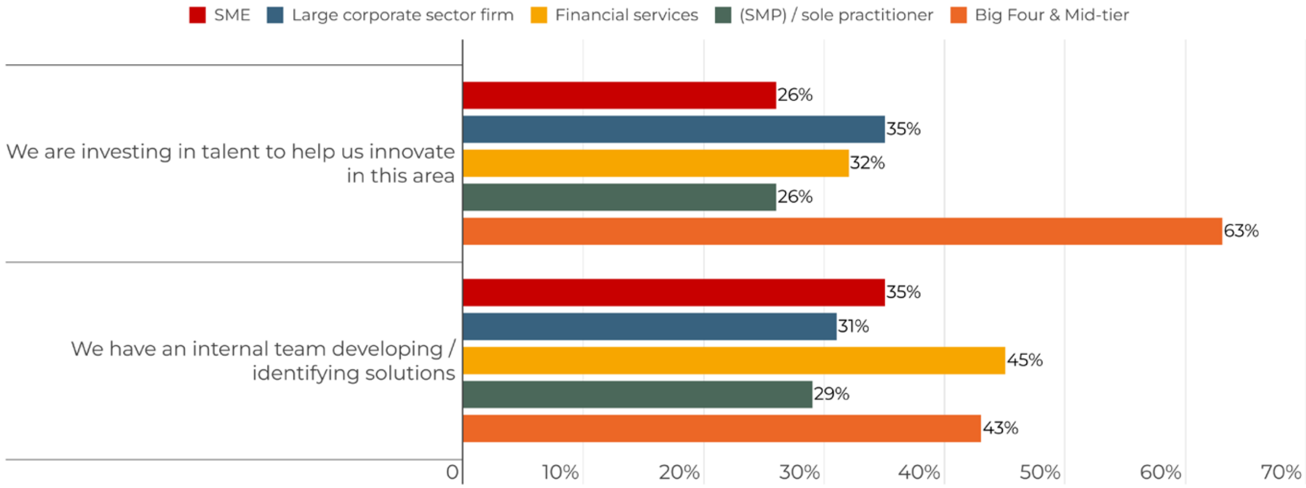


FIGURE 16: How organisations are approaching adoption



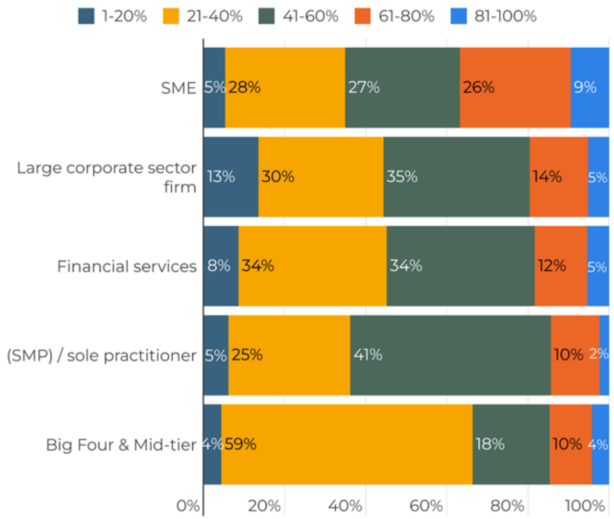
Summed figures will not equal 100% as some organisations are taking multiple approaches

FIGURE 17: Organisations are especially focused on internal capabilities



Summed figures will not equal 100% as some organisations are taking multiple approaches

FIGURE 18: The future finance function is expecting to bolster data skills with a higher proportion (%) of data-centric roles



NLP), with organisations favouring in-house talent when contemplating future investment. That could present a notable challenge in terms of attracting and retaining highly sought after skills.

In all types of AI, SMPs tend to fall slightly behind other sectors in terms of their in-house capabilities. This means they are more reliant on third parties for leveraging AI tools – and are faced with often difficult considerations identifying the best solutions on the market.

By contrast, mid-tier and large practitioners have invested in this talent and are expecting to continue investing in securing in-house talent, ahead of all other sectors.

MID-TIER AND LARGE PRACTITIONERS...ARE EXPECTING TO CONTINUE INVESTING IN SECURING IN-HOUSE TALENT.

As reported in our AI Monitor issue *Skills to drive responsible AI adoption*, August 2024, there is a clear expectation from AI adopters that they will require a higher mix of advanced data skills in the future (Figure 18).

There are some interesting sectoral variations, however:

Mid-tier accountancy practitioners, Big Four firms, financial services, and large corporates anticipate a slightly lower need for finance-specific additions while SMEs and SMPs expect a stronger need.

One clear distinction will be the presence of internal technical teams for whom there are already opportunities for collaboration. This will change the need for finance-specific data scientists, for example, whereas organisations without this resource may look to fill this gap by hiring such skills into their finance team.

4 Implementing AI and data strategies

As AI gradually becomes a cornerstone of modern accounting workflows, organisations are developing more structured and nuanced approaches to its implementation.

This is important because progress can come relatively quickly and easily with many forms of AI, but then becomes increasingly difficult and laborious towards deployment. To avoid floundering at the development stage calls for a clear strategy in place to manage the full lifecycle; understanding the technical complexity involved as data needs grow, and how to cope with probabilistic outputs that can lead to changes in tone, quality and consistency.[19]

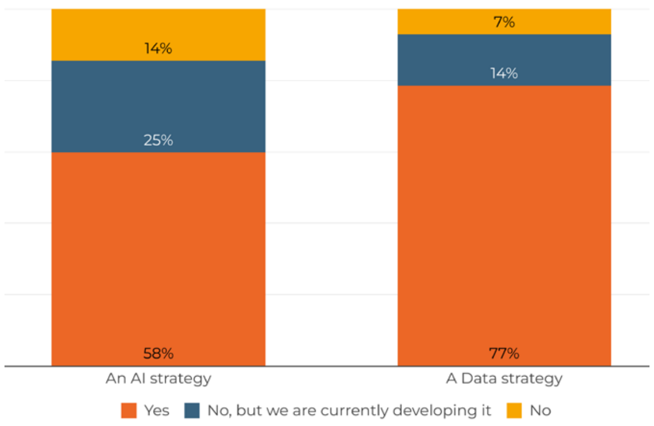
An interviewee notes, it's important to: 'look at how these technologies deliver value for the organisation rather than just an interesting use case. Particularly because at the moment, there's an awful lot of organisations that are very focused on being efficient but the value generation opportunity, found by unleashing that extra creativity in your people, is where the boom comes... where the business case is.'

THE VALUE GENERATION OPPORTUNITY...UNLEASHING THAT EXTRA CREATIVITY IN YOUR PEOPLE, IS WHERE THE BOOM COMES.

[19] Zwingmann, T. (2024, May 10). *The 80% fallacy: Why building your AI use case might be harder than you think*. The Augmented Advantage.

FIGURE 19: Organisations are taking a strategic approach

Does your organisation currently have...



Our survey reveals recognition of the importance of taking a strategic approach to AI initiatives, with over half of the respondents reporting that they have an AI strategy in place, and nearly a quarter in the process of developing one. This strategic mindset extends to data management as well – with an even higher proportion of organisations having established or currently developing data strategies.

Our survey reveals that many organisations recognise the need for a formal strategy to guide their AI initiatives:

- 58% of respondents report having an AI strategy in place
- 25% are currently developing an AI strategy
- 77% have a data strategy, with another 14% in the process of developing one.

The figures also indicate that data strategies may be relatively mature compared to AI strategies. There remains a significant contingent of AI adopters, at least initially, taking a more organic approach – particularly amongst smaller firms. But the relevance of having a strategy will become clearer as we determine some of the concerns and challenges facing organisations.

4.1 Establishing foundational elements

So, what are the foundational components that organisations are putting in place?

The first step is always to understand the current data situation and assess any additional data needs, including considerations around the type and quality of data required. No less important is having the appropriate infrastructure and governance to store, manage and oversee uses of that data.

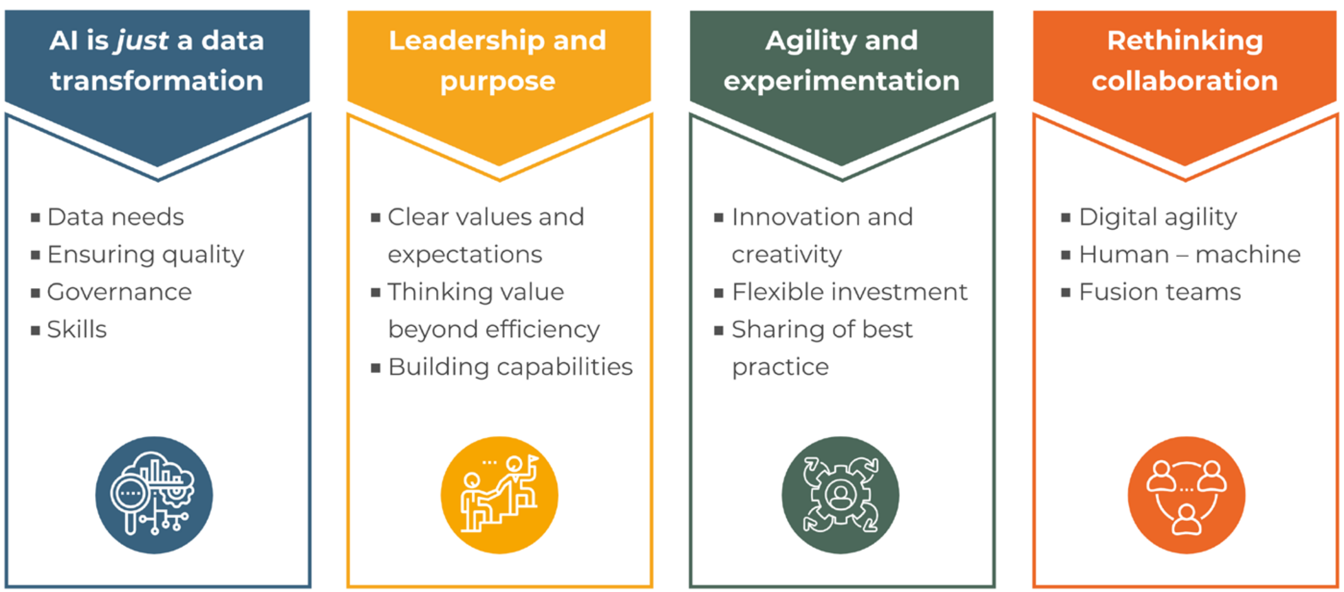
This requires understanding of different data types and requirements, and serious effort is involved – as pointed out by Surahyo, CFO, Simpli Home: 'One of the [major] challenges of course is getting the data cleaned, prepped and in the right format. That really takes a lot of time; looking for all of our old project data information and prepping it, finding data gaps, and gathering...[additional] information, etc.'

Bala Iyer, CEO at The Walnut.ai, highlights another important element: 'We have to ensure that whatever we do...is based on responsible practices. How do we ensure that privacy is protected? Our data is actually not our data – most of these are customers' data. So, we need to be aware of all our obligations.'

Effective innovation balances top-down strategy with bottom-up creativity, fostered by clear purpose and values. Leaders should focus on empowering employees to innovate, not

FIGURE 20: Organisations are taking a strategic approach

Strategic thinking entails a holistic approach



just improving efficiency. Our *Digital horizons: Technology, innovation and the future of accounting* research shows that confident digital leadership is crucial for leading innovators.

As noted by Navin Gadia, Global Controller, Wipro: 'We are encouraging all our finance personnel to upskill continuously...there is a tremendous amount of focus on training and driving adoption of latest technologies related to advanced data analytics and AI, among others. We did the same with RPA and now machine learning'.

By its very nature, AI also requires an element of flexibility and willingness to experiment. It can take significant time before a model is ready for deployment and that entails patience, learning, and an open mindset towards iterative improvements. The final product may require ongoing development – so it's important to build in strong feedback loops, and flexibility in how projects are monitored and financed.

It's more important than ever to be taking a collaborative approach that ensures knowledge and best practices are shared across organisations.

The Chief Accounting Officer (CAO) of a multinational IT company explains how: 'Every use case goes through a very robust governance process of approval... suppose somebody has an idea, the person will make an initial business impact analysis... it will come to a steering committee within finance and then it will go to our CFO and finally to a central AI governance committee for the entire organisation.'

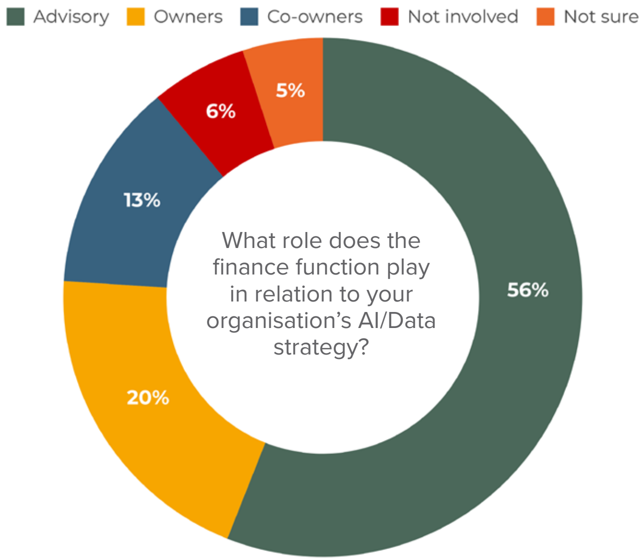
A collaborative approach ensures that AI initiatives are aligned with business objectives and have support across the organisation.

4.2 Role of finance in data and AI strategy

Finance departments are playing a pivotal role in shaping AI and data strategies. In the majority of organisations, finance teams are actively involved in an advisory capacity, – while in others, they take on full ownership or co-ownership of strategic initiatives.

This central role of finance in AI strategy underscores a critical point: successful AI implementation is not just about technology; it's about alignment across the organisation and tying technological capabilities to financial goals and regulatory requirements.

FIGURE 21: Finance is a key player in thinking strategically about data and AI



The finance function plays a crucial role in shaping AI and data strategies:

- 56% of finance functions play an advisory role in their organisation's AI/data strategy
- 20% are owners of the strategy
- 13% are co-owners with other departments.

4.3 Championing a collaborative approach to strategy and governance

As we look to the future of finance functions, data and AI strategy are significant topics, especially as organisations strive to become more data driven – that puts much greater emphasis on the need for trusted data.

Respondents were asked to share their views from the perspective of their internal finance teams or their clients, if that is their focus.

But as data becomes more central to organisations' current and future success, it's not possible for the burden to fall solely on the shoulders of individual teams that manage data. It is a shared organisational asset – and that means we need to be thinking about more flexible and collaborative models moving forward.

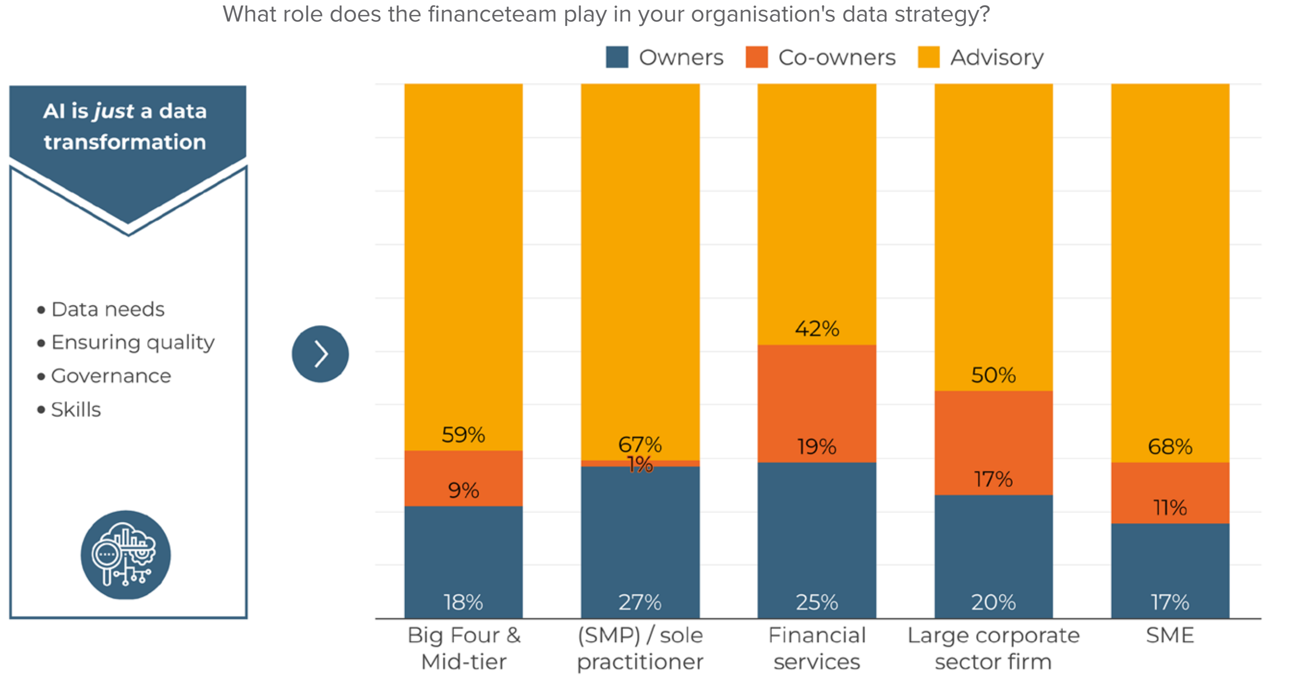
That is especially true as we look to leverage advanced analytics, like predictive and ML models, which have different data and architecture requirements. They are also the means through which organisations can be more pre-emptive – but, first, it is necessary to have data integrity.

It's not about finance taking control, but about championing and participating in a more collaborative approach and moving towards co-ownership roles. Overall, it's about finance being able to ensure trust and integrity over the data sources that it uses, and those data sources are more broad and varied than ever.

Moreover, there's an important connection to governance. Data governance is part of how an organisation's strategic vision for their data is operationalised. That means accounting for risk, compliance requirements, and establishing clear guidelines and good practice to promote reliable decision-making and delivery of products or services.

As is evident from the survey, we are already finding that finance functions are taking central roles in developing data and AI strategies – so it's natural that they steward parts of that strategy ahead and take responsibility for elements that fit within their established competence.

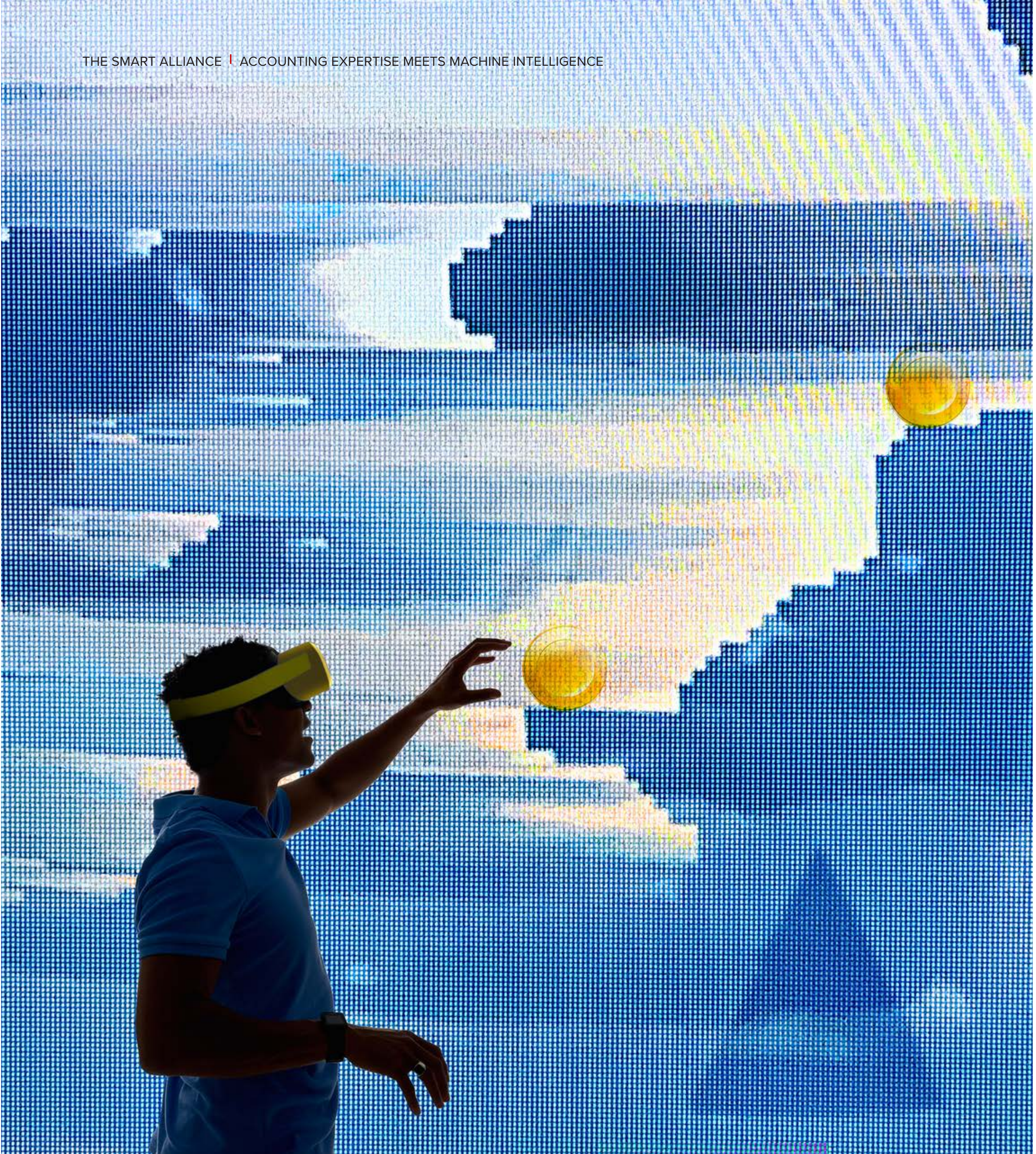
FIGURE 22: Finance are trusted sources of data



This isn't about setting rules for data storage or access. It's about enacting procedures to ensure that data drives every decision, from risk assessment to customer service. Finance is in an ideal position to build a bridge between organisational strategy and the day-to-day operations that make that happen – they are well-placed to understand the value associated with data.

When considering AI, collaboration across different departments is emerging as a key factor in successful implementation. Some organisations have already created cross-functional teams to identify AI innovation opportunities – with even more planning to do so in coming years (Figure 24). This collaborative approach helps ensure that AI initiatives are aligned with broader business objectives, and can leverage diverse expertise from across the organisation.

The strategic landscape of AI implementation in accounting is characterised by an increasingly sophisticated approach. While there's still significant variation in the maturity of these strategies, the most successful organisations are those that align their AI initiatives with clear business outcomes, foster cross-functional collaboration, and take a long-term view on building AI capabilities. As AI continues to evolve, having a robust and flexible strategy will be crucial for accounting firms and finance departments looking to harness its full potential.



5 Challenges and risks in AI adoption

The journey of AI adoption in accounting, while promising, is not without its hurdles. Organisations across the spectrum are grappling with a range of challenges as they seek to integrate AI into their operations.

Our survey reveals that uncertainty about choosing the most suitable AI solution tops the list of concerns – with over a quarter of respondents citing this as their primary challenge. This uncertainty reflects the rapidly evolving nature of AI technologies and the complexity of aligning these solutions with specific organisational needs.

Taking the results as a whole, the prevalent concerns also suggest that most organisations – even those who are already using AI – are still relatively early on in their journey. As such, they are still primarily concerned with problems around tool selection and establishing safeguards.

Close behind is the challenge of integrating AI with existing systems, a hurdle that underscores the technical complexities involved in AI adoption. Many accounting firms and finance departments are working with legacy systems that may not be readily compatible with cutting-edge AI

ORGANISATIONS ARE STILL IN THE EARLY STAGES OF DEVELOPING RISK MANAGEMENT STRATEGIES AND CULTURE TO SUPPORT.

technologies. This integration challenge is not merely a technical issue, but often requires a rethinking of established processes and workflows.

Data privacy and security concerns also loom large in the minds of accounting professionals considering AI adoption. With AI systems often requiring access to vast amounts of sensitive financial data – ensuring the security and privacy of this information is paramount. This concern is particularly acute in the regulated sectors, including financial services, where regulatory scrutiny is intense, and the consequences of data breaches can be severe.

Our survey identified several significant challenges in adopting AI:

1

Uncertainty about the right solution

(29%)

2

Integration with existing systems

(29%)

3

Data privacy and security concerns

(25%)

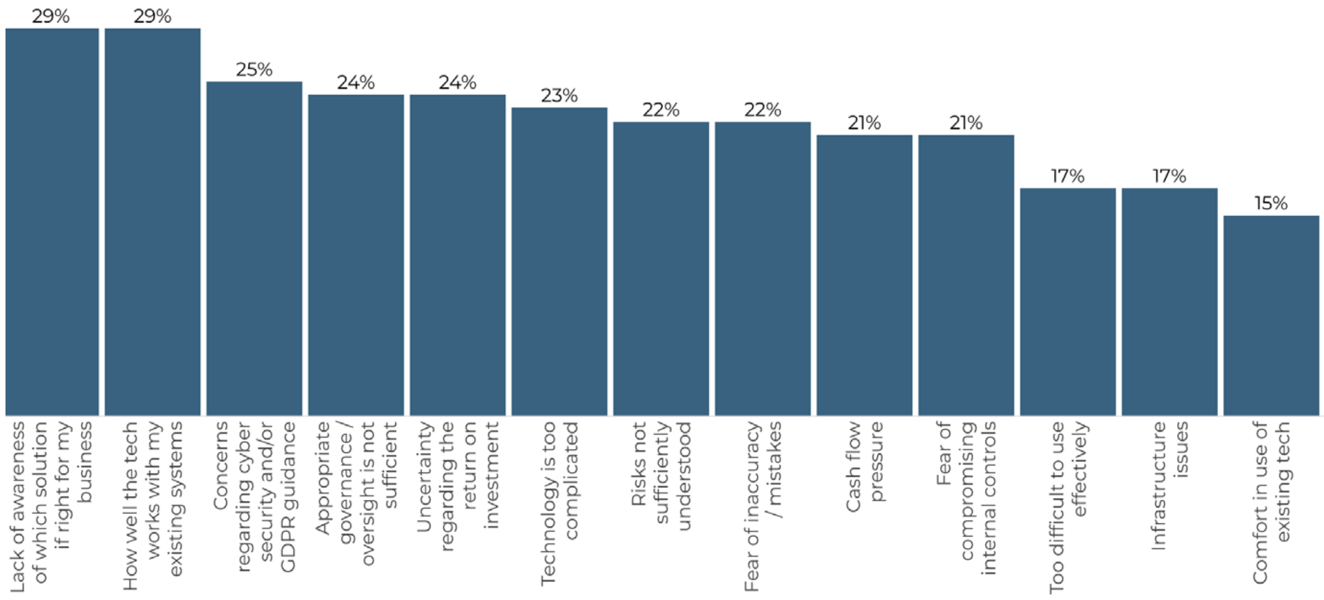
4

Insufficient governance and oversight

(24%)

These findings suggest that many organisations are battling with both technical and strategic challenges in their AI adoption journey.

FIGURE 23: Awareness and understanding remain limitations



5.1 Sectors face different considerations

The challenges are broadly consistent across sectors, though there is some variation in intensity depending on the type and size of the organisation:

- Larger firms – including the Big Four – mid-tier accounting firms, large corporate and financial services, are slightly more likely to be preoccupied with governance and oversight issues, including cybersecurity or data protection. This could reflect their complex organisational structures and the need to ensure consistent AI usage across multiple departments and geographies.
- By contrast, SMPs and sole practitioners are more likely to be daunted by the process of identifying and selecting the right solution, highlighting the need for more accessible AI solutions tailored to smaller organisations.

Dev Ramnarine, chair of ACCA's global forum for technology, points out that: 'Technology is the backbone of progress, yet smaller businesses often face significant resource constraints when it comes to adopting new technologies. Uncertainty is compounded for these businesses by the sheer number of available technologies and the lack of internal expertise to evaluate them. The risk of investing in an AI tool that doesn't deliver the expected return on investment is particularly acute, where every expenditure must be carefully justified.'

5.2 Confidence in risk and control measures

When it comes to managing the risks associated with AI, our survey reveals a mixed picture. While a third of organisations feel their risk and control measures are sufficient, many acknowledge the need to better understand and address specific AI-related risks.

FIGURE 24: There is also some notable variation in challenges across sectors

	Total	Big Four & Mid-tier	SMP	Financial services	Large corporate	SME
Don't know which solution is right	29%	30%	35%	27%	30%	27%
How tech works with existing systems	29%	31%	24%	32%	32%	24%
Concerns regarding security and/or GDPR	25%	29%	21%	29%	25%	16%
Governance / oversight not sufficient	24%	28%	17%	20%	27%	26%
Uncertainty regarding ROI	24%	24%	25%	27%	25%	22%
Technology too complicated	23%	17%	21%	32%	24%	25%
Risks not sufficiently understood	23%	16%	27%	18%	24%	20%
Fear of inaccuracy / mistakes	22%	22%	28%	22%	21%	18%
Cash flow pressure	22%	22%	26%	23%	21%	20%
Fear of compromising internal controls	21%	21%	19%	23%	24%	20%
Too difficult to use effectively	18%	21%	13%	13%	18%	22%
Infrastructure issues	17%	19%	16%	13%	21%	12%
Comfort in use of existing tech	16%	12%	22%	15%	14%	16%

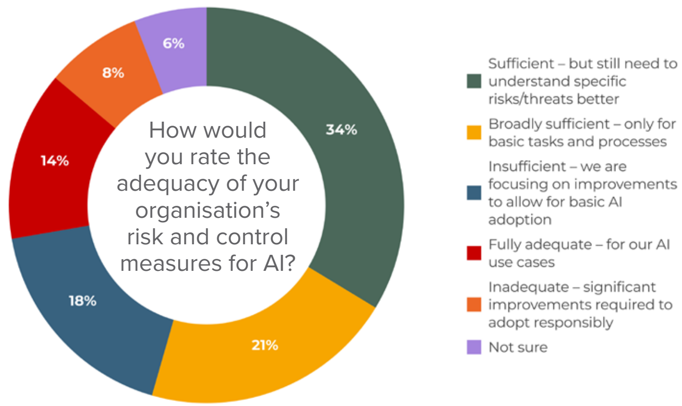
This sentiment echoes across the industry – there's a growing awareness of AI risks, but many organisations are still in the early stages of developing risk management strategies and culture to support them.

One of the most pressing risks in AI adoption is the potential for bias in AI systems. As Sian Townson astutely observes[20], the goal should not be to eliminate bias entirely – an impossible task – but rather to focus on mitigating and managing it effectively. This nuanced approach to AI bias is slowly gaining traction in the accounting world – as professionals come to terms with the complexities of AI decision-making.

Organisations' confidence in their AI risk management capabilities is mixed:

- 34% feel their risk and control measures are sufficient but need to understand specific risks better.

FIGURE 25: There is work to be done to increase confidence in risk and control measures*



*Figures have been rounded and will not add up to 100%

[20] Townson, S. (2023, January 26). *Manage AI Bias Instead of Trying to Eliminate It*, MIT Sloan Management Review.

- 21% believe their measures are broadly sufficient for basic tasks.
- 18% admit their measures are insufficient and are focusing on improvements.

This data points to a high-level understanding of risks, but persistent concerns over limited knowledge or capacity to address them.

The extent of the challenge is also highlighted in our *Risk culture: Building resilience and seizing opportunities* report where problems of misalignment and confidence were raised about whether risk and controls can detect emerging risks including related to AI. Confirmation bias tends to lead to a focus on known and quantifiable risks, which potentially raises serious blind spots. Overcoming these typically involves a more open, collaborative approach to risk that brings in diverse perspectives to help combat a rigid focus on existing forms of risk.

Large practitioners, also amongst the leading adopters of AI, are the most confident in their risk and control measures for AI. However, confidence doesn't merely follow from level of adoption.

Large corporates and financial services organisations are the most likely to express concern about the adequacy of their risk and control measures – potentially reflecting unique sectoral risks and complexities, including added difficulty when working across different jurisdictions and the competition for talent.

Organisations are also confronting a growing prevalence of fraud, increasingly aided by AI technologies. Our *Global Economic Conditions Survey (GECS): Q2*, noted that for financial services organisations, fraud has returned to top billing – rising into the top three risk-related concerns for the first time in several years.

FIGURE 26: Confidence in risk-related measures by sector

Inadequate ⟶ Fully adequate

Big 4 & Mid-tier	4%	12%	12%	53%	17%
(SMP) / sole practitioner	8%	14%	26%	30%	14%
Financial services	10%	19%	22%	22%	20%
Large corporate sector firm	11%	24%	27%	28%	5%
SME	5%	14%	18%	38%	20%
Overall	8%	20%	22%	36%	14%

5.3 Strengthening internal competence to tackle risks

The establishment of formal governance structures for AI use is still in its infancy in many organisations. In discussions with these organisations, many have been searching for clarity on regulations and standards to help guide their approach. Simultaneously, there's growing recognition in many jurisdictions that organisations will need to define their own boundaries and risk appetites to address gaps or delays in implementation.

When it comes to the adequacy of risk and control measures for AI, specifically, there are clearly outstanding concerns within organisations about their ability to understand and tackle the risks effectively.

Respondents highlighted several concerns:*

- **Data privacy and security:** one of the most frequently cited concerns was around data privacy, security, and potential data leaks. Many respondents worried about the risks of sensitive financial and customer data being exposed or misused due to inadequate AI risk and control measures. There were concerns about hacking, cybersecurity threats, and unauthorised access to confidential information.
- **Lack of knowledge and expertise:** another common theme was a lack of understanding and in-house expertise when it comes to AI and implementing appropriate risk measures. Many felt their organisations lacked the specialised skills and competency needed to properly oversee AI and put effective controls in place. Some mentioned needing to rely on external experts and auditors.
- **Bias and errors:** the risk of biased or inaccurate outputs from AI models was another worry. Respondents noted the potential for AI to perpetuate biases, make incorrect decisions, or 'hallucinate' wrong information if not properly controlled for. Impacts on areas like financial reporting and HR decisions were called out.
- **Resource constraints:** implementing proper AI risk and control measures was seen by some as prohibitively expensive and time-consuming, especially for smaller organisations. Lack of budget and stretched resources were noted as barriers.
- **Overreliance:** some worried about an overreliance on AI and people placing too much trust in the technology without appropriate human oversight and auditing. There were concerns that staff may blindly assume the AI is always correct.
- **Keeping pace with rapidly evolving technology:** the rapid pace of change in AI technology was seen as making it challenging to maintain adequate risk measures. Respondents felt that controls put in place one day could quickly become obsolete as the AI evolved – requiring constant updating of risk management approaches.
- **Balancing risk controls with performance:** a few respondents raised the need to balance strong risk and control measures with the ability to fully utilise AI's capabilities to improve business efficiency and results. Overly restrictive controls were seen as a potential hindrance.
- **Regulatory compliance:** concerns around regulatory compliance, especially with data protection regulations like GDPR, came up frequently. Respondents wanted to ensure AI risk and control measures would keep them compliant with relevant laws and requirements around data handling.

***This analysis is based on open-text survey responses using the Natural Language Toolkit (NLTK) in Python to identify word frequency, common themes and concepts and generate summary insights. An LLM was subsequently used to add an additional layer of narrative over the Python analysis.**

For a broad swathe of research participants, enhancing internal AI capabilities are an important solution. The emphasis on building in-house expertise is seen as crucial not only for effective AI implementation but also for managing the associated risks and challenges. But this also presents its own limitations, not least in terms of the availability of that talent. Instead, it may be necessary to start thinking about how to upskill staff to fit new roles, build on existing competencies so that they are grounded in existing domains (see our *Finance Evolution: Thriving in the next decade* report for analysis of how roles are evolving).

While the feedback from research participants exhibits a wide range of concerns that organisations are keen to address there is a mounting question around alignment between organisations' approach to risk management and their purpose. In particular, specific risks related to trust, – including impacts on reputation as a result of poor alignment – appear to be gaps in current thinking. Our *Risk culture: Calls to Action* details some ways in which organisations can begin to assess potential blind spots.[21]

5.4 Creating shared knowledge and understanding for risk mitigation

To overcome these challenges and to properly be able to address potential risks, organisations need to be thinking about how they can create a basis for shared knowledge and understanding. It's becoming clearer that to combat future risks, every employee has a role to play[22]. This is especially critical with AI as there can be significant knock-on impacts – negative consequences can scale quickly, if errors and inaccuracies are not caught early.

To develop and nurture that sense of collective responsibility, it is necessary to have the right policies and training in place.

As noted by one interviewee: 'You've got to try using it [AI] and have an approach within your organisation that is a recognised way of driving innovation. So again, you don't want to stop people doing innovative things... but you want to enable that with an element of control.

'You need to have the governance around that so the organisation can "say actually generally we're not going to do that thing because it's not the right thing to do". And they need to also have a feedback mechanism.'

[21] See our *Risk culture: Building resilience and seizing opportunities*, including the Calls to Action, for more insight into how good governance is contingent on a strong risk culture not only when it comes to AI, but all the rapid, interconnected transformations organisations face today.

ACCA's *Risk cultures in banking: Where next?* also explores how AI is advancing the detection of emerging risks, including how to identify and manage behaviours behind the risks, including those related to AI and cybersecurity.

[22] Mikes, A., & Kaplan, R. S. (2021, January). *When every employee is a risk manager*. Harvard Business Review.

What the survey makes clear, however, is that many organisations are still in the early stages of establishing these foundations, which also feed into the formal governance of AI:

- **29%** have established policies around the transparency of AI use.
- **29%** have policies covering the explainability of AI.
- **29%** have policies or standard around mitigating the potential for bias or discrimination.
- **30%** have procedures for monitoring or overseeing AI inputs and/or outputs.
- **31%** have adopted training programs for employees on responsible AI use.

Meanwhile, a significant portion (42-49%) plan to implement such measures in the future – indicating growing awareness of the importance of AI governance.

'We've got a foundation module that everybody has been required to complete... more around, you know, be aware of what our ethical policy is around the use of AI. That's been more the compliance-type training,' added an interviewee.

Across all sectors, the majority of respondents are aware of these issues and may have had discussions about developing specific policies, however fewer than a third have already done so.

SMPs tend to be behind other sectors in establishing these policies or practices alongside large corporate sector firms.

Ramnarine notes: 'For SMEs, establishing these frameworks can be daunting. Many small businesses may not have the necessary internal controls or expertise to effectively manage the risks associated with AI, such as data privacy, algorithmic bias, and the integration with existing legacy systems. This is an area where practical guidance and support are critical, and where industry associations and forums can play a vital role. That means SMPs also need to get up to speed so that so they can support these evolving needs.'

FIGURE 27: Policies and training are a work-in-progress

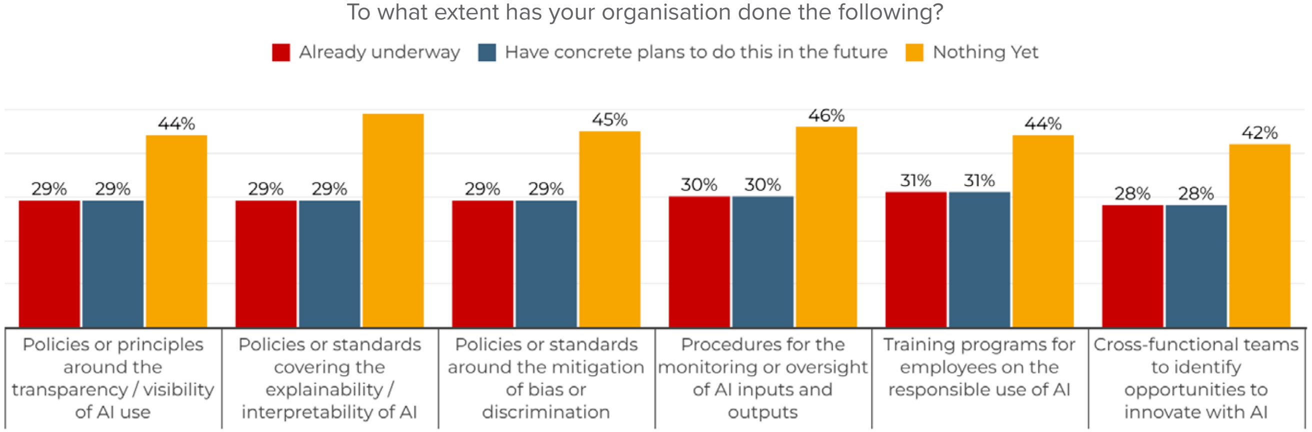
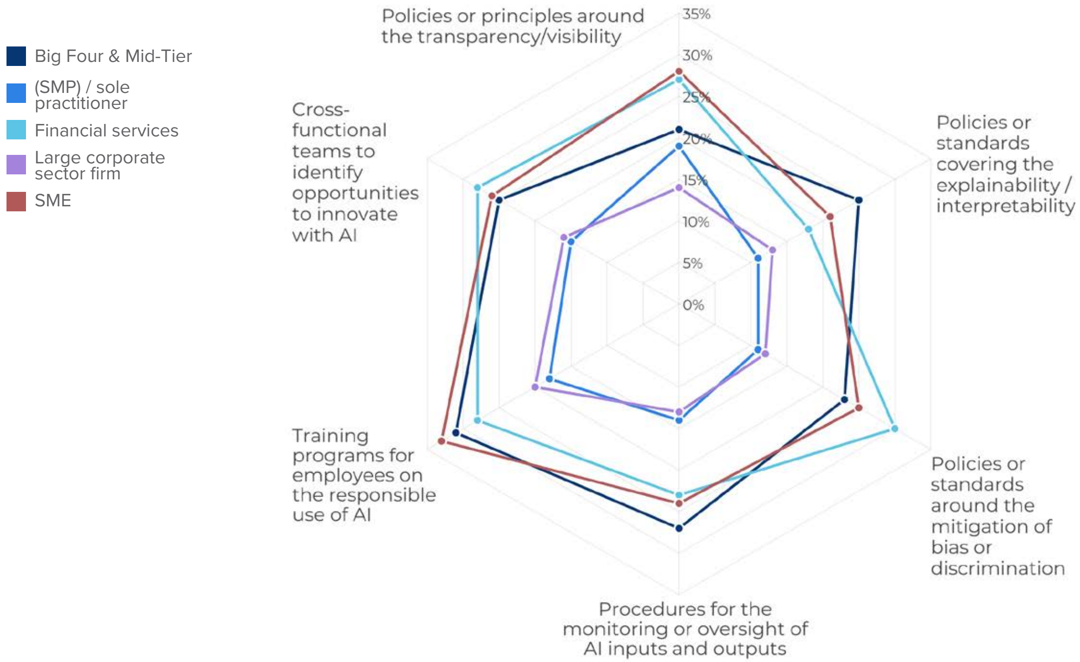


FIGURE 28: There is more to be done across all sectors. My organisation is already implementing...



6 Case studies:

How is AI being used?

6.1 UK GIAA's AI-powered Writing Engine[23]

The Government Internal Audit Agency (GIAA) has been at the forefront of the UK government in applying generative AI to support their work and drive efficiencies. One example of this is their Writing Engine which is used to help draft audit reports.

GIAA provides internal audit services to most UK government organisations and produces around 1,500 audit reports per year. Each audit report summarises the findings from fieldwork and recommends actions for the client to address any issues. An average audit takes 20-30 days to complete, with report writing taking two to five days – so a sizeable proportion of auditors' time is spent drafting text.

GIAA identified an opportunity to use generative AI to help improve efficiency in report writing and decided to build on the success of their Risk Engine to develop another customised tool, the Writing Engine. Their Data Analytics (DA) team spent time understanding how auditors used GIAA's audit management system, which centrally captures information and evidence relating to the audit, including notes from fieldwork. They then started to design a process auditors can easily extract certain fields from the audit management system, upload them to the Writing Engine – and then use generative AI to create a first draft of the audit report in 30 seconds.

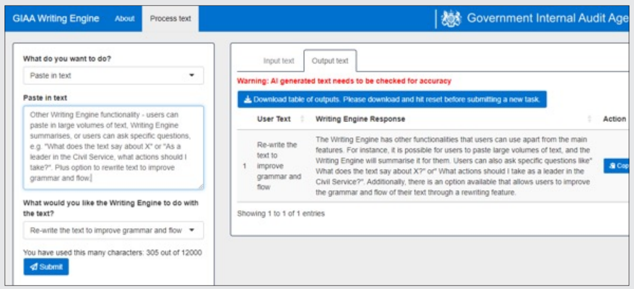
To ensure best practice, the DA team used the *Generative AI framework for Government* and worked closely with the GIAA's professional practice team. This ensured the engine extracts and writes relevant text in the house style, so the output conforms to standards. The output makes it clear that the text is generated using AI and must be checked for accuracy.

IAA IDENTIFIED AN OPPORTUNITY TO USE GENERATIVE AI TO HELP IMPROVE EFFICIENCY IN REPORT WRITING AND DECIDED TO BUILD ON THE SUCCESS OF THEIR RISK ENGINE TO DEVELOP ANOTHER CUSTOMISED TOOL

Evaluation and feedback on the Writing Engine shows it saves auditors between one and two days in the report writing process, and avoids the 'blank page anxiety' associated with writing – giving staff something to edit rather than starting from a blank page. Colleagues with dyslexia have found it particularly helpful in aiding them with grammar and punctuation.

GIAA is also working with other government departments to explore if the Writing Engine can be adapted to support their work, by creating custom pipelines to extract text from relevant sources and write it up. These writing pipelines allow easy scaling and reproducibility of output.

The Writing Engine has another feature, which enables users to write a rough outline of text, and then the engine rewrites the text to improve grammar and flow. The screenshot below shows notes which summarises the various Writing Engine features (in the 'Paste in text' box on the left). The resulting text on the right has been written by the Writing Engine into complete, logical sentences:



From a technological perspective, the Writing Engine was built in-house – using an R Shiny development framework – using the secure Microsoft Azure OpenAI models to convert the rough notes from fieldwork into prose. This approach ensures that the tool can be refined to best fit auditors' needs quickly and efficiently, and development can be an ongoing iterative process.

However, the biggest challenges in the adoption of AI tools can be cultural rather than technological. The GIAA DA team built on existing relationships they had with audit teams to receive open and honest feedback, which ensured the Writing Engine was optimised before general release. Since its launch in April 2024, the team has been demonstrating the engine at meetings, ensuring all staff can ask questions and air any concerns.

The other cultural shift concerns how auditors use the audit management system. So, the DA team worked with the professional practice team to communicate key points that roughly written notes are fine. The Writing Engine will fill in the blanks and present the output as narrative – and that the input needs to include sufficient context and information for the audit findings to be understood by a non-expert. These changes not only ensure the Writing Engine creates a good output – but also improves the quality of both the information stored in the audit management system, and the final reports.

6.2 Repairs and maintenance cost analysis at Parkdean Resorts[24]

This case study demonstrates how AI can transform routine financial processes – freeing up human resources for more strategic work. It highlights the importance of choosing the right tools, setting realistic expectations, and viewing AI implementation as a journey of continuous learning and improvement. Most importantly, it shows

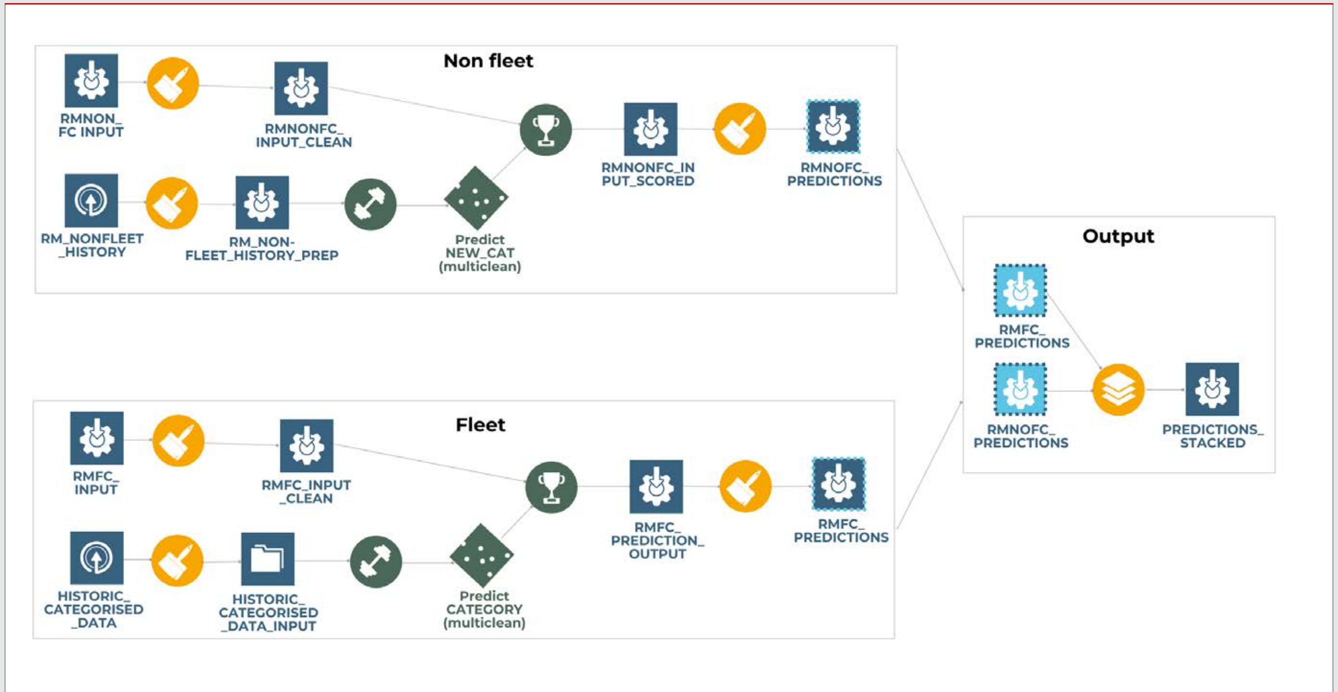
[23] Dr. Iain Macgregor, Director of Innovation and Technology, GIAA, Dr. Lauren Petrie, Data Analytics Specialist, GIAA
[24] Donna Peerless, Finance Business Partner, Parkdean Resorts

how AI can elevate the finance function's role – enabling more pre-emptive, data-driven decision-making across the organisation.

Parkdean Resorts, a major UK holiday park operator, implemented an AI solution to streamline the analysis of its repairs and maintenance (R&M) costs, one of the company's largest non-payroll expenses. The finance team, led by a senior finance business partner, collaborated with the company's internal data science team to develop and implement this AI-driven solution.

The team found that the XGBoost algorithm proved most effective for their needs. The AI system works by learning from a large set of pre-categorised data, using this to automatically categorise new entries. This approach allowed the finance team to analyse and categorise approximately 280,000 lines of R&M data annually – a task that previously required two to three days of manual work each month.

The primary goal was to provide detailed insights into R&M spending patterns, addressing investor queries and supporting strategic decision-making. The AI-powered analysis helps identify trends in repair costs, guides decisions on capital expenditure, highlights potential quality issues with specific products, and even assists in profit protection by flagging unusual spending patterns.



Implementation of the AI solution was a gradual process

The team ran the system in the background for 12 months, allowing the finance lead to monitor its performance and accuracy without formally launching it to the wider business. This period was crucial for refining the AI's categorisation abilities and ensuring the output was valuable to stakeholders.

The implementation process involved close collaboration between the finance team, data scientists, and operational stakeholders. The finance lead spent considerable time 'teaching' the AI, correcting miscategorisations, and refining its understanding. This process revealed how the AI could learn and perpetuate human errors from the initial data set – emphasising the importance of high-quality input data.

After the trial period, the team developed a user interface, spending two to three weeks creating a dashboard that would be useful for various stakeholders. Regional directors and general managers were consulted to ensure the tool met their needs. The resulting dashboard provides daily updates on R&M spending – a significant improvement over the previous monthly reporting cycle.

The AI system now achieves around 94-95% accuracy in categorising R&M costs. While not perfect, this level of accuracy is comparable to, if not better than, manual categorisation. The finance team continues to monitor and refine the system, dedicating time to review specific categories and make necessary adjustments.

The benefits of the AI implementation have been substantial

The finance team has saved two to three days per month previously spent on manual categorisation. This time is now reinvested in more value-added activities, such as analysing spending patterns, identifying cost-saving opportunities, and supporting operational decision-making. The system has also improved the ability of park managers to plan and forecast their R&M spending, providing historical context that is particularly valuable for new managers.

Key lessons learned from this implementation include:

1. **Start small:** choose a manageable, low-risk area for initial AI implementation to learn and refine the process.
2. **Be patient:** AI systems require time to learn and improve. The team saw significant improvements in accuracy over the first two to three months of operation.
3. **Maintain human oversight:** regular monitoring and correction are essential to keep the AI system on track and prevent the perpetuation of errors.
4. **Manage expectations:** stakeholders were informed that the system wouldn't be 100% accurate, setting realistic expectations from the outset.
5. **Focus on user needs:** involving end-users in the dashboard design process ensured the tool provided valuable, actionable insights.
6. **Embrace the learning process:** the implementation challenged preconceptions about AI and demonstrated its potential to enhance, rather than replace, finance roles.

The success of this project has encouraged Parkdean Resorts to explore additional AI applications in finance. The team is already considering testing a new AI tool that promises even greater accuracy.

6.3 Document analysis for financial spreading[25]

This case study highlights several key lessons for AI implementation in finance:

1. **Domain expertise** is crucial in developing effective AI solutions. The combination of accounting knowledge and technical skills has been vital to The Walnut's success.
2. **AI** should augment rather than replace human expertise. The "human-in-the-loop" approach ensures accuracy and allows for continuous improvement of the AI system.
3. Starting with **focused, high-value use cases** can demonstrate ROI and build support for wider AI adoption.
4. **Involving end-users in the development process** can lead to unexpected insights and ensure the tool meets real-world needs.
5. **AI implementation is an ongoing process** of learning and refinement, not a one-time deployment.

Iyer, an ACCA member with a background in mathematics and extensive experience in banking and finance, founded The Walnut.ai in Singapore. This startup focuses on developing AI solutions for document analysis, particularly in the realm of financial spreading - the process of standardising financial information from diverse annual reports.

The Walnut's AI tool addresses a significant challenge in financial analysis: the time-consuming and error-prone task of manually extracting and standardising financial data from annual reports. These reports often vary widely in format, presentation, and terminology, making comparison and analysis difficult.

The AI solution uses a layered approach, combining natural

[25] Bala Iyer, CEO, The Walnut.ai

THE WALNUT'S TEAM INCLUDES BOTH TECHNICAL EXPERTS AND QUALIFIED ACCOUNTANTS, ENSURING THAT THE AI'S OUTPUT IS NOT ONLY TECHNICALLY SOUND BUT ALSO PRACTICALLY USEFUL...

NLP, ML, and human oversight. The system works as follows:

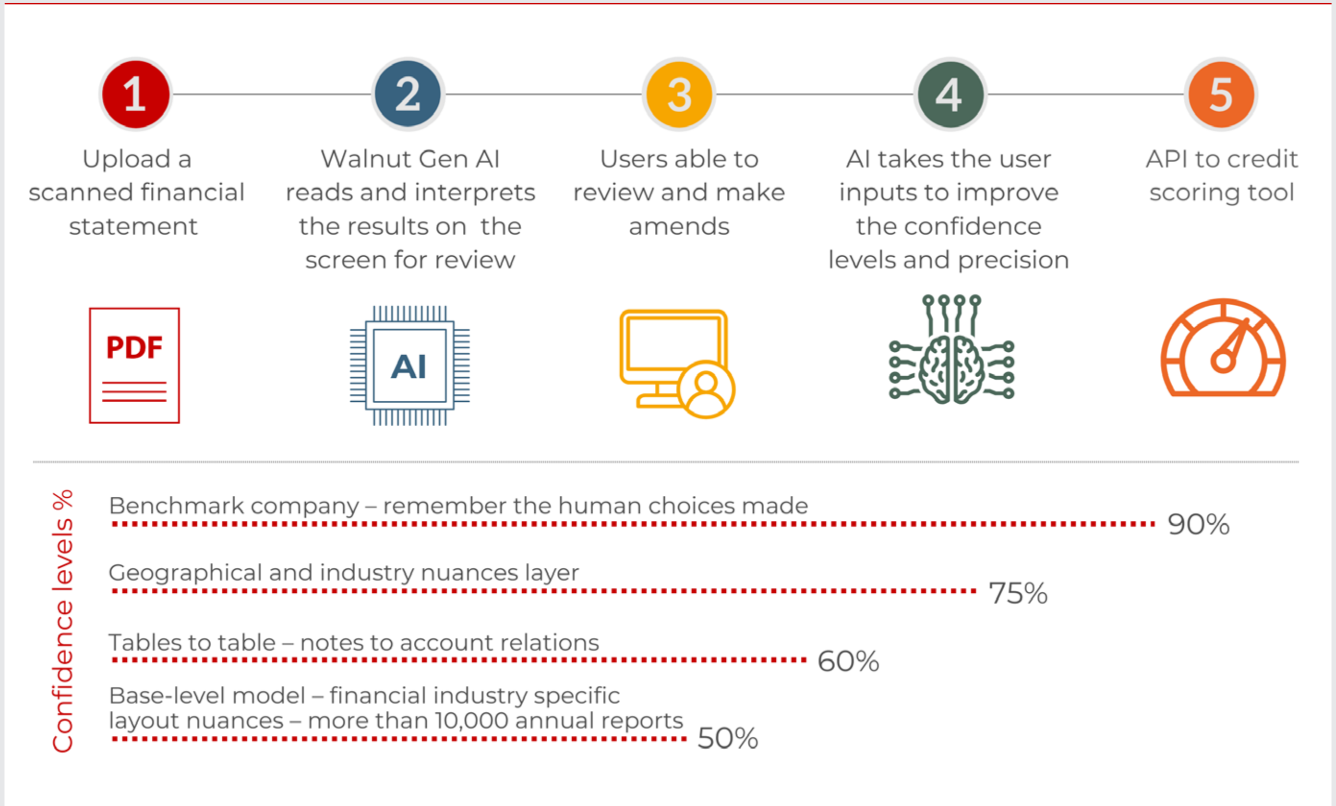
1. A generative AI layer **extracts information** from the document and organises it into a standardised structure.
2. The system then **applies previous human decisions** and adjustments to similar data.
3. It **performs validation checks**, generates alerts for discrepancies, and provides commentary.
4. Finally, it **flags items for human review** using a red, green, and grey system.

This approach allows the AI to learn and improve over time, gradually increasing its accuracy and ability to handle complex financial documents.

One key use case for this technology is in credit scoring for banks. The AI can quickly process thousands of annual reports, standardising the financial information to feed into credit scoring engines. This significantly reduces the time and effort required for financial analysts to review and compare company financials.

Implementation of such an AI system requires careful consideration. Iyer recommends:

1. **Identifying use cases with clear return on investment.** For example, a bank processing 20,000 corporate client reviews annually would benefit more than a company managing monthly competitor comparisons.



2. **Starting small and scaling up.** Rather than attempting to automate an entire process at once – focus on addressing specific bottlenecks.
3. **Conducting thorough proof-of-concept testing** in a sandbox environment to understand the system's limitations and assumptions.
4. **Involving end-users in the development process** to ensure the tool meets their needs and to foster adoption.

The development of this AI tool has revealed several challenges and insights:

1. **Data quality and quantity are crucial.** The AI's performance improves with more relevant data, which can be a challenge in the early stages of implementation.
2. **Setting and documenting clear expectations** about the AI's capabilities and limitations is essential to manage stakeholder expectations.
3. Unexpected benefits often emerge when end-users are involved in the development process – as they can **identify high-value use cases** that might not be apparent to management or developers.

The Walnut's team includes both technical experts and qualified accountants, ensuring that the AI's output is not only technically sound but also practically useful for financial professionals. The company even tests potential hires by having them perform manual financial spreading, ensuring they understand the process the AI is automating.

Looking to the future, The Walnut aims to expand its client base while continually improving its product. The goal is to make their tool the go-to solution for financial spreading, capable of reading notes, providing information in custom taxonomies, generating alerts, and offering qualitative insights.

As Iyer notes: 'this is an exciting time for accountants'. The rise of AI tools is shifting the focus from data gathering and report production to generating insights and creating valuable visualisations. For those entering the accountancy profession, combining traditional accounting skills with knowledge of technologies like Python can open up new opportunities to add value through data analysis and interpretation.

6.4 Construction cost estimation in retail[26]

This case study demonstrates how finance professionals can leverage AI and ML to solve specific business challenges. It highlights the potential for AI to streamline processes, reduce costs, and improve decision-making in finance functions. Moreover, it underscores the importance of data quality, skill development, and organisational readiness in successfully implementing AI solutions.

While working at a major cosmetics retailer, ACCA member Ian Carrier, implemented a ML solution to streamline the process of estimating construction costs for new retail store openings and refits at a major retail company. This case study highlights how AI can be applied to solve specific business challenges and improve decision-making processes.

The company relied on external architects to provide desktop reviews for initial construction cost estimates when considering new store locations. This process was time consuming, taking several weeks to schedule – costing between €1,500 and €2,000 per review. These estimates were crucial for creating business cases and determining project viability. However, the company had years of historical data from about 200 projects – suggesting an opportunity for a more efficient, data-driven approach.

Ian developed a ML model using Python and the scikit-learn library to predict construction costs based on various features such as store dimensions, location type (high street, shopping centre, retail park), and country. He chose a multilinear regression model after experimenting with other algorithms, finding it provided the best results for this particular use case.

Implementation process:

1. **Data preparation:** a significant portion of the work involved collecting, cleaning and formatting historical project data. This included filling data gaps and ensuring consistency across different projects.
2. **Feature engineering:** one key challenge was converting categorical data (like country names) into numerical values the model could process. Ian used one-hot encoding, a common technique in machine learning, to address this.
3. **Model development:** Ian built the model using Python, leveraging the scikit-learn library for the multilinear regression algorithm and other ML functionalities.
4. **Testing and validation:** The model was tested using training-test splits – achieving 70-75% accuracy in initial tests.
5. **Parallel running:** The AI model was run in parallel with the traditional architect estimates for about 50 projects to validate its performance in real-world scenarios.

[26] Ian Carrier, FCCA, Consultant

Results and benefits:
The AI model demonstrated remarkable accuracy, with approximately 75% of the projects coming within 1% of the actual construction costs. This level of accuracy was achieved much faster – and at a fraction of the cost – compared to the traditional method.

Key benefits included:
1. **Speed:** the model could provide estimates in seconds, compared to weeks for architect reviews.
2. **Cost savings:** eliminated the €1,500-€2,000 fee per review for standard projects.
3. **Improved decision-making:** faster estimates allowed for quicker evaluation of potential projects.
4. **Scalability:** the model could handle a high volume of estimates without additional cost.

Challenges and lessons learned:
1. **Data quality:** the importance of clean, well-structured historical data was paramount to the model's success.
2. **Outlier handling:** the model struggled with unusual projects (eg those requiring asbestos removal) – highlighting the need for human oversight in complex cases.
3. **Potential bias:** Ian noted the possibility of 'data leakage', where project managers might unconsciously work towards the AI-generated estimate, potentially skewing results.
4. **Skill development:** implementing this solution required Ian to upskill in data science and ML, which he did through online courses and self-study.
5. **Organisational readiness:** when Ian left the company, there was no one to maintain or update the model – underscoring the need for knowledge transfer and broader data science skills within the organisation.

Recommendations:
1. **Invest in data quality:** ensure historical data is clean, consistent and well-structured before attempting to build AI models.
2. **Start small:** begin with well-defined, high-impact use cases where AI can provide clear value.
3. **Combine AI with human expertise:** use AI for standard cases but maintain human oversight for complex or unusual projects.
4. **Encourage skill development:** support finance professionals in developing data science and machine learning skills.
5. **Plan for continuity:** ensure knowledge transfer and documentation to maintain AI solutions beyond individual contributors.
6. **Be open to new tools:** organisations should be open to using open-source tools like Python, which can foster innovation and engagement among staff.

6.5 Collections reconciliation at Wipro[27]

Wipro, a major global IT services and consulting company, implemented multiple AI solutions. One of them is a solution to streamline its collections reconciliation process. The company receives a vast number of payments from clients each month, which previously required manual reconciliation against outstanding invoices. This manual process was time-consuming, with risk of errors and diverted staff from more value-added activities.

The company implemented a third-party AI tool that uses NLP to understand and execute commands in plain English, eliminating the need for complex programming. This 'no-code/low-code' approach made the tool accessible to finance team members without extensive technical training.

The AI solution works by reading emails and attached PDF documents from clients, as well as bank statements. It extracts key information such as payment amounts, dates, customer names, and invoice numbers. The tool then compares this data with the company's records of outstanding invoices, automating the reconciliation process.

> **THE AI TOOL CAN AUTOMATICALLY MATCH 70% OF COLLECTIONS BY VALUE, REPRESENTING APPROXIMATELY $7-8BN ANNUALLY. THIS AUTOMATION HAS FREED UP SIGNIFICANT STAFF TIME.**

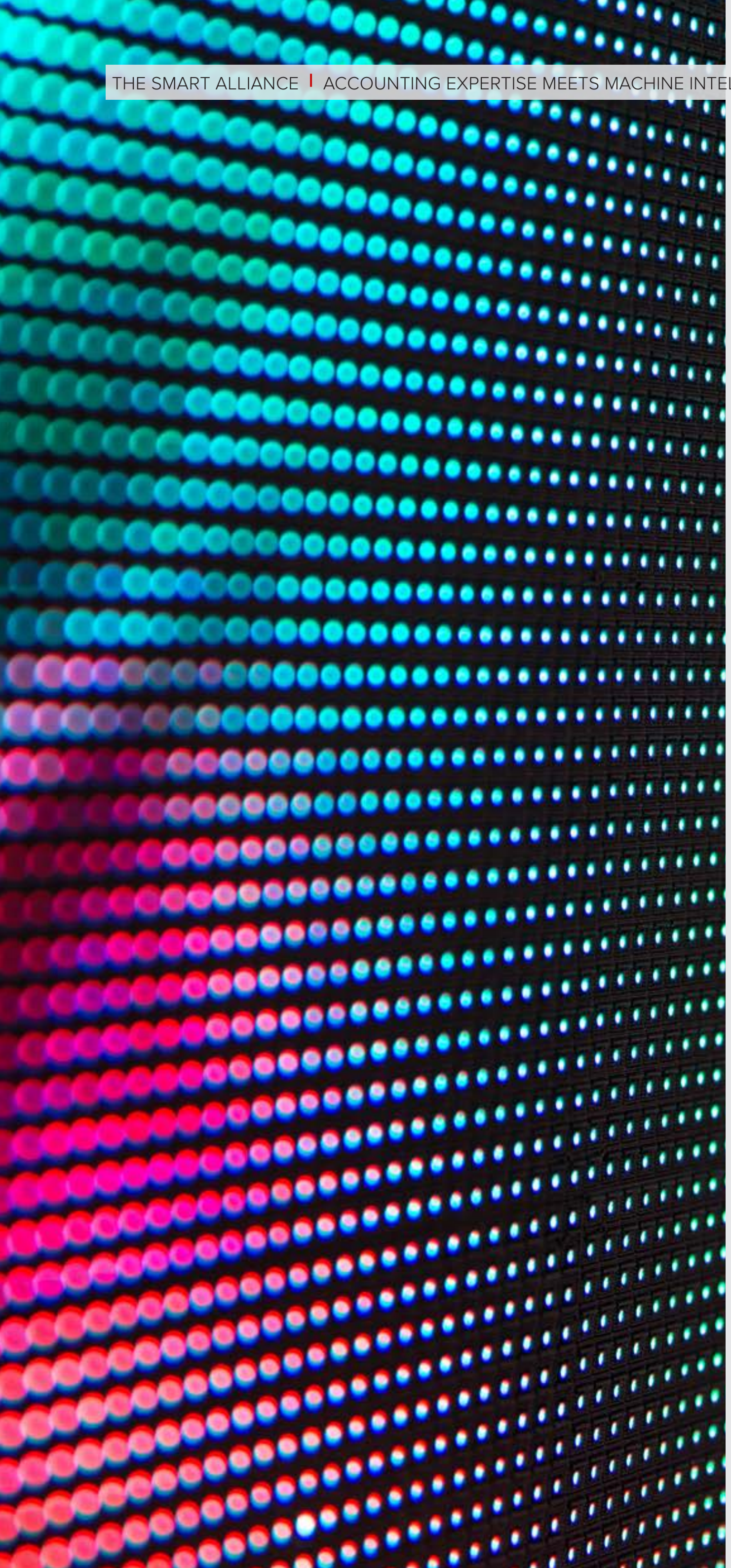
Implementation involved collaboration between the tool provider's technical team, the company's IT department, and finance subject matter experts. Given the sensitive nature of financial data, the company also engaged its security team to ensure the tool met strict data protection and confidentiality standards before deployment.

The implementation process faced initial challenges due to the unstructured nature of client communications and varying formats of payment remittance bank advices. The tool required time to learn and adapt to these variations through machine learning. Accuracy improved gradually, starting from a relatively low rate and reaching 70% after two to three months of operation and continuous learning.

Currently, the AI tool can automatically match 70% of collections by value, representing approximately $7-8bn annually. This automation has freed up significant staff time, allowing team members to focus on more analytical and value-added tasks. These include addressing long-standing issues like unreconciled small payments that previously received little attention due to the disproportionate effort required to resolve them.

The freed-up bandwidth is also being reinvested in further improving the tool's accuracy. Staff are working on addressing the remaining 30% of unmatched transactions, continuously refining the system's capabilities. Additionally, team members

[27] Navin Gadia, Global Controller, Wipro



can now dedicate more time to analysing overdue accounts and proactively following up with customers to improve overall collection rates.

One of the key benefits of this AI implementation has been its ease of use. The no-code/low-code nature of the tool meant that minimal training was required for finance staff to operate it effectively. This accessibility has facilitated rapid adoption and allowed team members to quickly leverage the tool's capabilities.

The company learned several valuable lessons through this implementation:

1. **Patience is crucial when implementing AI tools.** It takes time for machine learning algorithms to adapt to the specific nuances of an organisation's data and processes.
2. **Setting realistic expectations is important.** The team understood that perfection was not achievable immediately and viewed the implementation as a journey of continuous improvement.
3. **Human oversight and guidance remain essential, especially in the early stages.** Staff needed to "teach" the AI tool by pointing out key information in documents and correcting mismatches, which gradually improved its accuracy.
4. **The importance of choosing user-friendly AI tools cannot be overstated.** The low barrier to entry for this tool facilitated rapid adoption and allowed finance staff to focus on outcomes rather than technical details.
5. **AI implementation can lead to unexpected benefits beyond the initial use case.** In this instance, it opened up opportunities for staff to address long-standing issues and engage in more strategic activities.

The success of this project has encouraged the company to explore additional use cases for AI within its finance function. They are currently planning to expand the use of AI tools to at least three more areas, building on the positive experience and lessons learned from this initial implementation.

TEAM MEMBERS CAN NOW DEDICATE MORE TIME TO ANALYSING OVERDUE ACCOUNTS AND PROACTIVELY FOLLOWING UP WITH CUSTOMERS.

This case study demonstrates how AI can transform routine financial processes, freeing up human resources for more strategic work. It also highlights the importance of choosing the right tools, setting realistic expectations, and viewing AI implementation as a journey of continuous learning and improvement.

6.6 Enhancing finance operations at a multinational IT company[28]

The Chief Accounting Officer (CAO) of a global information technology company explains how they are at the forefront of implementing AI solutions across operations, with a particular focus on enhancing its finance functions. The CAO, also co-lead for Advanced Automation in Finance, provides insights into the company's AI journey and its impact on talent management and skill development.

Their approach to AI implementation is three-pronged:

- **In-house, fine-tuned chatbot:** an in-house version of ChatGPT for process-driven productivity across various departments, including finance.
- **Microsoft Copilot:** used for personal productivity, leveraging existing Microsoft licensing.
- **GitHub Copilot:** employed for software development and coding tasks.

In finance, they are leveraging their in-house chatbot for several use cases:

1. **Investor relations:** utilising public data to enhance investor communication and analysis.

[28] Chief Accounting Officer, Multinational Information Technology Company

2. **Credit analysis:** automating the review of customer financial reports for credit worthiness assessment.
3. **Internal manual processing:** converting accounting and finance manuals into interactive, AI-driven models.
4. **Balance sheet review:** using generative AI to produce initial narratives for flux analysis, reducing manual effort by up to 80%.

The implementation of AI has significantly impacted the company's finance operations. For instance, the accounting team consists of about 200 people, with 300 bots now handling various tasks. This shift has allowed finance professionals to focus on more value-added activities and strategic decision-making while the bots manage repetitive tasks.

This has also impacted their approach to talent management and skill development:

1. **Mandatory training:** all finance team members underwent a generative AI training program.
2. **AI champions:** select individuals receive advanced training in areas like prompt engineering and Python programming.
3. **Tiered approach:** training is tailored to different levels – from general users to technical specialists in the Centre of Excellence.
4. **Continuous learning:** employees are expected to dedicate 40 hours per year to self-development, with additional initiatives like 'Quiet Days' for focused learning.

The company recognises the importance of making AI accessible to all employees, likening the current AI revolution to the impact of Windows and Excel on personal computing. The company believes that familiarity with AI tools will become as essential for finance professionals as Excel proficiency is today.

However, they are also mindful of the challenges associated with AI implementation:

1. **Data privacy:** the company is cautious about using confidential data in AI systems, focusing initially on use cases involving public data.
2. **Governance:** a robust approval process is in place for AI use cases, involving finance, IT, legal, and cybersecurity teams.
3. **Responsible AI:** the company is committed to developing AI solutions that are ethical, unbiased, and environmentally sustainable.

The balance sheet review process serves as a prime example of AI integration. Previously, the process relied on RPA and ML for data calculation and accumulation. However, these tools were limited in their ability to generate narratives for flux variations. With the introduction of GenAI, the system can now produce initial draft narratives that are approximately 80% complete, significantly reducing the manual effort required from analysts.

This case study highlights several key lessons for AI implementation in finance:

1. **Holistic approach:** combine in-house solutions with third-party tools to address various productivity needs.
2. **Tiered training:** provide different levels of AI training to meet diverse employee needs and roles.
3. **Use case prioritisation:** start with applications that have clear ROI and minimal data privacy concerns.
4. **Governance:** establish robust approval processes and guidelines for AI use cases.
5. **Continuous Learning:** Foster a culture of ongoing skill development and adaptation to new technologies.

As the CAO notes: 'This is making AI accessible to everyone... Just like we had our people trained in Excel when these technologies were new 15-20 years back, this is again a "Windows moment".' This perspective underscores the transformative potential of AI in finance and the importance of pre-emptive skill development in the field.

6.7 Accounts payable optimisation in retail[29]

This case study demonstrates how AI and automation can transform traditional finance functions – not just by improving efficiency but by elevating the role of finance professionals. By automating routine tasks, the company enabled its AP team to focus on more strategic activities, improving both operational performance and employee satisfaction.

This transformation also laid the groundwork for further technological advancements in other finance areas – showcasing the potential of AI to drive continuous improvement in accounting and finance operations.

Sleep Country Canada, a Canadian retail company, with annual revenue of approximately $1bn, embarked on an ambitious project to transform its AP department using AI and automation. The company implemented a tool available from its software provider, enhanced with Optical Character Recognition (OCR) technology and a ML bot.

This AI-powered solution aimed to address several challenges within the AP department, including low employee morale due to repetitive data entry tasks, inefficient invoice processing, delayed month-end closings, and limited analytical capabilities.

'Our primary goal was to optimise the AP processes for greater efficiency and accuracy while empowering our team to take on more value-added tasks,' explained Bilal Surahyo, Chief Financial Officer (CFO). 'The intent was not to reduce headcount but to shift the focus towards more analytical work, such as understanding payment terms, maximising discounts, and refining various elements of the process.'

The implementation process was comprehensive and took over three years to fully execute and fine-tune. It involved deploying SAP Concur as the primary framework for expense management – integrating OCR technology for automated invoice capture and processing, and implementing the ML bot for invoice coding and routing. The company also undertook the significant task of onboarding vendors to submit invoices electronically, which was crucial for the system's success.

The project team included AP staff, contracted specialists, accounting team members, and external consultants. This cross-functional approach ensured that all aspects of the process were considered, from technical implementation to accounting accuracy and user adoption.

The transformation yielded significant improvements. Prior to the AI implementation, the AP department was inundated

[29] Bilal Surahyo, CFO, ACCA Global Forum for Technology

EMPLOYEE MORALE AND JOB SATISFACTION SAW A MARKED IMPROVEMENT AS STAFF WERE FREED FROM REPETITIVE TASKS AND COULD ENGAGE IN MORE MEANINGFUL WORK.

with manual sorting and coding of paper invoices, time-consuming data entry, and limited analytical capabilities. The new system automated invoice capture and processing, implemented ML-based coding and routing, and dramatically improved the accuracy of invoice coding.

One of the most tangible benefits was a faster month-end closing process, with the company saving one to two days in their closing cycle. The AP team's capabilities were also significantly enhanced, allowing them to produce aging reports, conduct vendor analyses, and contribute to improved cash flow management and forecasting.

Employee morale and job satisfaction saw a marked improvement as staff were freed from repetitive tasks and could engage in more meaningful work. ‘Employee morale was at an all-time high, which was the lowest in AP,’ noted Surahyo. ‘They were doing a more meaningful job.’

The new system also strengthened internal controls and created better audit trails – addressing important compliance and risk management concerns. Furthermore, it provided better visibility into vendor relationships and spending patterns, allowing for more strategic decision-making.

However, the project was not without its challenges. There was initial resistance to change from some employees, and the process of onboarding vendors to the new system was time-consuming. The company also faced a learning curve with the new technologies and processes, particularly in ensuring the accuracy of the ML bot during its first year of operation.

Several key lessons emerged from this implementation. First, the company found that starting with foundational projects that have a high likelihood of success and visible ROI helps build credibility for future technology investments. They also emphasised the importance of involving key stakeholders from AP, accounting, and IT from the beginning of the project.

Change management and employee upskilling were critical to the project's success. The company invested in training and support to help employees adapt to their new, more analytical roles. They also found that choosing cloud-based solutions facilitated easier integration and future scalability.

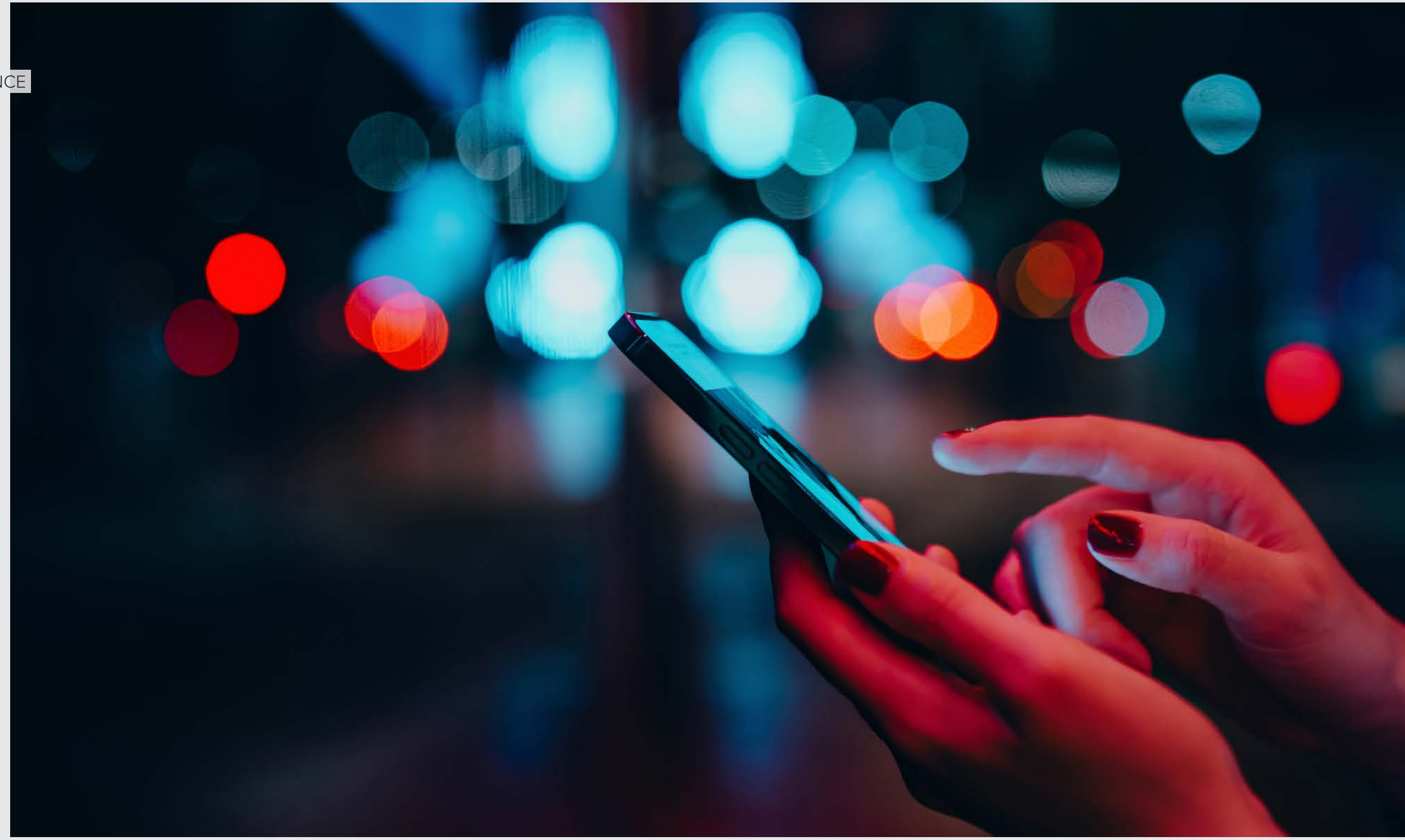
Interestingly, the company opted to leverage best-of-breed tools rather than building in-house solutions. ‘Why invest in developing AI functionality in-house when there are already sophisticated tools available? Let the specialised companies handle the innovation and testing, and we can simply purchase and implement the best solutions.’ Surahyo commented.

6.8 Ping An AI-ESG platform[30]

Ping An Group, a leading integrated financial institution in China, launched an AI-ESG platform in 2023. This platform can automatically generate ESG disclosure information for over 40 subsidiaries, reducing the complexity of compliance reporting and periodic information disclosure processes.

Ping An Group has numerous subsidiaries across various industries. With increasing regulatory and societal attention on environmental, social and givernance (ESG), and stricter requirements for group ESG information disclosure, Ping An Group had to invest significant human and material resources each year to collect, organise, and report ESG disclosure information for its subsidiaries.

[30] China Securities Journal. (2021, January 14). Ping An uses artificial intelligence to drive new ESG investment strategies and uses alternative data sources to uncover hidden risks and opportunities. https://www.cs.com.cn/ssgs/gsxl/202101/t20210114_6130250.html
Ping An Insurance (Group) Company of China, Ltd. (2021, July). AI-ESG solutions: The role of AI in enhancing environmental, social, and governance (ESG) practices. OCFT. https://www.ocft.com.sg/wp-content/uploads/2021/07/Ping-An-AI-ESG-Solutions.pdf



Application of AI technology

Data side: Ping An Group developed an AI-ESG database. The group designed an ESG scoring methodology framework that maps to seven major international ESG evaluation frameworks (eg MSCI, FTSE, and GRI) and also considers Chinese-specific indicators (such as green revenue and industrial structure adjustment).

Scoring dimensions: the company created unique ESG disclosure and performance indicators. Disclosure indicators measure the quality of self-disclosed ESG data, while performance indicators assess the company's actual ESG performance and its relative performance within the industry.

Data sources: Relying on AI technology, Ping An Group intelligently scored 1.15 million qualitative data points and standardised 1.1 million quantitative data points. AI models were used to mine alternative data – supplementing and cross-verifying the data to enhance comparability and reliability.

Platform side: the AI-ESG management platform incorporates various ESG evaluation requirements from regulators, exchanges, and rating agencies. It includes over 500 ESG indicators, and the system can automatically capture, analyse, and generate ESG disclosure content for all 40+ subsidiaries based on these standards.

Changes after application

The platform significantly reduced the manpower required to compile response documents for different institutions and organisations, streamlining the periodic information disclosure process. Since the platform's launch, it has saved a total of 800,000 yuan in annual labor costs and advanced ESG report disclosure time by 20 days.

Existing risks

The platform collects data from all subsidiaries within the group. If not adequately protected, this data can be leaked or misused, potentially impacting business operations.

Implementation difficulties

During the initial construction phase, the platform required system modifications and integrations across more than 40 subsidiaries, demanding substantial technology investment.

6.9 Yonyou BIP global treasury intelligent risk control platform

Yonyou AI is the artificial intelligence division of Yonyou Network Technology Co. Ltd., a leading provider of enterprise management software and services in China. Yonyou actively applies AI technology in enterprise management.

In October 2023, the State-owned Assets Supervision and Administration Commission (SASAC) issued the 'Notice on regulating trade management of central enterprises to prohibit various types of fake trade,' banning all types of fake trade activities. The SASAC continues to focus on persistent issues of fake trade – showing zero tolerance for financing trade, empty rotation, and false business transactions.

In response to this policy, Yonyou launched the BIP Global Treasury Intelligent Risk Control Platform, incorporating large models and intelligent algorithms to construct fake trade

China Business News. (2023, October 12). Yonyou enterprise service large model promotes the popularization and application of intelligence.
Sina Hong Kong. (2023, November 21). Industry's first! Yonyou BIP helps large enterprises achieve 'zero tolerance' for false trade.

monitoring models. The monitoring results are applied to the entire trade transaction process, covering all business, customers, and processes.

This platform is mainly aimed at large groups with numerous subsidiaries and regulatory bodies.

Challenges before application

For groups with many subsidiaries across various industries, managing the authenticity of their trades presents several challenges:

Large number of subsidiaries: collecting and verifying trade authenticity data requires extensive manual analysis and judgment, leading to inefficiency and potential errors.

Diverse industries: the diverse industries of subsidiaries demand high professional standards from analysts.

Poor timeliness: the timeliness of manually collecting and analysing data is poor.

Application of AI technology

Risk control of financing trade based on full transaction process: by fully mining the entire chain of trade business data, the platform accumulates the risk data assets needed to identify fake trade. It constructs fake trade monitoring models based on expert identification and intelligent algorithms, continually improving risk identification throughout the trade process.

Effective identification of upstream and downstream relationships in fake trade using intelligent algorithms: using depth-first search (DFS), the platform traces suspicious transaction paths with significant transaction values within a selected period – starting from specific trading entities and their customer nodes – to uncover abnormal transactions.

Refined identification of fake trade through data modeling methods: based on expert experience, the platform constructs fake trade scoring models using hierarchical analysis to clarify model indicator distinctions and binning methods to improve the precision of fake trade identification. Scientific data modeling methods are used to enhance the model's discriminatory and identification capabilities.

Customisable risk model construction: after establishing a risk indicator library, the platform builds models for 'financing trade', 'empty rotation trade', and 'fictitious trade.' Enterprises can select preset or customised risk indicators as needed.

Changes after application

The platform enhances the accuracy and timeliness of managing trade authenticity for groups.

Real-time risk identification: the platform continuously monitors risks throughout the trade process, automatically generating analysis reports and alerting for abnormal information, suggesting manual intervention, greatly improving financial management efficiency and accuracy.

Model optimisation: the platform continuously optimises models with feedback from manual reviews, improving the accuracy of the results.

Existing risks

Data privacy: the platform involves sensitive information of the entire group. Any data leakage could impact the group's operations.

Model bias: there might be some bias in the models in the early stages. If not promptly corrected through manual intervention, it could lead to false positives, wasting the group's resources.

Implementation difficulties

Data availability: AI-based risk assessments or fake trade evaluations require large data inputs, including external and internal data. However, some subsidiaries might be reluctant to provide data, and external data might contain errors.

Parameter adjustment: the AI model's calculation parameters and weights require extensive testing and adjustments.

Industry-specific parameters: different industries require different risk assessment parameters, needing expert input for recommendations.

7 Extracting best practice from our case studies

1

Be strategic

1.1 Start small and scale Up

- Begin with well-defined, high-impact use cases where AI can provide clear value.
- Run AI systems in parallel with existing processes to validate performance before full deployment.
- Gradually expand AI applications as confidence and expertise grow.

1.2 Focus on clear ROI

- Prioritise AI projects with tangible benefits and measurable outcomes.
- Consider both time savings and cost reductions when evaluating potential AI implementations.

1.3 Leverage best-of-breed tools

- Utilise existing AI tools and platforms rather than building everything in-house.
- Combine in-house solutions with third-party tools to address various productivity needs.

2

Data management and quality

2.1 Prioritise data quality

- Invest time in collecting, cleaning, and formatting historical data.
- Ensure consistency and completeness of data across different sources and projects.

2.2 Address data privacy concerns

- Start with use cases involving public data to minimise privacy risks.
- Implement robust data governance processes to protect sensitive information.

3

Human-AI collaboration

3.1 Think augmentation

- Think augmentation by assessing repeat tasks or costs.
- Look to automate chunks, not entire tasks, and eliminate others.
- Maintain human oversight, especially for complex or unusual cases.

3.2 Redefine responsibilities

- Shift finance professionals' focus from data entry and processing to analysis and strategic decision-making.
- Develop new roles, such as AI champions or specialists, to communicate value and bridge the gap between finance and technology.

4

Skill development and training

4.1 Invest in AI literacy

- Provide AI training for all finance team members.
- Offer tiered training programmes, from general awareness to technical skills.

4.2 Foster a culture of continuous learning

- Encourage ongoing skill development in areas like data science and ML.
- Allocate dedicated time for learning and experimentation with new technologies.

5

Change management

5.1 Set realistic expectations

- Communicate that AI implementation is a journey of continuous improvement.
- Be transparent about the AI system's capabilities and limitations.

5.2 Involve stakeholders early

- Engage end-users in the development process to ensure the AI tools meet real-world needs.
- Collaborate across departments (finance, IT, legal, etc) to address various aspects of AI implementation.

6

6. Technical considerations

6.1 Choose appropriate AI technologies

- Select AI tools and algorithms that best fit the objectives and requirements of specific use cases.
- Consider the needs around interpretability.

6.2 Ensure scalability and integration

- Consider whether the AI solution can handle changing volumes of data and transactions.
- Ensure seamless integration with existing financial systems and processes.

7

7. Governance and ethics

7.1 Establish clear governance structures

- Derive policies from your actual uses not general risks.
- Implement approval processes for high-risk AI use cases.
- Develop guidelines for responsible AI use prioritising transparency.

7.2 Monitor and refine

- Continuously assess the performance and impact of AI systems.
- Be prepared to adjust or retrain models as business conditions change.

8

8. Measuring success

8.1 Define clear metrics

- Establish key performance indicators (KPIs) for AI implementations, such as time saved, cost reductions, or improved accuracy.
- Regularly report on these metrics to demonstrate the value of AI investments.

8.2 Look beyond financial metrics

- Consider qualitative benefits, such as improved employee satisfaction or enhanced decision-making capabilities.
- Assess the strategic value of AI in terms of competitive advantage and innovation.

8 Outlook for AI in accounting

As we look to the horizon, the future of AI in accounting appears both exciting and transformative. Our survey data, coupled with insights from industry leaders, paints a picture of a profession on the cusp of significant change – driven by advancing AI technologies and evolving business needs.

The appetite for AI adoption shows no signs of waning. An overwhelming majority of organisations in our survey indicated plans to increase their investment in AI over the coming year. This surge in commitment is not merely about keeping pace with technological trends; it reflects a growing recognition of AI's potential to drive real business value in the accounting sphere.

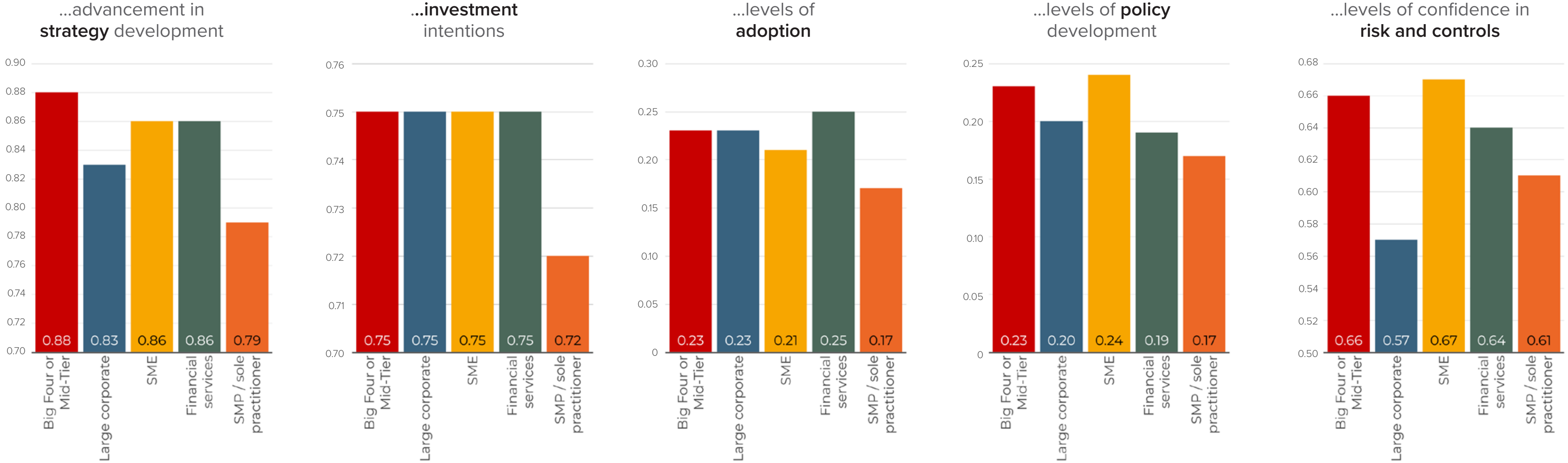
The potential for AI to enhance complex accounting tasks is also coming into sharper focus. Recent research from the University of Chicago[31] suggests that AI models like ChatGPT can outperform human analysts in certain financial statement analysis tasks. While this doesn't spell the end for human expertise in accounting, it does point to a future where AI and human intelligence work in tandem – with each amplifying the other's strengths.

> **THE CHALLENGE WILL BE TO HARNESS THE POWER OF AI WHILE MAINTAINING THE ETHICAL STANDARDS, PROFESSIONAL JUDGMENT, AND HUMAN INSIGHT.**

[31] Kelly, B., & Tsou, H. (2024, May). *Financial statement analysis with large language models*. Becker Friedman Institute for Economics at the University of Chicago.

FIGURE 29–33: Comparison across sectors showing relative...

Figures in charts 29-33 are normalised index figures comparing results across different sectors



As organisations continue to experiment with AI, we're likely to see a trend towards more targeted, specific use cases. As one interviewee noted: 'Focusing on narrower applications can lead to quicker wins and faster learning cycles'. This approach may help organisations overcome initial hurdles and build confidence in AI's capabilities, paving the way for more ambitious projects down the line.

The future of AI in accounting promises to be one of augmentation rather than replacement. By embracing AI technologies thoughtfully and strategically, the accounting profession can enhance its capabilities, deliver greater value to clients, and play an even more crucial role in guiding business decision-making.

As we move forward, the challenge will be to harness the power of AI while maintaining the ethical standards, professional judgment, and human insight that are the hallmarks of the accountancy and finance profession.

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