CHAPTER 1

Introduction

> *"By far, the greatest danger of Artificial Intelligence is that people conclude too early that they understand it."*
>
> —Eliezer Yudkowsky

No doubt, we, as a society, are entering into new advances in technology at ground-breaking speed. The rapid growth in digital data and advances in computing power open endless possibilities for transformation in every sphere of life. At the same time, these developments are also driving unparalleled change in human behavior, consumer demand, and expectations. It is believed that we are now entering the next wave of revolution: the fifth industrial revolution or the age of artificial intelligence (AI). In this age, it is said that machines are truly capable of varying degrees of self-determination, reason, and "thought," working with humans in unison. As a technology, AI is pervasive in every industry, including financial services. It is also starting to mature as a useful tool in risk management function.

However, *AI* is a broad term and defined by various industry bodies in different ways. The *Oxford Dictionary* defines it as "the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages."[1] The European Union defines it as "systems that display intelligent behaviour by analysing their environment and taking actions—with some degree of autonomy—to achieve specific goals."[2] The Office of the Comptroller of the Currency (OCC) in the United States defines it as "the application of computational tools to address tasks traditionally requiring human analysis."[3]

As a scientific discipline, AI includes several subdisciplines, such as machine learning (of which deep learning and reinforcement learning are examples), machine reasoning (which includes knowledge representation, deduction, and induction), and robotics (which includes sensors and the integration of other techniques into cyber-physical systems). Despite the enormous transformational benefits that true "AI" systems and platforms can bring to humanity, what is it about "AI" that sends shivers down our spines? Arguably, the shivers are caused by the fact that, for the first time in human history, we are engaging with the *intelligence* component of technology and the fear of the unknown. And another reason is Hollywood!

It is quite amazing that one of the most memorable moments in cinema is from Stanley Kubrick's 1968 production of Arthur C. Clarke's *2001: A Space Odyssey*.[4] In an iconic scene, the heuristically programmed algorithmic computer (HAL), responsible for controlling the systems of the *Discovery One* spacecraft, replies to astronaut David Bowman's request, "Open the pod bay doors, HAL," with "*I'm sorry, Dave. I'm afraid I can't do that.*" Perhaps this scene is so memorable, because it is unbelievable to think that an advanced, sentient machine like HAL can think, feel, and mimic human behavior and decide on its own.

There are scenes from other movies and science fiction novels that depict AI as ultimately rising and taking control of society. In many ways, AI-enabled systems are already safely integrated into our personal lives. Take, for example, virtual assistants like Google Assistant, Apple's Siri, and Amazon's Alexa that use the more traditionally derived and AI-puritan List Processing (LISP) for voice recognition. Such "AI" has been widely adopted[5] and will continue its advancements as more applications integrate AI methodologies. This is true for the traditional AI applications like machine learning and deep learning to computer vision and cognitive computing as employed by next-generation televisions, cars, and home appliances.[6] In addition, technologies or machines utilizing AI or developed using machine or deep learning algorithms (concepts we will cover in Chapter 3) have contributed to the advancement of robotic process automation (RPA), which refers to the automation of repeatable processes by computer-coded software programs that were traditionally done by humans. One of the reasons why RPA is starting to replace other, more traditional operational efficiency improvement strategies is because it runs at a fraction of the cost of human capital.[7] In addition to the cost-savings, RPA has reduced processing time and error rates. Examples of RPA deployments in banks include virtual assistants that handle repetitive tasks such as document-processing and verification, account opening and funds transfers, and correction of formatting and data errors that arise in customer requests.

By continuing to augment, and at times automate, manual jobs or daily tasks, AI-enabled applications continue to transform our personal and professional lives. AI is making what was once science-fiction into science-fact. This will continue to be the case when considering the consolidated impact of four major factors:[8]

- **Moore's law.** Computing power is said to double every two years and will continue to do so for the foreseeable future.[9]
- **Data.** The creation of data and replication have doubled each year. It is estimated that 1.7 megabytes of new information are created every second for every human being on the planet, meaning that from 2010 to 2020, there was a 5,000% growth in data—from 1.2 trillion gigabytes in 2010 to 59 trillion gigabytes in 2020. The exponential growth in data is largely driven by digitalization, and is expected to continue.[10] It is the fuel for AI-based algorithms, especially those that require large and rich amounts of data for training and development, like deep learning.[11]
- **Funding.** AI funding has doubled every two years, largely driven by the availability of required computational power.[12]
- **Test of time.** There is 50 years of established AI and quantitative research that is underpinning better algorithms.

Taking these four factors into account and the current state of play, AI is not merely hype. Although we are going through a hype cycle where expectations may not be realistic, there is great potential that will likely be realized in the coming years.[13] To remain relevant in the wake of the age of AI, it is critical for organizations to prepare for a large-scale adoption, integration, and use of AI-enabled systems in industries such as financial services. A word of caution, though—for AI and machine learning to realize short- and long-term business value in a responsible way, the foundational technological building blocks of data, people, and processes will need to be reconsidered. These building blocks will be discussed in more detail throughout this book.

RISK MODELING: DEFINITION AND BRIEF HISTORY

In recent years, the number of risk models employed by financial institutions increased dramatically, by 10–25% annually.[14] Let's define what a risk model is. A risk model involves the application of quantitative methods, analytics, and algorithms to quantify financial and nonfinancial risks. It is important to note that risk management applies to other industries besides financial institutions; however, the applications used in this book mainly relate to the financial services industry and particularly to the quantification of financial risks.

Henceforth, in this book, the term model refers to a financial risk model unless otherwise stated. Interestingly, most of the modern-day risk and probability theory evolved from innovation in science, economics, and technology in the last 200 to 300 years.[15] However, our ability to utilize mathematics to estimate probabilities and use it as a means to quantify risk in our modern world stems from developmental advances across multiple centuries. The English term *hazard*, referring to "chance of loss or harm, risk," likely originates from the Arabic term *az-zahr,* which means "the dice." Ground-breaking mathematicians like Fibonacci (the golden ratio), followed by Blaise Pascal (the father of modern theory in decision-making), laid the foundations for modern-day probability theory.

Moreover, Fibonacci learned the Hindu-Arabic numerical system from traders while visiting his father at a port in Algeria in the thirteenth century. Innovations in mathematics, trading, and finance seem inextricably linked—but that is perhaps a topic for another book. The use of risk models can likely be traced back to the precursor of what we now consider actuarial science in insurance. In the eighteenth century, these pre-modern-day analysts poured over data to estimate life expectancy on which to price insurance premiums.

Fast forward to modern times; based on the work of others like David Hume and Nicholas Bernoulli, Harry Markowitz developed portfolio theory in 1952. Today, we can define a model as a quantitative method, system, or approach that applies statistical, economic, financial, or mathematical theories, techniques, and assumptions to process input data into quantitative estimates.[16]

The use of risk models is now ubiquitous in financial services. One reason is the swaths of new regulations before and after the Global Financial Crisis. In the last decade, regulation after new regulation has expanded the volume of risk models that organizations need to manage. In addition, organizations have increased model usage to remain competitive—replacing manual activities and decision-making with analytical methods, while improving the sophistication of their models. Models are also used to keep up with industry trends such as big data and digitalization.

The effects of the Global Financial Crisis did not only increase the number of models to manage—it also increased their complexity. Organizations began adding different model types—including econometric models, financial and forward-looking models for provisioning, and enterprise stress testing. That resulted in a growing number of dependencies and interconnections between the models, how they operate, and the process that defines it (i.e., the risk model lifecycle).

New models have started to gain even more traction as the COVID-19 pandemic highlighted inefficiencies in the risk model lifecycle. The issues were particularly evident in the volatility observed in forward-looking loss models during the COVID-19 pandemic. Financial institutions realized that risk models need to balance their efficacy with potentially longer-term degraded conditions and increased macroeconomic uncertainty, caused by the COVID-19 pandemic. The longer-term conditions and increased uncertainty are likely to continue to create “shocks” to many different types of risk models. At the time of writing, many large banks have accelerated their recalibration efforts, including the use of alternative data and modeling approaches, due to:

- Risk-ranking and risk profiling discrepancies caused by shifts in consumer and portfolio behavior
- Risk models simply breaking down due to shifts in correlations with macroeconomic indicators

The use of AI and machine-learning-based algorithms for risk management requires a rethink of the risk model lifecycle. Typically, a traditional statistical model takes a risk modeling team several months of development effort. One can argue that a lengthy process is needed to ensure a desired level of accuracy, performance, and validation, but experience has shown that a lot of effort is spent on inefficiencies due to fragmented, legacy systems across the risk model lifecycle. For example, rigid processes that are entrenched in silos of business activity may delay signoffs and there can be a culture that supports a mentality to “reinvent the wheel” for each model development activity.

One lesson from COVID-19 is that long cycles of building and deploying models for risk-based decision-making lead to suboptimal decisions.

The use of AI and machine learning presents an opportunity to greatly reduce the "time to model" and reap the resulting rewards.

USE OF AI AND MACHINE LEARNING IN RISK MODELING

As a suite of tools, AI and machine learning have transformational potential to improve accuracy compared to traditional models, handle large structured and unstructured datasets, and help assist organizations with agile responses to changes in market conditions. Together, the suite has been effectively used in problem-solving, and is likely to accelerate given the faster adoption of big data technologies and digitalization.

In financial services, the use of AI and machine learning started some years prior to the COVID-19 outbreak and in many diverse areas of financial services, including risk management. To the risk function, AI and machine learning have delivered tangible benefits by automating mundane tasks and processing large volumes of diverse data. These tools can flexibly identify complex relationships hidden in data and thus achieve higher levels of model accuracy, compared to what is possible with traditional statistical methods. However, for the large-scale and long-term use of AI and machine learning, adoption of a scientific mindset needs to be better embedded in the culture and in the way innovation is approached by teams across the enterprise.

When applying the scientific mindset to AI and machine learning, technology is typically applied to solving a specific problem, rather than attempting to use the technology to *incidentally* solve an existing problem. Once a problem has been identified, then a hypothesis can be tested appropriately, utilizing the scientific fundamentals that involve data, people, and processes. We will next explain how the traditional function of risk management is changing in response to new and emerging risks, and how AI and machine learning can enable an easier response to the demands created.

THE NEW RISK MANAGEMENT FUNCTION

Risk management can be viewed as more than a collection of compliance measures and a function to meet continued demands and expectations of internal and external governance bodies. Current risk management frameworks are adapting to new and emerging risks, increased uncertainty in the macroeconomic environment, and addressing transparency and fairness in financial decision-making—especially those concerning customers and those that impact the environment. Emerging risks, digitalization, stronger competition, and new regulations demand more from the modern risk function, especially against a backdrop of COVID-19 and climate change.

At the time of writing, a tiny, single-stranded RNA called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that causes Coronavirus Disease-2019 (COVID-19) and potential life-threatening respiratory infections, had quickly spread to become a global pandemic.[17] Beginning about December 2019, the impact and devastation caused by that tiny strand of RNA was unprecedented in contemporary times. The impact of lockdowns on the global economy was sharp and steep: the worldwide unemployment rate peaked at 14.5% in April 2020[18] with a worldwide gross domestic product (GDP) contraction of at least 5.2%.[19] All economic factors pointed to one of the worst economic crises the world had experienced since the 1930s Great Depression.

Part of the dramatic volatility caused by containment measures were fortunately countered by fiscal policy, including short-term relief for borrowers and other programs introduced by national governments and central banks. Irrespective of the extent of containment measures, the resiliency built into banks' balance sheets—large capital buffers put in place as a result of enhanced regulatory scrutiny following the Global Financial Crisis[20]—were tested by the pandemic.

Who would have thought that a tiny strand of RNA could create such macroeconomic upheaval in as little as a few months? Many businesses had to adapt to a newly defined "normal."

Even though the impacts of the pandemic were quick and severe, the recovery was almost as quick, as countries and sovereign states emerged from the COVID-19 restrictions and trillions of dollars in stimulus measures boosted economies.

The macroeconomic effects at the peak of the pandemic created strong negative impacts on risk and profitability levels of organizations and demanded quick intervention from governments. For financial services, for example, risk and profitability are known to interact very closely with macroeconomic effects (as per the credit cycle or interest rate cycle). In addition, financial services play a necessary and important part in stabilizing markets for businesses to operate.[21] Such macroeconomic factors, continued uncertainty, and market responses may drive unexpected impacts on all types of financial risk, including credit, market, and liquidity risk.

The main types of financial and nonfinancial risks are summarized in Table 1.1.

Changes to the climate have been understood for many decades. Since 1992, the United Nations has recognized that changes to the global climate patterns, mostly due to greenhouse gas emissions, pose serious issues to the world.[22] The recognition has created notable accords by participating countries. However, more recently, data and scientific-based analysis suggest that more needs to be done sooner. We are at a crossroads of climate instability. Climate change, defined as "a significant variation of average weather conditions" (i.e., the increased likelihood of warmer, wetter, or drier climate conditions over the next several decades)[23] will start to have significant economic

Table 1.1 Types of Risk and Associated Definitions

Risk Type	Definition
Credit risk	Risk of financial loss due to a borrower's failure to repay loan obligations.
Market risk	Risk of loss to institutions earnings from movement in market prices.
Operational risk	Risk of loss from a failed internal process, people, system, or external event.
Insurance risk	Harmful or unexpected event, threat, or peril for which insurance is provided.
Liquidity risk	Risk arising from a firm's inability to meet its short-term obligations as they become due.
Reputation risk	Risk of financial and nonfinancial loss due to public opinion.
Strategic risk	Risk from adverse business decisions or lack of responsiveness to changes in the industry and operating environment.
Compliance risk	Risk from violations of laws or regulations, internal policies and procedures, or ethical standards.
Interest rate risk	Risk of loss due to movements in interest rates.

and socioeconomic impacts under different warming scenarios from now until 2100.

The stability of the climate and financial services industry is intricately connected by complex layers of interaction between the macroeconomic, financial, and climate systems.[24] Stability can be best addressed by understanding what the climate change–associated risks are to the finance sector. We discuss these along with addressing the analytics framework, covering data, models, and scenarios that are needed to understand the impacts of climate change in Chapter 9. Importantly, climatic change is an area where advanced analytics and innovative applications of AI and machine learning have added value.

OVERCOMING BARRIERS TO TECHNOLOGY AND AI ADOPTION WITH A LITTLE HELP FROM NATURE

At this point you may be asking yourself, is it purely that we are waiting for true "AI" to be created before it becomes mainstream in its use, or are other factors at play acting as barriers of uptake? One way to narrow down the naturally derived barriers of larger-scale adoption of new technologies is to look back in time at periods of industrial revolutions.

When a new technological advancement like means of communication and societal systems synergize, it has created industrial revolutions that in turn have acted to modernize society through innovation.[25] Quite paradoxically, in practice, the ensuing new ways of working and organizational change required have been less glamorous, and often challenging. There are many such examples of innovative techniques and associated technologies where genuine concerns were held that prolonged the required change and delayed adoption at scale. Take, for example, the first industrial age during the eighteenth century, where the change of wood power to coal power led to the replacement of hand tools with power-driven machines like the steam engine.[26] The second industrial age saw the use of electric power for mass production and rapid standardization. Yet the humble telephone was believed to cause deafness or simply send people mad.[27] Fast forward to the third industrial revolution that began in the 1950s to 1970s, where technology advanced from analogue electronic and mechanical devices to electronic computing, digital record-keeping, and the advent of the internet. Yet the first version of the automated teller machine (ATM) called the "Banko graph" was met with concern that customers would lose all their money! Customers were promised that the machines were safe and convenient, allowing them to make deposits or withdraw cash at any hour of the day or night.[28] Photographs of money entering the machine as a form of direct receipt[29] were not enough to allay fears. It took the semi-catastrophic weather event of the 1977 blizzard in New York that caused mass bank closures for many days for ATM usage to become more widespread.[30] The rest, with no intentional pun, is history, as other cities around the world followed New York's lead.[31]

A little push to drive change like the ATM, coupled with a climate event, is at times needed to accelerate the adoption of technological innovation. However repetitive and mundane, transformation is not easy and requires hard work. For organic innovation to progress, technological changes like the ATM and even telephone often require experience through experimentation rather than mandates so that the needs and necessities of change, as well as its opportunities and risks, can be fully understood. With that in mind, eventual desire for change can even be created.[32]

Similarly, the mainstream adoption of AI and machine learning in risk modeling requires both experimentation and experience to be fully understood. As suggested by the ATM example, while adoption of new technology may, at times, require a shock, broad adoption occurs when the technology improves the customer experience. If that does not take place, then the tangible benefits of AI and machine learning may not be fully leveraged.

THIS BOOK: WHAT IT IS AND IS NOT

With this book, we aim to provide examples and information to demystify the concepts of AI and machine learning, thereby increasing the awareness of its many benefits and how it can be applied to solve everyday risk management problems (e.g., how to evaluate the financial impact of extreme events such as global pandemics and changes in climate). We also highlight some of the incremental risks and unintended consequences associated with AI and machine learning in risk management and ways to address these, thereby enabling organizations to be better prepared for its adoption and responsible use. As far as possible, we aim to provide practical examples of use cases where AI and machine learning have delivered tangible benefits in risk management.

ENDNOTES

1. Oxford Reference, *The Oxford Dictionary of Phrase and Fable* (2006), https://www.oxfordreference.com/view/10.1093/oi/authority.20110803095426960
2. The European Commission's High Level Expert Group on Artificial Intelligence, *A Definition of AI: Main Capabilities and Scientific Disciplines* (European Commission, 2018).
3. Office of the Comptroller of the Currency, *Comptroller's Handbook: Safety and Soundness. Model Risk Management Version 1* (Federal Reserve Bank, 2021), https://www.occ.gov/publications-and-resources/publications/comptrollers-handbook/files/model-risk-management/pub-ch-model-risk.pdf
4. Grant Feller, *Future Technology: A Force for Good or a Source of Fear?* (Coventry, UK: The University of Warwick, 2015).
5. Anand S. Rao, Gerard Verweij, and E. Cameron, *Sizing the Prize—What's the Real Value of AI for Your Business and How Can You Capitalise?* (Boston: PricewaterhouseCoopers, 2017).
6. Margot O'Neill, *Explainer: What is artificial intelligence?* (Melbourne, Australia: ABC News, 2017); Rao et al., *Sizing the Prize*.
7. Shane O'Sullivan and Brandon Stafford, *RPA and Your Digitisation Strategy* (Australia: PricewaterhouseCoopers (Australia) Pty Ltd., 2016).
8. Tara Balakrishnan, Michael Chui, Bryce Hall, and Nicolaus Henke, *The state of AI in 2020* (London: McKinsey & Company, 2020), https://www.mckinsey.com/business-functions/quantumblack/our-insights/global-survey-the-state-of-ai-in-2020
9. Dave Vellante and David Floyer, "A new era of innovation: Moore's Law is not dead and AI is ready to explode," *SiliconAngle* (April 20, 2021), https://siliconangle.com/2021/04/10/new-era-innovation-moores-law-not-dead-ai-ready-explode/
10. Gil Press, "54 Predictions about the state of data in 2021," *Forbes* (December 30, 2020), https://www.forbes.com/sites/gilpress/2021/12/30/54-predictions-about-the-state-of-data-in-2021/?sh=30985b47397d
11. Joe McKendrick, "AI adoption skyrocketed over the last 18 months," *Harvard Business Review* (Sept 27, 2021), https://hbr.org/2021/09/ai-adoption-skyrocketed-over-the-last-18-months
12. PricewaterhouseCoopers, *UK Economic Outlook: Propsects for the Housing Market and the Impact of AI on Jobs* (United Kingdom: PricewaterhouseCoopers, July 2018), https://www.pwc.co.uk/services/economics/insights/uk-economic-outlook/july-18.html
13. PricewaterhouseCoopers, *UK Economic Outlook*.
14. Ignacio Crespo, Pankaj Kumar, Peter Noteboom, and Marc Taymans, *The Evolution of Model Risk Management* (New York: McKinsey & Company, 2017), http://dln.jaipuria.ac.in:8080/jspui/bitstream/123456789/3127/1/The-evolution-of-model-risk-management.pdf

15. Philip F. Stahel, Ivor S. Douglas, Todd F. VanderHeiden, and Sebastian Weckbach, "The history of risk: a revie," *World Journal of Emergency Surgery* (March 14, 2017).
16. Federal Reserve Bank, *SR11/7—Supervisory Guidance on Model Risk Management* (Washington DC: Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency, 2011), https://www.federalreserve.gov/supervisionreg/srletters/sr1107.htm
17. Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), *COVID-19 Dashboard* (2020), https://coronavirus.jhu.edu/map.html
18. OECD, *Unemployment Rate—Tackling coronavirus (Covid19), Château de la Muette* (Paris, France: OECD, 2020).
19. The World Bank, *The Global Economic Outlook During the COVID-19 Pandemic: A Changed World* (Washington, DC: The World Bank, 2020).
20. Fabio Natalucci, *Global Financial Stability Amid Covid-19 Pandemic* [Interview] (April 2, 2020).
21. Marianne Gizycki, *The Effect of Macroeconomic Conditions on Bank's Risk and Profitability* (Melbourne, AUS: Reserve Bank of Australia, 2001).
22. United Nations, *UN Climate Talks 1992–2020* (New York: The United Nations, 2020).
23. Melissa Denchak, *Global Climate Change: What You Need to Know* (New York: NRDC, 2017).
24. Network for Greening the Financial System, *NGFS—Central Banks and Supervisors Network for Greening the Financial System* (Accessed 2021), https://www.ngfs.net/en
25. Joseph A. Schumpeter, *Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process* (New York and London: McGraw Hill Book Company Inc., 1939); Goncalo de Vasconcelos, "The Third Industrial Revolution—Internet, Energy and a New Financial System," *Forbes* (March 4, 2015).
26. Punit Renjen, *Industry 4.0: Are you ready?* (Philadelphia, PA: Deloitte Review, 2018), https://www2.deloitte.com/content/dam/insights/us/articles/4364_Industry4-0_Are-you-ready/4364_Industry4-0_Are-you-ready_Report.pdf; Peter Temin, "Two views of the British Industrial Revolution," *Journal of Economic History* 57(1) (1997): 63–82.
27. Natasha Lomas, *Humanity has Always Feared Technology. In the 21st Century, Are We Right to Be Afraid?* (Palo Alto, CA: ZD Net.com, 2011); Melissa Dickson, *The Victorians Had the Same Concerns about Technology as We Do* (Oxford, UK: The Conversation, 2016).
28. Elizabeth S. Anderson, *10 Unnecessary Fears People Had of Everyday Things* (UK: Listverse Pty Ltd., 2015); History.com, *Automated Teller Machines* (A&E Television Networks, 2010; updated 2018), https://www.history.com/topics/inventions/automated-teller-machines; Cornelis Robat, *ATM—Automatic Teller Machine* (2006), thocp.net
29. Elizabeth S. Anderson, *10 Unnecessary Fears People Had of Everyday Things* (UK: Listverse Pty Ltd., 2015).
30. History.com, *Automated Teller Machines*.
31. Robat, *ATM*.
32. Richard Beckhard and Reuben T. Harris, *Organizational Transitions: Managing Complex Change*, 2nd ed. (Reading, MA: Addison-Wesley, 1987); John Kotter, *Leading Change*, 1st ed. (Boston, MA: Harvard Business School Press, 1996).