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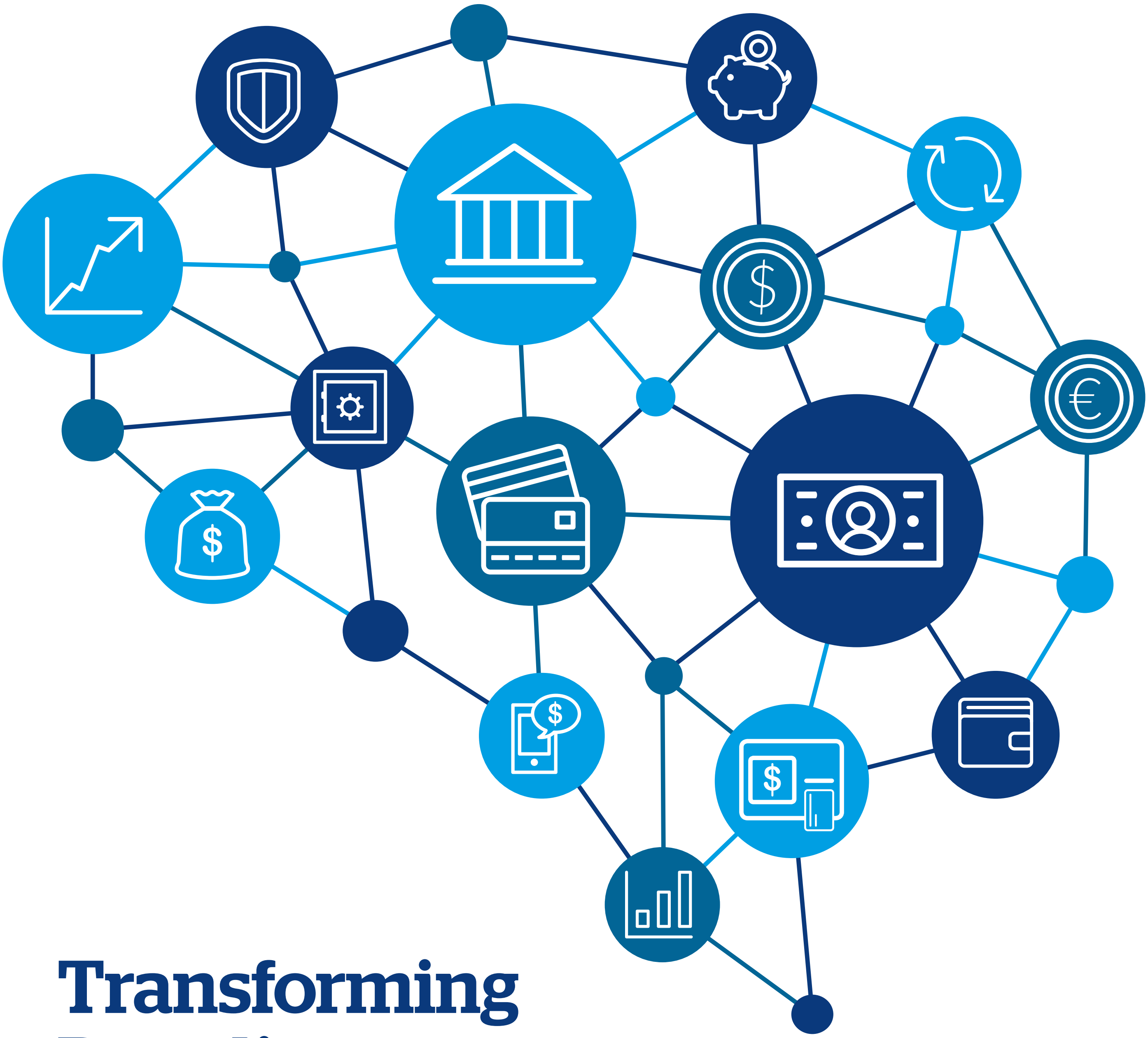

Transforming Paradigms

A Global AI in Financial Services Survey

January 2020

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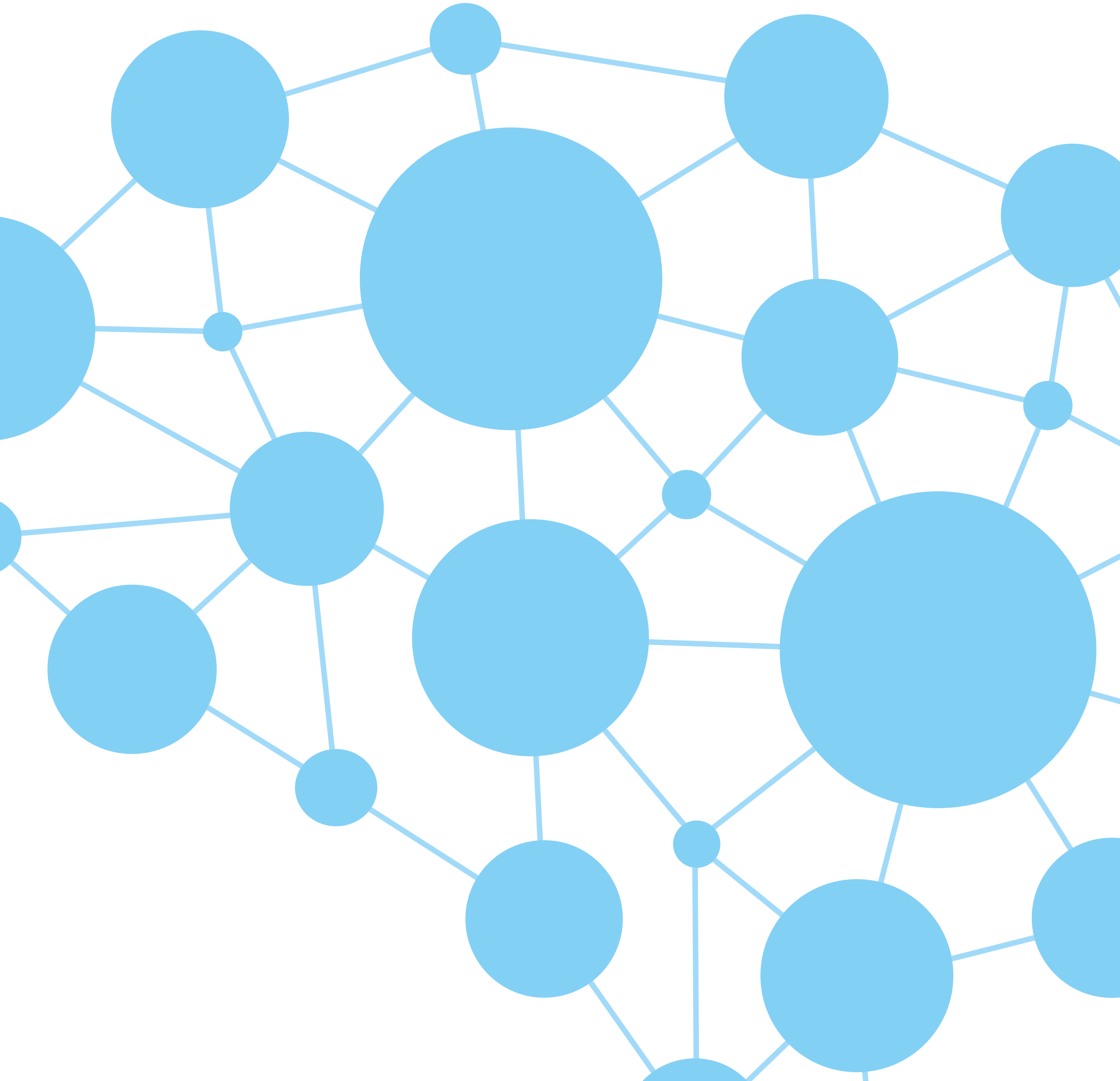
A Global AI in Financial Services Survey



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In 1950, five years before the term ‘Artificial Intelligence’ (AI) was coined by John McCarthy, Alan Turing already posed the question “Can machines think?” and devised the Turing Test. 70 years on, the world’s computational capability has grown by leaps and bounds, and so has the application of AI across a wide array of industries, including Financial Services. However, beyond the news headlines and opinion pieces, there is still very limited empirical evidence available on the current state of AI adoption in finance and its implications. This global survey, jointly conducted by the Cambridge Centre for Alternative Finance (CCAF), at the University of Cambridge Judge Business School and the World Economic Forum, is aimed at going beyond the hype and hyperbole, to provide some empirical data and shed light on the evolving landscape of AI-enabled Financial Services.

Based on a survey sample of 151 firms which included both FinTechs and Incumbents, this study was able to depict a global Financial Services sector that is undergoing profound digital transformation underpinned by the advancement in AI. The research findings point to increasing adoption of AI in finance, as firms are leveraging AI to revamp existing offerings and create new products and services. AI is helping firms transform practices, processes, infrastructure and underlying business models, for example selling AI as a service. This research unveils how Financial Services firms are facing hurdles to AI implementation, including access to data, access to talent, and regulatory uncertainties. This study also examined potential and realised risks with growing adoption of AI in finance, the impact on workforces in both the short and long term across industry verticals, and strategic learnings from the current frontrunners of AI implementation.

Nevertheless, it is evident that more research needs to be done in order to better understand the opportunities and challenges brought about by the eventual mass adoption of AI in Financial Services. For instance, how can finance firms open up the ‘black box’ of AI and facilitate more explainable and transparent applications? As AI is becoming increasingly autonomous, what will the roles of humans be and how would an effective human-in-the-loop AI system manifest itself? What are some socio-economic repercussions and ethical implications of AI-induced biases and risks? How can regulators and policymakers harness technology solutions to effectively regulate and supervise AI in finance?

This report, therefore, marks just the beginning of a long journey for us to collectively comprehend the potential, possibilities, and boundaries of AI in finance. We are profoundly grateful to EY and Invesco for enabling us to produce this empirical study and for their helpful feedback during the research process. We are also very thankful to the financial service providers who took part in our global survey. Finally, we would like to thank the interdisciplinary CCAF-Forum research team led by Lukas Ryll, which over the last many months worked tirelessly and collaboratively to create this study.

Bryan Zhang
Executive Director
Cambridge Centre for Alternative Finance

Matthew Blake
Head of Financial & Monetary Systems
World Economic Forum

I am delighted that EY have once again had the opportunity to work with the Cambridge Centre for Alternative Finance at the Judge Business School, University of Cambridge on the publication of a ground breaking study. Not only does this report provide a comprehensive view of the adoption of AI in Financial Services, it highlights the challenges, opportunities and future considerations that the industry faces.

Over recent years, artificial intelligence (AI) has been an area of focus across a range of industries, triggered by the need for increased speed and efficiency, automation of manual processes, and intelligent computer-based decision-making. Institutions are investing significant time and money in implementing the technology and understanding how its potential can be unlocked to deliver benefits across industries.

At EY, we are focused on the challenging business problems for which AI may present a compelling new solution, and in doing so, enable the business models of the future. The key characteristics of the technology, built from the principles of intelligent automation, machine learning (ML), and automated decision-making, rely upon AI's ability to predict, adapt, learn and empower business decisions. However, to really see AI's full potential in a tightly regulated Financial Services industry, there is still work to be done to build trust and confidence in areas such as explainability, security and compliance, integration alongside the human workforce, and ultimately, identification of the richest opportunities to deliver business value.

This global study provides an important reference for leaders in all sectors to better understand current areas of focus, attitudes toward AI and future considerations that need to be addressed. We look forward to working with our clients, both traditional Financial Services businesses and FinTechs, to deploy AI technology to transform their businesses.

We would like to thank the Cambridge Centre for Alternative Finance, the World Economic Forum, Invesco, and the survey participants for making this comprehensive and ground-breaking study possible.

Nigel Duffy
Partner, Global Artificial Intelligence Leader
EY

The global asset management industry is in the midst of unprecedented change. A recent report from the U.S. Securities and Exchange Commission's Asset Management Advisory Committee says that, "Drastic changes in the capital markets in which shops operate, as well as new demands that younger generations will expect of the advice market, are creating the 'strongest shifts' asset managers have seen in more than 40 years." Facing such strong external forces, asset managers are looking for ways to embed emerging technologies like artificial intelligence into their operational strategies in order to create competitive advantage. This study highlights how AI is affecting the global Financial Services industry, with 72% of decision makers stating that they believe AI is the business advantage of the future.

The report begins with addressing the nuanced differences between artificial intelligence and machine learning, making the important distinction that the two, while interdependent, are not interchangeable.

"Transforming Paradigms" digs into the five thematic areas where AI will have the most impact and highlights the amazing opportunity ahead of us in Financial Services for using artificial intelligence and machine learning to the benefits of our customers and our organisations. Technological advances such as leveraging intelligence to define investments for customers tied to their personalised goals, improving customer experience through the use of intelligent bots, additional alpha generation via insights from alternative datasets, and operational efficiencies through machine learning automation, will soon become the norm for our industry.

Among the most notable insights are the idea that combined efforts of adopting AI/ML across the Financial Services industry are raising the bar for client expectations, that there is a widening gap between leaders and laggards in adopting and implementing AI and the changing dynamics between fintechs and incumbents, who are no longer seen as mutual threats, but potential allies with the right strategic fit. Lastly, the study introduces the idea of the "AI Flywheel", the tendency for AI models to exhibit self-reinforcing economies of scale.

As with other emerging technologies, AI faces similar challenges with nascent regulatory frameworks and issues with identifying and recruiting qualified talent.

Real value from AI/ML projects comes from having clear business use cases, and it is unsurprising that 61% of investment managers look to AI to generate new revenue potential. The findings validate our own experiences, as we deploy AI/ML tools to help our investors make better decisions and make our distribution professionals more efficient. Invesco is especially committed to using "augmented intelligence" to supports, rather than replaces, humans and to upskilling our employees to self-serve with AI/ML tools.

We'd like to thank everybody who contributed to the collection and synthesis of data for this report, as findings such as these provide valuable insights to help inform a wider audience about the implementation of emerging technologies around the world.

Donie Lochan
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Finally, we thank Louise Smith for her meticulous work on designing the report.

The research team is grateful for the support of these organisations and associations for their generous support in distributing the survey across the globe:

We would like to thank all the financial companies and institutions that took part in the survey *(Please note that many participants preferred to keep their participation confidential and are thus not listed here):*

Executive Summary

This report presents the findings of a global survey on AI in Financial Services jointly conducted by the Cambridge Centre for Alternative Finance (CCAF) at the University of Cambridge Judge Business School and the World Economic Forum in Q2-Q3 2019. Representing one of the largest global empirical studies on AI in Financial Services, a total of 151 respondents from 33 countries participated in the survey, including both FinTechs (54% of the sample) and incumbent financial institutions (46% of the sample). The study was supported by EY and Invesco.

The study's objective was to analyse and understand the current state of AI adoption in Financial Services, as well as its subsequent implications. This was done through the comparative analysis of empirical data collected via a web-based questionnaire.

This research provides a comprehensive picture of how AI is currently being applied in Financial Services by both FinTechs and Incumbents; driving different business models; underpinning new products and services; and playing a strategic role in digital transformation. The findings also reveal how financial service providers across the globe are meeting the challenges of AI adoption with its emerging risks and regulatory implications, as well as the impact of AI on the competitive landscape and employment levels.

The overarching findings of the study suggest that AI is expected to transform a number of different paradigms within the Financial Services industry. These anticipated changes include how data is utilised to generate more actionable insights; business model innovation (e.g., selling AI as a service); changes to the competitive environment with the entrance of 'Big Tech' and consolidation; various impacts on jobs and regulation; impacts on risks and biases; and the further development and adoption of game-changing technologies.

The pace of AI application in Financial Services is clearly accelerating as companies begin to leverage AI to increase profitability and achieve scale. This has complicated and multifaceted implications and repercussions.

The key findings of this empirical study are as follows:

- **AI is expected to turn into an essential business driver across the Financial Services industry in the short run,** with 77% of all respondents anticipating AI to possess high or very high overall importance to their businesses within two years. While AI is currently perceived to have reached a higher strategic relevance to FinTechs, Incumbents are aspiring to catch up within two years.
- **The rising importance of AI is accompanied by the increasingly broad adoption of AI across key business functions.** Approximately 64% of surveyed respondents anticipate employing AI in all of the following categories – generating new revenue potential through new products and processes, process automation, risk management, customer service and client acquisition – within the next two years. Only 16% of respondents currently employ AI in all of these areas.
- **Risk management is the usage domain with the highest current AI implementation rates (56%), followed by the generation of new revenue potential through new AI-enabled products and processes, adopted by 52%.** However, firms expect the latter to become the most important usage area within two years.

- **AI is expected to become a key lever of success for specific Financial Services sectors.** For example, it is expected to turn into a major driver of investment returns for asset managers. Lenders widely expect to profit from leveraging AI in AI-enabled credit analytics, while payment providers anticipate expanding their AI usage profile towards harnessing AI for customer service and risk management.
- **With the race to AI leadership, the technological gap between high and low spenders is widening** as high spenders plan to further increase their R&D investments. These spending ambitions appear to be driven by more-than-linear increases in pay-offs from investing in AI, which are shown to come into effect once AI investment has reached a 'critical' mass of approximately 10% R&D expenditure.
- **FinTechs appear to be using AI differently compared to Incumbents.** A higher share of FinTechs tends to create AI-based products and services, employ autonomous decision-making systems, and rely on cloud-based offerings. Incumbents predominantly focus on harnessing AI to improve existing products. This might explain why AI appears to have a higher positive impact on FinTechs' profitability, with 30% indicating a significant AI-induced increase in profitability compared to 7% of Incumbents.
- **FinTechs are more widely selling AI-enabled products as a service.** Successful real-world implementations demonstrate that selling AI as a service may allow large organisations to create 'AI flywheels' - self-enforcing virtuous circles - through offering improved AI-driven services based on larger and more diverse datasets and attracting talent.
- ***AI Leaders* generally build dedicated corporate resources for AI implementation and oversight – mainly a Data Analytics function – to work with their existing IT department.** On average, they also use more sophisticated technology to empower more complex AI use cases.
- **Leveraging alternative datasets to generate novel insights is a key part of harnessing the benefits of AI** with 60% of all respondents utilising new or alternative forms of data in AI applications. The most frequently used alternative data sources include social media, data from payment providers, and geo-location data.
- **Incumbents expect AI to replace nearly 9% of all jobs in their organisation by 2030, while FinTechs anticipate AI to expand their workforce by 19%.** Within the surveyed sample, this implies an estimated net reduction of approximately 336,000 jobs in Incumbents and an increase of 37,700 jobs in FinTechs. Reductions are expected to be highest in Investment Management, with participants anticipating a net decrease of 10% within 5 years and 24% within 10 years.
- **Regardless of sectors and entity types, quality of and access to data and access to talent are considered to be major obstacles to implementing AI.** Each of these factors is perceived to be a hurdle by more than 80% of all respondents, whereas aspects like the cost of hardware/software, market uncertainty, and technological maturity appear to represent lesser hindrances.
- **Almost 40% of all respondents feel that regulation hinders their implementation of AI, whereas just over 30% perceive that regulation facilitates or enables it.** Organisations feel most impeded by data sharing regulations between jurisdictions and entities, but many also deem regulatory complexity and uncertainty to be burdensome. Firms' assessments of the impact of regulation tend to be more positive in China than in the US, the UK, or mainland Europe.

- **Mass AI adoption is expected to exacerbate certain market-wide risks and biases, and at least one in five firms do not believe they are well placed to mitigate those.** Firms are particularly wary of the potential for AI to entrench biases in decision-making, or to expose them, through shared resources, to mass data and privacy breaches. Nevertheless, many firms are involving Risk and Compliance teams in AI implementation, and those who do tend to be more confident in their risk mitigation capability as a result.
- **Long-established, simple machine learning algorithms are more widely used than complex solutions.** Nonetheless, a large share of respondents is planning to implement Natural Language Processing (NLP) and Computer Vision, which commonly involve Deep Learning, within two years.
- **Nearly half of all participants regard 'Big Tech'[1] leveraging AI capabilities to enter Financial Services as a major competitive threat.**

1 Defined as major technology companies, such as Google, Facebook or Tencent

1. Introduction

Chapter 1: Introduction

1.1 A Brief Juxtaposition of AI and Machine Learning

Artificial Intelligence

Artificial Intelligence (AI) is a term shaped by socio-behavioural rationales of human capabilities – essentially, expectations that machines could emulate human cognition and behaviour. Expectations of AI are derived and often benchmarked against human intelligence. The corollary is understanding that AI may be approached by attempting to understand human intelligence itself. While various definitions of intelligence have been proposed, Gottfredson notes in his editorial *Mainstream science on intelligence* that intelligence may be defined as:

"A very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—'catching on', 'making sense' of things, or 'figuring out' what to do" (Gottfredson, 1997)

Extrapolating these traits to a set of distinct machine capabilities, this report follows the definition adopted by previous World Economic Forum reports[2] in characterising AI as a suite of technologies, exhibiting some degree of autonomous learning and enabling:

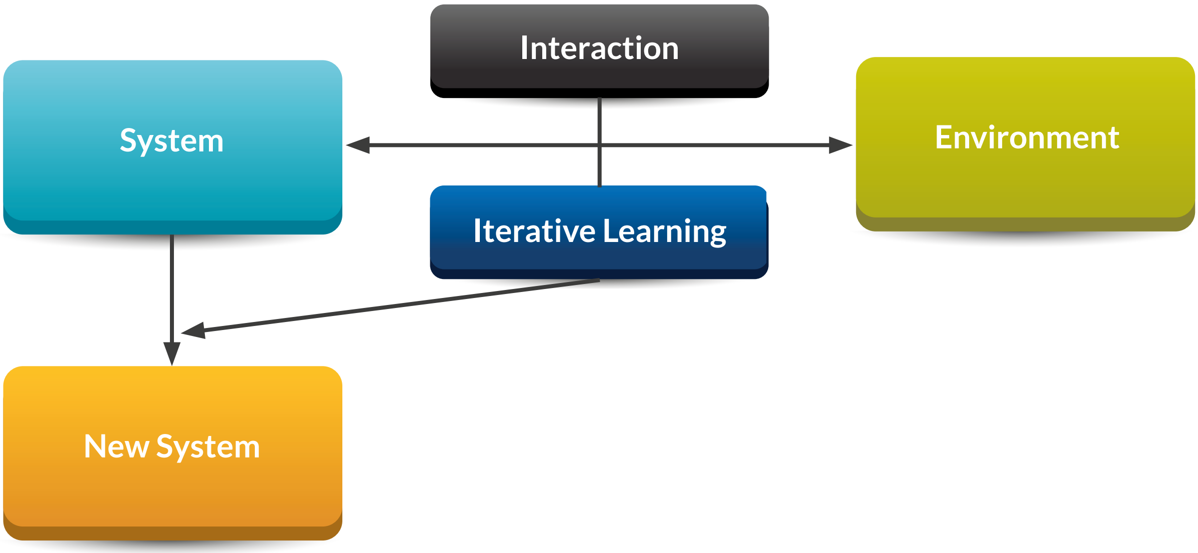
- **Pattern detection** by recognising (ir) regularities in data
- **Foresight** by extrapolating learned patterns in the presence of uncertainty
- **Customisation** by generating rules from specific profiles and applying general data to optimise outcomes
- **Decision-making** by generating rules from general data and apply specific profiles against those rules
- **Interaction** by communicating with humans through digital or analogue mediums

Machine Learning

While underlying concepts of AI and machine learning suggest significant overlaps, the term 'machine learning' is more distinctly derived from existing frameworks in neuroscience, computer science, statistics, and mathematics. According to a definition which was originally coined by Mendel and McLaren (1970) and refined by Haykin (1994), machine learning describes the change of a system resulting from an interaction with its environment, as shown in Figure 1.1 below. A system interacts with its environment in such a way that the structure of the system changes, in turn transforming its interaction with its environment, creating an iterative process.

2 The New Physics of Financial Services (McWaters *et al.*, 2018)

Figure 1.1: A high-level diagram of machine learning



In computer science, machine learning is part of a broader field called 'Soft Computing'. This encompasses systems that find approximate (or 'soft') solutions to problems which do not possess exact (or 'hard') solutions.

As such, machine learning algorithms can be clearly distinguished from traditional computer programs which follow a static set of predetermined instructions. A rule-based computer algorithm will always arrive at the same solution given a set of inputs, whereas training a machine learning algorithm multiple times will largely yield different solutions.

In summary, comparing AI and machine learning reveals that the term 'Artificial Intelligence' focuses on the meaning and impact of the system's interaction with its environment whereas 'machine learning' focuses on the nature of the system involved in the interaction, as well as the nature of the interaction itself. Machine learning may thus be seen as a technical term for what is essentially an enabling subset of the AI paradigm. This also means that the terms cannot be used interchangeably.

It is important to note, however, that most of the technologies firms[3] currently apply in their businesses may be explained by the term 'machine learning'. Salient characteristics of human intelligence such as meta-learning[4], self-reflection and human interaction, which essentially fill the gap between the terms 'machine learning' and 'AI' are still underdeveloped. Nonetheless, the suite of technologies investigated in this study is subsumed under the umbrella term 'AI' and named as such to ensure completeness. References to machine learning are made where the findings are specific enough to distinguish these denotations.

1.2 Literature Review

According to the OECD (2019) "AI has pervasive, far-reaching and global implications that are transforming societies, economic sectors and the world of work, and are likely to increasingly do so in the future." With the potential of AI in mind, many public and private institutions have investigated the application of AI on Financial Services, resulting in various research reports comprising unique perspectives and methodologies. These reports may be categorised into five thematic dimensions of AI, (i) adoption, (ii) application, (iii) business model

3 The terms 'firms', 'organisations', 'businesses', 'companies', and 'institutions' are used interchangeably throughout this study

4 The trait of applying learnings from one domain to another

creation and transformation, (iv) workforce transformation, and (v) regulation. The following literature review provides context for the research on AI in Financial Services led by CCAF and the World Economic Forum.

Adoption

The adoption of AI allows for differentiated product and service offerings and therefore the potential to expand an organisation's client base. Financial institutions are seeking to differentiate themselves by using AI to build new products and data ecosystems (McWaters *et al.*, 2018). For incumbent institutions, digital transformation continues to be an obstacle to growth. The rise of new technologies is increasing user expectations and attracting competitors to the market (Dhar, Holly, Ryan and Galeaz, 2017).

In an effort to understand hurdles to AI adoption, EY and the Massachusetts Institute of Technology surveyed 112 US business leaders. The study revealed while organisations are keen on implementing AI, they face many practical challenges to its implementation including leadership, expertise and data quality. In fact, almost 50% of those surveyed do not trust the quality of their organisations' AI data (EY, 2019). To mitigate this and effectively implement machine learning and AI at scale, organisations will likely need to make considerable investments in data capabilities to ensure the organisation has widespread access to high-quality and relevant data, both internally and externally (McWaters *et al.*, 2018).

Alongside investments in data, organisations have invested heavily in AI implementation itself. In a 2017 survey, 52% of respondents in the Financial Services industry indicated they were making 'substantial investments' in AI. 66% said they expected to be making 'substantial investments' in AI over the next three years, and 72% of business decision-makers believed that AI would significantly advantage their business in the future (Curran, Garrett and Puthiyamadam, 2017). A 2019 survey of financial institutions in the UK reaffirmed these findings, with 66% of respondents already leveraging AI and machine learning in some form in their organisations (Jung et al., 2019).

To remain competitive, incumbent institutions are leveraging data and analytics to predict client needs and improve profitability. They may eventually implement AI to unlock insights and reallocate staff to higher-value work (Dhar, Holly, Ryan and Galeaz, 2017). Deriving maximum impact from AI, and the wider embracing of digitalisation, will require organisations to have the necessary infrastructure and talent. Financial disruptors, FinTechs, who do not need to transform their core business offerings, may therefore be at an advantage in the race to the adoption of AI.

Application

Organisations are applying AI in a variety of ways to streamline back-office processes, to enhance the digital customer experience and to improve revenue models. Among the suite of AI applications, research to date has found that the capabilities of AI are strongest when leveraged in tandem with other technologies and that many applications of AI use a combination of automation and enhancement of existing processes. For example:

- The World Economic Forum publication, *The New Physics of Financial Services*, affirmed that cloud computing provides the data storage and the processing power necessary to train new AI models, making cloud infrastructure critical in implementing AI solutions (McWaters *et al.*, 2018).
- The 2019 Refinitiv Machine Learning Survey found financial organisations increasingly rely on data and analytics to drive business decisions, gleaning insights through the application of Artificial Intelligence (Verwij, 2016).
- In addition to cloud technology and big data, Application Programming Interfaces (APIs), open-source algorithms and the Internet of Things (IoT) are often applied in tandem with AI (Duin and Bakhshi, 2018).

Looking forward, experts imagine an ecosystem in which firms move towards 'augmented intelligence.' The application of AI is predicted to become increasingly sophisticated not only by automating simple tasks, but also through helping humans make decisions and learning from the interactions between humans and the technologies (Dhar, Holly, Ryan and Galeaz, 2017).

Business model creation and transformation

The use of AI in Financial Services has wide-ranging implications for competitive positioning and dominant business models within the industry. The most notable of these shifts is the tendency for AI algorithms to exhibit a 'flywheel' effect that rewards early movers with the potential to establish barriers to entry. This 'AI flywheel' is the tendency of AI models to exhibit self-reinforcing economies of scale wherein an accurate model attracts new users and additional data that increases the model's accuracy. This flywheel effect will redefine how organisations establish successful business models in the Financial Services sector, increasing the importance of granular data flows and the likelihood of 'winner-takes-all' dynamics (McWaters *et al.*, 2018).

With these competitive dynamics in mind, organisations are making bets on new capabilities and business models enabled by AI. Businesses are using AI to make smarter decisions by leveraging advanced data science to optimise business outcomes and integrating large quantities of data to derive better insights across business units. Organisations are going as far as to build new products, services and business models with AI at their core (McWaters *et al.*, 2018).

Many new AI-enabled business models place emphasis on creating a reimagined customer experience, allowing customers' finances to run themselves and acting as a trusted adviser in moments of need. As financial institutions continue to apply AI to customer advice and interactions, they lay the groundwork for 'self-driving finance' which will upend existing competitive dynamics, and ultimately push returns to the owner of the customer experience (McWaters *et al.*, 2018).

This need to rapidly acquire new capabilities may have played a role in the increased interest of incumbent financial institutions in forming partnerships with FinTechs that they once viewed as potential competitors. When these partnerships work, both institutions stand to benefit. Incumbent Financial Services firms are able to leverage the technological expertise of FinTechs and the FinTech is able to rely on the pre-existing reputation and customer reach of the incumbent firms (FinTech Innovation Lab, 2018). The literature suggests that the impact on competitive dynamics will be a key determinant of the overall impact of AI. As such, this research seeks to further understand these dynamics.

Workforce transformation

As AI evolves, financial service providers will race to be the quickest to adopt the technology, to acquire the most valuable AI talent, and to create the most value (MMC Ventures, 2019). The innovations driven by this small cadre of workers has transformed the talent needs within financial institutions. With the streamlining of back-office processes, organisations may become leaner.

According to Nedelkoska and Quintini (2018), the jobs with the highest probability of becoming automated are those which do not require specific skills or training. In their study of OECD countries, researchers found higher levels of education translated into a lower risk of job automation (Nedelkoska and Quintini, 2018). The increased use of AI will largely impact routine low- and middle-complexity roles. However, because these roles account for a considerable number of jobs in the Financial Services industry, net job losses are likely.

It is notable that other studies assert that AI will not be significantly impactful on the number of employees at financial organisations over the next three years, or even that the number of roles will increase among the most technologically advanced companies (Chui and Malhotra, 2018).

Regulation

AI is also changing how organisations interact with regulators. As the sophistication of algorithms and the volume of data rises, the uses of AI in finance are expanding, and so are pertaining risks (Proudman, 2018). The Financial Stability Board (FSB) and the Bank of England, amongst other regulators and supervisors, have highlighted this concern, citing the potential additional and unknown challenges associated with new technologies (Financial Stability Board, 2017). With these additional and unknown challenges, there are also implications for user trust. As the industry continues to transform, regulation will be integral to managing the risks, appropriately regulating the use of AI and instilling trust in consumers.

While regulation may increase costs and ultimately delay product development, it also provides a pathway to user trust. In particular for new entrants, regulation provides reassurance for users and investors as they do not have an established brand name. The role of generalised trust in promoting FinTech adoption has been highlighted as significant in previous studies (Sarkar, Chauhan and Khare, 2020).

There is an ongoing debate regarding whether there are appropriate frameworks in place for the gathering, storing, sharing and usage of data. However, policy is generally lagging the development and deployment of AI (KPMG, 2019). The current regulatory environment is also fragmented, with regulation which affects AI being initiated by state, national and global regulatory authorities, both financial and non-financial. Regulatory themes relevant to AI include everything from non-bank supervision to financial stability, operational resiliency and cybersecurity to consumer protection (KPMG, 2019). Both regulators and the industry are still searching for the optimal regulatory approach to AI (KPMG, 2019).

Given the complicated nature of the regulation of new technologies, organisations are seeking additional guidance on how to interpret current regulatory regimes (Jung *et al.*, 2019). The Monetary Authority of Singapore (MAS) has worked with a range of public and private sector organisations to develop principles for the use of AI and data analytics as they relate to decision-making in Financial Services. The principles aim to:

- Provide financial firms with a set of foundational principles to consider when using AI in decision-making
- Assist firms in contextualising and operationalising governance of AI use in business models and structures
- Promote public confidence and trust in the use of AI and data analytics (Monetary Authority of Singapore, 2019)

The World Economic Forum's latest report on AI, *Navigating Uncharted Waters*, calls for further public-private cooperation. The report maintains that unlocking the potential of AI will require an understanding of its risks to the financial system. Financial institutions, regulators and policymakers should seek to deploy AI systems in the current financial ecosystem and harness the potential of a financial ecosystem built on responsible AI (McWaters, *et al.*, 2019). In doing so, regulators must consider the following:

- AI systems operate fundamentally differently than systems of the past, thus creating new risks and regulatory challenges.
- Given these differences, the appropriate regulation of AI requires openness to new models of governance.

Fully understanding how business models, regulatory practices and talent needs have shifted as a result of the adoption and application of AI is essential to gain insights into the current Financial Services ecosystem. This survey conducted by CCAF and the World Economic Forum aims to add to the literature on, and deepen the collective understanding of, AI and its impact on Financial Services.

1.2. Survey Methodology and Sample Statistics

Survey fieldwork and methodology

This report is based on a global survey which was designed in Q1 and Q2 2019 and distributed to participants in June 2019. The survey took place over four months via a web-based questionnaire, comprising 55 questions of which nine were compulsory. The primary respondents targeted were relevant senior management within Financial Services firms in a number of Financial Services sectors, including Deposits and Lending, Payments, Insurance, Investment Management, Capital Markets, as well as Market Infrastructure and Professional Service providers. Given the breadth of the questionnaire, the collective contribution from multiple respondents within organisations was particularly encouraged. Unless otherwise stated, all data and estimates highlighted in this study are based on this global survey.

Survey data sample

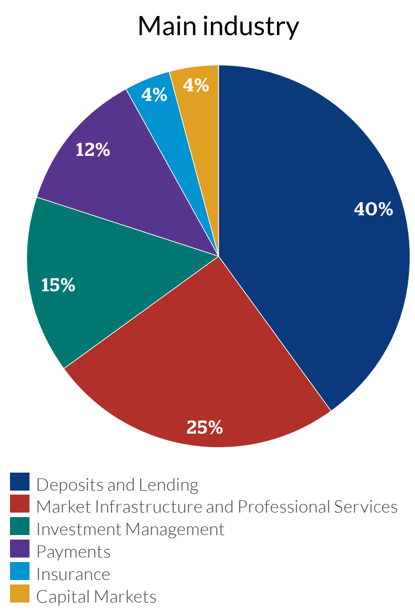
Overall, the survey fieldwork yielded 151 completed responses from institutions across 33 jurisdictions. Respondents were classified according to six main industry sectors which include the following:

- Deposits and Lending
- Investment Management
- Payments
- Market Infrastructure and Professional Services
- Capital Markets
- Insurance

Geographically, China, the US and the UK are the top three jurisdictions represented in the survey sample, with 17%, 15% and 14% of respondents respectively. Financial Services firms headquartered in Europe represent 36% of all survey entries, equaling that of the Asia Pacific region, followed by North America (19%), Middle East & Africa (7%) and Latin America (2%).

Globally, among all respondents, 40% of respondents are primarily active in Deposits and Lending, followed by Market Infrastructure and Professional Services (25%), Investment Management (15%), Payments (12%), and Insurance and Capital Markets (4%, respectively).

Figure 1.2: Financial Services sectors represented in the survey sample



The survey sample consists of FinTechs (i.e. relatively newly established technology-enabled financial service providers, which have often emerged outside of the traditional Financial Services industry) and incumbent financial service institutions (i.e. established financial companies primarily offering traditional products and services). These are almost equally represented at 54% and 46% respectively.

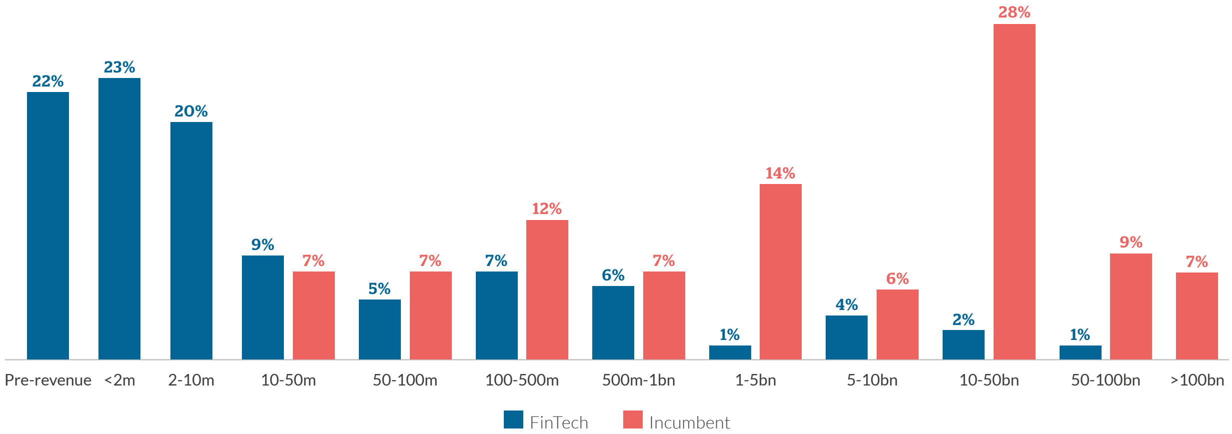
The survey captures firms with total estimated annual revenues between $1.11 trillion and $2.39 trillion[5]. FinTechs respondents are estimated to have a combined revenue range of between $89 billion and $244 billion, with total revenue for incumbents estimated at between $1.02 trillion and $2.15 trillion.

5 The range is attributable to the fact that revenues were surveyed in segments, where the highest segment was open-ended

Table 1.1: Captured annual revenue range ($)

FinTech	0.089 tn. – 0.244 tn.
Incumbent	1.023 tn. – ≥2.149 tn.
Total	**1.112 tn. – ≥2.393 tn.**

Figure 1.3: Revenue segments represented in the survey sample by entity type ($)



Many FinTechs within the sample fall in the SME category. Around 74% of the surveyed FinTechs have annual turnover under $50m, whilst 28% of surveyed Incumbents can be found in the $10-50bn annual revenue segment[6]. These proportions are similarly reflected in staff size numbers, with the majority of FinTech companies in the survey sample having fewer than 50 employees. In contrast, Incumbents exhibit a relatively even distribution across the higher segments of workforce sizes.

Additional notes on terminology

In this study, to distinguish between financial service providers at the forefront of AI implementation and those are relatively lagging behind, the terms *(AI) Leaders* and *(AI) Laggards* are used. More specifically, *AI Leaders* are defined as respondents with an above-average level of AI adoption across the organisation in revenue generation, risk management, process re-engineering and automation, customer service and customer acquisition. These organisations tend to state that AI is of 'high' or 'very high' importance to their business model. *AI Laggards* are characterised as those with firms with a below-average level of AI adoption in their current businesses and have stated 'low', 'very low' or 'no' importance of AI to their business model. At the same time, for the purposes of this research, organisations must be currently implementing or planning to implement AI in some way to be defined as an *AI Laggard*.

According to this definition, 23% of sampled respondents are regarded as *AI Leaders*, 16% are regarded as *AI Laggards*, and 61% are somewhere in between.

6 Please note that the figure for Incumbents does not add up to 100% as some of them declined to indicate annual revenue. Further figures in the report may occasionally not add up to 100% due to rounding of individual values.

2. The Adoption of AI in Financial Services

- AI is on its way to becoming mainstream in Financial Services within the short term. 85% of all respondents in the survey are currently using some forms of AI, with FinTechs being slightly ahead of Incumbents in AI adoption. When adjusted for size, FinTechs also invest slightly higher proportions of their R&D in AI.
- Out of all Financial Services sectors, investment managers have most widely adopted AI, especially for generating new revenue potential. This is followed by payment providers, who have mostly implemented AI for process re-engineering and automation.
- The most common area for firms to use AI is in risk management, where it is utilised by 56% of firms. This is followed by the generation of new revenue potential, where AI is used by 52% of firms. Firms expect AI to become most widely used in the latter field, with 95% expecting to be harnessing AI capabilities in the generation of new revenue potential within two years.
- The most common specific use cases for AI are AI-enabled data analytics (adopted by 43% of firms), fraud/anomaly detection and surveillance (42%), and AI-enabled customer communication channels (36%).
- FinTechs are more widely leveraging AI to create new products and services while Incumbents mainly use it to enhance existing ones. A larger share of FinTechs is pursuing a more product-oriented approach to implementing AI, by selling AI-enabled offerings as a service. In contrast, Incumbents tend to focus more on leveraging AI capabilities to foster process innovation within existing product portfolios.
- There is a trend towards AI mass adoption, with half of all *AI Leaders* having simultaneously implemented AI in several key areas such as generating new revenue potential, process automation, risk management, customer service, and client acquisition. All *AI Leaders* expect to be mass adopters within two years, solidifying the hypothesis that there are significant economies of scale in the application of AI in Financial Services.
- Mass adoption appears to require specialised organisational resources. Firms which are at the forefront of AI implementation frequently operate dedicated departments for overseeing and implementing AI, as well as strategically involving a broader range of business functions.

Key Findings

Chapter 2: The Adoption of AI in Financial Services

2.1 State and Development of AI Adoption

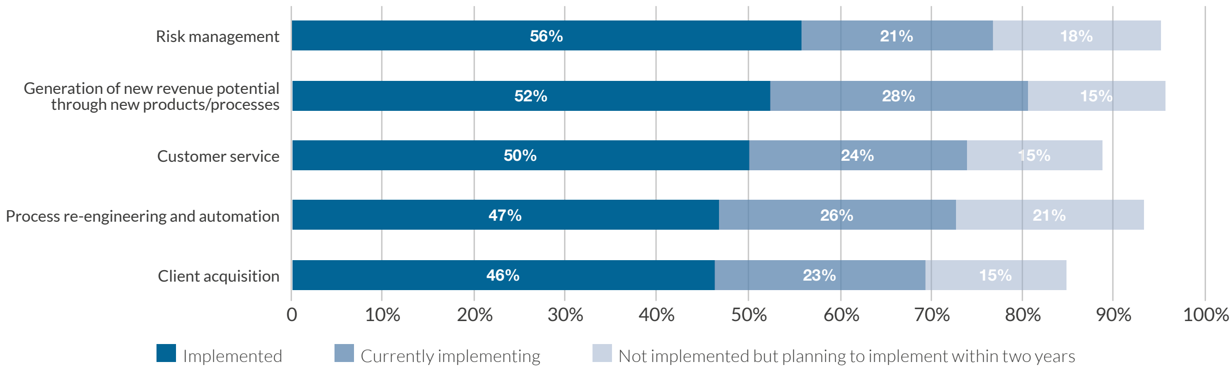
Across the entire sample, 85% of all respondents have implemented AI in some way, with FinTechs leading Incumbents by a slight margin (90% vs. 80%).

In order to better understand varying usage profiles across Financial Services, this study further separates AI adopters by different application domains:

- Generating new revenue potential
- Risk Management
- Process re-engineering and automation
- Customer service
- Customer acquisition

Risk management currently represents the leading AI implementation area, followed by the generation of revenue potential through new products and processes (Figure 2.1). However, according to implementation plans and current implementation statistics, within two years AI will be most widely used for revenue generation.

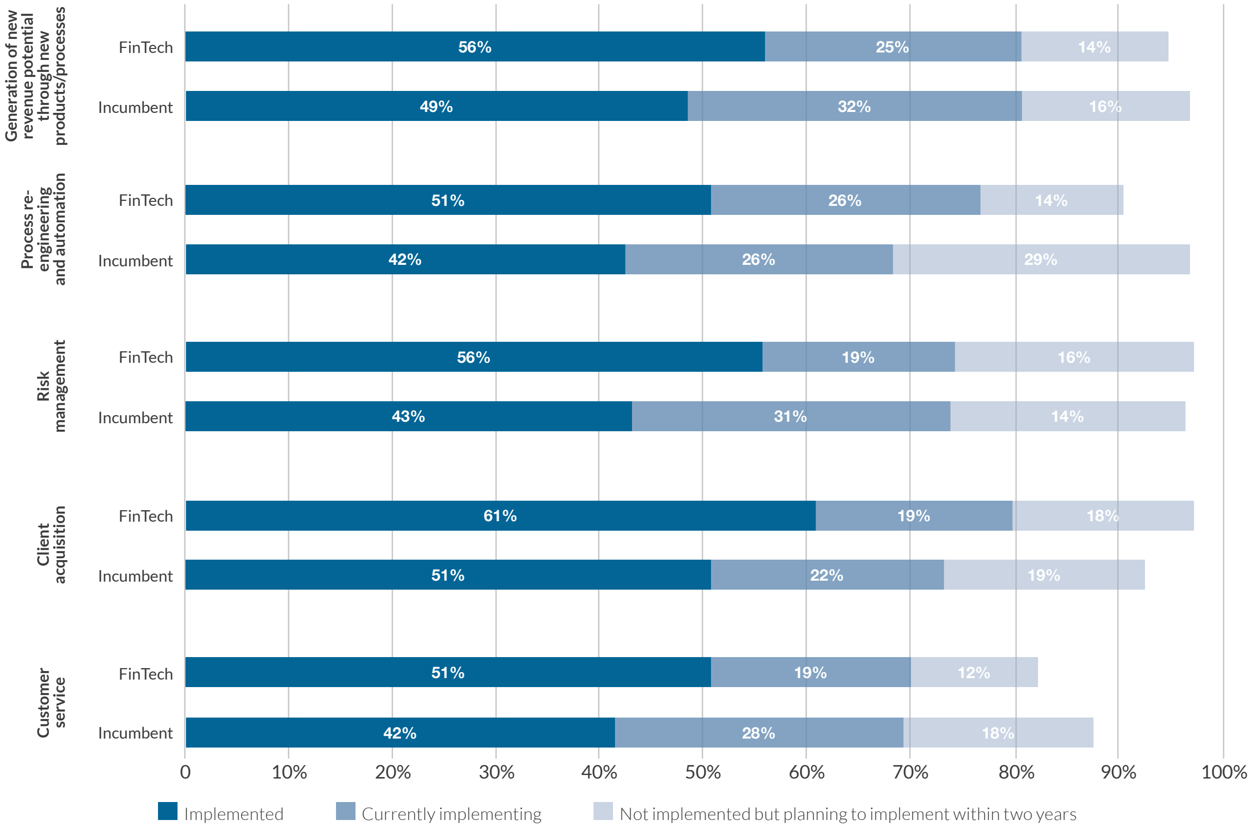
Figure 2.1: Sample-wide adoption statistics of AI in main business domains



FinTechs are frontrunners in AI implementation across all investigated business areas (Figure 2.2). FinTechs lead Incumbents in using AI for generating new revenue potential, which, conversely a higher share of Incumbents is currently implementing. FinTechs and

Incumbents use AI to a similar extent in three application areas: the generation of new revenue potential through new products or processes (80%), customer service projects (74%), and client acquisition (69%).

Figure 2.2: Adoption statistics of AI in main business domains by entity type



They differ in the use of AI for process re-engineering and automation (77% FinTechs and 68% Incumbents), and risk management (80% FinTechs and 73% Incumbents). However, this AI adoption gap is likely to narrow, as more mature financial service companies are currently implementing or planning to implement AI in the short term.

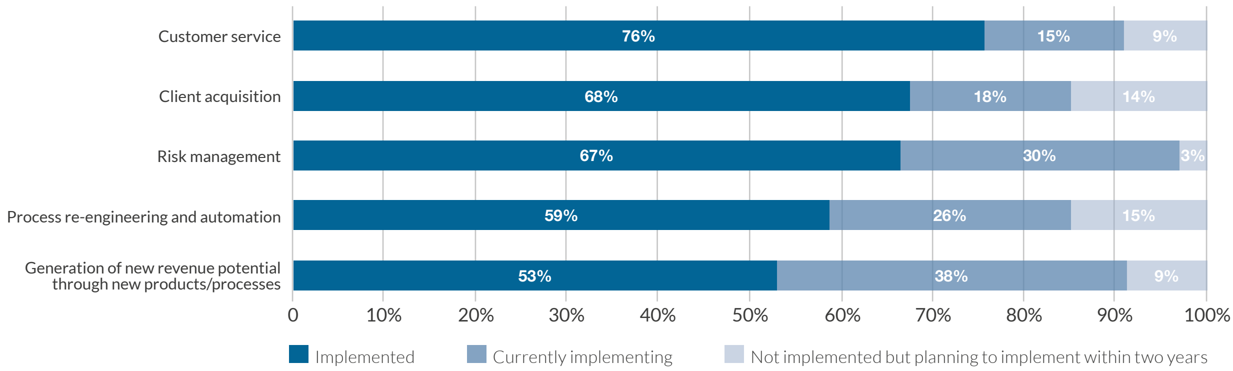
Table 2.1: Adoption statistics of AI in main business domains across the Financial Services industry

	Deposits and Lending	Payments	Market Infrastructure and Professional Services	Investment Management
Generation of new revenue potential	46%	44%	52%	61%
Process re-engineering and automation	43%	56%	42%	50%
Customer service	52%	44%	55%	45%
Risk management	56%	56%	53%	55%
Client acquisition	39%	50%	44%	50%

Adoption statistics from different financial service sectors reveal that while average implementation rates are homogeneous across the sample, outliers prevail in certain areas. Most notably, investment managers appear to specialise in the use of AI to generate new revenue potential (61%) which is the least active field of implementation in payment providers (44%). Similarly, the use of AI for process re-engineering and automation as well as client acquisition also vary strongly between sectors.

Taking an isolated view of those few companies which are at the forefront of utilising AI at the core of their business reveals an unequivocal trend: all *AI Leaders* included in the survey are converging towards mass adoption of AI in all five domains within two years, as seen in Figure 2.3. This overarching trend is further underpinned by *AI Leaders*' apparent shift from mainly using AI for cost reduction to harnessing its capabilities to generate new revenues. 38% of *AI Leaders* are currently implementing AI in this domain, representing the most active area of current adoption efforts.

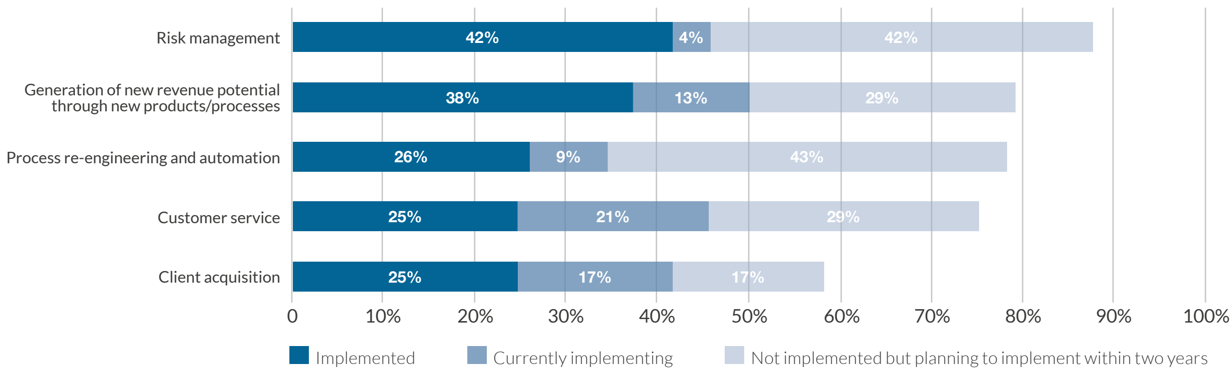
Figure 2.3: Adoption statistics of AI in main business domains in *AI Leaders*



AI Laggards, on the other hand, still appear to be far away from organisation-wide adoption, and especially lag behind in applying AI within customer service and customer acquisition (Figure 2.4).

Taking into account the overall adoption gap between *AI Leaders* and *Laggards*, this could imply that the lifecycle view of gradually moving from simplistic automation use cases towards AI-based value propositions may not be straightforward. Areas like risk management appear to offer more accessible (or, indeed, universally relevant) use cases for AI than re-engineering or automating complex processes.

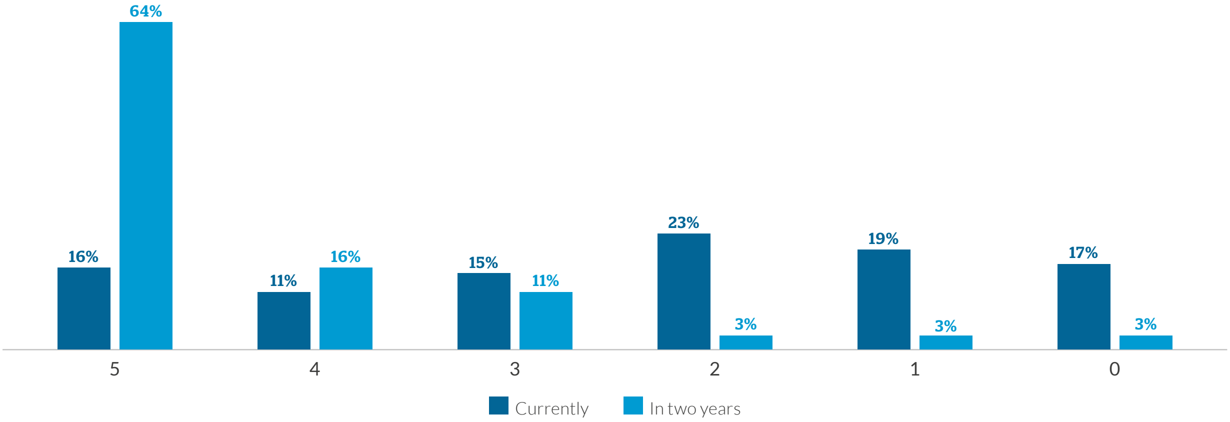
Figure 2.4: Adoption statistics of AI in main business domains in *AI Laggards*



A trend towards intra-organisational mass adoption

Firms generally appear to be moving towards mass adoption, with a significant number of respondents striving towards simultaneously implementing AI across different domains within their organisation. Figure 2.5 shows that 91% of all respondents state that they expect to see AI implemented in three or more areas of their business within only two years, compared to a current figure of 42%. According to participants' expectations, 'true' mass-adopters with AI applications across all five areas will quadruple within two years to reach a figure of 64%.

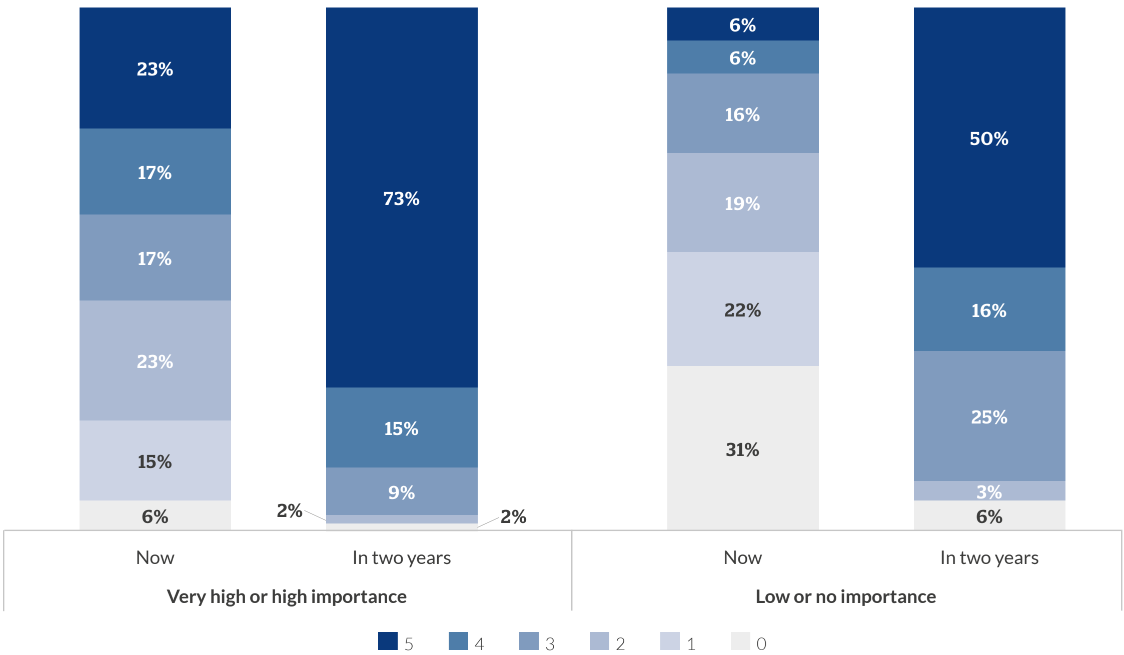
Figure 2.5: Number of AI implementation domains



This trend may relate to the fact that AI benefits from scale. Existing infrastructure (e.g. data pipelines, in-house programming frameworks, computational resources) can easily be shared across different use cases within an organisation. Furthermore, larger datasets tend to yield richer insights, and data types may also be used across different use cases. This is shown in the social media case, where insights on users may be used for credit analytics, while insights on posting activity may be used to predict stock returns.

Mass adoption can also result in significant commitment to building technological infrastructure and overcoming early-stage implementation hurdles. Figure 2.6 illustrates that firms which currently place 'high' or 'very high' importance of AI to their business are clearly shown to be adopting AI on a broader scale, with nearly three quarters projecting use of AI in all five domains.

Figure 2.6: Number of AI implementation domains by current importance of AI to organisations' business



The tendency towards adopting AI across multiple business functions proves to be clearly present in both groups. Half of all respondents where AI is currently of low importance to doing business expect to evolve into mass adopters within two years. However, given the tremendous gap between current usage and forecasted future plans, these figures are to be treated with a certain amount of caution.

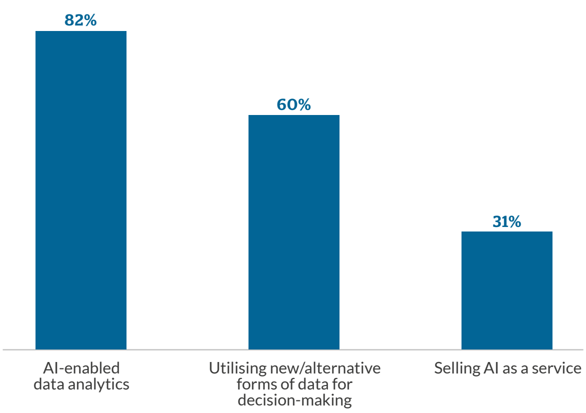
Overall, these results point towards the notion that AI represents a set of technologies which provide such fundamental value for financial service companies that they are applicable in many different modes, and do not necessarily require or reward specialisation. Accordingly, subsequent chapters will elaborate more on the advantages of using AI at scale as well as potential early adopter advantages.

2.2 Specific Application Areas of AI

Leveraging AI to generate new revenue potential through new products and processes

As described earlier, AI offers financial institutions a multitude of opportunities to build new value propositions by capitalising on monetisable insights drawn from data, or by developing AI as a service for other organisations, which will be further explored in Chapter 3.

Figure 2.7: Top three AI use cases in generating new revenue by rates of current adoption [7]



Use cases that leverage AI to create new revenue potential mainly revolve around AI-enabled data analytics, as well as leveraging alternative data to generate novel insights (Figure 2.7). In fact, these applications appear to be among the most widely implemented applications in every major Financial Services sector included in the survey sample.

AI-enabled data analytics encompass a multitude of capabilities for discovering insights in data and linking them to business decisions. For example, Mastercard uses near-real-time purchase data and AI-enabled analytics to produce automated reports on macroeconomic trends on a weekly basis for a wide variety of industries and geographical areas (McWaters *et al.*, 2018).

Listed below are different subcategories and pertaining usage proportions for AI-enabled analytics. Among all organisations employing AI-enabled data analytics, sales analytics represent the most widely utilised subcategory, followed by credit analytics.

7 Percentages shown for this graph and following graphs in this sub-chapter (2.2) represent proportions relative to the total number of AI adopters in that specific domain

Table 2.2: Adoption statistics of AI-enabled data analytics

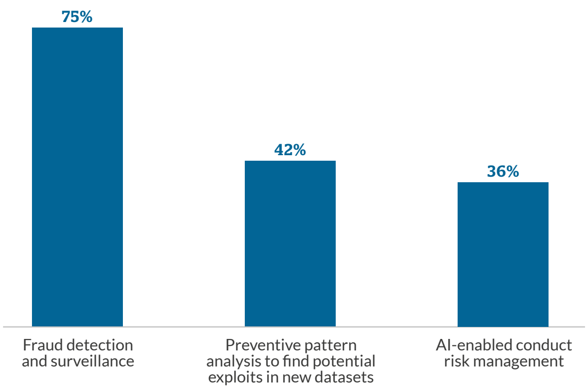
Sub-categories of AI-enabled analytics	Proportion currently using analytics category*
Sales analytics	66%
Credit analytics	55%
Market sentiment analytics	53%
Corporate finance analytics	34%
Macroeconomic forecasting	29%
M&A analytics	14%

**Proportions shown are relative to the number of firms which use any form of AI-enabled data analytics*

Further survey results not shown in the figures above demonstrate that both Incumbents and FinTech primarily utilise AI in data analytics and for generating insights from new/alternative datasets. This area is especially active in Investment Management, with asset managers attempting to generate informational advantages to predict market events and/or developments. For example, the London-based hedge fund Man Group has been a pioneer in using AI and alternative data in its investment process to support alpha generation in its funds (Stier, Ehrsam, Gaughan and Newsome, 2019).

AI-enabled risk management

Figure 2.8: Top three AI use cases in risk management by rates of current adoption

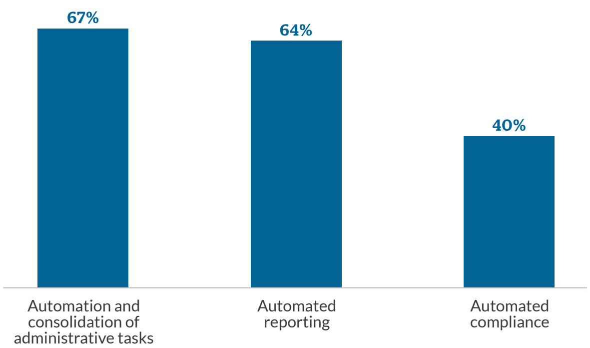


On aggregate, risk management represents the domain where most entities currently use AI. This may be due not only to the universality of risk management as a necessary business function but also commoditisation of pertaining AI solutions (Sweezey, 2019). From regulatory compliance to conduct risk management or fraud detection, AI can reduce economic costs and human intervention in delicate activities, making risk management processes quicker and more efficient (Arslanian and Fischer, 2019). The dichotomy between AI-induced risk and AI-enabled risk management, which may both grow in significance with the scale of AI application within an organisation, will be further explored in Chapter 6.

The most prevalent use case is fraud/anomaly detection and surveillance, used by 75% of all adopters of AI in risk management (Figure 2.8). The effectivity of AI in fraud detection and surveillance could be attributable to the sheer volume and frequency of transactions, as well as the multidimensionality/granularity of fraudulent patterns, across networks which may span multiple entities, jurisdictions, and industry sectors (Mastercard, 2018). This is illustrated by real-world examples like FICO's Falcon Platform, which uses AI-driven predictive analytics to provide fraud-detection services to institutions (McWaters *et al.*, 2018).

Automation and process re-engineering

Figure 2.9: Top three AI use cases in automation and process re-engineering by rates of current adoption



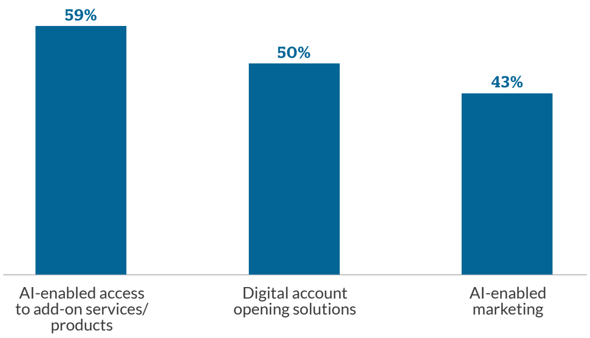
AI-enabled automation is still far from being ubiquitous, and indeed represents a nascent implementation target for a wide range of entities, especially those that lag behind in AI adoption. Current adopters of AI in automation and process re-engineering largely employ its capabilities to automate and consolidate administrative tasks, automate reporting, or, to a significantly lesser extent, automate compliance (Figure 2.9).

Automated compliance may be harder to implement than automated reporting, due to a higher extent of human judgment required in evaluating compliance for individual cases or actions. Automated reporting, on the other hand, often merely refers to automatically condensing information from various data sources and creating visual representations. More complex, nascent use cases in this area include Natural Language Generation (NLG), which uses AI capabilities to compose full-text reports with little or no human input (Financial Reporting Lab, 2019). Evidence from *AI Leaders* confirms this hypothesis, with 55% of all *Leaders* utilising AI to automate compliance compared to 33% of *AI Laggards*.

In the context of this study's understanding of AI, automation and consolidation of administrative tasks includes selected facets of robotic process automation (RPA). These tasks include those typically native to back-office activities, such as data entry, data engineering, and communication, which require moving beyond static, rule-based algorithms. For example, Google's Smart Reply automatically composes appropriate responses to short e-mails (Kanna *et al.*, 2016). Current trends demonstrate that automation may proliferate to even higher levels, with tools on their way to attaining the ability to generate code themselves (Nye *et al.*,2019).

AI-enabled customer acquisition

Figure 2.10: Top three AI use cases for customer acquisition by rates of current adoption



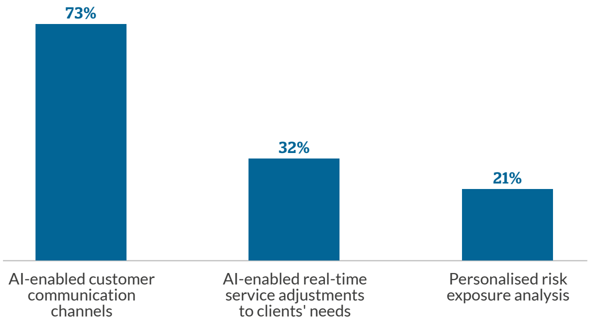
AI has various uses in customer acquisition, including making outreach more personalised, speeding up onboarding procedures (for instance, through the usage of computer vision to automatically process identification documents), and up- or cross-selling based on insights generated by AI from current user data. This may initially appear like a narrow area of implementation compared to others previously mentioned. However, the finding that it is the second-most adopted use case by *AI Leaders* (68%) implies that this field, albeit challenging, holds significant value for financial service institutions. AI enables financial companies to surpass the traditional cost-personalisation trade-off. Theoretically, it allows them to offer fully personalised financial products at zero marginal cost, favouring customer acquisition and retention, which are crucial matters in a highly complex competitive environment (Arslanian and Fischer, 2019).

As shown in Figure 2.10, most respondents have implemented AI to expand existing clients' usage of products and services. This, in turn, is largely due by AI-empowered consolidation, for example through offering services via platforms which capitalise on shared datasets such as a client's risk appetite or communication preferences.

On the other hand, digital account opening solutions such as Alipay's Smile to Pay, which uses facial recognition as a method of authentication and consent, are less widely implemented at a 50% adoption rate. Only 9% out of all *Laggard* adopters of AI in customer acquisition use AI in digital account opening solutions, compared with an adoption statistic of 65% for *AI Leaders*.

AI-enabled customer service

Figure 2.11: Top three AI use cases for AI-enabled customer service by rates of current adoption



Results from the survey confirm the fact that customer service remains one of the areas where AI can be leveraged most effectively (Brett, Laurent, Gianturco and Durao, 2017). As seen in Figure 2.11, the most frequently used solutions in this field are AI-enabled customer communication channels (adopted by 73%), followed by AI-enabled real-time service adjustments to clients' needs and personalised risk exposure analysis at much lower implementation rates (32% and 21%, respectively).

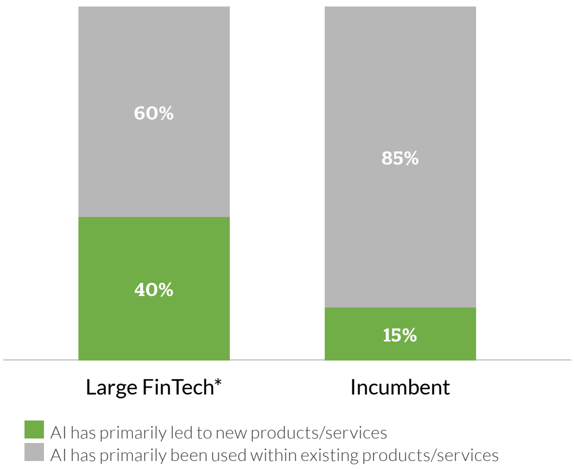
The ubiquity of AI-enabled communication channels is likely attributable to the increasing proliferation of chatbots, and rising trends of building smarter solutions which come closer to replicating real human interaction. For instance, UBS initiated a pilot project with its *Companion* which allows wealth management clients to pose questions question to a virtual avatar of the firm's Chief Investment Officer.

As seen at the beginning of this chapter, customer service is the most active area of current AI usage for *AI Leaders*. It surpasses by a considerable margin uses such as revenue generation through new products and processes. Meanwhile, it appears to represent a lesser priority for *AI Laggards*, perhaps because the use of AI in customer service may be a late-lifecycle implementation area which is easier to scale up than continuously building new revenue-generating value propositions based on AI. Companies which are just entering the field of AI adoption may be initially drawn to the more commoditised portions of revenue-generation, and may only start implementing AI-enabled solutions in fields like customer service and customer acquisition after maximising its attainable use cases for revenue generation.

2.3 AI-Empowered Product- and Process Innovation Approaches

According to the survey responses, FinTechs are more widely using AI to create new products and services, while Incumbents predominantly harness AI to enhance existing ones (Figure 2.12).

Figure 2.12: Primary utilisation of AI by entity type



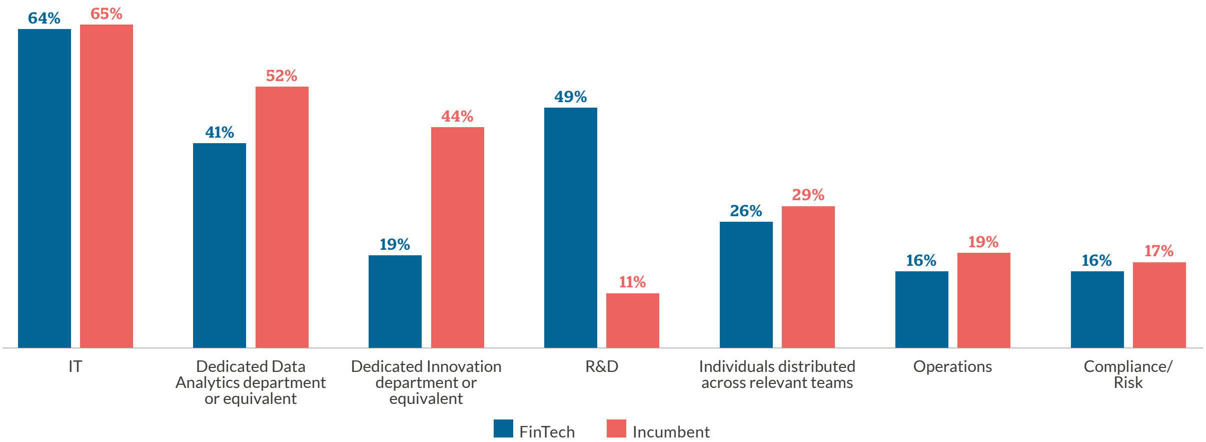
**Annual revenue ≥$100m*

This gap may be attributable to crucial differences in organisational complexity and maturity. Previous studies have stated that incumbent firms are limited in their AI experimentation and implementation process by a mix of legacy talent (Mittal, Kuder and Hans, 2019), fragmented and unstructured data, and legacy IT infrastructure. On the other hand, digitally-native, data-driven, and agile FinTech companies can quickly deploy AI within their organisations in a more cost-effective way.

As a likely consequence to these distinctly different approaches to AI-enabled innovation, FinTechs and Incumbents take different directions in managing AI on an organisational level (Figure 2.13).

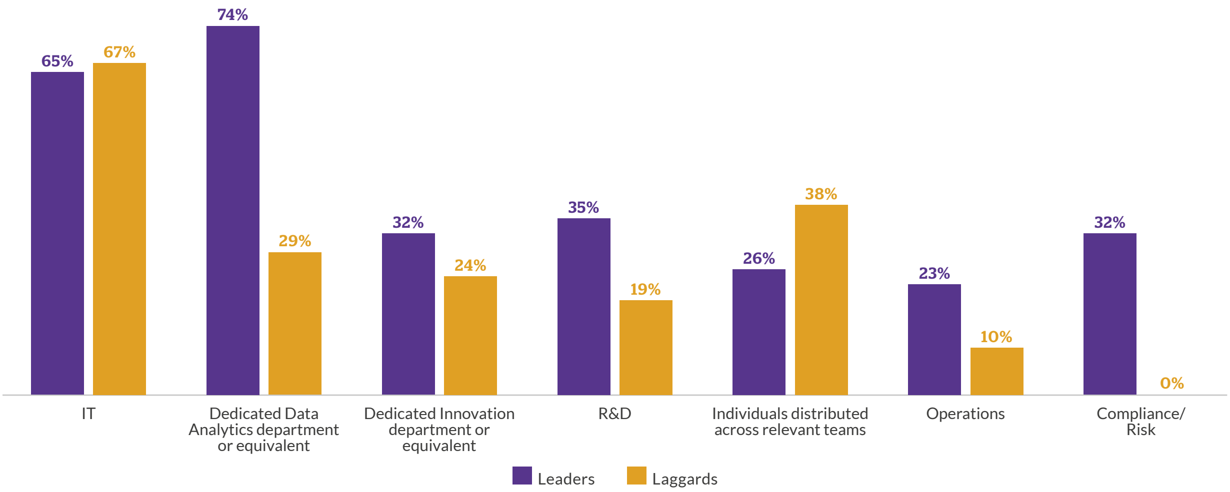
Moving beyond purely IT-centered AI strategy, many Incumbents maintain dedicated resources, such as an analytics or innovation department, in deploying and overseeing AI within their business. Conversely, the average FinTech firm does not concentrate resources in specialised departments responsible for AI implementation.

Figure 2.13: Departments responsible for AI implementation and oversight by entity type



However, survey findings highlight that most *AI Leaders*, including FinTechs and Incumbents, operate a dedicated data analytics department (74%) (Figure 2.14). This approach may be necessary to run an agile, experimental, and adaptable organisation, consequently enabling AI at scale (Fountaine, McCarthy and Saleh, 2019). It also illustrates that financial service providers may be incentivised to develop in-house research capabilities, to move from a perception of AI as a tool for driving profit to building and fostering long-term in-house capabilities.

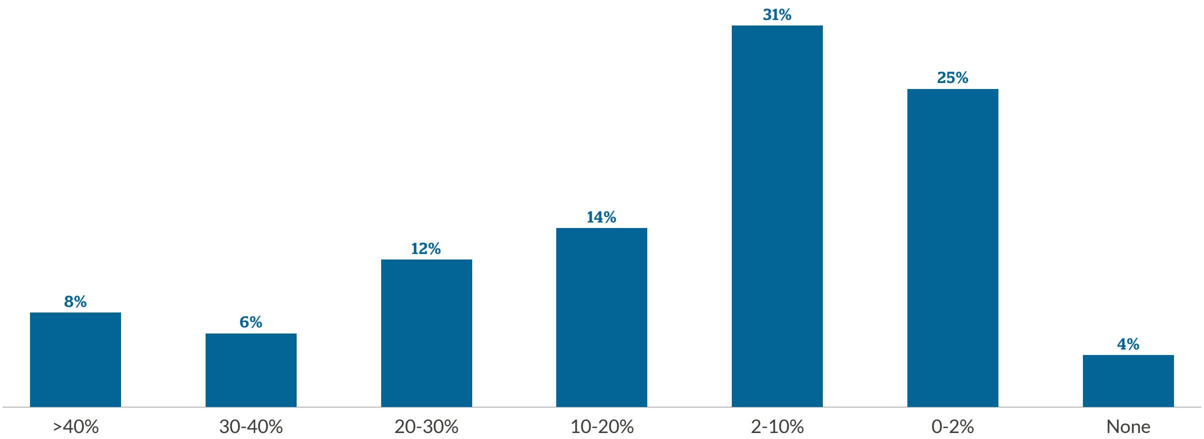
Figure 2.14: Departments responsible for AI implementation and oversight by maturity of AI adoption



2.4 Investment in AI

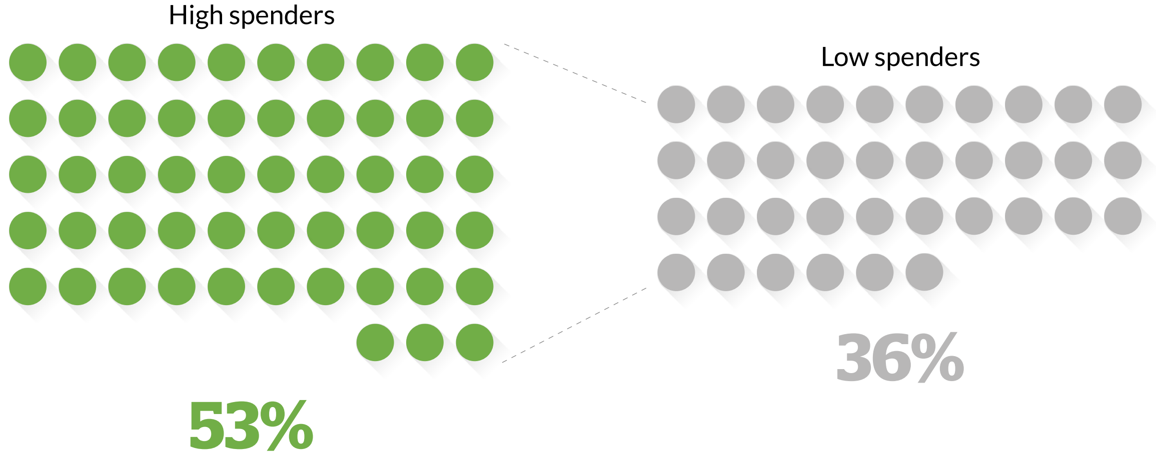
Spending on AI is not currently a large part of total R&D expenditure in most firms. Only 40% of all survey respondents are shown to invest more than 10% of overall R&D resources in AI (Figure 2.15).

Figure 2.15: R&D expenditure spent on AI



Following ambitious adoption plans highlighted earlier in this chapter, most financial companies anticipate increasing their AI spending in the short term. This trend is particularly true for those firms which already spend more than 20% of their R&D on AI, as approximately more than half of them expect to significantly increase investment within the next two years (Figure 2.16).

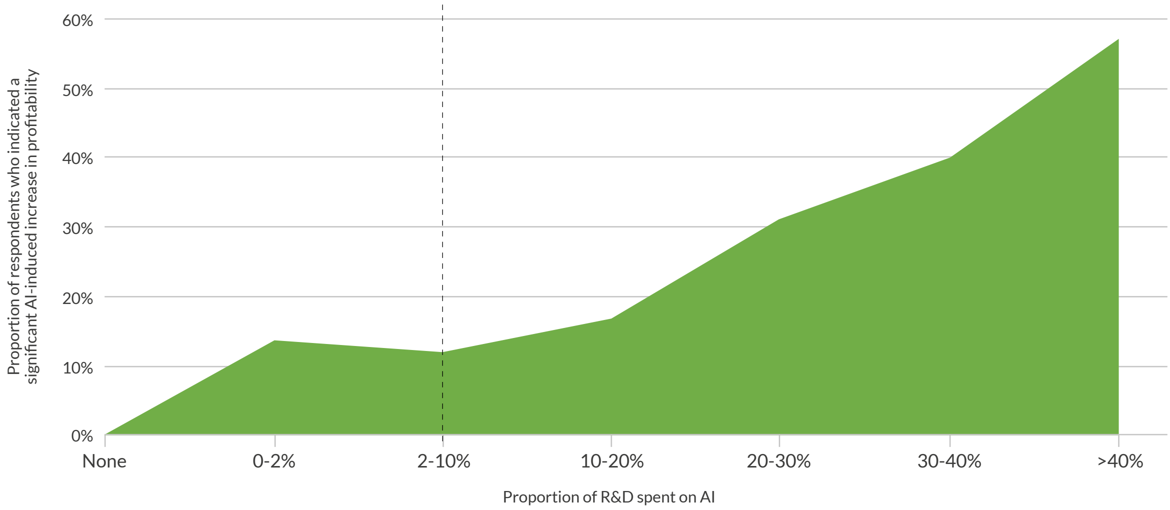
Figure 2.16: Plans to significantly increase AI R&D spending in the short termwithin two years by current R&D spending segment



If firms realise their spending ambitions as indicated in the survey, the extent to which AI is applied across the Financial Services industry will likely become more and more heterogeneous as the gap between low spenders and high spenders grows. This trend was previously investigated by the World Economic Forum in 2018, concluding that first movers in AI deployment would be able to "compound their lead".

Indeed, Figure 2.17 shows that there seems to be an almost constantly positive relationship between investing in AI and resultant pay-offs. While one might expect diminishing returns, it is actually observable that pay-offs appear to accelerate with increasing R&D expenditure, especially between 10% and 30% as well as 30% and >40%.

Figure 2.17: Percentage of reported 'significant' AI-induced increases in profitability by current R&D expenditure on AI



The figure also identifies a 'critical mass' of R&D investment in AI at 10% (shown as a dotted line), after which there is a constant perceived increase in associated pay-offs.

While there is not enough evidence to universally declare an exponential growth relationship between investments in AI and increases in profitability, the fact that the relationship is not diminishing may be attributable to two key factors:

- Causal response: coinciding with findings on the growing bifurcation of large spenders and small spenders, observed increases in profitability may result in an instant response by increasing spending.
- Scale effects for companies that are built around AI and are accordingly spending the majority of their R&D budget on AI. This might include the scale of technical infrastructure, technology and applications, as well as data.

This relationship highlights that the race to AI supremacy might be decided between high spenders vs. low spenders rather than Incumbents vs. Disruptors – in summary, high spenders are planning to further increase spending on AI, as there appears to be a direct impact on profitability.

3. The Business Impact of AI

- While FinTechs currently place more emphasis on the strategic importance of AI to their business, the majority of both Incumbents and FinTechs expect AI to become a significant business driver within two years.
- Similarly, while the perceived strategic relevance of AI currently differs significantly across key Financial Services sectors, findings illustrate that firms expect AI to reach ubiquitous importance within two years, with the largest increases expected in Payments.
- Survey findings suggest that Incumbents' expectations may be explained by them increasingly moving from using AI for attaining leaner, more cost-efficient operations, to pursuing differentiation strategies through process innovation and AI-enabled customer service solutions.
- Many FinTechs, on the other hand, are already seen to pursue a differentiation-oriented AI strategy which is based on harnessing AI to create new products and services. Furthermore, a larger proportion of FinTechs are selling AI-enabled products as a service. This is shown to be a distinct, new, AI-enabled business model which leverages the economies of scale in AI by utilising larger and more diverse datasets to offer AI-driven services through shared platforms.
- With certain AI-enabled solutions becoming a commodity, firms are incentivised to harness AI for creating genuinely new value propositions to establish resilient competitive advantages through product differentiation.

Key Findings

Chapter 3: The Business Impact of AI

3.1. The Future Business Relevance of AI

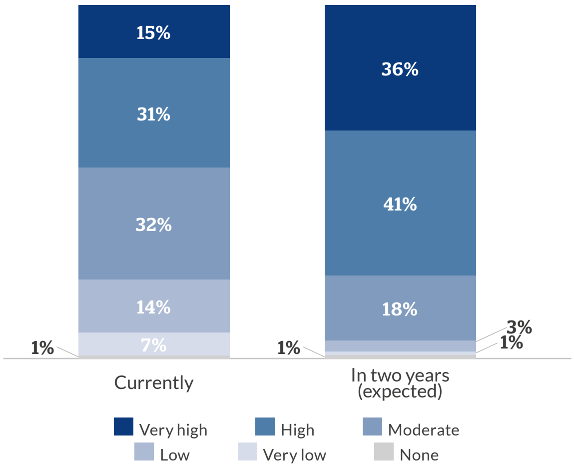
"A century ago, factories electrified without rethinking their production lines and therefore saw no productivity benefits. In much the same way, machine learning technology without management and organisational change will be ineffective."

- *Erik Brynjolfsson, Director of the MIT Initiative on the Digital Economy and Professor at MIT Sloan School of Management (Johnson, 2019)[8]*

Chapter 1 highlighted the strong aspirations and hopes that many in the Financial Services industry hold regarding the development of AI. However, this also stimulates a number of questions. How important will AI be for different Financial Services sectors? How can organisations leverage AI as an effective catalyst for their success? Does investing in R&D yield consistent pay-offs in terms of profitability increases? Moreover, there remains an open question around which resources will foster long-term business transformation through AI, as well as whether there is one 'right' AI strategy for all Financial Services sectors. In this concern, *The New Physics of Financial Services* (McWaters *et al.*, 2018) concludes that talent and technology represented two main drivers of long-term business transformation, and that financial institutions should attain a balance between the optimisation of current activities and evolving talent strategies.

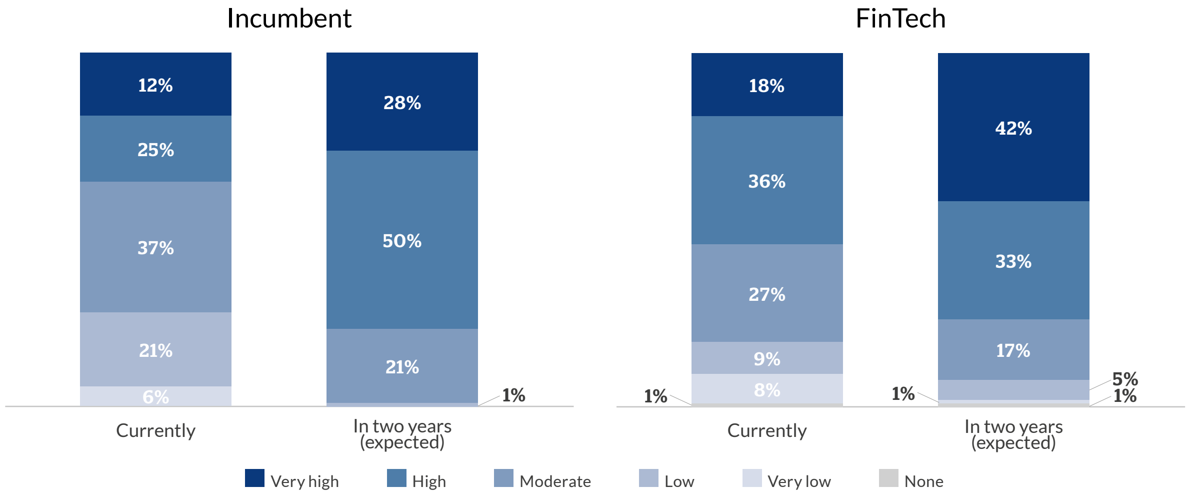
Figure 3.1 illustrates that more than three quarters of all respondents expect AI to form an integral part of their business within two years. Currently, less than half of all participants perceive AI to possess 'high' or 'very high' importance to their business. While this shift is observable across both Incumbents and FinTechs across all Financial Services sectors, the driving forces behind this differ. This will be further explored throughout this Chapter.

Figure 3.1: Perceived strategic importance of AI over time



8 All subsequent quotes are, unless otherwise stated, sourced from the survey underlying this study.

Figure 3.2: Perceived strategic importance of AI over time by entity type

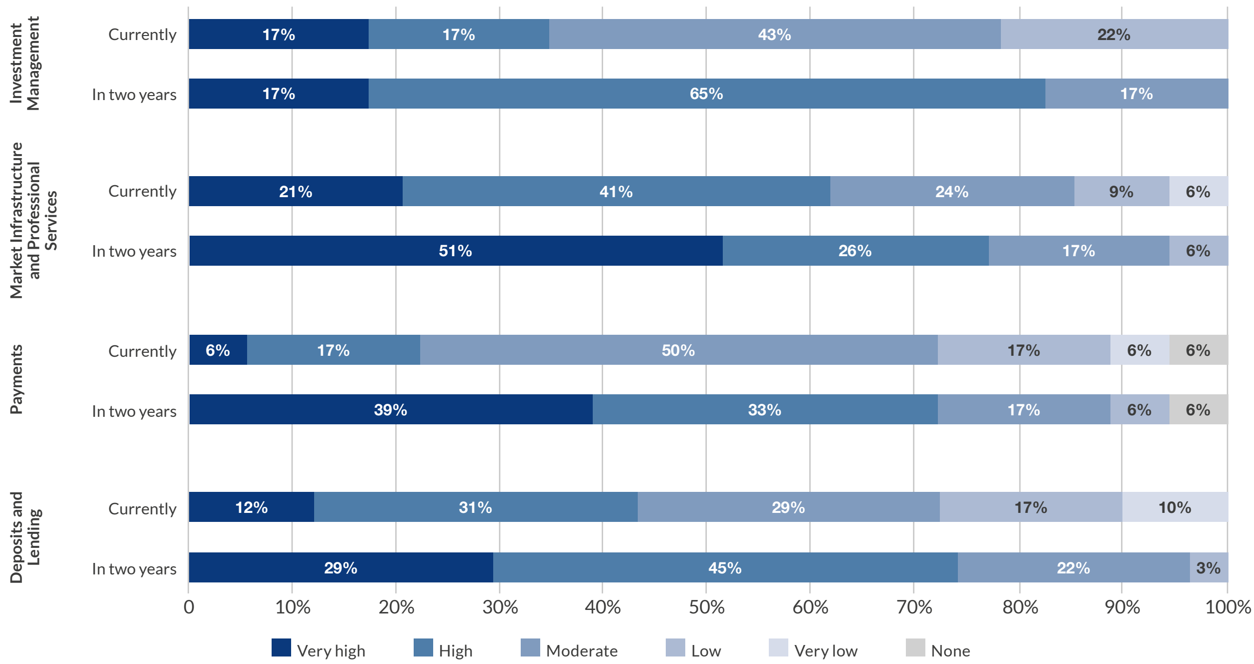


AI is currently perceived as more important to their business by FinTechs (54% stating AI to be of 'high' or 'very high' importance compared to 37% of Incumbents). However, Incumbents have high expectations of AI reaching similar significance to their businesses within two years (Figure 3.2).

While future outlooks should naturally be treated with caution, these expectations may be justified. In order to accelerate AI adoption, Incumbents may use their typical size advantage to achieve AI at scale through amassing larger amounts of data or better organising the oversight and implementation of AI through dedicated corporate resources, such as innovation departments (Chapter 2, Figure 2.13). Creating these data pipelines has the potential to boost the current process-oriented approach to innovation which Incumbents are taking, which mainly focuses on utilising AI to enhance existing products and services (Chapter 2, Figure 2.12).

FinTechs, on the other hand, expect slightly lesser increases in the significance of AI to their businesses compared to incumbents when counting 'Very high' and 'High' responses (two-year increases amounting to 21% and 41%, respectively). On aggregate, this may imply that adopting AI across an organisation becomes increasingly difficult with increasing complexity (and business importance) of pertaining use cases, meaning that it is more likely for firms previously devoid of AI to expect a slightly higher importance in two years than for firms which already place high value on AI to anticipate even further increases in importance.

Figure 3.3: Perceived strategic importance of AI over time in key Financial Services sectors



As seen in Figure 3.3, AI is currently perceived to be most important by Market Infrastructure and Professional Services organisations, with 62% stating that AI is 'high' or 'very high' importance. Organisations in the Investment Management and Deposits and Lending sectors exhibit similar numbers, while the current importance of AI to payment providers is notably low.

Around three quarters of respondents across all sectors expect AI to be of 'high' or 'very high' importance to their business in two years' time. AI is therefore expected to be of high importance to business transformation in the short term.

The relative increase in the importance of AI is highest in payment providers, with 72% anticipating a 'high' or 'very high' importance in two years compared to 23% currently. This increase may be attributable to the broader usage profile of AI in the sector compared to the Investment Management and Deposits and Lending sectors, as seen in Chapter 2. For instance, Payments ranked highest in implementing AI for process re-engineering and automation, while coming last in the adoption of AI for the generation of new revenue potential through new products/processes.

These findings suggest that current use cases, which are already automation-heavy, do not redefine the business models of payment providers. However, firms may perceive value propositions of AI in Payments which are more business-relevant in terms of generating revenue – and planning to implement these in the short term.

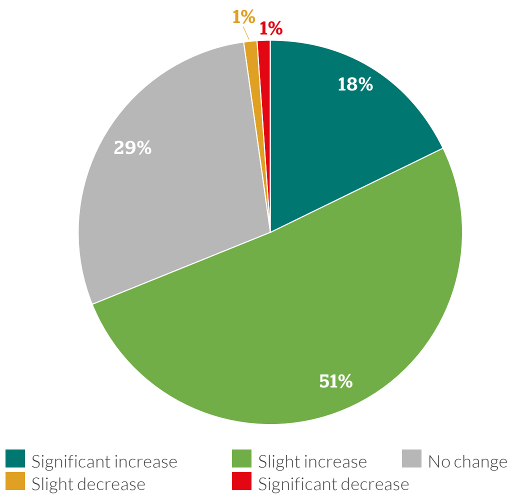
While AI currently appears to play a lesser role for investment managers compared to organisations in Deposits and Lending as well as Market Infrastructure and Professional Services, firms' perceptions imply that AI will become essential for most investment managers, with 82% expecting AI to be of 'high' or 'very high' importance within two years, and none expecting AI to less than 'moderately' relevant. However, it is evident that the proportion of those asserting a 'very high' importance does not increase from today to two years' time. This may suggest that while AI technology has come far, it still falls some way short of being able to replace human investment decision-making.

74% of firms active in Deposits and Lending anticipate AI to be of 'high' or 'very high' importance in two years, compared to a current figure of 43%. The rise in relevance of AI is underpinned by adoption statistics discussed in Chapter 2. These show that many organisations are still at a stage preceding AI implementation, especially in the generation of new revenue potential, customer acquisition, and process re-engineering and automation. However, more than 40% of respondents are either currently implementing or planning to implement AI in these domains within two years.

3.2 How AI Affects Existing Business Attributes

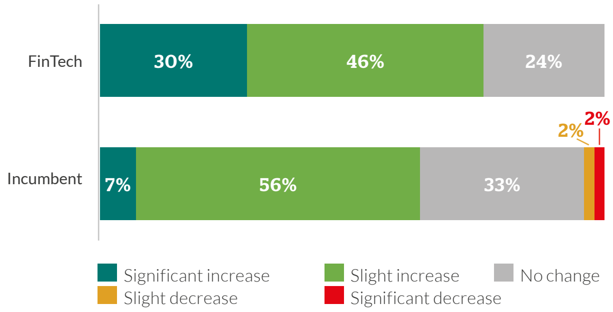
Judging from respondents' perceptions displayed in Figure 3.4, it can be observed that AI appears to largely exert a positive impact on organisations' profitability.

Figure 3.4: Perceived impact of AI on profitability



In total, over half of all respondents reported an AI-induced increase in profitability (although only 18% indicated a significant increase). Examining this together with R&D spending on AI reveals that 88% of all organisations which are spending more than 10% of their R&D on AI perceive increased profitability. Given that most organisations are still predominantly using AI to reduce cost and enhance existing products and services, rather than creating new value propositions (see Chapter 2), these results imply that AI presents a favourable investment opportunity. However, there is a strong difference in the perceived impact of AI on profitability between Incumbents and FinTechs (Figure 3.5) which demonstrates that that AI appears to have a higher impact on profitability for FinTechs than Incumbents. This finding also corresponds to the differing importance of AI to organisations, as set out in Section 3.1.

Figure 3.5: Perceived impact of AI on profitability by entity type



The perceived impact of AI on leanness among FinTechs and Incumbents is quite similar, as set out in Figure 3.6. However, there is a tangible gap in the perceived impact of product differentiation on FinTechs and Incumbents, with 46% of FinTechs indicating a significant increase compared with just 18% Incumbents. These findings are set out in Figure 3.7 and also correlate with FinTechs making higher use of AI to create new products and services (as per Section 3.3).

Whereas Incumbents do show strengths in applying AI to re-engineer processes and generate new insights through AI-enabled data analytics, these findings suggest that the more process-oriented AI strategy of Incumbents is less impactful compared to utilising AI to create new value propositions.

Figure 3.6: Perceived impact of AI on leanness by entity type

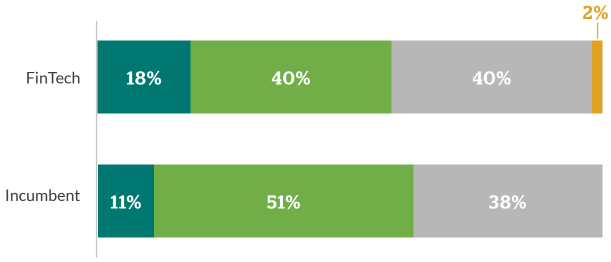
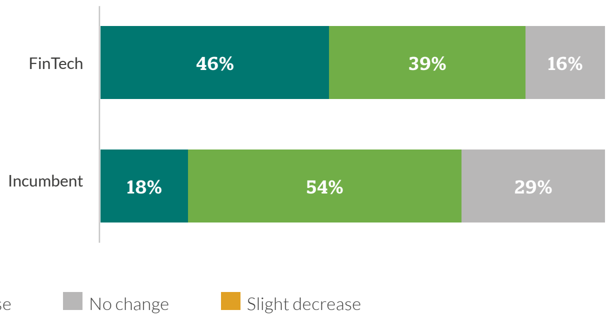


Figure 3.7: Perceived impact of AI on product differentiation by entity type



While significantly more *AI Leaders* than *Laggards* (38% vs. 10%) are shown to perceive AI to cause significant increases in product differentiation, the gap is almost nonexistent for AI-induced increases in leanness (19% vs. 20%) (Table 3.1). These findings imply that AI may only optimise operations to a certain extent and that scaling up AI across entire organisations might require creating new organisational infrastructure to oversee and manage AI, which might come at a significant upfront (complexity) cost and reduce leanness in the short term.

Table 3.1: Perceived impact on product differentiation and leanness *AI Leaders* and *Laggards*

	Proportion of respondents which reported significant AI-induced increases	
	Leaders	Laggards
Product differentiation	38%	10%
Leanness	19%	20%

These findings also pose the question of whether a proliferation of AI, especially in use cases which merely increase leanness and do not constitute new value propositions, could lead to eroding competitive benefits. For instance, more and more firms utilising AI to enhance the delivery (especially concerning speed and accuracy) of their services might lead to industry-wide increases in standards and, in turn, customer expectations.

3.3 Propelling Novel Business Value Through AI-Enabled B2B Offerings

Whereas previous sections have demonstrated how AI may boost prevalent business models by providing novel insights based on new or existing datasets, the survey further found that selling AI as a service is a distinct new value proposition for firms to successfully leverage AI in a B2B context.

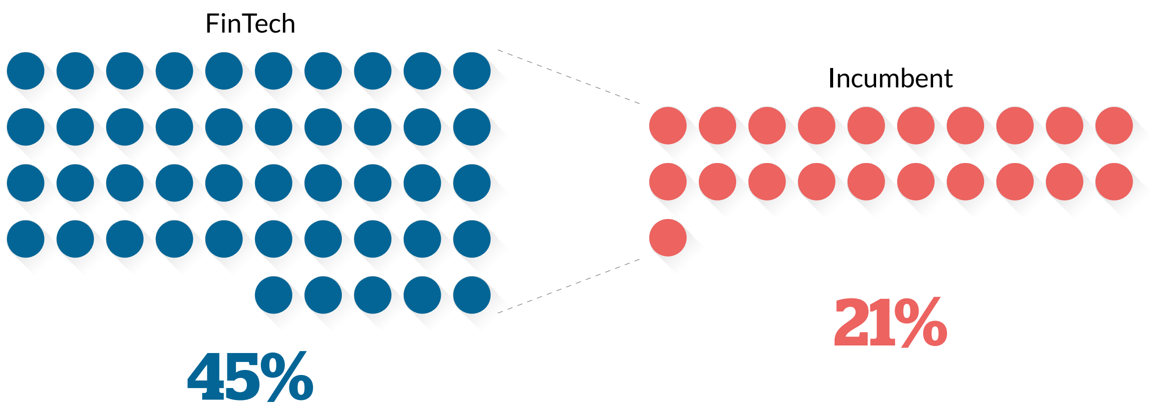
Selling AI as a service in this context is defined as selling pure AI capabilities (i.e., algorithms) or digital products and platforms which are partially or entirely based on AI, with most real-world examples representing the latter (McWaters *et al.*, 2018).

One of the key AI-related advantages which might lead organisations to consider selling AI as a service is the possibility to gain access to new datasets by gathering data from interactions with clients through multi-purpose digital platforms.

By amassing more datasets, in turn, organisations may be able to achieve two-fold economies of scale – in training AI on the one hand, and being able to service new business areas on the other. This, subsequently, propels organisations' capabilities to offer superior services to clients or even competitors, thus fostering the creation of unique selling points, forming a self-reinforcing cycle of business innovation (previously referred to as 'AI flywheel') based on and sustained by AI capabilities. The effort involved in creating and maintaining industry-wide platforms which harness massive datasets might favour firms which already possess significant experience as well as the infrastructure (e.g., data infrastructure as discussed in Chapter 3) necessary to operate different large-scale AI applications across their own businesses.

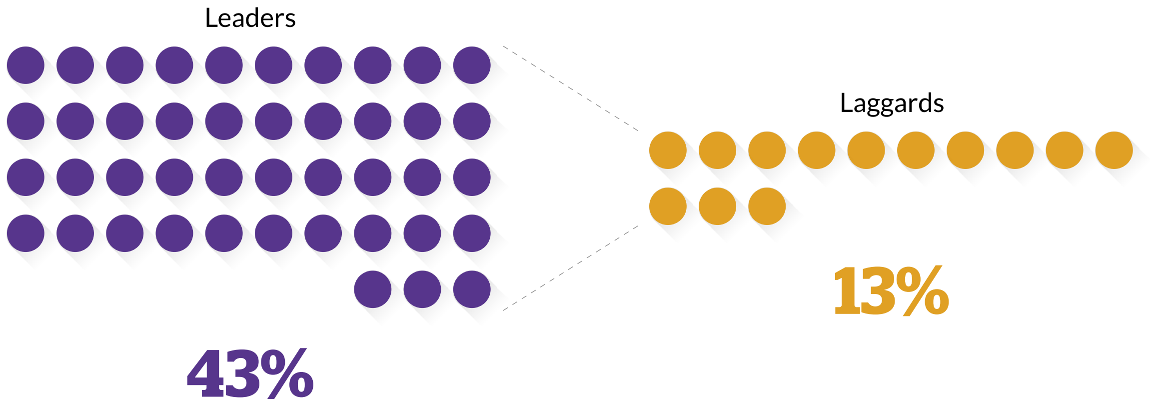
Findings demonstrate that selling AI as a service clearly differs across entity types, with significantly more FinTechs in the survey sample selling AI-enabled products as a service (45% vs. 21% Incumbents), correlating with the fact that FinTechs more frequently use AI to create new products while Incumbents largely use AI in existing products and services (Chapter 2, Figure 2.12).

Figure 3.8: Proportions of respondents selling AI as a service by entity type[9]



The practice of selling AI as a service is shared by *AI Leaders* at nearly equal proportions, while only 13% of *AI Laggards* sell AI as a service. This finding corroborates the hypothesis that the B2B perspective of AI usage represents a major business model innovation for firms which put AI at the core of their business and leverage their experience in utilising AI within their business to offer superior service platforms to other firms.

Figure 3.9: Proportion of *AI Leaders* and *Laggards* selling AI-enabled products as a service[10]



9 Excluding B2B-only companies

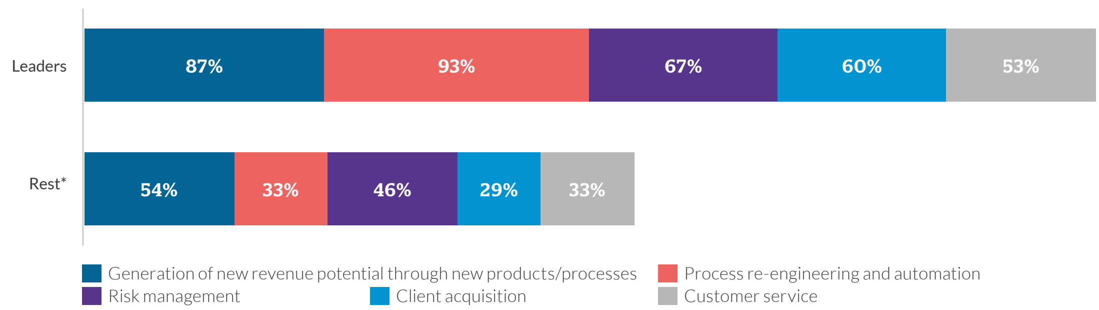
10 *Ibid*

While there are several other aspects than data and product scale involved in the dynamic described above, one of the most important ones – especially concerning the hurdles presented in Section 3 – is that organisations which manage to create these 'AI flywheels' may find it easier to attract top talent. However, results from the survey show that the difference in perception is marginal – with 72% of all organisations selling AI as a service rating access to talent as a hurdle to AI implementation against 84% overall. This might indicate that while more B2B-focused companies might have a slight advantage in attracting talent, financial service institutions might still be in the early stages of being able to build significant economies of scale from selling AI as a service.

Nonetheless, examples from 'Big Tech' companies such as Google and Facebook demonstrate how early adopters might be able to use this 'snowball effect' to outpace their competition by making clients (and competitors) dependent on their datasets and/or services through building ubiquitous digital platforms.

Figure 3.10 illustrates that generating new revenue potential is the most frequently represented area for which AI is sold as a service overall, with *AI Leaders* significantly ahead of the rest in selling AI-enabled solutions for process re-engineering and automation. It is further notable how far *AI Leaders* are ahead in selling AI-enabled products for multiple purposes, pointing towards the construction of platforms which distribute and manage an entire portfolio of digital products and services which harness AI capabilities.

Figure 3.10: Business domains for which AI is sold as a service



**AI Laggard sample size proved to be insufficient to be explicitly included for comparison in this split*

EXAMPLES

- **Acorn machine**
  OakNorth's ACORN Machine harnesses alternative datasets to create customised loans for SMEs. Having originated £800 million worth of loans in two years, they are offering their technology as a service to other lenders.
- **Ping An**
  Ping An's OneConnect is a universal technology platform, leveraging AI, Blockchain and capabilities for Big Data Analytics in various products which are offered as a service to financial institutions of different sizes in China. So far, the platform has amassed a client base spanning more than 600 banks and 3000 other financial institutions.
- **Neocova**
  Neocova provides a cloud-based core banking system for community banks and credit unions, incorporating AI in various applications, such as AML.
- **BlackRock**
  BlackRock's platform Aladdin offers 'Collective Intelligence', encompassing a range of services for risk management, portfolio management, investment operations, and trade execution to a variety of financial service providers. In 2019, the platform was reportedly managing $17tn in assets on aggregate (BlackRock, 2019).

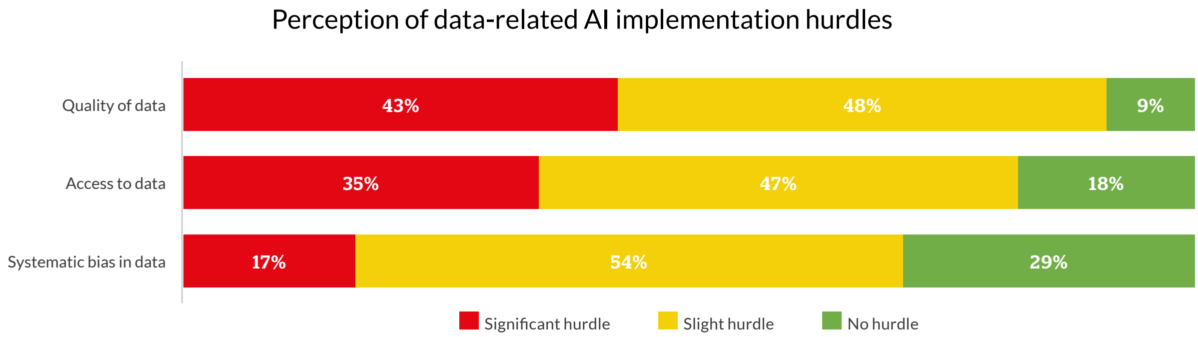
4. Hurdles to AI Implementation

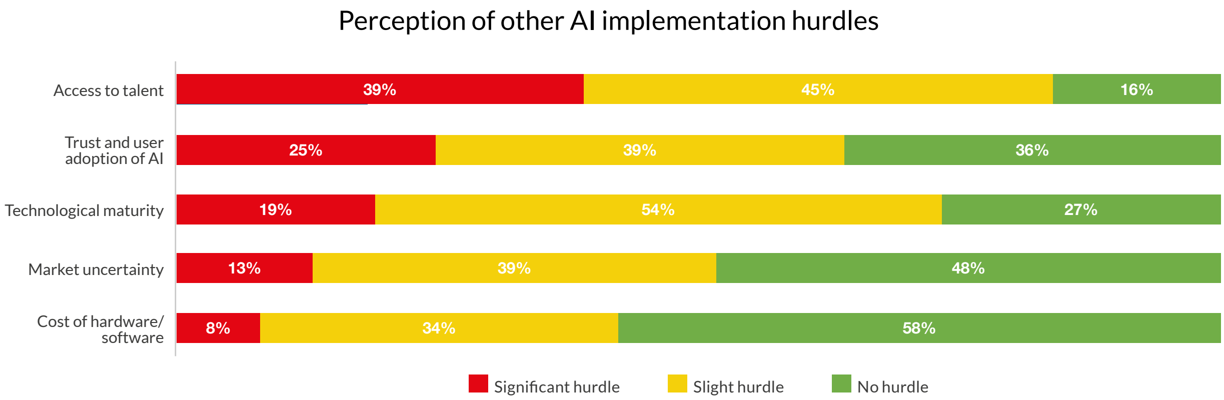
- Data fuels AI and allow firms to scale their AI applications. Access to and quality of data remain key hurdles to AI implementation across all respondents, as does access to talent.
- Issues with data quality may imply costly processing steps or, in the worst case, unusable datasets while access to data might be limited by organisations lacking infrastructure for collection, storage, and transfer.
- Access to talent appears to be the most important hindrance for *AI Leaders* which implies that more sophisticated AI solutions demand different employee capabilities.
- Investment managers struggle most with access to data, likely attributable to their overall data-heavy usage profile. Payment providers generally show little concern about hurdles, correlating with the fact that most of them are not yet using AI as a core value proposition and may not be aware of potential obstacles to AI implementation
- While issues surrounding the explainability of AI are currently perceived to be less of a hindrance than other hurdles, these problems may become more apparent as adoption increases and firms overcome initial obstacles to implementation.

Chapter 4: Hurdles to AI Implementation

4.1 Overall Implementation Hurdles

Figure 4.1: Hurdles to AI implementation by respondents' perceptions





Survey results displayed in Figure 4.1 demonstrate that quality of data, access to data, and access to talent represent key obstacles, while the cost of hard- or software, as well as market uncertainty, seem lesser impediments.

Quality of data

Machine learning algorithms learn iteratively and have a hard time extrapolating outside the range of their input data. Therefore, attaining large, high-quality datasets may pose a significant challenge to any entity seeking to adopt AI. Indeed, as shown in Figure 4.1, 91% of respondents consider data quality issues to be a hurdle to AI implementation. Data quality itself can be divided into multiple issues which complicate the successful training of AI systems:

- Collected data, especially text, visual or sound data, may be lacking in structure. Such data usually requires a significant amount of human input to annotate.
- Data may be high-dimensional, which typically applies to text that may contain thousands of unique words which may each be interpreted as one input dimension. Utilising these sparse, high-dimensional datasets in training machine learning algorithms may hinder models to spot meaningful patterns in the data. However, there are unsupervised machine learning techniques which address the issue of high dimensionality. For instance, Word2Vec represents words as a vector of user-defined length, thus reducing input dimensionality from the size of the vocabulary to a user-

defined number (Mikolov *et al*, 2013).

- Another factor is data noise[11], for which resulting difficulties correlate – to some extent – with dataset sizes. Depending on its level, noise may slow down training or even prevent the convergence of certain AI techniques, especially for small datasets, this making additional steps in data pre-processing necessary.
- Missing data points may also represent a major hindrance to the usability of data, especially if gaps are non-random (in case of randomness, there exist simple heuristics for filling gaps). With increases in data volume, dealing with missing data in machine learning problems has become an active research field of its own (Marlin, 2008).
- Another aspect is class balance, encompassing cases where one class within a dataset contains significantly more instances than another, especially relating to datasets for classification. A simple example would be a supervised classification task of credit defaults using a neural network. Given a set of inputs (i.e. a set of features representing an individual client), the network would be trained on outputs indicating whether the client defaulted or not. However, datasets will typically contain a significantly higher number of positive examples (in this case, no default), which leave very few adverse examples for the algorithm to train on. This may lead to distorted results in practice.

Access to data

Access to data, which respondents consider an almost equally significant hurdle as data quality, may be limited by cost barriers (for instance, high-frequency limit order book datasets which may easily span millions of timestamps per day) as well as general availability.

Some datasets must be collected by entities themselves if there is no reference in the public domain, however, this may be arduous for organisations which do not have the necessary infrastructure. Pre-processing and de-noising may represent a challenge for internal data collection, as public datasets, especially from chargeable sources, often already provide these steps as a service. Disparate internal infrastructure may pose additional challenges – especially in incumbent firms with a history of semi-completed post-merger integrations which leave silos and pipelines disconnected.

On the other hand, the collection of internal data can benefit those organisations which do possess the right infrastructure, as the origin and generating process of data is known as opposed to external data. Consequently, these firms may be able to capitalise on smoother data pipelines, free from unpredictable external influences.

Access to talent

Survey findings also show that sourcing suitable talent in AI remains one of the most significant overall hurdles, with 84% indicating it to be an obstacle to AI implementation. This reflects findings from a 2018 report by Baker McKenzie which stated that 38% of respondents to their study found that the shortage of specialist skills concerning AI technology was the most significant obstacle to implementation (Bschor, Budworth and Boston, 2018).

With increasing adoption, the competition for AI experts is beginning to involve a greater range of entities and geographies. First and foremost, future financial institutions will likely face fierce competition of 'Big Tech' firms. Most financial institutions would be disadvantaged in such comparison – especially those incumbents which remain stolid in their pace of implementation due to legacy infrastructure and technology. A possible – yet expensive – solution to this problem might indeed be the creation of spin-off research labs, also explored in Chapter 3, which provide the technology-focused culture and corporate agility necessary to provide an agreeable environment for AI talent.

11 In this case, referring to random perturbances in data

In light of a progressing war for AI talent, the question of whether this development can be sustainable for academia is apparent. An article in Nature in 2016 stated that the 'talent grab' by firms like Google was raising concerns about whether attracting researchers straight out of academia with high salaries might destroy its foundation, by removing these academics from where they can supervise PhD students (Gibney, 2016).

Explainability

Explainability in AI has been a recurring research topic which has picked up traction both in academia and industrial research (Information Commissioner's Office, 2019). Many algorithms which form part of AI exhibit a so-called 'black-box' characteristic – meaning that it is very difficult or impossible to explain a model's results by its inputs. While several approaches to solve this issue have been explored, ranging from game-theory based solutions (Lundberg and Lee, 2017) to local model approximations (Ribeiro, Singh and Guestrin, 2016), a widely applicable, scalable approach which is independent of model complexity is yet to be found.

In this study, the issue of explainability is split into two main factors:

- Trust and user adoption of AI
- Regulatory requirements concerning the explainability of AI-supported decisions (addressed in Chapter 7)

Figure 4.1 shows that 64% of respondents perceive deficits in trust and user adoption to be a major hindrance to AI adoption. However, combined figures (not shown in the chart) show that 84% of respondents feel impeded by any of the two abovementioned explainability shortcomings.

Moreover, explainability appears to be a late-lifecycle hurdle, with 91% of *AI Leaders* indicating concerns from either the user/trust-oriented or regulatory perspective, against 78% *AI Laggards*. As it may be unfeasible to start constructing AI systems without high-quality datasets, many firms might not have yet been confronted with problems which revolve around understanding or interpreting AI systems.

4.2 Hurdles for *AI Leaders* and *Laggards*

Figure 4.2: Select AI implementation hurdles by maturity of AI adoption

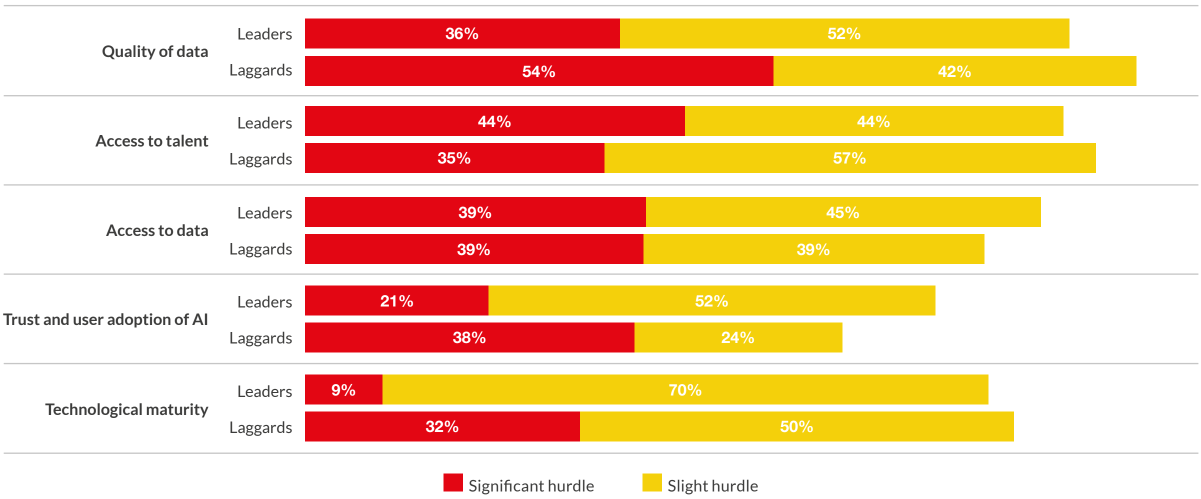


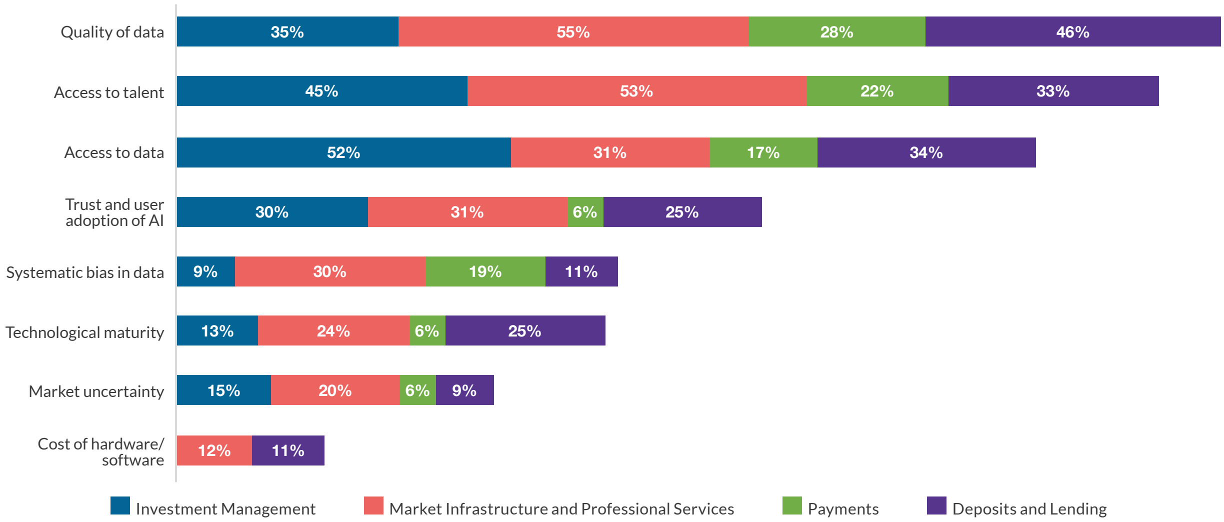
Figure 4.2, which displays the five most significant implementation hurdles for *AI Leaders* and *Laggards*, reveals an interesting picture: While *AI Laggards* show higher indications of hurdles being significant, fewer *Leaders* indicate certain factors to be no hindrance to their implementation of AI.

An explanation for this finding might be that *AI Leaders* are using more sophisticated machine learning algorithms to power more complex use cases. This may lead to increased requirements for engineers, as well as bringing together two broader profile types: those with varied STEM backgrounds which may only be able to use high-level machine learning libraries, and those with specialised research degrees which are capable of building tailored, modular solutions or even create fundamentally new solutions altogether.

The fact that data quality appears to be a more material issue for *AI Laggards* (54% indicated it to be a significant hurdle compared to 36% of *AI Leaders*) may seem surprising, given that *Leaders* are likely to use a significantly larger and more diverse range of datasets and might thus be exposed to higher variability of data quality. However, this could indicate that *AI Leaders* who operate a larger variety of machine learning solutions may on average also possess more means to overcome quality issues in data, such as specialised data engineering teams.

4.3 Hurdles Across Financial Services Sectors

Figure 4.3: AI implementation hurdles by sector



While hurdles are perceived similarly by FinTechs and Incumbents (and are not explicitly displayed as a consequence), significant differences in perception can be observed between different Financial Services sectors, as shown in Figure 4.3.

In general, Market Infrastructure and Professional Services firms appear to be most hindered in their implementation of AI, most notably by the quality of data, which 55% perceive to be a significant hurdle. This may relate to the fact that most of these firms captured in the survey sample are FinTechs selling data-intensive B2B software solutions. Operating these may yield datasets originating from clients with relative ease (accordingly, only 31% of Market Infrastructure and Professional Services firms feel impeded by lacking access to data); however, this data may exhibit shortcomings in quality due to heterogeneous origins.

Conversely, payment providers do not seem widely impeded in their AI implementation. This may be because prevalent hurdles, especially data-related ones, may be less relevant to payment providers' usage profiles which are primarily geared towards harnessing AI in automation, as opposed to creating new value propositions (as shown in Chapters 2 and 3).

For investment managers, access to data represents the largest hurdle, with 52% stating it to be a significant obstacle to AI implementation. This may be attributable to the fact that their most frequently used AI applications are remarkably data-centric, especially AI-enabled data analytics, and using new or alternative forms of data. Trust and user adoption are also shown to be a higher hindrance to investment managers compared to other financial service firms, potentially as investment managers' clients may be especially sensitive to issues surrounding algorithmic explainability.

Companies active in Deposits and Lending are shown to be similarly impeded by issues revolving around data. They are also more hindered by technological maturity than other sectors, which 25% deem an obstacle.

4.4 Management Teams' Understanding of AI

In addition to the questions discussed in the previous subsections, the survey also included a free text option at the end. There, respondents could share give their opinion on AI-related aspects which they felt their senior management needed to understand better given their organisations' future AI ambitions.

The subject voiced most often – especially by banks – proved to be the prevailing uncertainty around the value proposition of AI. Respondents commented on the importance of identifying AI-driven business cases with attractive Return on Investment (ROI), as well as communicating the potential of AI and enabling factors to senior management.

"The impact/value proposition of AI is underestimated. Funding of AI initiatives is too low to be able to prove the value of AI to the business (...)."

– Senior executive at a multinational investment- and retail bank

This snapshot reveals the prevalent uncertainty around AI, especially in incumbent firms. This uncertainty could stem from convoluted corporate structures which inhibit the dissemination of information, meaning Incumbents must establish leaner communication channels with key technology decision-makers, as well as potentially creating new roles geared towards technology for higher executive levels.

Respondents also frequently noted the lack of space and resources for AI experimentation. Several participants stated they believed that their company should allow the use of open-source software, offer a sound methodology for developing and testing AI-enabled solutions, and build platforms for model construction and implementation. These concerns reinforce the abovementioned need for technology-oriented roles in senior management, as well as pointing towards the importance of AI sandboxes. As these points were exclusively remarked by Incumbents, they might also provide a clear rationale for creating spin-off entities to establishing less hierarchical and more agile environments, which are more conducive to AI development and testing.

5. Market-Wide Implications of AI Implementation

- In summary, it is clear that the adoption of AI will bring with it some profound changes to Financial Services. Whilst the technology may drive more job growth in FinTechs, this will be dwarfed by the reduction of jobs in operations and other areas of Financial Services, with an overall 9% anticipated 10-year job reduction in Incumbents, but over 20% in some industry segments.
- Whilst AI facilitates new and innovative propositions, especially as a core of many FinTechs' propositions, the impact on the overall competitive landscape is not expected to be very significant.
- However, the way that AI technology could be deployed by 'Big Tech' firms, who are in many ways a leading source of AI innovation, is causing great concern amongst Incumbents. Concerns are particularly pronounced in China and the UK while being less prevalent in the US.

Chapter 5: Market-Wide Implications of AI Implementation

5.1 The Impact on Jobs

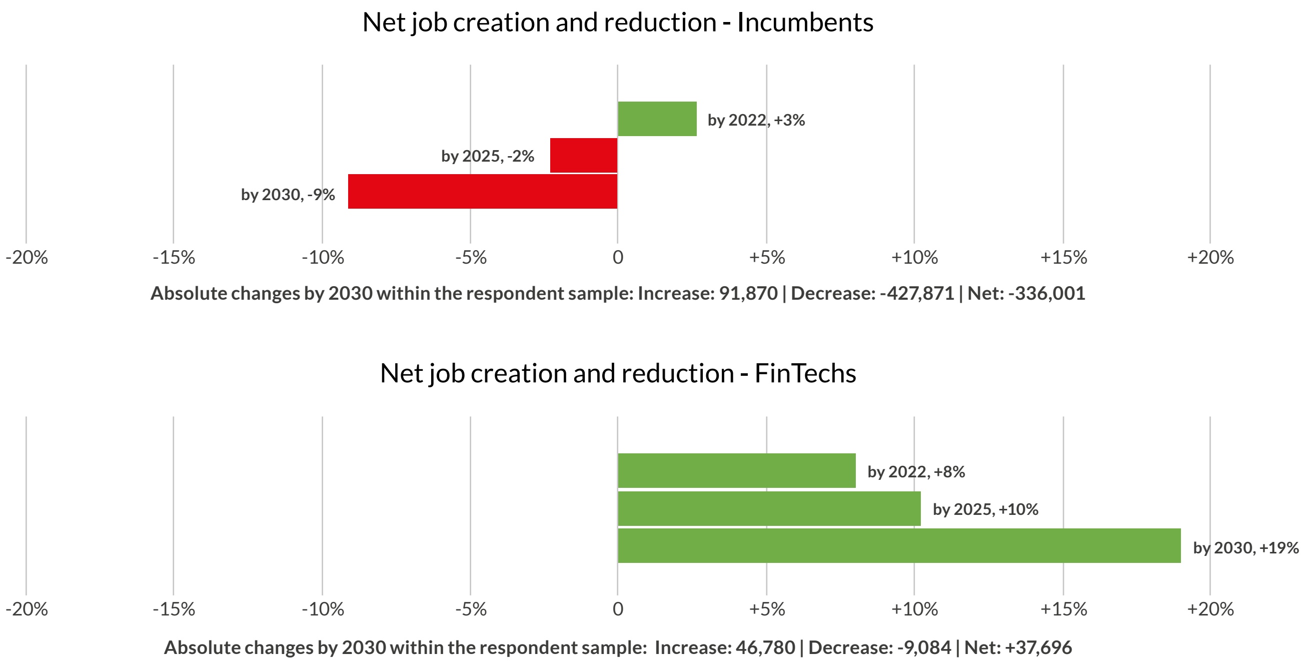
The impact of AI on employment has been much heralded across all industries. One study estimates that over 25% of jobs are at risk due to automation and AI by the end of the 2020s, tailing off thereafter (Hawksworth and Berriman, 2018). The Financial Services sector is expected to be one of those most impacted in the near future. The employment impact of automation and AI on Financial Services is expected to be the greatest of all industries into the late 2020s, with only the transport industry experiencing greater impact in the long term (Hawksworth and Berriman, 2018).

The World Economic Forum has estimated that by 2027, 23% of the jobs in China's financial sector will either be removed by AI or will be transformed into new positions. The Forum asserts that the remaining 77% of jobs will not be replaced, but the efficiency of these positions will increase, with about 2.3 million people being affected by the impact of AI, that is 23% of the total workforce in the financial sector (He and Guo, 2018).

Given the large numbers of people employed within Financial Services in labour-intensive tasks in back-office functions, it is perhaps unsurprising that the impact of automation and AI will be large, and has already commenced in many areas.

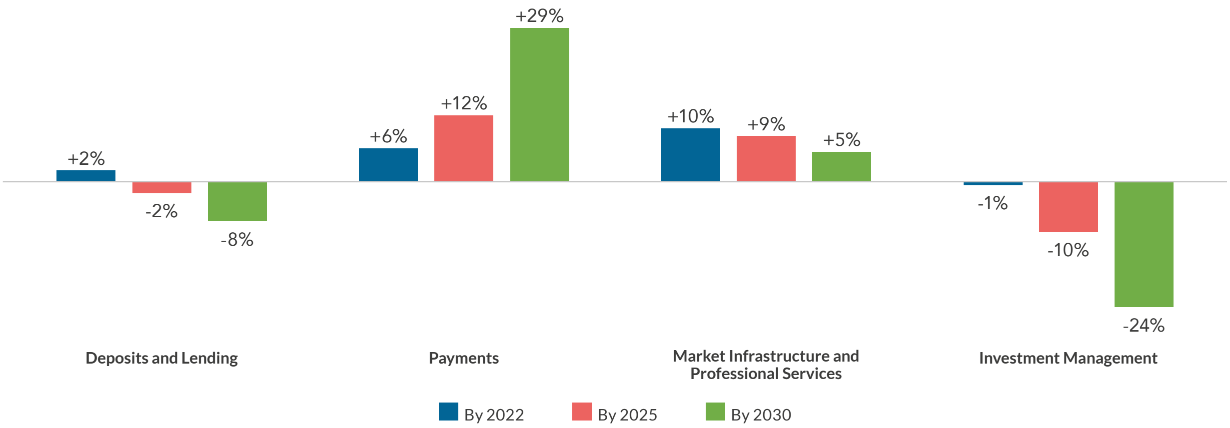
Notwithstanding, the survey indicates that fears on the extent of potential job losses may be exaggerated. Rather than the estimated over 20% of jobs at risk highlighted further above, survey responses received across all Financial Services sectors indicate a more modest 9% replacement of jobs by AI technology by 2030 (Figure 5.1). This loss of employment is offset to an extent by the creation of new jobs facilitated by AI deployment within FinTechs, where workforces are expected to grow by 20% as a result of increasing AI adoption.

Figure 5.1: Anticipated AI-induced net job changes in Incumbents



Of course, not all areas of Financial Services will be impacted equally by AI. For example, survey results show that over 23% of jobs could disappear in Investment Management by 2030, which is more in line with some of the other analyses referred to above. However, the impact on other financial sectors is estimated to be less significant, as can be seen in Figure 5.2 below. The net job creation in the Payments sector may be attributable to the fact that most payment providers in the survey sample were FinTechs.

Figure 5.2: Anticipated AI-induced net job changes in FinTechs

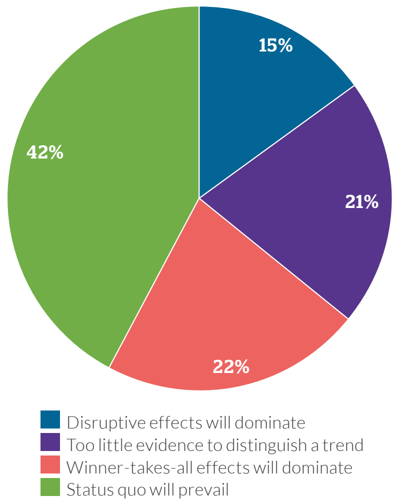


In summary, whilst exact quantification on the influence of AI on employment is challenging, it is clear that jobs will be impacted. This is especially the case in those financial sectors prone to repetitive manual tasks. It should also be noted that AI will potentially have an even bigger impact on the content of many jobs than the top-line employment numbers imply. An illustrative example of this IBM's Watson being used to handle routine emails at Credit Mutuel - AI handles 50% of the 350,000 emails received by the bank every day (IBM, 2019)

5.2 The Potential for Competitive Disruption

AI represents a significant innovation with the potential to disrupt Incumbents and their value propositions. FinTechs, in particular, have developed platforms using AI to provide more effective credit analytics, customer service propositions and robo-investing capability. However, the results of this survey suggest that participants believe that AI will not be as disruptive as is popularly theorised. This view is shared by Incumbents and FinTechs alike. Figure 5.3 below illustrates that 42% of respondents believe that the current status quo will prevail.

Figure 5.3: Expected influence of AI on the competitive environmentcompetitive dynamics within Financial Services



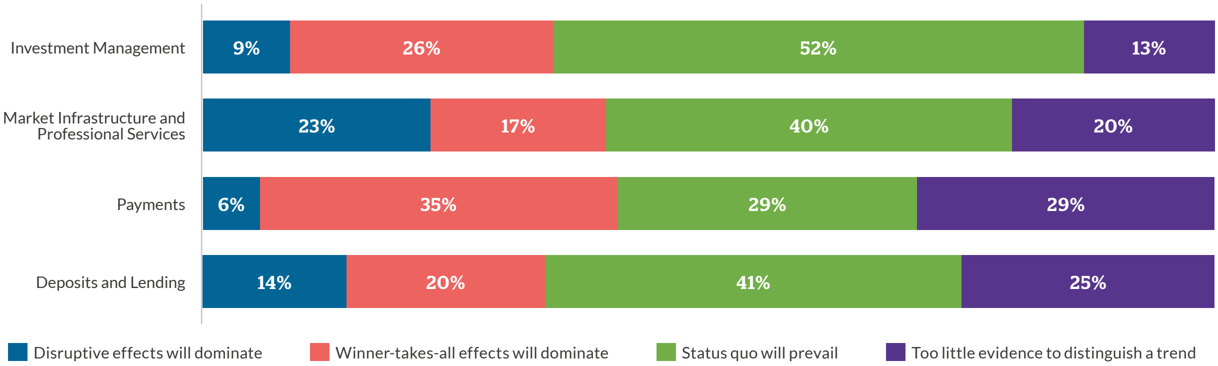
However, when seen through the lens of *AI Leaders* vs. *AI Laggards*, it is clearly visible that *AI Leaders* are certainly ambitious on their ability to disrupt Financial Services. Over 20% of *AI Leaders* believe that they will be able to further disrupt the sector.

The survey also examined which Financial Services sectors were most likely to be disrupted by AI, as set out in Figure 5.4 below. Perhaps surprisingly, participants felt that Market Infrastructure and Professional Services is the sector most likely to be disrupted. This may be related to the perceived impact of AI Financial Market Infrastructure use cases such as:

- Market surveillance
- AI-based market utilities, such as for meeting KYC requirements
- The use of AI in front line trading innovation (e.g. quant investing)

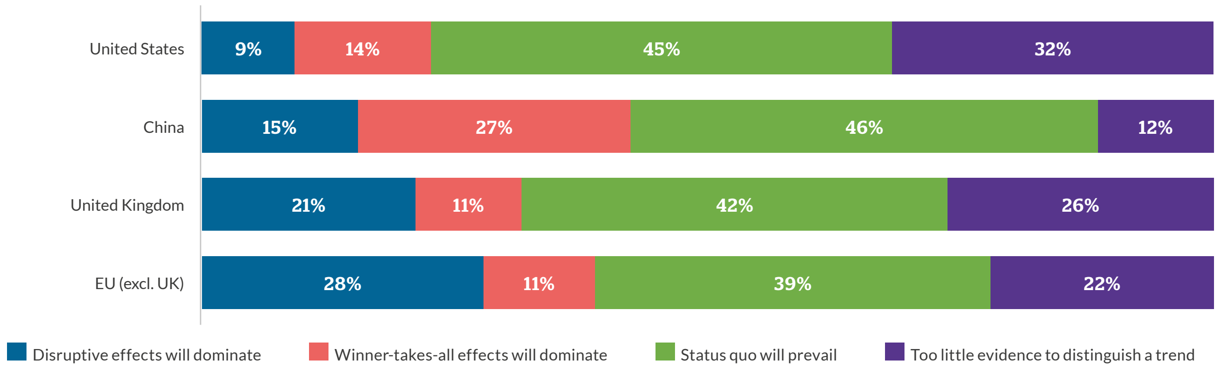
The impact on Professional Services is most likely attributable to lower level contracting services being replaced by automation, as referred to (see Chapter 2).

Figure 5.4: Expected influence of AI on competitive dynamics by sector



Examining the results by jurisdiction, EU-based firms had much higher expectations of disruption than US and Chinese firms, where greater consolidation was expected (Figure 5.5). This might be explained by the strong emphasis on promoting competition in Financial Services in many EU markets and by the EU itself (European Commission, 2015).

Figure 5.5: Expected influence of AI on competitive dynamics by region

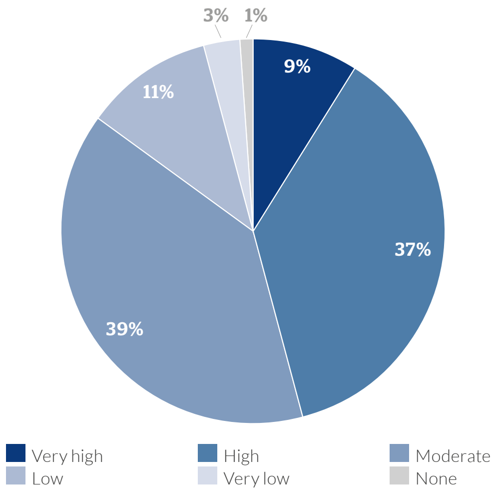


5.3 The Impact of 'Big Tech'

The survey found that nearly half of all participants regarded the entry of 'Big Tech' firms into Financial Services as a major competitive threat, as seen in Figure 5.6 below. Large Chinese players such as Ant Financial and Tencent have already had a huge impact on the domestic Chinese market. There are also multiple examples of 'Big Tech' and similar firms entering the Financial Services industry, for example:

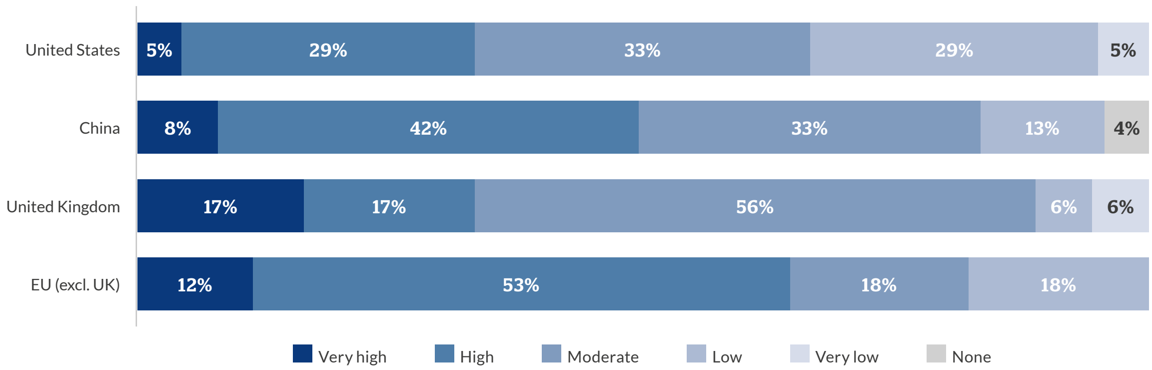
- Facebook's announcement of Libra to facilitate payments and promote financial inclusion (Libra, 2019).
- Uber setting up a financial services division (Son, 2019).
- The ongoing development of financial service offerings from Amazon, such as payments (Pay With Amazon) and SME Lending, where Amazon has already issued $3bn in loans (CBInsights [1], 2019).

Figure 5.6: Overall perceived AI-induced competitive threat of 'Big Tech'



'Big Tech' leveraging AI to enter the Financial Services is most frequently perceived to be a competitive threat by firms which are based in the EU (excluding the UK) and China[12], where 65% and 50% respectively of respondents feel that the threat is 'high' or 'very high'. This is perhaps unsurprising given the market impact to date by Chinese TechFins, and the sensitivity of 'Big Tech' approaches to competition and data privacy (CBInsights [2], 2019) in the EU. It is also notable that the UK has the highest number of respondents perceived a 'very high' perceived competitive threat. This can be seen in Figure 5.7 below.

Figure 5.7: Perceived AI-induced competitive threat of 'Big Tech' in major jurisdictions



12 Taking into account the four jurisdictions with the largest sample sizes

6. AI as a Risk Driver in Financial Services

- Firms believe that mass AI adoption will introduce significant risks, most notably in relation to data privacy and discrimination. At least one quarter of firms do not believe they are well placed to mitigate those risks.
- Firms' assessments of the risks related to mass AI adoption are influenced by whether they see AI as a consolidating or a disruptive force. Firms anticipating consolidation see AI creating industry-wide points of failure; firms expecting disruption focus on threats to market function, the pricing of assets and risks.
- There is a persistent gap between the expected market-level impact of AI adoption on risk and the impacts firms perceive today. The latter are generally modest and AI emerges as a net mitigant of risk much of the time.
- This perception gap cannot be dismissed as simply due to ignorance or bias. It is prevalent regardless of firms' experience or resources. Firms likely anticipate emergent risks under mass adoption that are not applicable today.
- Regulation, and the involvement of Risk and Compliance teams in AI implementation, both provide important assurances to firms, but might also risk creating blind spots – causing firms to prioritise risks that are explicitly regulated over those that are not.
- While risk management is the most common domain for the application of AI within firms, it is not clear whether firms employing this have yet seen any better outcomes than their competitors.

Key Findings

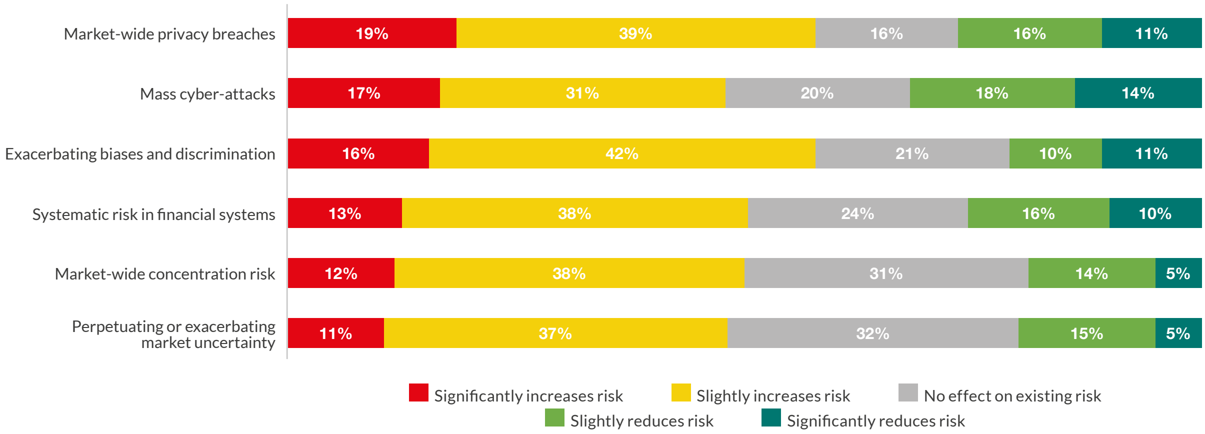
Chapter 6: AI as a Risk Driver in Financial Services

6.1 The Risk Landscape in an AI-Enabled Industry

To better understand how AI adoption interacts with the risk environment of financial service providers, the survey asked respondents to rate the contribution of AI implementation to a range of risks. These risks included both current organisational level risks, as well as potential market level risks once a *mass adoption* scenario has been reached- which might for some industries be only a distant one. These included privacy breaches, cyber-attacks, concentration risk, exacerbated biases and discrimination, weakening of service accountability mechanisms, and systemic risk in financial markets.

Firms expect mass AI adoption to be a significant net contributor to market-wide risks. As illustrated in Figure 6.1, between 48% and 58%[13] of all respondents believe that mass AI adoption would exacerbate market-level risks, while 19% to 32% believe that on balance it would reduce them. Respondents were particularly concerned about the prospect of AI applications resulting in systemic data breaches and entrenched bias in algorithmic decision-making: each was cited by 58% of firms as a domain where AI is likely, on balance, to have a negative impact. However, the way in which firms understand the risks of AI mass adoption depends on how far along they are in their own implementation journeys and what they think the AI adoption endgame across their industries will look like.

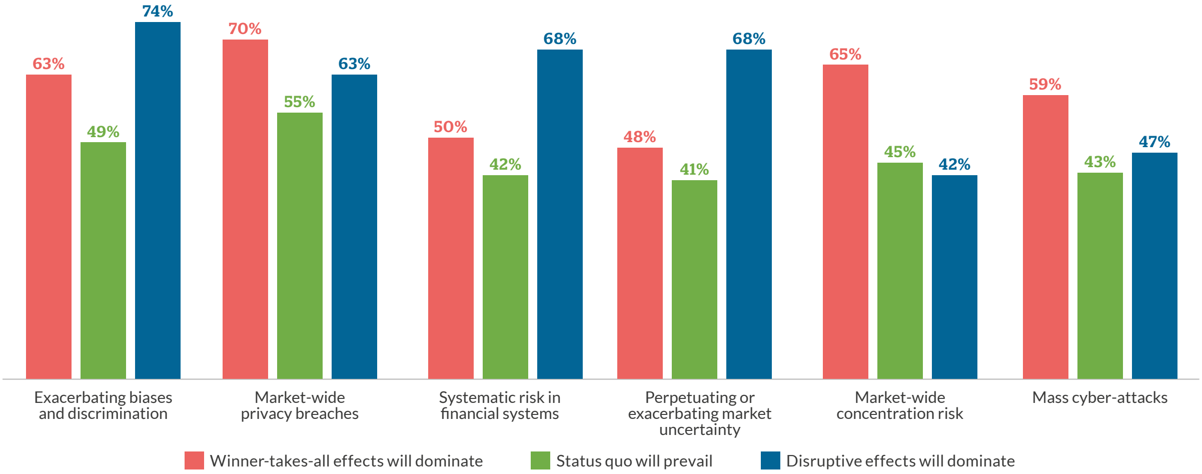
Figure 6.1: Perceived influence of AI mass adoption on market-wide risks



As Figure 6.2 demonstrates, there are crucial differences in perception between those who see AI as an ultimately consolidating influence on the industry and those who see it as a primarily disruptive one. Those who see consolidation as the prevailing force tend to worry more about the emergence of shared operational vulnerabilities and high-impact points of failure for the Financial Services industry, such as mass data and cyber-security breaches or over-exposure to a small number of vendors. Those who, on the other hand, see disruption as the prevailing force, tend to focus on threats to the market's ability to accurately understand and price risks, such as market uncertainty, biases and systemic risks.

13 The ranges reported in this section relate to the multiple types of risks respondents were prompted with (see e.g. Figure 6.1.). The top end of each range represents the most-cited risk, and the lower end of each range represents the least-cited risk.

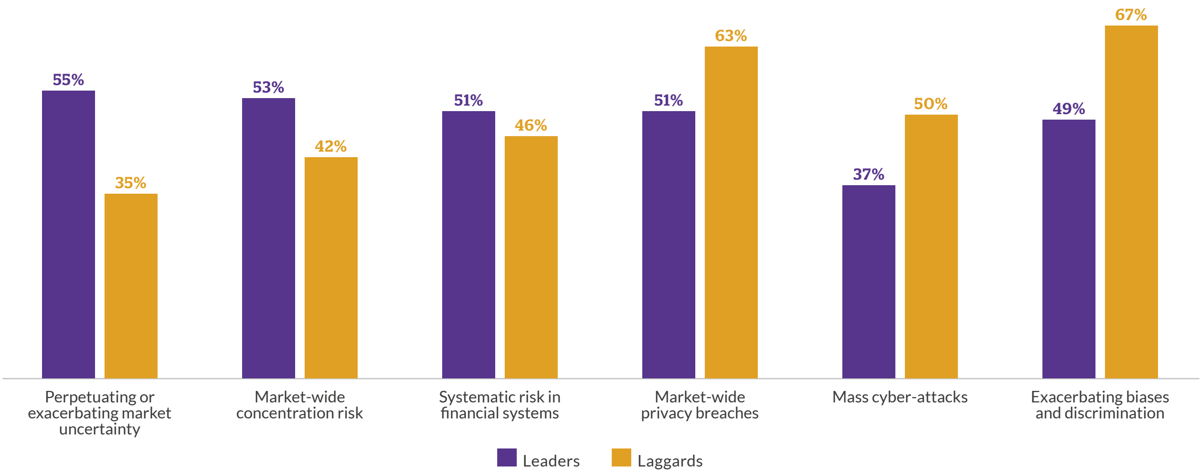
Figure 6.2: Percentage of firms expecting AI mass adoption to increase market-wide risks, by firms' perception of the competitive impact of AI adoption..



The views of *AI Leaders* and *Laggards* also differ but do so along a different axis (Figure 6.3). *AI Laggards* tend to be more concerned with customer-facing or conduct issues, such as biased algorithmic processing or data security breaches. These issues are driven by the way in which data is managed and processed, and might threaten the ongoing acceptance of AI. *AI Leaders*, on the other hand, are more concerned about risks to market function – such as competitive distortions and heightened uncertainty.

There is less evidence of contrasting views between FinTechs and Incumbents. Large FinTech firms and large Incumbents, in particular, have very similar views of the risks from mass AI adoption, perhaps reflecting their emphasis on serving mass-market retail customers at tight margins.

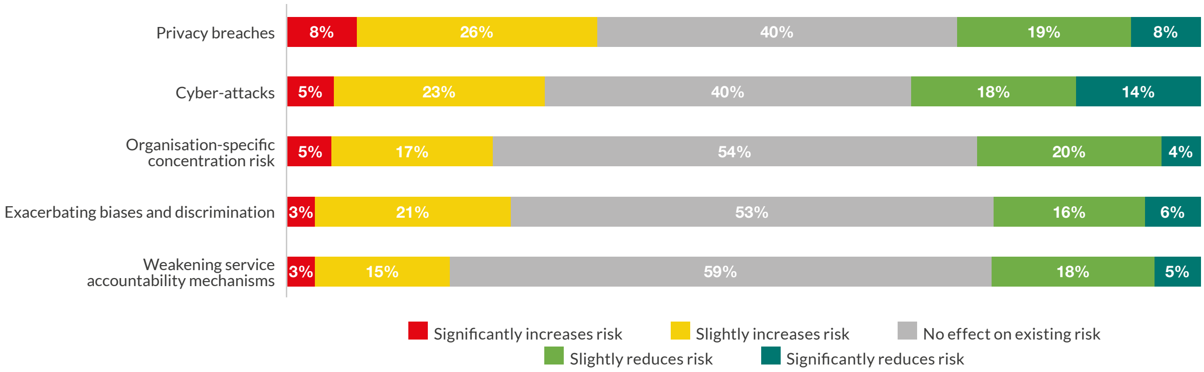
Figure 6.3: Percentage of *AI Leaders* and *Laggards* expecting mass AI adoption to increase market-wide risks



6.2 Reconciling the Market- and Firm-Level Risk Outlook

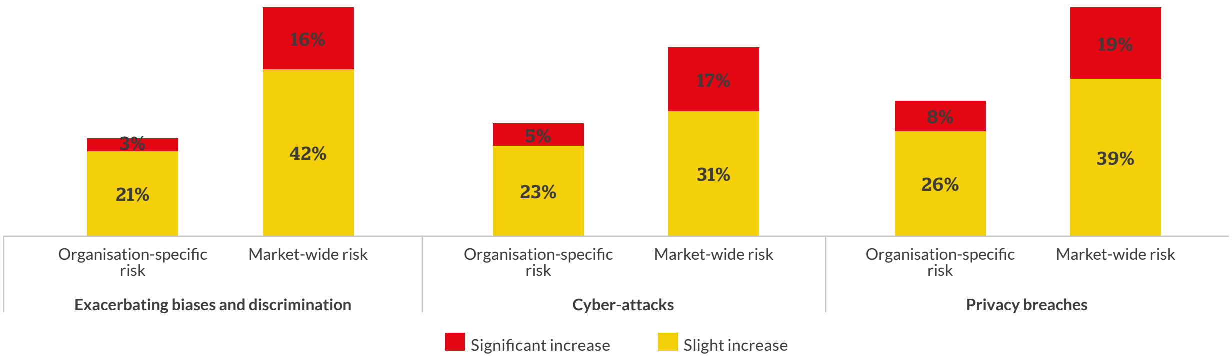
Even though firms expect that mass AI adoption will significantly increase risk at the market level, they see little evidence of this currently happening in their own organisations. As Figure 6.4 shows, firms see today's levels of AI implementation as making only a modest contribution to risk: 18% to 34% anticipate a net negative impact, while 23% to 32% anticipate a net positive one.[14] Barring potential data breaches, none of the potential risks listed was seen by a significant majority as being exacerbated by current levels of AI implementation. In contrast, organisational cyber-security and -resilience was seen as likely to be strengthened by implementing AI, presumably in risk management (see Section 6.3).

Figure 6.4: Perceived influence of AI implementation on organisation-specific risks



Where market-wide risks emerging from mass adoption and firm-specific risks emerging from AI implementation were directly comparable (Figure 6.5) the current firm-level impacts of AI were consistently much more benign than the expected impacts of mass AI adoption on market-wide risks. For example, only 24% of firms anticipated that AI implementation would exacerbate biases within their organisations, but 58% anticipated that mass adoption would lead to this effect across the market.

Figure 6.5: Expected AI-induced increases in comparable organisation-specific and market-wide risks



There is, therefore, an important disconnect between the firm-specific risks of AI implementation and the market-wide risks of mass adoption as reported by firms, and it requires explanation.

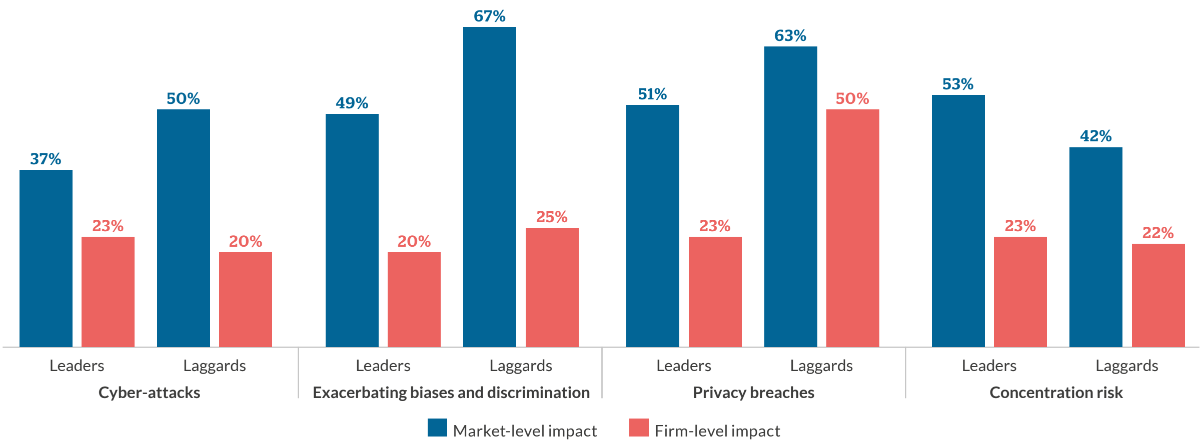
This perception gap might be driven by self-serving bias, i.e. respondents may be overconfident or defensive about their own organisations' ability to handle AI-related risks in the medium term. They might also have clearer

14 These ranges describe responses relating to multiple types of risk.

insights on some types of risks than on others – leaving potential blind spots. Alternatively, the gap might reflect emergent risks that are unique to a mass adoption scenario and cannot be simply extrapolated from risks observed at the firm level. Each of these hypotheses has very different implications that can be tested against survey findings.

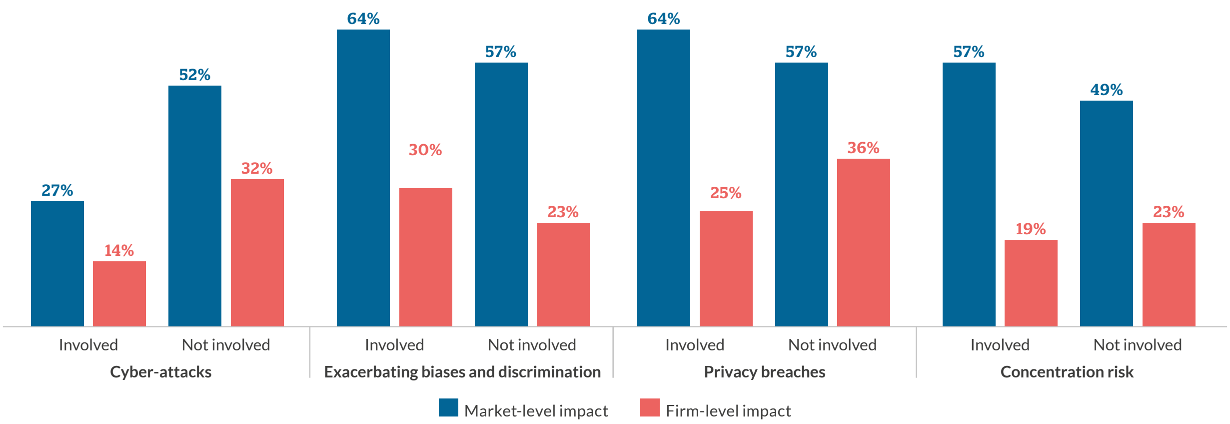
As Figure 6.6 shows, differences in knowledge and expertise cannot explain a significant proportion of the perceptions gap. When expectations are averaged across all types of risks with which respondents were prompted, *AI Laggards* are more likely to anticipate adverse impacts from mass adoption, but also more likely to see risks emerging from their own present state of AI implementation. The perception gaps for *AI Leaders* and *Laggards* are thus statistically the same and zooming into the detailed risk categories yields no meaningful pattern.

Figure 6.6. Expected AI-induced increases in comparable firm-specific vs. market-wide risks by maturity of AI implementation



The perception gap is also not significantly greater, on average, among firms where Risk and Compliance teams are closely involved in AI implementation, suggesting that complacency and simple self-serving biases are unlikely to be at play.[15] However, such averages mask important nuances; compared to their peers, firms with Risk and Compliance-led implementation teams anticipate fewer negative impacts of mass AI adoption on systemic risk and algorithmic bias, and report fewer negative impacts from current AI implementation on cyber-security, data protection and accountability risks.

Figure 6.7: Expected AI-induced increases in comparable firm-specific vs. market-wide risks, by level of involvement of Risk and Compliance teams



15 This view is additionally supported by the fact that according to survey results, firms' self-categorisations as *AI Leaders* vs. *AI Laggards* tend to be fairly accurate.

One explanation for this pattern might be that it reflects the way in which regulation has historically come to apply to AI use cases (see also Chapter 7). Firms whose AI implementation is led by Risk and Compliance teams might be focusing their assessment of current risks on those areas where regulatory requirements already exist, and their assessment of future risk on those areas where regulations are likely to emerge in future. They might also consider risks that are explicitly regulated against to be more manageable.

As Chapter 7 discusses in more detail, regulatory frameworks for cyber-security, data protection and senior management accountability are already in place in many jurisdictions today. And as could be seen earlier, firms with compliance and risk teams involved in AI implementation report a greater preparedness to deal with those specific risks. On the other hand, the focus of regulators might be more likely to move on to matters such as systemic risk and bias once with the increasingly widespread adoption of AI across Financial Services.

If this interpretation is correct, then there are likely to be some firms, including *AI Leaders*, whose focus on regulatory compliance might provide a false sense of security in relation to emerging AI-related risks, or lead to a narrower interpretation of such risks than is necessary.

Overall, it seems unlikely that organisational characteristics alone can account for the gap between the expected market-level impact of mass adoption and the firm-level impact of AI implementations currently in use. Part of the remaining gap is likely to be best explained in terms of emerging risks resulting from mass adoption. This might mean, in particular, that firm-level risks will be exacerbated by network effects, shared dependencies (e.g., on the same vendors, methodologies, data lakes, or latent explanatory variables in alternative data), as well as financial and reputational contagion, in ways that aren't reducible to issues observed at the firm level.

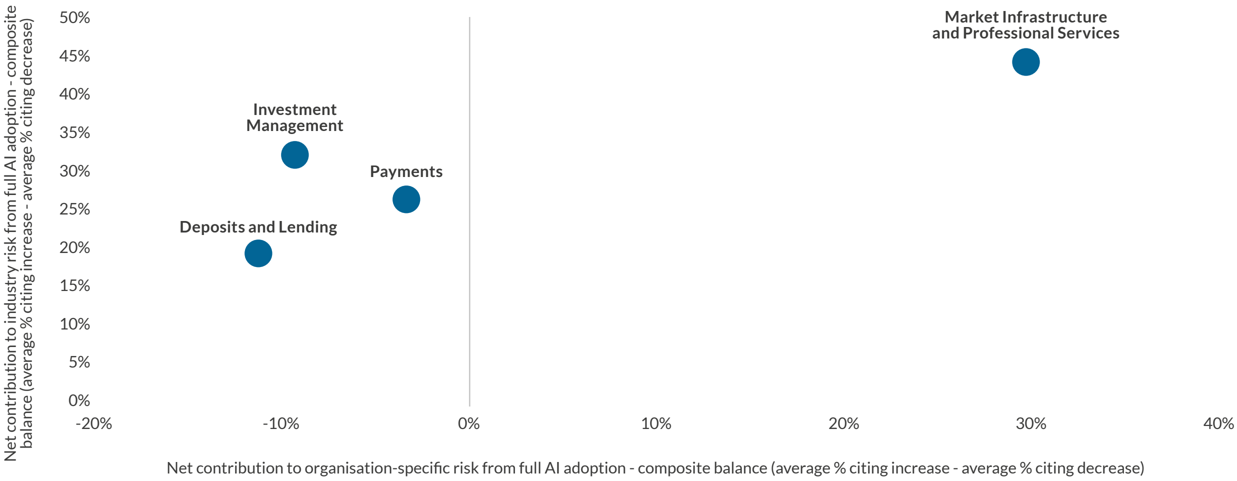
6.3 Mapping AI-Related Risks by Sector and Jurisdiction

The impact of AI adoption on organisational risk needs to be examined in its full context, taking into account the influence of the relevant organisation's sector and the jurisdiction in which it operates.

In survey responses, the financial Market Infrastructure industry stood out for its strong views on the likely impact of mass AI adoption (Figure 6.8). Out of all the industries surveyed, respondents in this sector reported the worst risk outlook for all but one of the survey's firm-level risks and for half of the market-level risks. Theirs was also the only sector in which the impact of current AI implementation on risk was seen on balance as negative. Their assessment of the impact of AI on market uncertainty was especially negative, with 63% anticipating that such risks would increase with AI adoption, versus 25% to 50% for other sectors. A particularly dramatic example of the kind of market impact such firms might be concerned about is 'flash crashes': short spells of extreme market volatility across asset classes during which prices become clearly untethered from fundamentals.

Chapters 4 and 5 in this report have already hinted at some of the general reasons for such firms' concerns – this is the sector in which firms anticipate the highest level of disruption from AI in future, as well as the sector where implementation is most hindered by data quality concerns. It is understandable that leaders in a highly regulated sector might see high-impact applications leveraging sub-optimal data as a threat.

Figure 6.8: High-level summary of the impact of AI adoption on risk by sector

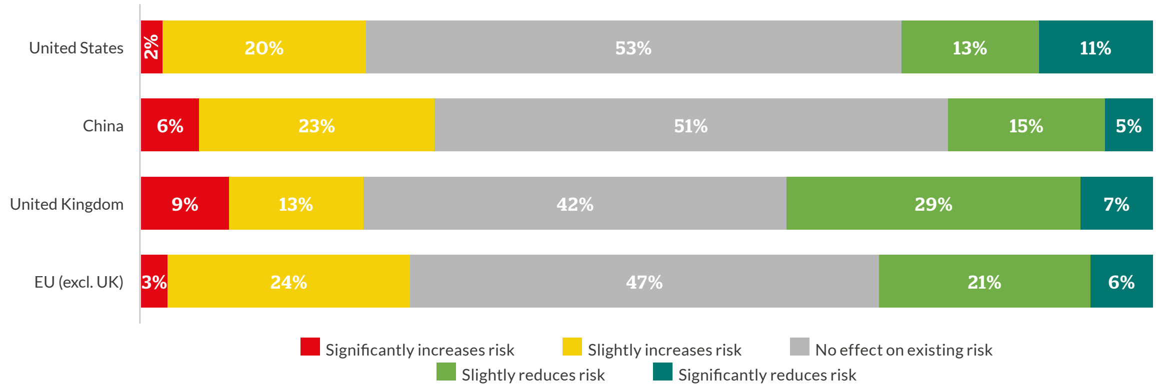


Elsewhere, sectors tend to be attuned to one particular category of AI-related risks at a time. Firms in the Payments sector, for example, are particularly conscious of the risk of bias, for example in anti-fraud controls or the identification of suspicious transactions. Those in the Investment Management sector are particularly concerned by the potential for highly damaging data breaches in both the near and long term, while respondents in deposit-taking and lending institutions stood out for the intensity of their concern about privacy and cyber-security risks in the short term.

Perceptions of AI-related risk are likely to involve judgments not just on industry dynamics but also on the relative adequacy of regulations. If it is true, as already suggested in this chapter, that firms perceive highly regulated activities as relatively safer for themselves and for the public, then one would expect firms in jurisdictions with less stringent or more recent regulations to report higher levels of risk.

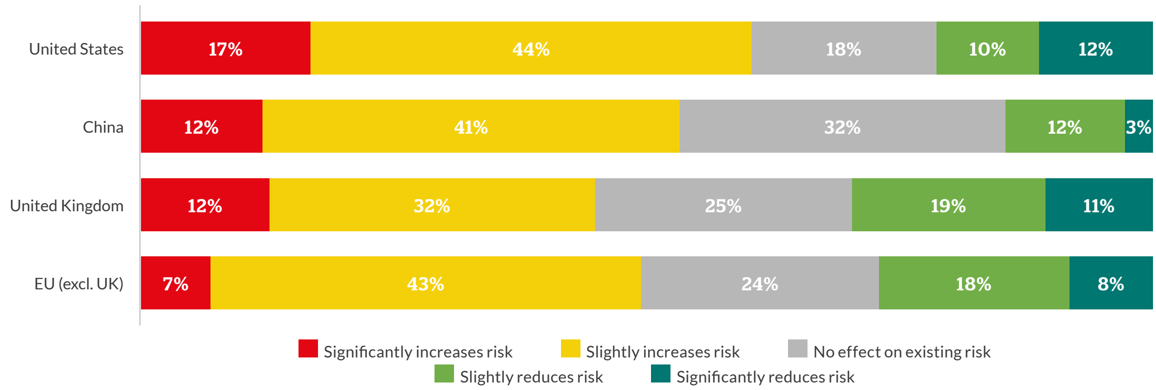
This is broadly true of organisation-level risks. As discussed in more detail in Chapter 7, China has only recently introduced stringent regulatory requirements for data protection and privacy and firms have for some time operated in a lighter regulatory environment, while US and UK (and more recently other EU countries) have faced tougher regulations, especially around data protection. Accordingly, firms in the US and even more so in the UK appear to recognise AI as a net mitigant of risks to their respective organisations, while Chinese firms see their current level of AI implementation as a net contributor to organisational risk (Figure 6.9).

Figure 6.9: Averaged views on the influence of AI on organisation-specific risks across different jurisdictions



Whether this finding generalises to other jurisdictions or not, it clearly does not generalise to market-wide risks under a mass AI adoption scenario. When looking at market-level risks under mass adoption, both US and Chinese firms are very pessimistic, with majorities in both countries expecting widespread adoption to increase risks (Figure 6.10). Only firms based in the UK come close to a balanced outlook, but even there 44% expect market-wide risks to increase on average and only 30% expect them to be reduced. It is difficult to establish the underlying country-level drivers of such perceptions – however it is possible that firms see larger domestic markets as favouring AI-driven consolidation or at least reinforcing the status quo. This is supported by the findings from chapter 5, which suggest that Chinese and US firms are less likely to expect AI to deliver disruption as opposed to consolidation (or further entrench the status quo) than European firms. There appears to be a correlation between such attitudes and firms' expectations that mass AI adoption will exacerbate market-wide risks.

Figure 6.10: Averaged views on the influence of AI on market-wide risks across different jurisdictions



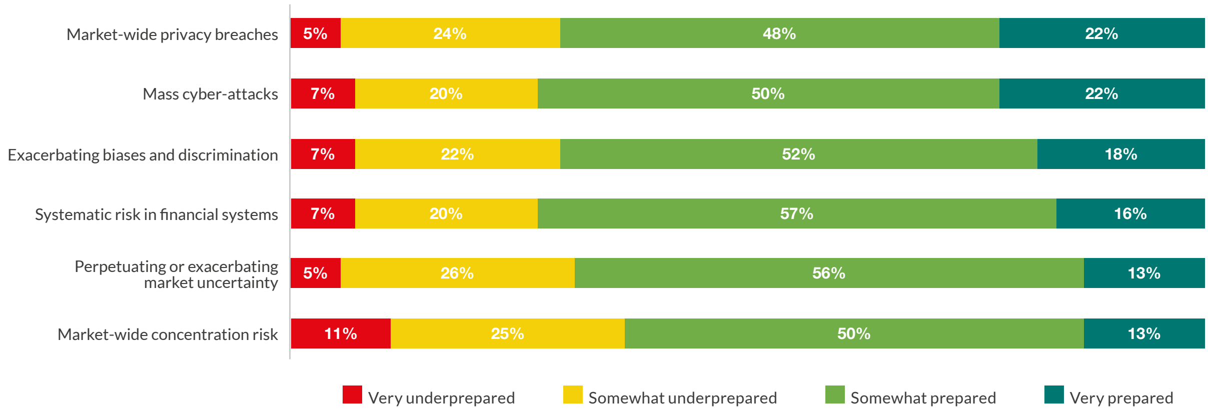
6.4 Risk Mitigation and the Role of AI

Although firms anticipate mass AI adoption to give rise to or exacerbate risks, this does not mean that the impact of such risks cannot be mitigated and that plans are not underway to ensure this. Clear majorities of the sample (63% to 73%) believe that they are well placed to deal with such risks, with systemic risks and cyber-security threats seen as the most tractable. Conversely though, only 13% to 22% claim to be 'very well' prepared. Even those less-threatening market-level risks pose a mitigation challenge to more than a quarter of firms, and more than a third (36%) are not confident they are well placed to mitigate concentration risks (Figure 6.11).

Preparation appears strongest where firms are subject to fairly prescriptive regulation, and the challenge is to monitor and manage vulnerabilities. Examples of this can be seen in data security and privacy and cyber-security.

Preparation is, on the other hand, weakest where risks are at a higher market level for which firms' individual influence is limited, such as growing market uncertainty and market concentration.

Figure 6.11: Perceived preparedness to mitigate the potential impact of market-wide AI-related risks

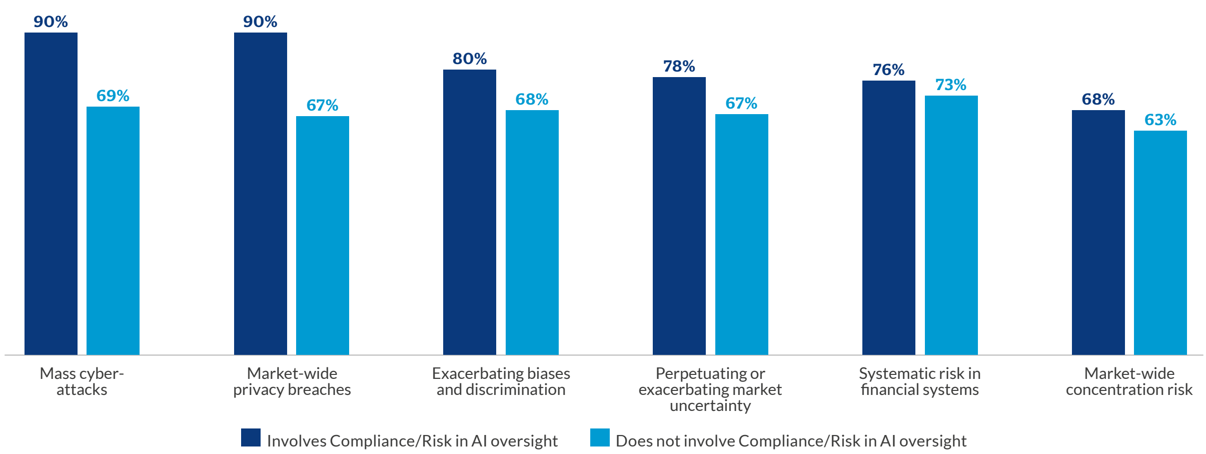


The percentage of firms that aren't certain of their mitigation capability would be much higher if it weren't for the contribution of Risk and Compliance staff embedded in AI implementation projects. As Figure 6.12 shows, firms that involve such staff in AI implementation are almost uniformly assured that they can manage their exposure to market-wide data protection and cyber risks. They are also slightly more confident than others about their ability to deal with bias and market uncertainty.

The benefit from involving Risk and Compliance teams in AI oversight is, therefore, strongest where regulatory requirements are already in place. This result echoes a more tentative finding discussed in Section 6.2 – specialists might, over time, develop blind spots and focus on the risks that are most explicitly addressed in regulation as opposed to the ones that matter most to the firm.

That said, most firms do not involve risk specialists in AI implementation. Those who do are more likely to be *AI Leaders* with a broad range of AI use cases explored and AI programmes in place.

Figure 6.12: Perceived preparedness to mitigate the impact of market-wide AI adoption risks, by involvement of compliance and risk teams in AI implementation

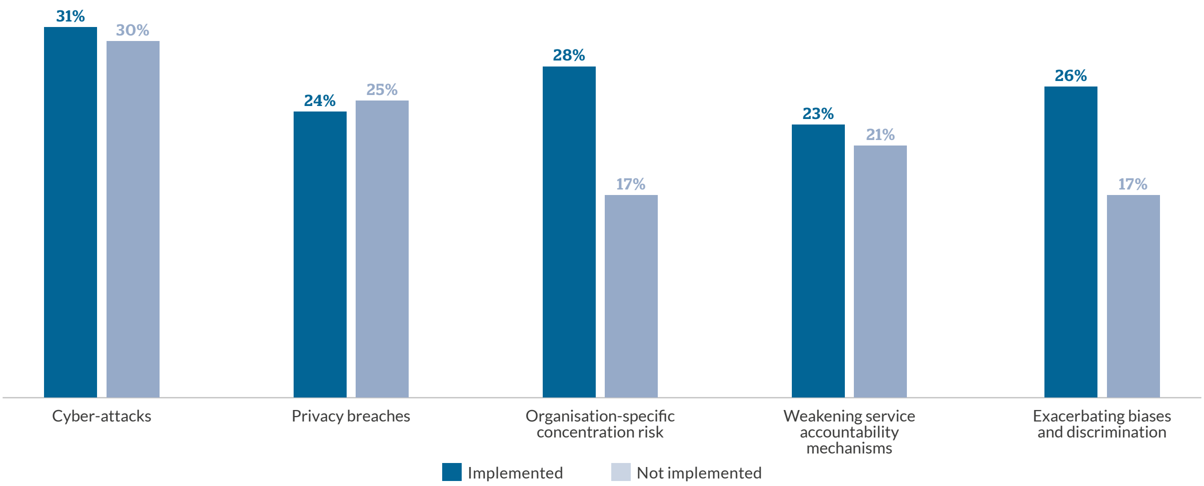


In discussing firms' risk mitigation plans it bears repeating that a significant percentage of survey respondents expect AI adoption to, on balance, reduce risks across the board (19% to 32% of firms in the case of market-wide risks; and 23% to 32% in the case of firm-specific risks). This should not come as a surprise. As discussed earlier in this report, risk management is the most commonly cited domain for AI implementation within organisations, with over half (54%) of all respondents reporting live applications. (See Chapter 2 and Figure 2.4). Moreover, a large share of the growing RegTech industry also relies on AI-adjacent technologies, including the 56% of vendors who employ machine learning, or the 35% of vendors who use natural language processing (NLP) to parse regulatory content (Schizas *et al.*, 2019).

As discussed in Chapter 2 (Figure 2.8), most AI-enabled risk management relates to the detection of suspicious or anomalous patterns indicating misconduct or fraud. Less common are predictive applications, extrapolating from historical data to new datasets, and rarer still are applications to conduct risk management – using AI to pick up patterns of problem behaviour leading to operational failures or customer detriment. All these activities would normally rely on human effort and judgment, which are expensive and challenging to apply consistently. With an effective data mining strategy in place, AI can, in principle, have a strong advantage over humans in establishing and comparing patterns, freeing human intelligence for higher value-added tasks (Baquero et al., 2018).

Whatever the theoretical case for AI-enabled risk controls, it is not clear that firms implementing these have an advantage compared to those that do not. As Figure 6.13 shows, the likeliest area where firms applying AI-enabled risk management might be said to be outperforming their peers is the detection of concentration risks and outsize exposures. In this area, 28% of those applying AI to this problem reported that their application of AI in total was leading to lower levels of risk, as opposed to 17% of all other firms. Whether this modest difference can be causally attributed to the use of AI is, however, unclear, particularly as many risk management applications are likely to be fairly recent.

Figure 6.13: Perceptions of a positive impact of AI on organisation-specific risks, by state of AI implementation in risk management



7. Regulation of AI in Financial Services

- Survey responses suggest that regulation can be a burden on AI-implementing firms; however, the impact of regulation is nuanced and many firms, including most *AI Leaders*, see net benefits from the regulation of AI.
- Data protection and data sharing requirements appear to be the first and, generally, largest regulatory hurdles to AI implementation. As AI programmes mature, however, it is regulatory uncertainty, rather than any individual compliance burden, that becomes the major concern.
- Where firms see regulation as enabling their implementation of AI, this positive effect is rarely reducible to the effects of individual regulatory requirements or obligations. Firms typically see the latter as net impediments to AI implementation.
- It is possible that the certainty provided by a stable and consistent regulatory framework, and the trust this engenders among consumers and key business decision-makers, accounts for much of the net enabling effect of regulation.
- There are significant differences across jurisdictions in firms' perceptions of the impact of regulation. Chinese firms generally report a more positive impact of the local regulatory framework than European and American ones, likely due to historically fewer demanding data protection rules. Perceptions of the regulatory framework correlate strongly with firms' views of the competency and knowledge of the regulators themselves, and the two are likely mutually reinforcing.

Key Findings

Chapter 7: Regulation of AI in Financial Services

7.1 AI – A Nascent, Global Regulatory Agenda

Algorithmic processing of information has been subject to regulation in several jurisdictions for some time, prompted by authorities' concerns about built-in bias and hard-to-reverse, high-impact errors. The broadening application of AI has heightened these concerns, as have more fundamental, macro-level concerns about ethical decision-making, the wholesale substitution of human labour and the reshaping of commerce, government, and human interaction (G20 Trade Ministers and Digital Economy Ministers, 2019)

In response, a number of international thematic policy initiatives have emerged in recent years to help shape the development of AI in a sustainable and responsible manner. Areas of focus include data protection and privacy, transparency, human oversight, surveillance, public administration and services, autonomous vehicles, and lethal autonomous weapons systems.

At the macro level, the G20 countries first agreed non-binding, high-level principles for 'human-centred' AI in the summer of 2019. The G20 principles, which broadly echo those agreed by OECD countries and others earlier that year, include (OECD, 2019):

- Inclusive growth, sustainable development and well-being
- Human-centred values and fairness
- Transparency and explainability
- Robustness, security and safety
- Accountability

At the country level, transparency and explainability (as defined in Chapter 4) are becoming priorities for regulators (Information Commissioner's Office, 2019). Regulators are wary of 'black box' AI systems that are hard for them and for firms to oversee, and harder still for consumers to challenge when faced with adverse effects (Croxson, Bracke and Jung, 2019). There is also broader public and political concern that AI will exacerbate or even vindicate pre-existing social biases. While firms might have financial incentives to correct or override algorithmic decision-making when it performs poorly or introduces further risks as a result of bias (as discussed in Chapter 6), they may not be incentivised to address instances of bias which are not commercially detrimental.

Characteristics such as gender, race or age have historically correlated with key decision-making variables for the financial sector, such as income, occupation, access to security or educational level; partly as a result of persistent social inequalities. Similar influences have contributed to the correlation between personal characteristics and firm decisions in relation to, e.g., creditworthiness assessments, financial advice or insurance pricing. Training AI systems on data containing these historical social influences can lead to models in which personal characteristics, or close proxies thereof, influence outcomes disproportionately.

AI is subject to greater regulatory scrutiny in some industries than in others. Financial services provision has historically been a data-rich business with potentially high impact on consumers, and also one in which 'soft' information and personal judgment have been deployed alongside quantitative and supposedly objective inputs. Regulatory concerns about transparency and bias are understandable, and calls for accountability in the use of AI is likely to be more pronounced in Financial Services than in other sectors. Moreover, as regulators embrace new types of statutory and strategic objectives, including objectives to promote competition and financial inclusion (Rowan *et al.*, 2019), the range of AI-related harms that they are alert to continues to broaden.

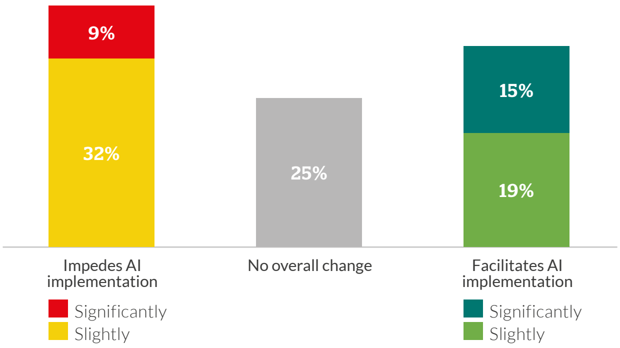
'Bespoke' AI regulations specific to Financial Services are not the norm, however. Instead, pre-existing regulatory obligations are influencing the use of AI in this sector. The implementation of AI involves obtaining, storing and using masses of personal, often sensitive, information. This consequently triggers regulations in relation to data protection and consent for data processing, cyber-security and cyber-resilience, or conduct regulation and obligations to treat customers fairly. This is particularly the case for areas such as credit and insurance underwriting.

This chapter considers the impact of regulation on AI implementation in Financial Services to date, based on the perceptions of regulated firms. It also draws an important distinction between the aggregate and particular impacts of regulation, in order to establish where the true costs and benefits of regulation arise.

7.2 Beyond the Regulatory Burden

Popular narratives around the impact of regulation on financial innovation are still evolving, but the relationship is now a persistent feature in press coverage of the FinTech industry (Zavolokina, Dolata and Schwabe, 2016). The survey results suggest that regulation can be both an enabler and an impediment to innovation in Financial Services. While 41% of respondents felt that regulation has been a (slight or significant) impediment to the implementation of AI initiatives in their organisations, more than a third (34%) reported that regulation has been supportive of AI implementation (Figure 7.1). Looking at just those respondents who characterised the impact of regulation as 'significant', more felt it was positive, i.e. enabling or facilitating AI implementation in their organisations, than negative (15% vs. 9%).

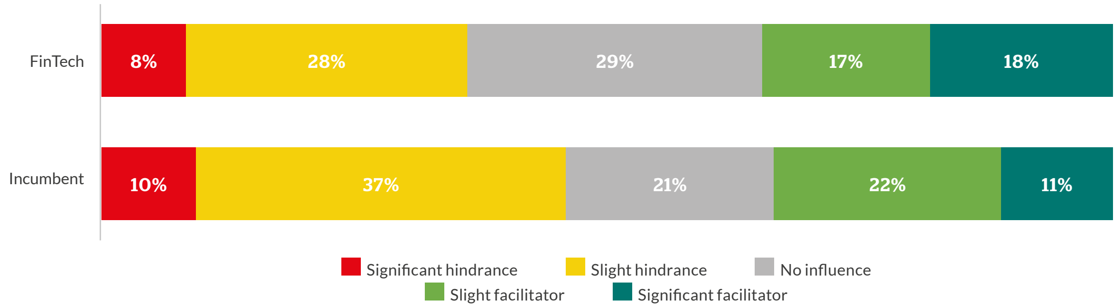
Figure 7.1: Perceived overall impact of regulation on AI implementation



These findings should not come as a surprise. Regulation may impose costs and delay product development, but it can also provide legal or regulatory certainty and promote user trust, with these, in turn, boosting investment in a sector. The benefits of regulatory certainty and trust should be most important for FinTech start-ups, which lack an established brand-name that would reassure consumers, and the track record that would reassure venture capitalists. The role of generalised trust and particularly structural assurance in promoting FinTech adoption is reasonably well-studied, and typically emerges as significant in relevant studies (Sarkar, Chauhan and Khare, 2020)

Accordingly, the survey shows that FinTechs are marginally more likely than Incumbents to report a positive impact on AI implementation (Figure 7.2). Indeed, as many FinTechs perceive net benefits from regulation as those which perceive net costs (36%), while Incumbents are less likely to see benefits than costs (33% vs. 46%).

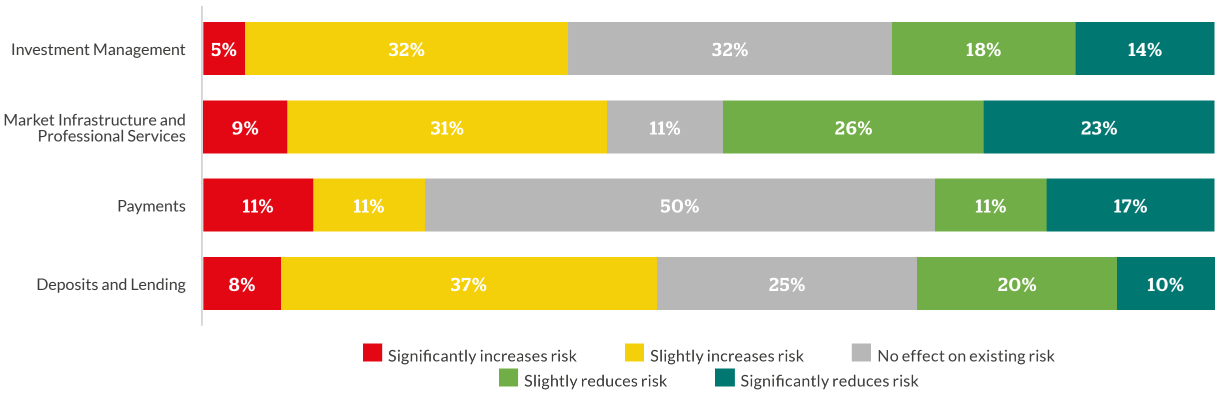
Figure 7.2: Perceived overall impact of regulation on AI implementation by entity type



Much of the positive regulatory impetus appears to relate to the use of AI to improve the efficiency of market infrastructure. In the operations of exchanges and trading facilities, 49% of firms in the sector reported that regulation facilitated or enabled the implementation of AI in their organisations (Figure 7.3). One interpretation is that new regulations applicable to the sector have provided strong incentives to apply AI for the purposes of compliance with regulatory obligations such as market surveillance requirements. Since the publication of the global Principles for Financial Market Infrastructures (PFMI) in 2012, requirements under local regulations have aligned with global standards, and Market Infrastructure providers are growing in importance as potential clients of the RegTech industry (Schizas *et al.*, 2019).[16]

The attitude of Market Infrastructure players contrasts sharply with that of the Payments sector, where regulation has had much more limited interaction with the pace of AI implementation. While on balance the impact of regulation is judged to be positive, fully half of the sample felt that it had made no difference to their own implementation of AI. Given that the most likely applications in this sector relate to compliance with KYC or fraud detection, both of which are long-established requirements, it is hard to argue that recent regulation has added to the business case for using AI.

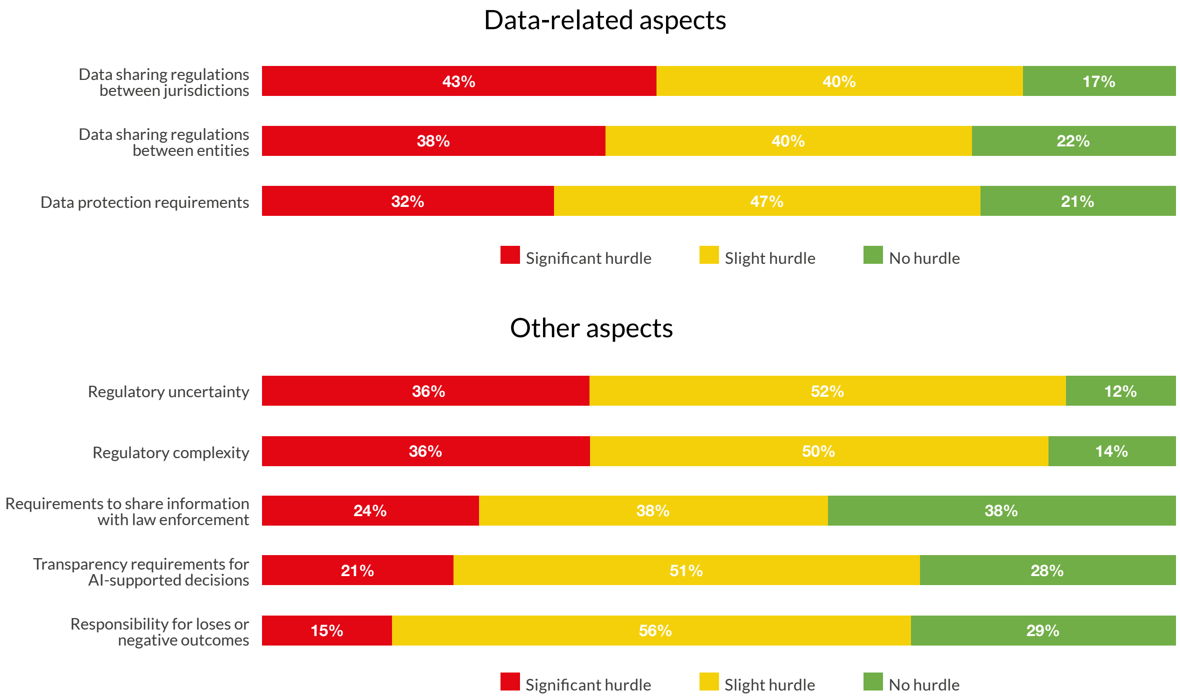
Figure 7.3: Perceived overall impact of regulation on AI implementation by sector



16 CCAF defines RegTech as "any use of technology to match structured and unstructured data to information taxonomies or decision rules that are meaningful to both regulators and the firms they regulate, in order to automate compliance or oversight processes" and notes that the latter is achieved by "facilitating compliance workflow, decision-making, and reporting, and the resulting linkages between data and actions enable efficient oversight."

To account for differences in the impact of regulation across industries, and to understand more fully the impact of regulation, it is useful to assess the perceptions of specific types of regulation, as illustrated in Figure 7.4. Overall, it is not the case that regulation imposes unsustainable liability on firms for the potential impact of their use of AI. Fewer than 15% of organisations saw such provisions as a major barrier to the implementation of AI. Requirements related to the sharing of personal data between organisations, and separately across jurisdictions, are instead seen as the most onerous by respondents. 38% and 43% of respondents respectively reported a significant negative impact on the implementation of AI.

Figure 7.4: Perceived burden of different regulatory framework aspects



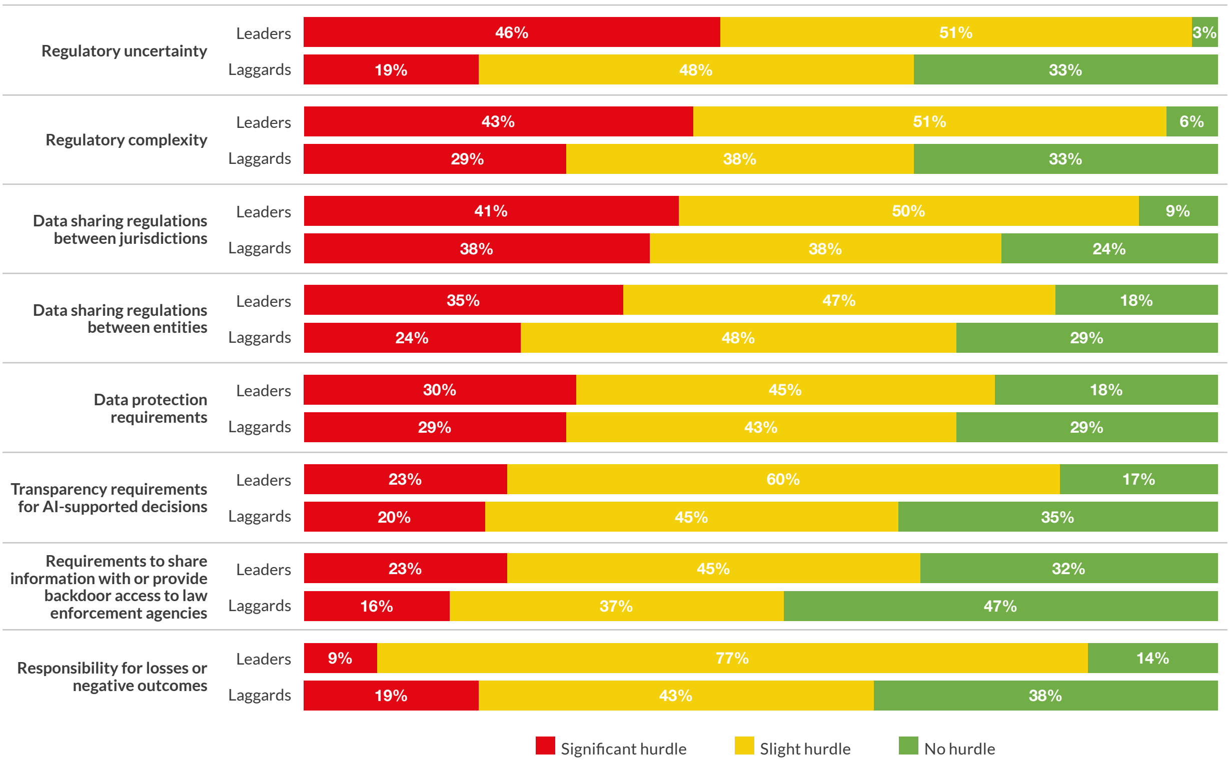
"New regulation from the EU GDPR and otherwise means that there are strict requirements for Data Scientists and machine learning teams in the Financial Services sector. A large percentage of the time one either cannot use certain data sources, or has a strict requirement to have models with a high degree of explainability. There is a performance-explainability trade-off which occurs, meaning expectations cannot be met due to regulation."

Data Scientist at a UK insurer

Further nuance is required in the analysis of the impact of regulation, in order to account for the lifecycle of AI innovations. In their assessment of regulatory barriers, *AI Leaders* differ markedly from *AI Laggards*. As Figure 7.5 below shows, *AI Leaders* are more likely to see their implementation of AI hindered by unclear regulations or by the likelihood of unpredictable regulatory change, rather than by the cost of compliance with regulatory requirements. Intuitively, this may be due to *AI Leaders* breaking new ground while *Laggards* are operating in spaces where the former have previously established regulatory clarity.

It is also possible that *AI Leaders* tend to have well established, proven business cases and delivery plans for key AI applications, while firms with limited applications are more likely to still be exploring or making the case for their programs. If the latter have less robust lower-bound cost estimates or cannot yet demonstrate the scalability of their AI implementations, they could be more vulnerable to the significant upfront costs imposed by data protection requirements.

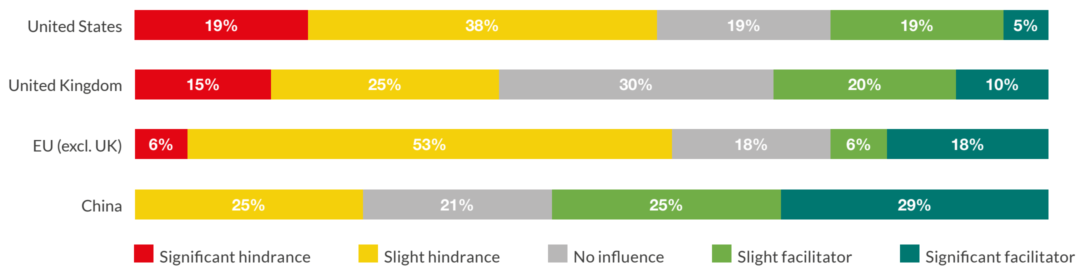
Figure 7.5: Perceived burden of different regulatory framework aspects by maturity of AI adoption



7.3 Supportive Regulation as Comparative Advantage or Under-Regulation as Unfair Advantage?

Previous findings which displayed regulation as an enabler of AI implementation are, however hopeful, not uniformly present across different jurisdictions. For example, there is a clear difference between Chinese firms, which on balance see regulation as conducive to the development of AI, and firms in the US, UK and continental Europe which on balance do not. As Figure 7.6 shows, less than a quarter (24%) of US and mainland European firms and less than a third of UK firms (30%) see regulation as helpful on balance, while more than half (53%) of Chinese firms do. Even allowing for small base sizes and a more deferential attitude towards regulators in China, these are significant differences.

Figure 7.6: Perceived impact of regulation on AI implementation by jurisdiction



Much of the positive perception that Chinese firms have of regulation might be due to historically less rigorous regulatory requirements, particularly in relation to data sharing between organisations and the transparency of AI implementation. Respondents in China were less likely to see these as acute challenges than their US, UK and European counterparts. They were also more likely to report that they saw benefits from data protection standards, and to report no adverse impact from regulatory complexity or regulations imposing liability on firms for AI deployment.

These results are partly explained by the fact that comprehensive data protection regulation was only enacted recently in China. The regulatory framework was relatively light until the coming into force of the Personal Information Security Specification in May 2018 (TC260, 2017) and the release of the National Cyberspace Administration's new data protection law[17], in May 2019 (Cyberspace Administration of China, 2019). Even more recently, guidelines were released on the cross-border movement of personal data, and key Chinese corporates have issued an influential white paper on AI security (China National Information Security Standardisation Technical Committee, 2019). Thus, the trend in China is towards the increasing regulation of AI and personal data use, and future editions of a survey such as this one might reflect a shift in opinion among Chinese firms.

If relatively lighter regulation has given Chinese firms a perceived commercial advantage in at least some aspects of AI implementation, active supervision going forward should reveal areas where this advantage has simultaneously propagated poor practices.

Equally, perceptions of the net impact of regulation on AI implementation might be influenced by differences in the perceived *quality* of regulation. In fact, perceptions of the net impact of regulation on AI appear to correlate with views of regulators' and policymakers' understanding of the technologies used in AI implementations. More than a third of Chinese firms (35%) feel that regulators have a 'good' or 'very good' understanding of AI applications in Financial Services, compared to 15% in the UK, 18% in the rest of Europe, and just 5% in the US.[18] Causal links between perceptions and net impact could, of course, run in either direction, or both at once.

Taking responses at face value suggests that regulators have work to do to understand which elements of the relevant technologies and use cases give rise to risks. Survey respondents were not asked whether they feel their own organisation needs to invest further in understanding the regulatory implications of their more innovative work. However, some provided unprompted feedback to this effect:

"[Senior management needs to better understand] ***the regulator****[y]* ***framework around autonomous decision making****."*

CEO, FinTech solutions provider to investment managers

7.4 Are Regulations Enabling or Impeding AI Adoption?

To assess the potential of (under)regulation to confer a commercial advantage to firms in certain jurisdictions, it is useful to reconsider whether regulation – as a whole – impedes or enables AI implementation, and how.

AI Leaders rate the *overall* impact of regulation more positively than those with more limited implementations of AI. 40% of *AI Leaders* see a positive overall impact and 34% see a negative one, while 33% of *AI Laggards* see a positive impact and 38% see a negative one (see Figure 7.7 further below).

Yet as already discussed (see Figure 7.5), when prompted with specific examples of types or aspects of regulation (e.g. data protection standards) as opposed to 'regulation' as a whole, *AI Leaders* rate the impact of regulation more negatively.

These findings appear contradictory. However, in responding to the two underlying questions, firms are likely talking about two very different things.

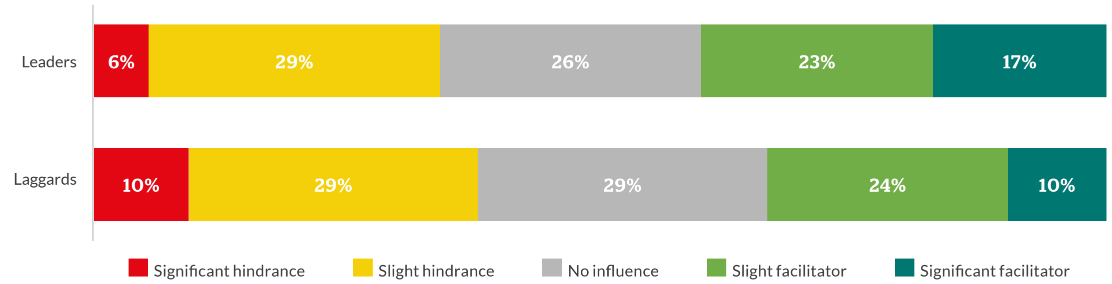
17 Among other things this mandates the clear signposting of data collection intended for algorithmic processing

18 As a sense-check, firms were also asked whether regulators and policymakers had a good understanding of the firms' own AI implementations. The ranking of jurisdictions is identical when using this phrasing, but the distance between each jurisdiction and the one immediately above or below it in the ranking, in terms of firms' net rating of regulators' understanding, is larger.

The breakdown in Figure 7.5 deals narrowly with the impact of compliance. Firms that implement AI in many different parts of their organisations (i.e. *AI Leaders*) should naturally come across a broader range of regulatory issues (and incur higher costs in the process) than firms which apply AI in very limited and self-contained projects. Alternatively, the need to coordinate regulatory compliance across numerous projects might necessitate the retaining of dedicated AI compliance specialists, who might, in turn, have the expertise (and incentive) to raise the profile of regulatory risk across the organisation. The involvement of compliance teams appears to be proportionate to the scale and breadth of AI implementation. As discussed in Chapter 2, about a third (32%) of *AI Leaders* reported having compliance departments that take an active role in overseeing AI implementation. Of those firms that had the least or narrowest involvement in AI, none reported that compliance teams were involved in implementation.

Figure 7.7, on the other hand, likely reflects the impact of having a regulatory framework in place at all. Earlier in this chapter, it is argued that AI implementations in FinTechs should benefit more from regulation than those in Incumbents because FinTechs are seeking to develop more trust and regulatory certainty. These benefits are not easily reduced to the benefits of specific requirements but arise from the regulatory framework as a whole. The main mechanism by which regulation supports AI implementation in *AI Leaders* (of which 49% are FinTechs) may be similar. General trust in AI and regulatory certainty might be crucial to winning senior-level support for (1) investing in AI, and (2) making big, strategic bets on AI.

Figure 7.7: Perceived impact of regulation on AI implementation by maturity of AI adoption



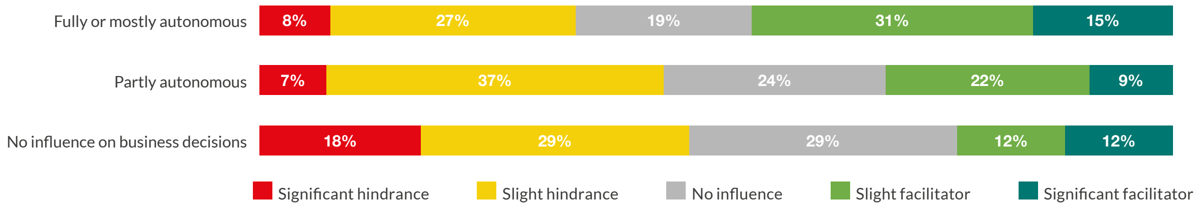
Findings across the total sample are consistent with a positive effect of trust on the level of AI investment, while a link between generalised trust and the emergence of *AI Leaders* is not documented. In fact, the gap between overall and particular regulatory impacts persists regardless of a firm's level of engagement with AI.

The beneficial effect of regulatory certainty might help explain one final paradox. Given regulators' emphasis on making AI more transparent and explainable, and to ensure human input is not eliminated in an uncontrolled fashion, one might expect that the burden of regulation would fall disproportionately on those implementations that allow for the least human input into decisions. None of the evidence collected for this study supports this, as per Figure 7.8. If anything, the net effect of regulation appears mildly more positive among firms implementing more autonomous AI.[19]

It is hard to dismiss this (null) finding as a case of lax regulation attracting riskier applications. There are no statistically significant differences between the UK, EU, US and China in the share of implementations that are substantially autonomous – and no respondents in the US or China reported any fully-autonomous implementations.

19 Respondents with fully-autonomous, unsupervised applications of AI were very rare in this sample, as discussed in Chapter 11. Anecdotally, such respondents were just as likely as others to say that regulation was an impediment (to any degree) to AI implementation. They were more likely than others to report that regulation is a 'significant impediment'. However, the difference is not statistically significant.

Figure 7.8: Perceived impact of regulation on AI implementation by autonomy level of AI systems currently in use



Instead, it is more likely that substantially-autonomous AI is only tolerable to firm decision-makers and policymakers in environments of high generalised trust, underpinned by predictable and stable regulation. The positive net effects reported by respondents with autonomous AI applications might then result from a combination of high costs but even higher perceived benefits.

The survey findings might nonetheless understate the relative burden of regulation due to survivorship bias. If very few substantially autonomous systems make it past their earliest stages without some degree of regulatory approval, the survivors ought to report a more moderate regulatory burden than less successful innovators would.

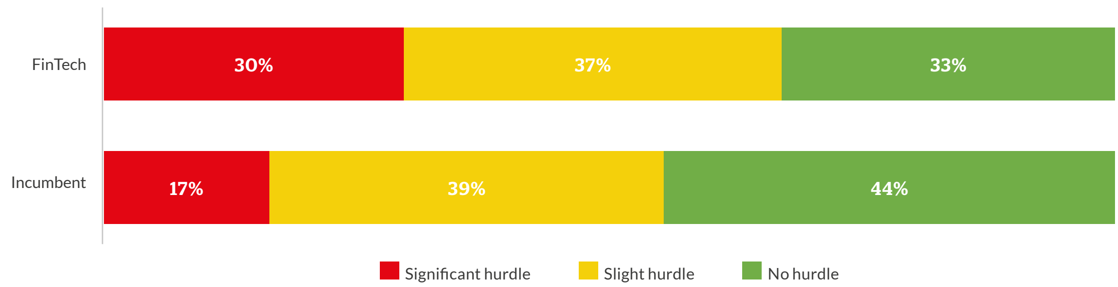
7.5 Relationship with Law Enforcement

As discussed in the introduction to this Chapter, AI is affected not only by specific regulation, but also by wider policy and regulation regarding other technologies or financial products. Just as AI is affected by broader regulation regarding data protection, it is also caught up in the broader political and social debate around balancing personal privacy with societal security.

In recent years there has been growing concern within governments, law enforcement agencies and security services that new technologies, in particular, the use of end-to-end encryption, are creating unacceptable barriers to their objectives. US Attorney General William P. Barr has labelled this a serious threat to national security (Barr, 2019), arguing that it is reducing or removing the ability of law enforcement agencies to lawfully obtain information. A communiqué following the 2019 meeting of the Interior Ministers of the Five Eyes countries, namely Australia, Canada, New Zealand, the United Kingdom and the United States, stated that technology companies should include mechanisms by which governments could legally obtain access to data that are otherwise encrypted or secured, known as 'backdoors'. (Five Country Ministerial, 2019).

Most firms consider information-sharing requirements or requirements to provide backdoor access a burden. However, while approximately the same proportion of firms across sectors consider these requirements to be a slight implementation hurdle, FinTechs are far more likely than incumbent firms to consider the implementation of these requirements to be a serious challenge (see Figure 7.9 below).

Figure 7.9: Concerns about sharing information with law enforcement by entity type



There are various possible explanations for this difference. It might be that FinTechs tend to have more complex technology, which leads to greater obstacles for law enforcement agencies requesting data, and therefore a greater regulatory burden around information sharing. This seems unlikely considering the evidence provided in Figure 7.5: there is little difference between *AI Leaders*' and *Laggards*' attitudes to sharing information with law enforcement agencies.

However, FinTechs are likely to have fewer or less developed offline service channels and may thus be more vulnerable than Incumbents to suggestions that their online offerings are not secure. Some FinTechs have made considerable investments in branding themselves as challengers, disruptors and outsiders, such that their customer relationships might suffer from appearing too eager in their co-operation with the authorities. Finally, it could be that Incumbents have had more previous experience providing information to law enforcement agencies. Having established their risk appetite, controls and perhaps some degree of trust with regulators, they are thus better placed to consider applicable regulations earlier in the design phase.

On the other hand, law enforcement agencies acknowledge AI as a technology that has the potential to bring great benefits to the detection of illegal activities (Home Office, 2019). It is likely that AI will continue to be affected by, and influence, ongoing debates around new technology and its effect on security issues.

8. The Use of Data for AI in Financial Services

- Data plays an integral role in creating differentiating AI capabilities. Specifically, novel or alternative datasets enable firms to generate insights which allow them to gain competitive advantages in existing offerings, or expand to new business areas.
- Internally generated data from operations, as well as customer-generated data (including, for instance, customer preferences) are heavily used by the majority of firms, while external customer data unrelated to customers' interactions with the business (e.g., social media), exhibit lower usage intensities.
- FinTechs use more customer data than incumbents – both internal data generated from interactions with customers as well as external customer data (e.g., social media), correlating with a higher focus on AI-enabled customer service and customer acquisition in FinTech.
- 60% of respondents utilise AI to develop novel insights from alternative datasets, making it the second-most frequently implemented usage area of AI within the broader purpose of generating new revenue potential. Social media is the most frequently used alternative data source, illustrating its informational value concerning socio-economic behavioural patterns of individuals, which are especially beneficial for use in credit analytics or market sentiment analysis. Indeed, the Investment Management and Deposits and Lending sectors are shown to be the biggest users of social media in AI applications.
- Overall, investment managers harness the broadest portfolio of alternative data sources in their AI applications, being especially far ahead of other financial sectors in utilising news data and datasets originating from social media.

Key Findings

Chapter 8: The Use of Data for AI in Financial Services

8.1. The Importance of Data

Regardless of how innovative an AI technology is, its ability to deliver real economic value is contingent upon the data it consumes. Financial institutions may have a wide range of internal data to leverage in their AI initiatives, including client, transactional and demographic data. FinTechs, on the other hand, may have access to only externally available data from partners or commercial providers, until such time as their business has scaled to give them a greater quantity and range of data.

A key theme in traded and other markets in recent years has been the use of alternative data sources, (such as satellite photography, social media or weather reports), together with the new investment insights that can be generated by combining these sources with AI techniques. In a 2017 survey, Greenwich Associates found that 80% of investors wanted access to alternative data sources in their search for alpha.

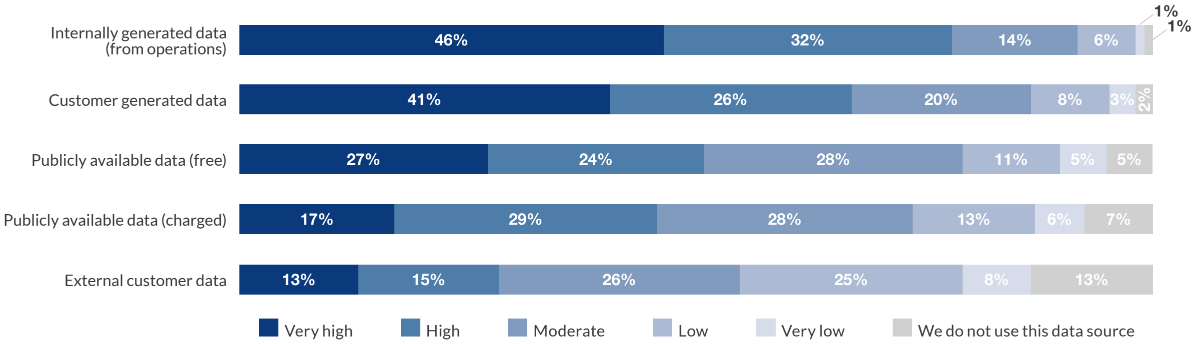
As an indication of the growth of alternative data in the Financial Services industry, Alternativedata.org, an industry trade group, identified 447 providers of alternative data to institutional investors in September 2019, up from a total of 375 in 2018 and less than 250 in 2013. They also noted that spending by hedge funds, pension funds and mutual funds on such data increased from $232 million in 2016 to $1.1 billion in 2019 and $1.7 billion in 2020 (BattleFin and AlternativeData, 2019).

The combination of AI and alternative data sources can yield powerful insights. For example, satellite data can be used to analyse land use, housing growth, parking lot activity and shipping in real time. When combined with AI, new insights with impact on corporate earnings become available, such as predicting supermarket sales as measured by parking lot density or supply chain issues measured by ship, train and truck movements.

8.2. Data Sources

The starting point for many AI applications is the data available internally. As illustrated in Figure 8.1, the data most commonly used was internally generated data from operations (46% making 'very high' use) or internally customer-generated data (40% making 'very high' use). Publicly available data was next most commonly used (either obtained free or on a commercial basis, 27% and 16% respectively), followed by external customer data such as social media or geo-location, with only 13% making 'very high' use of such sources.

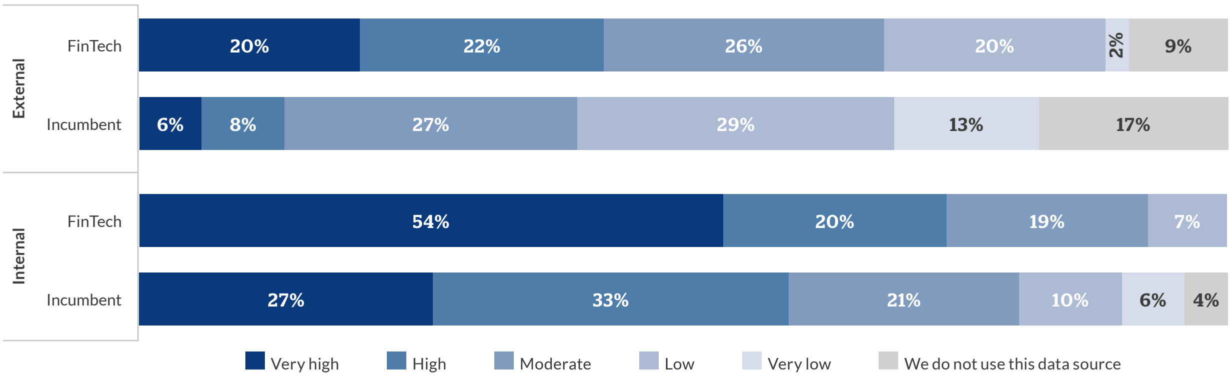
Figure 8.1: Usage levels of different data sources for AI applications



8.3. Usage of Customer Data

As noted earlier, incumbent organisations should have access to much richer and varied data sources, particularly for customer data where clients may have multiple product relationships with a large institution. However, Figure 8.2 shows that FinTechs made significantly more use of customer-generated data than incumbent organisations. This was the same whether the data was from internal sources[20] (where 53% of FinTechs made 'very high' use of such sources vs. 26% for incumbent institutions) or external customer-originated data[21] (e.g., social media, geo-location) where approximately 20% of FinTechs made 'very high' use of such sources vs. just over 5% for Incumbents.

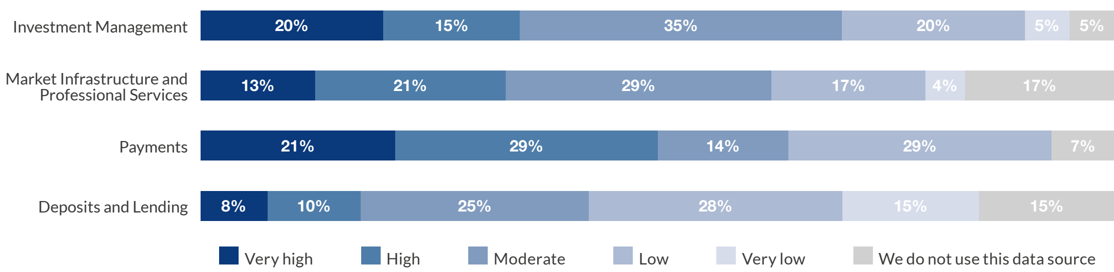
Figure 8.2: Usage levels of customer data for AI applications



In many ways, this mirrors broader observations of many retail and commercial banking environments, where challenger or neo-banks make extensive use of geo-location and other data sources to deliver novel customer-oriented functions, whereas incumbent banks frequently fail to innovate as quickly due to legacy or other reasons.

Analysing by industry sector, Figure 8.3 shows that externally generated customer data was most heavily used by the Payments sector (50% making 'high' or 'very high' usage of such data) and the Investment Management sector (where 35% made 'high' or 'very high' use of such data). This contrasted greatly with Deposits and Lending, where only 18% stated they were making 'high' or 'very high' use. The predominance of Payments in utilising external customer data is not altogether surprising given the role that, e.g., geo-location data, has in use cases such as fraud detection.

Figure 8.3: Usage levels of external customer data in AI applications



20 Data related to clients' interactions with an organisation

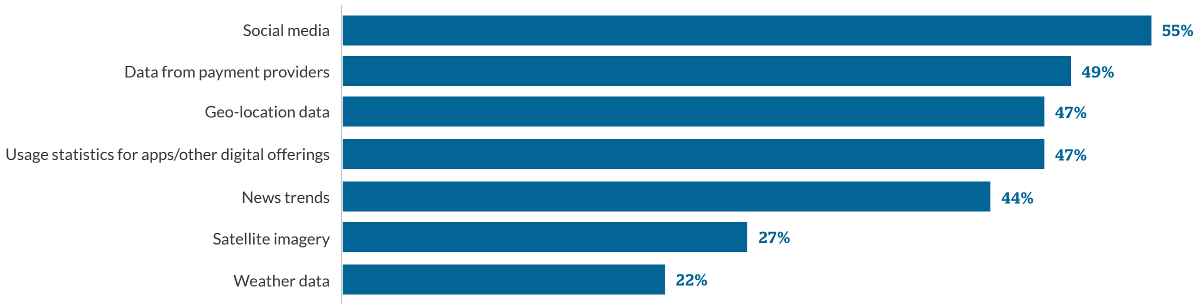
21 Any data, related to individuals or groups, which do not arise from interactions with clients

8.4. Usage of Alternative Data

Overall, 60% of all respondents use AI to generate new insights from non-traditional datasets, a figure which is uniform across Incumbents and FinTechs.

Social media is the most frequently used data type, with an adoption rate of 55% among those firms that use alternative datasets to bolster their AI applications, closely followed by data from payment providers and geo-location data (Figure 8.4).

Figure 8.4: Most widely used alternative data types[22]



It doesn't come as a surprise that datasets originating from social media are predominant. Behavioural user data from social media contain rich (albeit unstructured) information encompassing the identity of individuals and other attributes. These may be beneficial for applications such as credit analytics, although this use case might not yet be at a stage of mainstream adoption. Chapter 9 shows that around 43% of lenders surveyed that use AI-enabled credit analytics harness social media data.

In addition, social media allows firms to capitalise on the role of influencers in shaping individuals' views and opinions. For instance, the European Central Bank found in a 2015 study that tweets which meet certain criteria may serve as a viable predictor of short-term returns in selected stock markets; this relationship has since been affirmed by a number of research papers (Oliveira, Cortez and Areal, 2017; Pagolu *et al.*, 2016; Azar and Lo, 2016).

On the other end of the spectrum, satellite imagery and weather data remain the least-used types of alternative data. These datasets are usually costly to obtain and firms may require significant specialist knowledge to process the data and extract insights (Partnoy, 2019). Possible use cases may also be limited to specific applications which are only relevant to certain industry groups. For instance, satellite images of parking lot traffic have been found to contain significant predictive value for corporate earnings news. However, despite the fact that the datasets have been available for almost a decade, few appear to be capitalising on them (Katona, Painter, Patatoukas and Zeng, 2018).

Across the Financial Services landscape, payment providers lead in generating AI-enabled insights from alternative data (currently adopted by 69%), followed by investment managers (64%), Market Infrastructure and Professional Services firms (61%), and Deposits and Lending firms (57%).

However, investment managers lead in terms of the variety of datasets used, as shown in Figure 8.5. It can be assumed that this finding results from the characteristics of utilising AI in the investment process (further explored in Chapter 10). In an environment where even marginal informational advantages may lead to significant competitive edge, investment managers may be attempting to gather as much insight from

22 Percentages in this and subsequent charts in section 8.4 are based on the total number of respondents who indicated to be using AI to generate insights from new/alternative datasets.

diverse datasets as possible, while the same kind of breadth may not be necessary for use cases in other sectors.

The two most striking outliers in the alternative data portfolio of investment managers are social media and news trends. Other data sources are underused compared to other sectors. This could reflect the fact that investment managers mainly leverage predictive properties of alternative data to generate investment returns, instead of capitalising on customer insights.

Figure 8.5: Usage statistics of alternative data types across key sectors

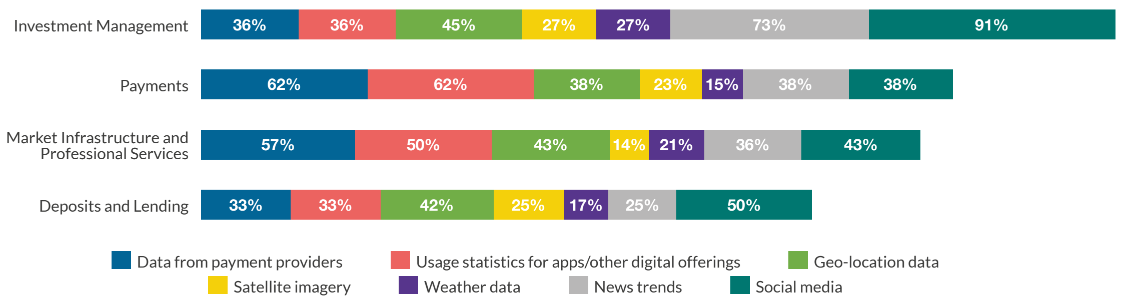
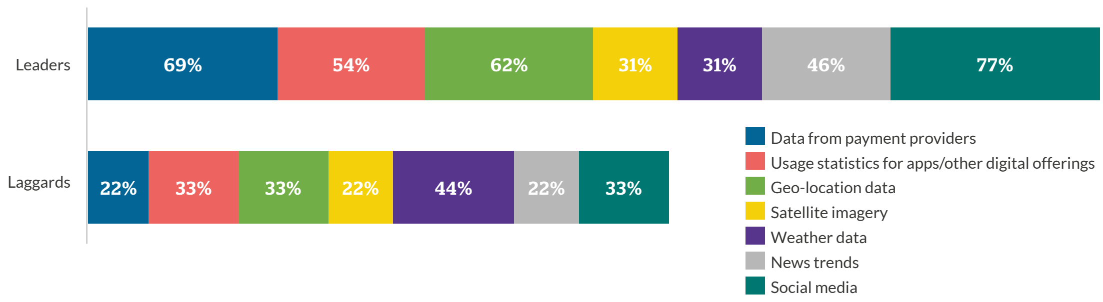


Figure 8.6: Usage statistics of alternative data types by maturity of AI adoption



Out of all respondents that use AI capabilities to create insights from alternative datasets, *AI Leaders* are seen to be using a significantly broader data portfolio (Figure 8.6). They exhibit a significantly higher adoption rate than *AI Laggards* in social media data, geo-location data, and data from payment providers. However, the gap is much smaller for satellite imagery and weather data (where *AI Laggards* are actually ahead), possibly underlining the difficulty of successfully leveraging these types of data.

It does not come at a surprise that *AI Leaders* prove to be mass adopters once more in utilising a large variety of data sources, empowering more AI implementations across their organisations, while *Laggards* tend to be more specialised. As more *AI Leaders* sell AI as a service, they might also be gaining scalable access to customer data from different domains which might not be readily accessible through other means.

9. Deep Dive – AI-Enabled Credit Analytics

Chapter 9: Deep Dive – AI-Enabled Credit Analytics

Utilising AI to make credit decisions provides a range of obvious benefits for lenders – it makes for a faster, more accurate, and more automated decision-making solution. 38% of all respondents in the Deposits and Lending sector use AI-enabled credit analytics.

Harnessing existing datasets of loan applications, AI-enabled credit decision-making systems can be trained to predict default probabilities, determine risk-based interest rates or directly make lending decisions. Alternatively, AI may be used to calculate alternative credit scores which serve as an aid to conventional human decision-making.

9.1. Expected Benefits of AI-Enabled Credit Analytics

The survey results show that on average, users of AI-enabled credit analytics expect a resulting short-term decrease of 10% in credit defaults. Around 15% of respondents expect AI to facilitate a more than 25% decrease in credit defaults, as illustrated in Figure 9.1. At consumer default rates below 1%, these figures may not appear to be substantive on an absolute level. However, this is the equivalent of the entirety in the total reduction in consumer defaults over the last five years (at around 12%)[23].

Figure 9.1: Expected AI-induced credit default reduction over two years[24]

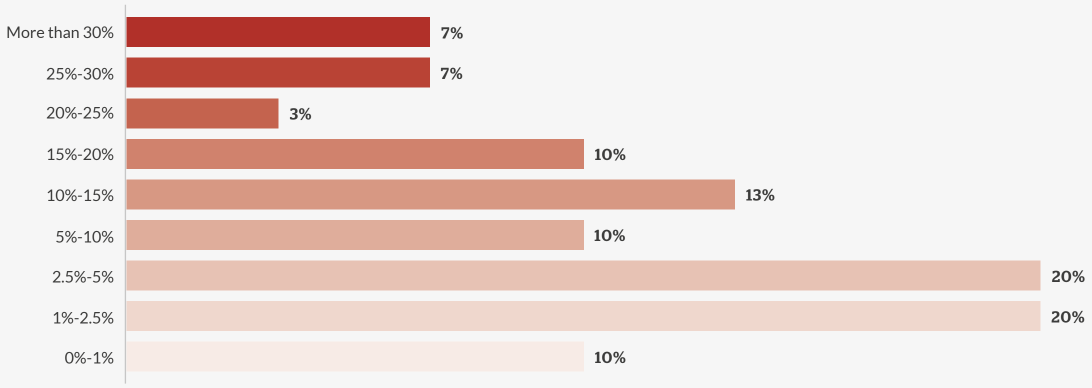


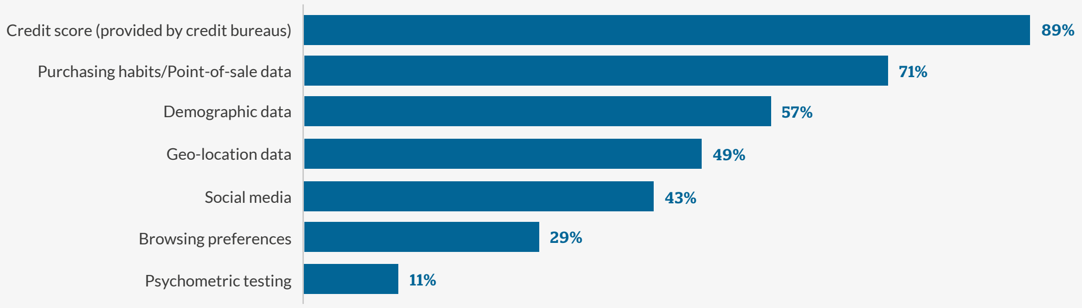
Figure 9.2 shows that users of AI-enabled credit analytics are generating insights on lenders from a wide range of data sources. While conventional credit scores are used most, more than half of all respondents are leveraging purchasing habits/ POS data, as well as geo-location data.

Just 13% of survey respondents are exclusively using conventional data sources (credit score/ demographic data), with only 4% relying entirely on credit scores.

23 S&P/Experian Consumer Credit Default Composite Index

24 The respondents were asked to anticipate future reductions in default rates to reflect the expected lag between implementing new technology its impact on defaults. Thus, while the further maturation of technology might be in part represented in this figure, it may be broadly interpreted as the expected impact of current technology.

Figure 9.2: Data sources used for AI-enabled credit analytics[25]



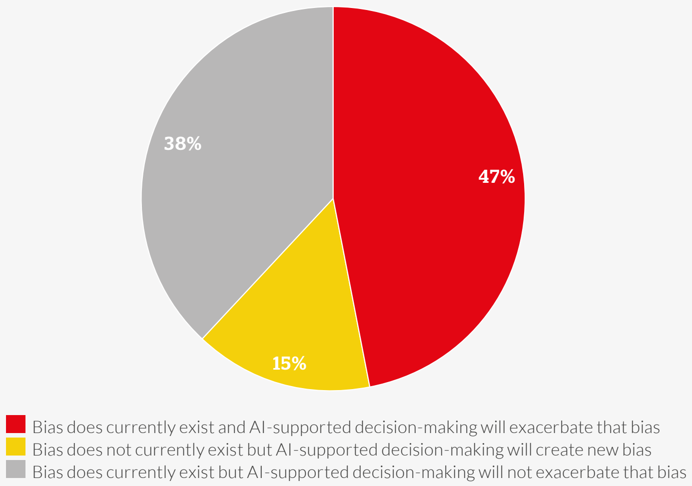
9.2. Will the Usage of AI in Credit Analytics Exacerbate Bias?

A 2019 paper conducted by researchers at UC Berkeley found significant racial discrimination in the American consumer lending market, with Latinx/African-American borrowers being charged nearly 8 basis points more for mortgage products[26]. Algorithms used by FinTechs were found to reduce pricing discrimination by approximately one third, with no discrimination occurring in binary lending decisions (accept/reject).

The research also found that discrimination was declining throughout the examined timeframe (2009-2015) which may suggest a positive outlook through making the lending market more accessible for previously disadvantaged groups (Bartlett, Morse, Stanton and Wallace, 2019).

Conversely, the results of this study show that almost half of all participant organisations state that bias in credit analytics does currently exist and that AI will exacerbate that bias, with a further 15% stating that AI will, in fact, introduce bias. This can be seen in Figure 9.3 below.

Figure 9.3: Perceived influence of AI on bias in credit decision-making



While it might seem intuitive that replacing the human component in credit analytics could reduce bias, the use of AI for lending decisions does possess potential shortcomings, some of which relate to the wider risks of AI.

The first major issue – especially for organisations with little to no existing control over and/or awareness of bias in datasets – is bias propagation. Using existing, biased datasets to train new AI systems will carry this bias

25 This question was distinct from the general findings on alternative data types presented in Chapter 8

26 Controlling for borrower characteristics

forward into subsequent decision-making. More specifically, there is a fundamental question around whether previous credit rejections should be factored into the training process of AI. The alternative, solely using data on actual defaults, leads to sparse datasets, relating to the technical issue around class imbalance discussed in Chapter 4: Historic data on accepted loans and subsequent repayments will (naturally) contain a much higher number of non-defaults compared to defaults, which may complicate training machine learning algorithms to detect defaults.

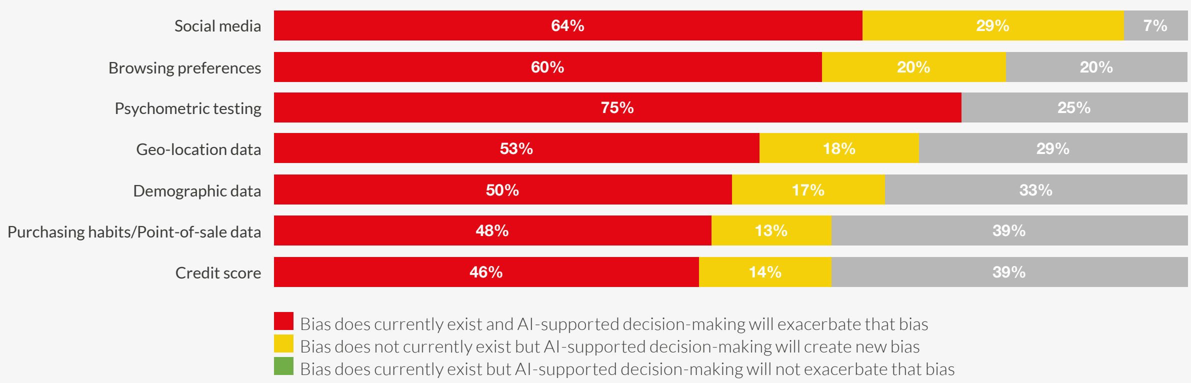
Bias propagation may be further exacerbated through the 'black box' characteristic of many systems which underlie AI – the notion that certain learning processes and decision-making in most machine learning algorithms are difficult to explain, especially regarding contributions of individual inputs.

Besides the obvious issue of depriving lending decisions of insight into the influence of input factors, the lack of an explainable decision-making framework might also make it difficult to handle appeals and customer complaints.

The survey results also demonstrate that users of non-traditional data (such as social media, browsing preferences, or psychometric testing) in AI-enabled credit analytics are more inclined to state that AI will exacerbate or create bias. This can be seen in Figure 9.4 below.

75% of all respondents anticipated that the use of psychometric testing in AI-supported decision-making could exacerbate bias already present. This was followed by social media data (64%), browsing preferences (60%) and geo-location data at 53%. Credit scores, on the other hand, were considered the least prone to increasing bias, at 46%.

Figure 9.4: Perceived influence of AI on bias in credit decision-making by data source used



Intuitively, one would expect more granular datasets which encompass more individualised behavioural patterns to reduce ethnic or other biases. However, the results indicate that the lack of structure and the multitude of information contained in these sources might lead to the loss of overview over the correlation between the data at hand and biased features, meaning that input features may effectively serve as proxies for biased factors if not monitored and controlled appropriately.

Where the technical and/or organisational hurdles towards implementing these controls become too high, third-party solutions may become an alternative. Notably, there are organisations which actively address this issue in a B2B context, such as the FinTech ZestFinance, which is applying contemporary research on algorithmic explainability to construct credit models with associated indications of fairness for input signals (Fuscaldo, 2019).

On a final note, survey results shown in Table 9.1 reveal that expected credit default reduction does not change significantly with the usage of alternative data. The average expected short-term default reduction caused by AI was highest for users of psychometric testing at approximately 13%, whereas differences between users of other data sources are marginal, as all of them lie between 9.4% and 10.3%. In light of findings from Figure 9.4 on the exacerbation of biases through alternative datasets, it thus remains questionable whether these truly add value to existing credit scoring systems.

Table 9.1: Average expected short-term AI-induced reduction in credit default by data source used

Data source	Expected short-term AI-induced reduction in credit defaults
Psychometric testing	13.1%
Social media	10.3%
Demographic data	10.1%
Purchasing habits	10.0%
Credit score	9.8%
Browsing preferences	9.5%
Geodata	9.4%

10. Deep Dive – Investment Management

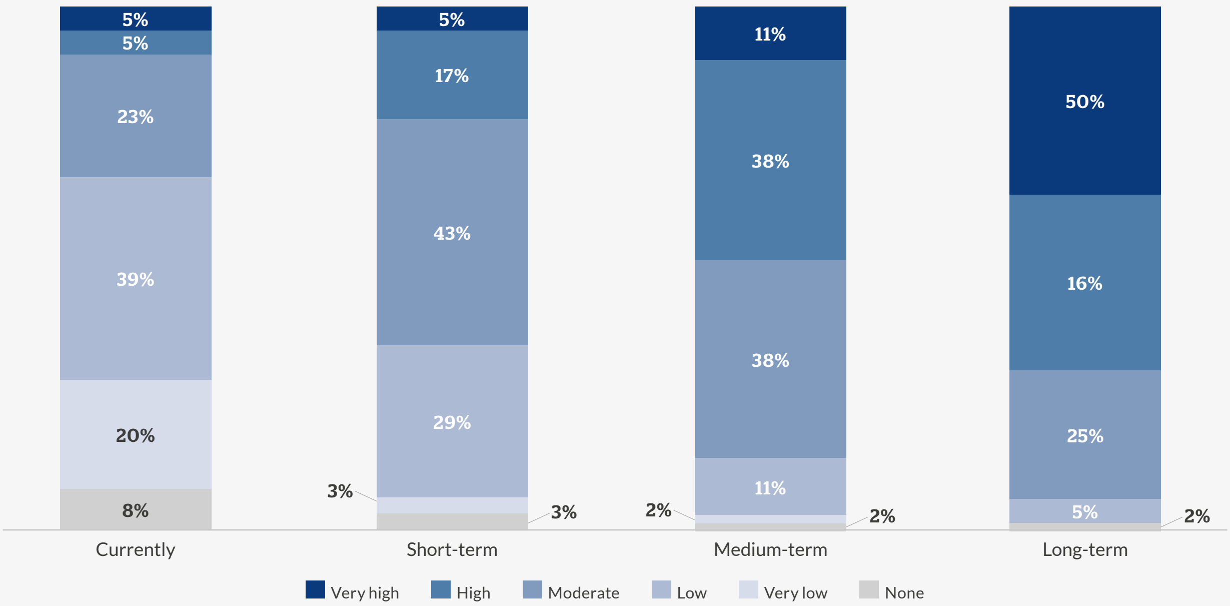
Chapter 10: Deep Dive – Investment Management

As discussed in Chapter 2, AI is widely adopted in the Investment Management sector, where it is becoming a fundamental driver for revenue generation. Further detailing the value proposition of AI for asset managers, the survey also yielded findings on the direct contribution of AI towards investment returns in the short, medium, and long term, perceived by those investment managers already using AI in their investment process (Figure 10.1).

The results constitute a clear trend. While only 10% of respondents currently perceive AI to contribute 'highly' or 'very highly' to their investment returns, this figure grows to almost 70% in the long-term (5-year) outlook.

Taking into account the different strategies which will be highly supported by AI for generating investments returns, a few observations can be made.

Figure 10.1: Anticipated contribution of AI towards investment returns over time[27]



10.1 Using AI in the Investment Process

Findings from the survey show that 59% of all surveyed investment managers are currently using AI in their investment process. As shown in Figure 10.2, portfolio risk management is currently the most active area of AI implementation at an adoption rate of 61%, followed by portfolio structuring (58%) and asset price forecasting (55%). Often, these use cases are combined, leveraging the economies of scale of AI which have been discussed in previous chapters.

27 Base numbers include all investment managers currently using some form of AI in their investment process

Figure 10.2: Usage rates of AI in investment-related activities

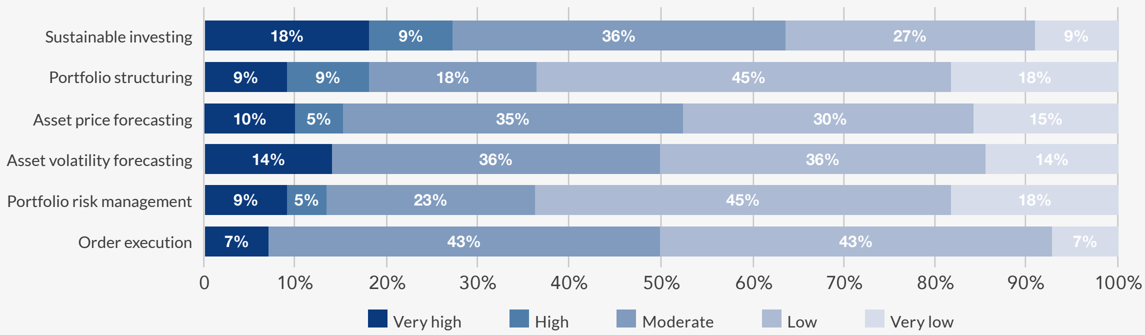
Judging from respondents' perceptions on the current contribution of AI to investment returns, AI-enabled impact assessment and sustainable investing appears to possess the highest correlation with high AI-induced returns (Figure 10.3). Approximately 27% of firms using AI in that area perceive AI to possess a 'high' or 'very high' current impact on investment returns. This points towards a direct effect of the convergence between digitalisation and sustainability (Kiron and Unruh, 2018), allowing financial organisations to extract value by the combination of these two trends.

Examples of companies applying AI-enabled impact assessment and sustainable investing strategies are Arabesque Asset Management, Clarity AI and Motif:

- Arabesque integrates environmental, social and governance (ESG) big data with quantitative investment strategies using datasets which combine over 200 (ESG) metrics with signals coming from 30,000+ sources published in over 170 countries (Arabesque Asset Management, 2019)
- Clarity AI quantitatively tracks the social responsibility of firms, which can be used by fund managers to optimise socially responsible portfolios
- Motif helps investors to weigh their portfolio against specific sustainability themes, such as renewable energy, or water scarcity

On the other hand, it is notable that users of AI for asset price forecasting do not widely perceive AI to significantly increase actual investment returns, despite its relatively high implementation rate illustrated in Figure 10.2.

Figure 10.3: Perceived current impact of AI on investment returns by use case

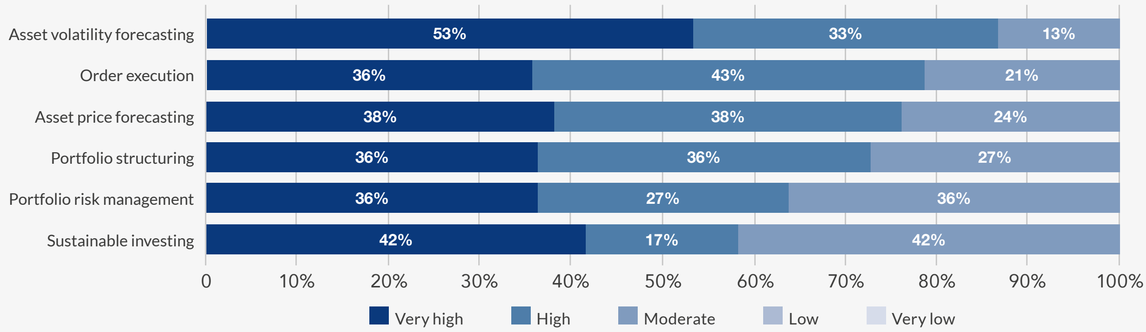


10.2 Future Outlook

In the long-term, respondents expect other AI-enabled use cases than sustainable investing to contribute more significantly towards increasing investment returns. 87% and 76% of AI adopters currently using asset volatility forecasting and asset price forecasting, respectively, in anticipate AI to contribute 'highly' or 'very highly' to investment returns in the long term. This suggests that there remains considerable room for improvement in these usage areas, and that organisations might expect technological maturity to reach a point where accurately forecasting financial market time series is possible. This prediction is in part supported by research confirming that machine learning algorithms, such as neural networks, systematically outperform simpler (linear) models in certain financial forecasting tasks (Ryll & Seidens, 2019).

As revealed in earlier chapters, however, real-world adoption may still be thwarted by data-related issues and a lack of algorithmic explainability.

Figure 10.4: Expected long-term impact of AI on investment returns by use case



11. The State of AI-Enabling Technology

- Long-established, simple machine learning algorithms are currently more widely used than complex solutions. Consequently, many firms are not yet using highly sophisticated AI applications – even those that are already commoditised to a certain extent. This is due to the primary hurdles which prevent the construction of AI systems in the first place.
- Autonomous decision-making – one of the defining technological facets of AI – remains difficult to implement in organisations. Underlying technologies, such as reinforcement learning, do not seem to have reached a state of maturity comparable to other established algorithm classes used in natural language processing or computer vision. Furthermore, the implementation of autonomous decision-making in organisations is shown to be hindered by deficits in trust and user adoption.
- *AI Leaders* use a larger portfolio of more demanding AI techniques which are, in turn, enabled by a range of more complex underlying algorithm classes. These findings complement earlier conclusions and demonstrate the commitment that AI Leaders have made to shaping their business through AI.
- FinTechs' training and deployment of AI systems are widely centred around cloud-based solutions, whereas many Incumbents still rely on legacy computational infrastructure. However, evidence from *AI Leaders* shows that firms with heavy organisation-wide computational workloads might also consider on-premises GPU solutions.

Chapter 11: The State of AI-Enabling Technology

11.1 Autonomous AI – the Future of Financial Services?

Previous chapters established that the determining components of leveraging AI for business success encompass a number of strategic considerations. However, understanding the potential of AI inevitably demands understanding the state of underlying technologies. Tying together high-level techniques in AI as well as enabling low-level machine learning algorithm classes and algorithms, the survey produced a range of robust findings on technology adoption, usage, and deployment. These results permit forming hypotheses around the relevance of technology to organisations and evaluating the potential impact of current research trends surrounding AI.

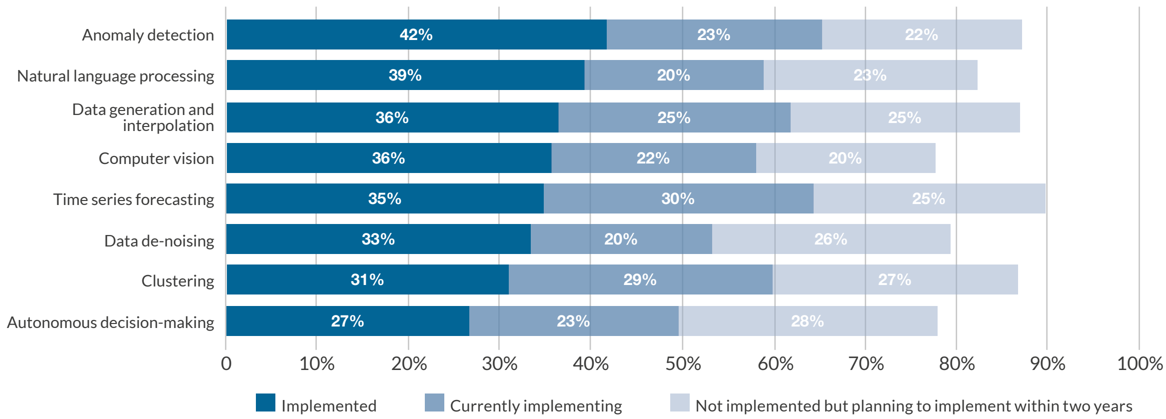
Autonomous decision-making remains the least-used usage field of AI among respondents, while other applications exhibit higher adoption rates, as can be seen in Figure 11.1.

The top three applications are anomaly detection with usage by more than 40% of all respondents, followed by Natural Language Processing (NLP) – which encompasses various tasks revolving around using AI to generate insights from human language at 39%, and data generation and interpolation at 36%.

Data generation and interpolation typically encompass a whole range of new use cases around generating and interpolating between image, video (Tulyakov, Liu, Yang and Kautz, 2018) or structural data (Jin, Barzilay and Jaakkola, 2018). These, in turn, empower a range of use cases around creating synthetic datasets or exploring/discovering new data representations (e.g., drug discovery).

Computer vision, which includes applications such as image and video recognition as well as object tracking sees a surprisingly high track record of implementation, with 36% of respondents having adopted computer vision and another 42% currently implementing- or planning to implement it within two years.

Figure 11.1: Overall state of implementation for selected AI application fields [proportions are relative to those companies which are utilising AI to some extent]



AI Leaders demonstrate significantly higher adoption rates than the overall average, with anomaly detection, clustering, data generation and interpolation reaching combined rates of adoption and implementation of 80-90% as can be seen in Table 11.1. Unsurprisingly, *AI Laggards* demonstrate a lower rate of adoption for virtually all AI application fields included in the survey, with the gap between the two groups being largest in the field of clustering as well as data generation and interpolation.

Moreover, it is striking that despite an adoption rate of only 6% for autonomous decision-making, over half of all *AI Laggards* state that they are planning to implement AI solutions in the field of autonomous decision-making within two years. This would elevate their adoption rate to current *AI Leaders'* levels. However, it remains uncertain if fulfilling this ambition is realistic given the significant organisational and technical challenges of adopting autonomous AI outlined earlier.

Table 11.1: Implementation rates of key AI application fields among *AI Leaders* and *Laggards*

	Leaders		Laggards	
	Implemented	Currently implementing or planning to implement in the short term	Implemented	Currently implementing or planning to implement in the short term
Anomaly detection	67%	27%	12%	65%
Clustering	65%	27%	6%	59%
Data generation & Interpolation	64%	36%	6%	72%
Natural language processing	61%	27%	11%	67%
Data de-noising	55%	36%	5%	53%
Time series forecasting/classification	52%	42%	11%	79%
Computer Vision	37%	43%	12%	47%
Autonomous decision-making	35%	55%	6%	59%

The fact that autonomous decision-making remains the least-implemented application field of AI with an overall implementation rate of 27%, and that even *AI Leaders* do not show significantly higher adoption rates (35%) illustrates how far the Financial Services industry remains from harnessing AI systems which make independent decisions free from human input. While earlier chapters discussed general hurdles to AI adoption, there are three reasons which specifically impede companies from implementing autonomous AI:

- **Regulation**
  While the regulation of AI is an ongoing consideration for regulators, autonomous decision-making poses specific challenges which policymakers are just beginning to address. For instance, a 2019 bill proposed in the US state of Washington (State of Washington, 2019), intends to investigate different notions concerning the human influence on algorithmic decisions (including whether decisions are final, contestable or reversible), bias against groups or individuals, explainability of decisions, as well as data management, storage, and security. This area of regulation might also become a priority for organisations to navigate, with one respondent specifically expressing the need for a better understanding of the regulatory framework around autonomous decision-making.

- **Trust**
  Trust issues may be caused by the lack of explainability inherent in many prevalent AI solutions. Thus, this aspect remains especially relevant for investment managers – where the ability to substantiate AI decisions may be prioritised over accuracy.
- **Technological limitations**
  Whereas technological advances such as deep reinforcement learning have attained impressive levels of algorithmic decision-making capabilities in closed environments, real-world applications (in open environments) are more challenging. Furthermore, meta-learning – applying learned rules and patterns to completely different environments – remains a major challenge (Wang *et al*., 2018).

Indeed, survey findings illustrate that trust and user adoption are perceived to be the most significant hurdle to AI implementation for those stating that use AI for fully autonomous decision-making, followed by access to talent, as well as access and quality of data (Figure 11.2).

Figure 11.2: Hurdles indicated to be significant by respondents who predominantly use autonomous AI

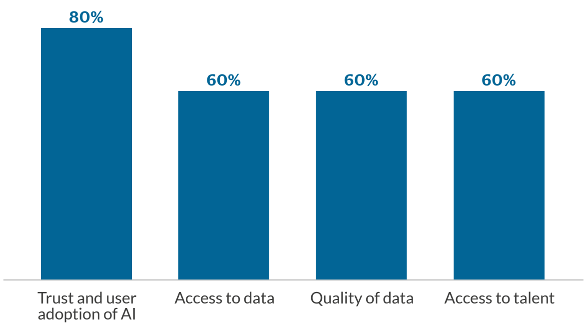
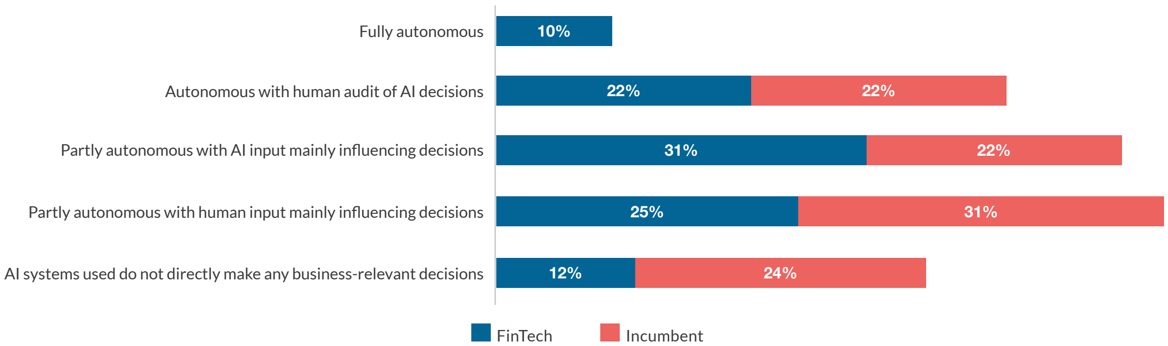


Figure 11.3 illustrates that while both Incumbents and FinTechs still overwhelmingly utilise AI as a tool which merely complements human decision-making, 10% of all FinTech respondents stated that their AI solutions could overall be characterised as 'fully autonomous', while twice as many Incumbents as FinTechs stated that the AI solutions that they employ do not make any business-relevant decisions.

Figure 11.3: Autonomy of AI systems currently in use by entity type



This finding raises an obvious question as to whether the increased autonomy of AI in FinTechs can be explained by more advanced technology or higher trust and willingness to adopt coming from the user side. Indeed, the survey results find that slightly more Incumbents (73%) see trust and user of adoption of AI as an implementation hurdle, whereas only 56% of all FinTech respondents feel burdened by this.

11.2 Implementation of Underlying Machine Learning Paradigms

The figure discussed in 11.1 illustrates the higher-level application fields which underlie the business use cases covered in Chapter 2. Taking the analysis to an even more granular level, the survey also investigated adoption statistics for the machine learning fundamentals underpinning these application fields. Machine learning may be divided into three main learning paradigms:

Supervised learning

In supervised learning, a system is fed (shown) multiple iterations of labelled training samples. Throughout the training process, the system learns to correctly classify inputs according to desired output labels defined by the user (hence 'supervised' learning – by providing 'correct' answers to the system, the user is supervising it).

Supervised learning is the most frequently implemented domain among respondents by a wide margin, being used by 88% of all respondents having adopted AI to any degree as seen in Figure 11.4. Figure 11.5 further illustrates that supervised learning is similarly adopted both by *AI Leaders* and *Laggards*. The wide proliferation of supervised learning is likely attributable to the fact that many mainstream applications of AI, especially in the areas of classification and forecasting, are based on supervised learning algorithms.

Unsupervised learning

Unsupervised learning algorithms discover the underlying (latent) structures in chaotic datasets which are not labelled. An unsupervised learning algorithm may, for example, cluster random images according to the aggregate similarity of their pixels. The resulting cluster can then be used for supervised classification after being labelled.

Among current AI users in the survey, unsupervised learning exhibits significantly lower adoption rates compared to supervised learning, with about half of all AI adopters using some form of unsupervised learning. This correlates with the results displayed earlier in Figure 11.1 which demonstrated that Clustering – an application field of AI which is mainly based on unsupervised learning techniques – remains scarcely applied by survey respondents.

A more granular analysis (not shown in the figure below) shows that Generative Adversarial Networks (GANs) is the algorithm used by most (62%) adopters of unsupervised learning. GANs are, as its name implies, used for generating data, and have reached unrivalled performance in tasks such as high-fidelity image generation (Brock, Donahue and Simonyan, 2018). This, in turn, coincides with relatively high implementation rates of data generation & implementation found earlier.

Reinforcement learning

Reinforcement learning is radically different from the two aforementioned paradigms in that it is based on an action-response model. Reinforcement learning algorithms learn certain action policies which maximise expected rewards in environments that are governed by a set of rules (or laws). In theory, a trained reinforcement learning algorithm is capable of making autonomous decisions in dynamic environments.

At the same time, it remains pivotal to differentiate between autonomous decision-making and reinforcement learning. While the terms are certainly correlative, reinforcement learning may also be used in an assistive capacity, e.g., by making recommendations which are acknowledged by human decision-makers. Similarly, (un)supervised learning algorithms can – once trained – make autonomous decisions by tying simple automation interfaces to the algorithm outputs (e.g., a supervised learning algorithm for credit analytics which predicts a credit default probability that, in turn, is fed into an algorithm which rejects or approves the credit request by utilising simple decision thresholds.).

Overall, generalising the use of reinforcement learning algorithms to real-world problems which might be complex and more uncertain still represents a major challenge in contemporary machine learning research.

"Reinforcement learning is promising in a lab environment but challenging to implement in a real-world environment, particularly working out use cases - for example, reinforcement learning makes sense for having internal testers rapidly training a system but getting financial services professionals on board with that or making it invisible in the background is much more challenging."

CEO, FinTech B2B solutions provider

Indeed, as seen in Figure 11.4, reinforcement learning exhibits the lowest adoption rate (51%) out of all forms of machine learning which illustrates that employing reinforcement learning may be challenging for a wide range of organisations. Figure 11.5 shows that the adoption gap in reinforcement learning between *AI Leaders* and *Laggards* amounts to 42%, suggesting that pertaining use cases may be complex and/or require existing AI capabilities.

Figure 11.4: Implementation rates of select machine learning classes and algorithms

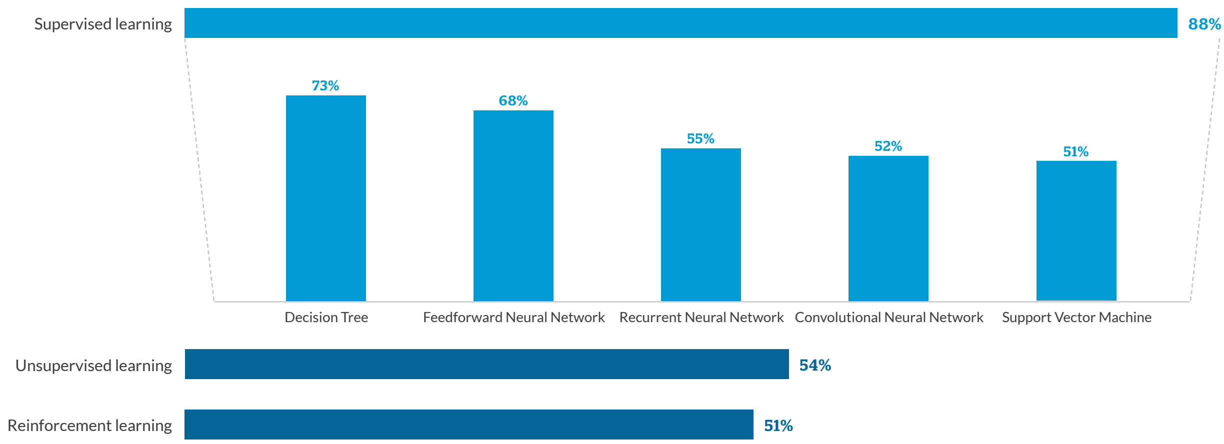
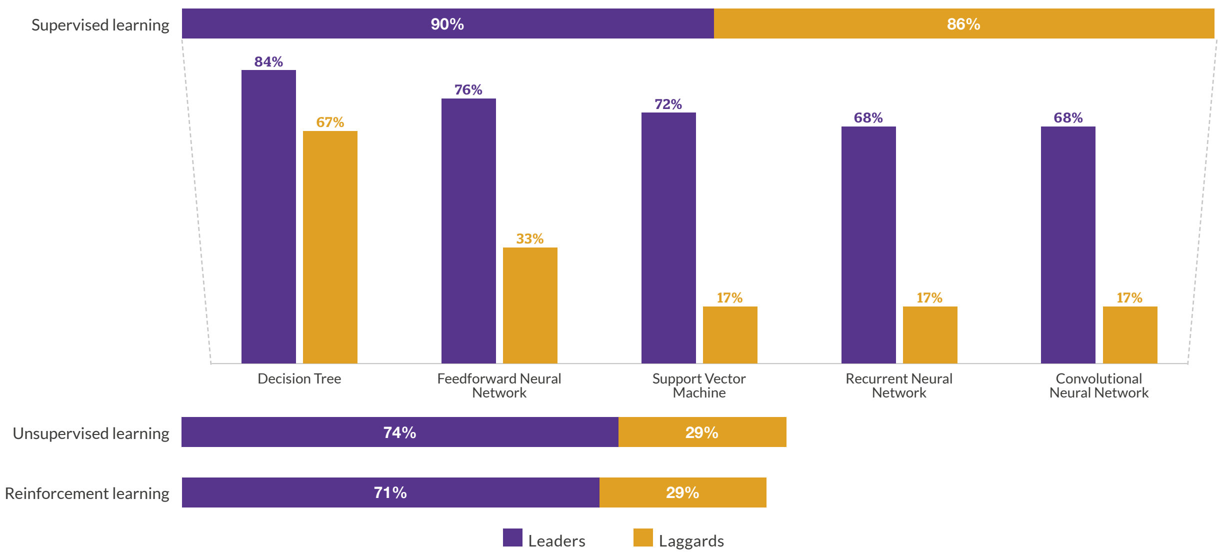


Figure 11.5: Implementation rates of select machine learning classes and algorithms by maturity of AI adoption



11.3 The Use of Computational Resources

Survey findings reveal that the computational infrastructure powering the AI applications discussed previously differs significantly across entity types. Figure 11.6 shows that 88% of FinTechs make utilise cloud computing compared to 35% and 23% for local GPU- and CPU-based solutions, respectively, whereas Incumbents appear to be using a diverse mix of computational solutions. This might be attributable to the fact that Incumbents still use legacy infrastructure to train and run AI systems whereas the cloud offers the (financial) flexibility and agility needed for FinTech's use cases. Cloud offerings have increasingly grown more tailored towards AI use cases, with most products including the possibility of scaling GPU configurations. Cloud computing also offers considerable advantages in easy set-up and seamless integration with machine learning libraries and back-ends as well as maintenance, and easy upgrading to newer hardware, which is pivotal given the speed of advances in processing power.

Figure 11.6: Hardware solutions used for training and running AI systems by entity type

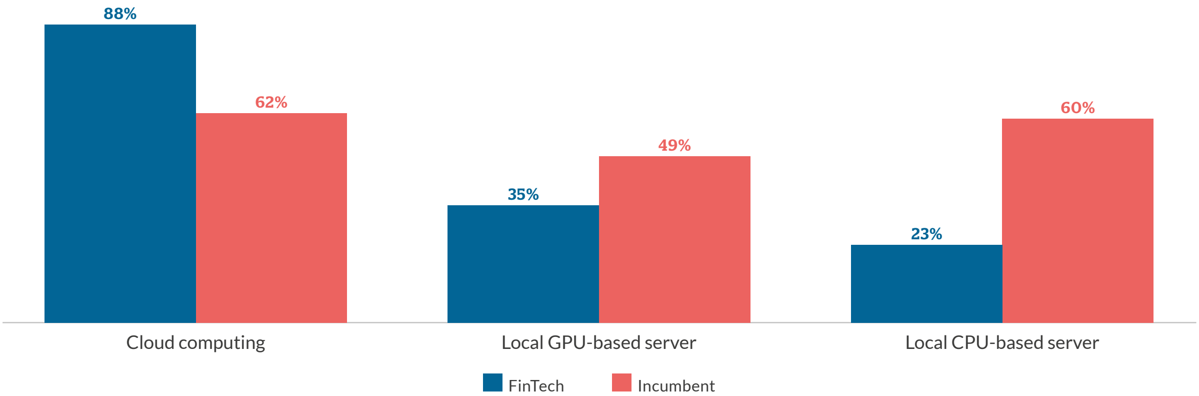
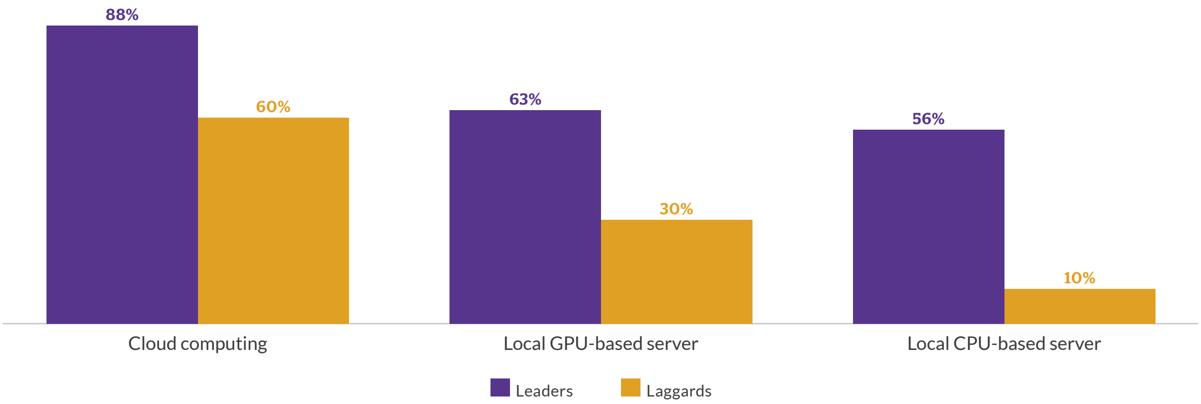


Figure 11.7: Hardware solutions used for training and running AI systems by maturity of AI adoption



When scrutinising this subject in the context of *AI Leaders* and *Laggards*, one finds that while cloud computing prevails as a commonly popular computational solution, a significantly higher percentage of *AI Leaders* utilise local GPU-based servers.

However, heavy, consistent users of GPUs may be better off utilising an on-premise computational solution. Aside from obvious benefits in data protection and security, on-premise computational facilities may also end up being less costly at full utilisation compared to mainstream cloud solutions (Villa, 2018).

Consequently, Figure 11.7 may imply that *AI Leaders* have reached a 'critical mass' of AI implementations in terms of total quantity and consistency of training times, as well as utilising machine learning algorithms which benefit from GPU acceleration (especially RNNs and CNNs) which were shown earlier (Figure 11.5).

12. Learnings and Outlook

Chapter 12: Learnings and Outlook

12.1 Generalising Findings Across the Financial Services Industry

The components necessary to build an effective AI model are generalisable across sub-sectors of Financial Services, and indeed across every industry; however, successful ways of applying these models to drive commercial success are likely to differ across sectors and entity types.

Generalisable properties are as follows:

- AI models are a product of the combination of algorithms and training data. While the algorithms enabling AI are complex, the majority of underlying resources are open source (e.g., TensorFlow). As a result, the primary differentiation between strong and weak AI models is the data that can be used to train it. This means that for any firm seeking to develop a successful AI model, securing training data is critical. Ideally, this training data would be a constantly refreshing (and growing) flow, not a 'one time' stock of data, thus allowing the AI model to learn and develop in response to the evolving data flow.
- The most competitively defensible AI models in any industry establish a 'moat' in one of two ways. The first is to secure a unique and useful set of data from which they can exclude other parties. The second is to leverage the 'AI flywheel' effect to continuously draw in more training data, and in doing so to establish a scale of data that is difficult for any newcomer to compete with.
- The overriding need for data makes digital platform models that form a data-rich interface between buyers and suppliers for a set of services highly amenable to the development of AI models. This is well illustrated in the tech sector by players such as Google who have leveraged the self-reinforcing characteristic of AI at scale to establish dominance in search. Areas where digital platforms and AI meet may be even more likely than other digital platforms to exhibit a 'superstars and long tails' set of dynamics. Under this dynamic, a few large firms establish an entrenched dominance in a product or service, and the remaining firms engaged in this space satisfy themselves with serving as highly specialised niche providers.

At the same time, the results of this study have shown that many aspects of what makes for a successful implementation of AI may be contingent on company sizes, company maturity, existing organisation structures, as well as being specific to certain financial service sectors.

While the fundamental dynamics of AI may be consistent across industries, it is not clear how the pressures they create will reshape the structure and competitive dynamics of the financial sector, nor can it be concluded that they will have the same impact across multiple sub-sectors of Financial Services.

For example, many players in Investment Management are clearly focused on identifying unique training data inputs (e.g. satellite imagery) in order to improve the accuracy of their stock-picking models. Meanwhile, network players in Payments and Capital Markets are seeking to leverage the scale of data flowing through their systems to create new advisory and value-added security (e.g. anti-fraud capabilities).

Moreover, while *AI Leaders* appear to be using more complex technology compared to *Laggards*, this higher degree of sophistication follows from the fact that *AI Leaders* have been able to create viable use cases for these technologies and overcome pertaining hurdles such as acquiring data, talent, and trust from stakeholders. Employing state-of-the-art technology is thus secondary to identifying the most profitable use cases of AI (which, as suggested by various results of the survey, differ across industries) – not the other way round. However, this might change with future advances in autonomous decision-making and AI systems becoming more generalisable to various problem domains.

12.2 Developing AI Capabilities – a Must for Financial Service Providers?

The results of this survey provide strong support for the hypothesis that the overwhelming majority of financial institutions believe that AI will be a critical aspect of their business moving forward.

However, while firms of many types and sizes may have a vision of being *AI Leaders*, it is apparent that the dynamics of AI offer significant returns to scale for first movers, and survey results suggest that *AI Leaders* are experiencing more benefits from those investments than *Laggards* who are further down the curve. In a scenario where the economies of scale in AI yield tangible advantages for early adopters, organisations are incentivised to be on the distributing end of AI-enabled products and services rather than the receiving one. Developing AI-enabled products and services for B2B business models is largely a matter of human, technological, and organisational resources – yet, the resulting access to novel data sources through selling AI as a service may be much more valuable in the long term than the upfront investment.

The survey further shows that most financial institutions continue to predominately use internal data. Those who are frontrunners in the development of AI will be better positioned to increase the scale of internal data flows, allowing them to improve the quality of their AI systems. However, while *AI Laggards* may not be well-positioned to develop their own AI systems as a point of differentiation, this does not mean that they will not be able to use AI across their organisation, potentially consuming one of the many offerings of AI as a service the survey shows are being developed. Although these systems will likely be useful at supporting certain commodifiable use cases – for example cutting costs or basic customisation of offerings – they will not independently offer opportunities for differentiation, particularly for investment managers seeking to use AI to generate excess returns.

12.3 The Future of AI-Enabling Technology

While technology is a key element in advancing AI applications, the survey shows that it is not currently a major obstacle to AI implementation as financial service providers are not yet widely leveraging technology which has been in existence for more than half a decade.

This, in turn, is attributable to hurdles revolving around data, talent, trust, and regulation which might thwart the introduction of AI-enabled applications that would demand a higher degree of sophistication in the underlying algorithms used. In this regard, it is notable that sophisticated AI technology is gradually becoming easier to access in multiple ways:

- Through high-level machine learning libraries such as Keras, sophisticated deep learning algorithms may be constructed with very little technical knowledge.
- Furthermore, pre-trained machine learning algorithms represent a significant value proposition as they eliminate the need for curating massive datasets and/or building complex neural architectures from scratch. Paired with the fact that many of the aforementioned high-level machine learning libraries directly integrate ready-to-use datasets as well as pre-trained algorithms, the implementation of deep learning solutions, especially in the field of computer vision, has become easier than ever.
- Another approach to increase accessibility to AI is to simplify interfaces, for instance, by offering users the option to build programs using natural language instead of written code.

Besides facilitating access to technology, these advances also enable programmers to focus on modularising and tweaking the datasets and/

or systems for real-life applications. Despite simpler solutions possibly delivering slightly worse performance than specialised systems built from scratch, they offer a decisive cost advantage as well as letting inexperienced users integrate their domain knowledge in the system, which may easily make up for a lack in purely technical sophistication. Thus, all things considered, most organisations will likely not be able to create general-purpose machine learning solutions which offer ground-breaking increases in performance as this portion of the data science pipeline is becoming increasingly commoditised, with AI utilised in industry applications largely lagging behind the state of the art in research.

Instead, most organisations seeking to differentiate themselves through technological advances may explore different directions, some of which might include:

- Combining modular technologies to create powerful multi-purpose platforms and services
- Creating tailored solutions for specific purposes, potentially empowered by niche datasets
- Focusing on challenges revolving around algorithmic explainability, interpretation of results, and other issues in the field of machine-human interaction
- Specialising in other parts of the data pipeline (e.g., data collection and processing, feature engineering, visualisation)

12.4 Future Power Dynamics in Financial Services

While the survey yielded conclusive findings on the aspects which differentiate Incumbents and FinTechs in the way they leverage AI, results have also shown that there is a significant amount of uncertainty around how AI will affect the competitive environments existing within Financial Services. Incumbents, FinTechs, and 'Big Tech' all bring complementary capabilities to the table:

- FinTechs have the privilege of starting from scratch, allowing them to build new IT systems that have a significantly lower cost base and can be built from the ground up around potential AI 'flywheels'. However, they don't have existing customer scale, which is proving expensive and time-consuming to acquire in both B2C and B2B domains.
- Incumbents have the scale of customers that FinTechs lack. They also have recognised brands and, for the most part, the trust of customers and regulators. However, most Incumbents are also burdened by legacy systems that leave them with an extremely high cost base, as well as heavily siloed data structures that limit their ability to leverage the data that they have. As a result, AI projects at Incumbents risk being 'bolted on', making it difficult to establish 'flywheel' effects around the core business of the organisation, especially when attempting to bypass deficits in corporate agility by setting up spin-off entities which stand far from the parent organisation. Incumbents also predominantly use AI to augment existing products, while FinTechs are harnessing new AI-enabled offerings to differentiate their product portfolio which may allow them to more effectively harness AI as a driver of profitability.
- 'Big Tech' companies usually possess vast stores of data, customer interactions at a massive scale, and a superior understanding of how to build successful businesses around AI. However, they are subject to intense political/ regulatory pressure in their core areas of operation and, as the recent announcement of Libra shows, face the risk of significantly higher scrutiny as a result of moves into finance.

It is difficult to predict how these elements could fit together to build businesses that truly take advantage of the power of AI to drive differentiated competitive value propositions. A few possible scenarios include:

- FinTechs and Incumbents could combine their skills to try to hold 'Big Tech' at bay
- Incumbents could try to build new FinTech-like propositions internally (an example of this is Marcus by Goldman Sachs)
- FinTechs could team up with 'Big Tech' – bringing their knowledge of financial products to the distributional scale of the tech firm
- Selected Incumbents could explore collaborations with 'Big Tech', such as, for example, the Apple/Goldman Sachs collaboration on the Apple credit card

While it is challenging to assess how the adoption of AI by different groups within Financial Services will impact the industry on a higher level, it is important to consider that AI-driven consolidation may play out at the functional rather than the organisational level or product level.

For example, large technology companies are well-positioned to leverage their existing customers' relationships and associated personal data to develop AI systems that advise their customers on financial matters and help them compare various financial products. However, offering such a service would not necessarily require the firm to become a bank – instead, they could offer a service that is both 'wider' and 'shallower' than those offered today; advising the client on every aspect of their financial lives (payments, insurance, investments, loans, etc.) but not providing any of the underlying products. Combined with a platform model for the distribution of third-party financial products this could serve as a powerful generator of training data for AI personalisation and advisory models.

The potential for such an approach to succeed will be highly dependent on the evolving regulatory environment, particularly at a time when both US and European regulators are re-examining aspects of competition policy with an eye to limit the power of 'Big Tech'.

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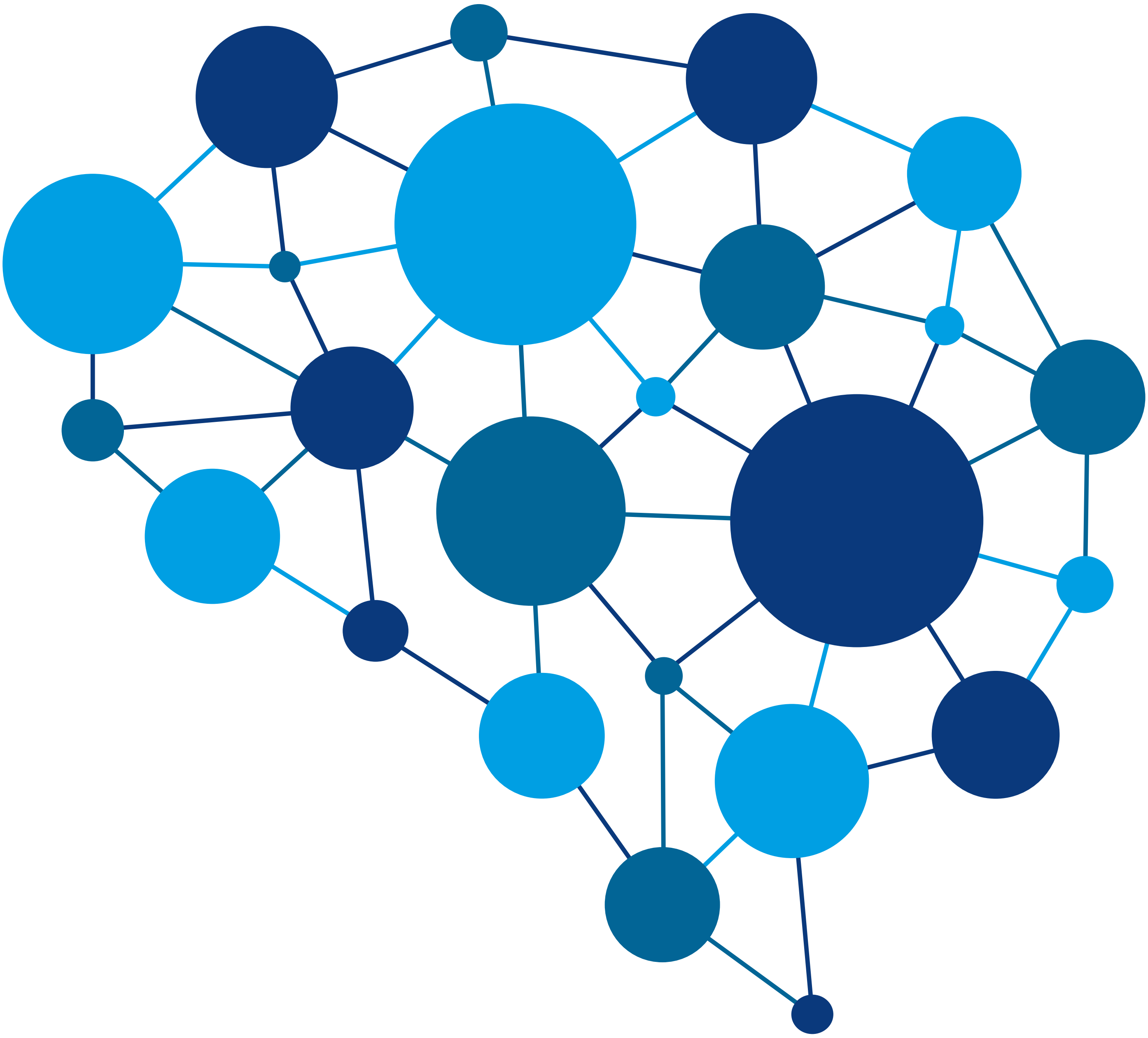

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