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# Applications of Artificial Intelligence in financial services

How this technology is reshaping the industry,
a case study from Ant Group.

**Supervisor**
Ch. Prof. Marcella Lucchetta

**Graduand**
Serxho Lila
Matricolation number 853115

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# INTRODUCTION

Following the global financial crisis of 2008, the entire financial sector has experienced profound changes. Traditional financial institutions have witnessed a growing distrust of consumers in them. On the other hand, the exponential acceleration of new technologies, combined with the spread of the internet and smartphones among people, enabled a massive transformation within the entire financial sector.

These changes have allowed new players, FinTechs, to enter the scene. Their fully digitized structures and the use of new technologies have enabled them to gain a competitive advantage over traditional financial institutions, forced to implement renewal plans to implement the new technologies and restructure their antiquated physical organizations.

Like any revolution, there will be winners and losers. Some will be able to adapt and succeed in the face of these changes, while others will fight to reinvent themselves in the ways required to remain relevant. It is impossible to know who will rise triumphant from this period of tumultuous change, but we can explore the technological innovations that are changing the financial services ecosystem.

The fundamental innovation of the FinTech revolution is Artificial Intelligence (AI), a technology whose applications today influence every aspect of people's daily life and leads to innovations in every field, from autonomous vehicles to smart assistants. AI techniques have found an ideal application space in the financial field, and they are now commonly used in several ways. They enable automating some tasks that were done manually, analyzing massive amounts of data, and boosting analytical capacity in a decidedly superior way compared to traditional techniques.

This thesis consists of a qualitative research, through document analysis of papers, books, and reports, with the aim to examine how AI is being implemented in the financial field.

The first chapter introduces AI, giving the definition and the historical background, less recent than is usually thought. The chapter continues with the investigation of today's AI landscape, the adoption among different sectors, firms, and national approaches toward this innovation. The chapter closes with an analysis of the different types of AI, based on capabilities or functionalities.

The second chapter explores the different AI techniques, like machine learning (ML), natural language processing (NPL), machine vision, and expert systems (ES). Given the subject's dimension, the tools examined are limited to those applied in the financial field.

The third chapter deals with all the applications of AI in the financial field. It begins by introducing the fintech revolution and then focuses on each sector involved in it, examining the innovations in financial services made possible by the development and adoption of AI technologies. The sectors analyzed are lending, payments, insurance, chatbots and Robo-advisory systems, capital markets, trading, and the so-called RegTech.

The fourth chapter consists of a case study on Ant Group, an affiliate FinTech company of the Chinese Alibaba Group, which represents the ideal prototype of a twentyfirst century company, masterfully exploiting AI. The case study analyzes the company's history, the services offered, its business and operating models, and how the exploitation of AI and other technological innovations led to its success, offering today services to hundreds of millions of people.

The fifth chapter explores future predictions regarding the financial services sector, the possible role of FinTechs, traditional financial institutions, and new potential entrants. Furthermore, the chapter concludes with an analysis of AI's future, its impacts on jobs, dangers and potential ethical concerns, and the risk of creating a singularity.

The conclusive chapter illustrates the study's main findings, recommendations, and an autobiographical reflection about the thesis' subject.

# CHAPTER I. WHAT IS ARTIFICIAL INTELLIGENCE?

## 1.1 DEFINITIONS

In AI history, many definitions have been given. Russel and Norvig[1] distinguish four different dimensions. The first two categories concern thought processes and reasoning, while the other two address behavior. Two of them measure success by fidelity to human performance, while the other two face an ideal performance measure, called rationality. A system is rational if it gives the "right thing", given what it knows.
The four categories of AI definitions are:

- **Thinking Humanly**
  "*The exciting new effort to make computers think . . . machines with minds, in the full literal sense*". (Haugeland, 1985)
  "[The automation of] *activities that we associate with human thinking, activities such as decision-making, problem-solving, learning* . . ." (Bellman, 1978)
  This perspective refers to the replication of human thinking processes. The field of cognitive science is a significant manifestation of this approach to AI. It uses computer programs and insights from experimental psychology to emulate the human mind.

- **Thinking Rationally**
  "*The study of mental faculties through the use of computational models.*" (Charniak and McDermott, 1985)
  "*The study of the computations that make it possible to perceive, reason, and act.*" (Winston, 1992)
  It refers to using rules for reaching logical conclusions based on premises assumed to be true.
- **Acting Humanly**
  "*The art of creating machines that perform functions that require intelligence when performed by people.*" (Kurzweil, 1990)

[1] Russell, S., & Norvig, P. (2011). *Artificial Intelligence: A Modern Approach* (3rd ed.). Pearson.

"*The study of how to make computers do things at which, at the moment, people are better*." (Rich and Knight, 1991)

From this point of view, AI refers to the challenge of creating computers capable of performing tasks in ways that are similar to how humans perform them.

- **Acting Rationally**

  "*Computational Intelligence is the study of the design of intelligent agents.*" (Pool et al., 1998)

  "*AI . . . is concerned with intelligent behavior in artefacts.*" (Nilsson, 1998)

  It aims to build agents that act rationally to achieve the best outcome.

All four ways to deal with AI have been followed, each by various individuals with different methods. A human-centered methodology must be part of empirical science, including observations and hypotheses about human behavior. A rationalist approach includes a blend of arithmetic and engineering. Historically, the different groups have both denigrated and helped one another.

Until a few decades ago, most AI research fell into the category of reasoning, while nowadays, the acting rationally dimension is more widespread. The term "artificial intelligence" is now commonly used to define human intelligence processes' simulation by "intelligent agents". These can be any device or machine that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. These goals include learning, acquiring information and rules to use the information and reach conclusions, reasoning and self-correction.

## 1.2 THE HISTORY OF ARTIFICIAL INTELLIGENCE

### *1.2.1 The gestation of AI*

The history of AI is a history of fantasies, possibilities, demonstrations, and promises. Ever since Homer wrote of mechanical "*tripods*"[2] serving dinner to Gods, these mechanical assistants took part in our culture. However, only in the last half-century, the AI community has built experimental machines that test the hypotheses on the mechanisms of thought and intelligent behavior and thereby demonstrate mechanisms that formerly existed only as theoretical possibilities.

In human history, many philosophers[3] wrote about the possibility of intelligent machines as a device to help us to define what it means to be human or to help us in formulating laws of thought. Gottfried Wilhelm Leibniz, for example, invented in 1673 the Step Reckoner[4], an improved mechanical calculator, which by using rules of logic, was able to settle disputes mechanically. Many sci-fi writers have written about machines with human attributes and intellect; for example, Jules Verne in the nineteenth century or Isaac Asimov or L. Frank Baum in the twentieth century.

The major milestone in AI was marked when Alan Turing (1912-1954) proved that mathematical logic has limits. Within these limits, any form of mathematical logic could be mechanized. In 1936, Alan Turing proposed an abstract universal computing machine called the Turing Machine, capable of computing any computable function. However, Turing also showed that there were some functions that no Turing machine can compute. This invention inspired many scientists and researchers to begin discussing the possibility of thinking machines.

The first work that is generally recognized as AI was done by Warren McCulloch and Walter Pitts. In 1943, they published a paper called "*A logical Calculus of the Ideas Immanent in Nervous Activity*"[5], in which they proposed a model of networks of

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[2] Automatic tripods are machines of a non-human form built by Hephaestus. These androids carried food during the banquets of the gods.

[3] Leibniz, Spinoza, Hobbes, Locke, Kant and Hume just to name a few.

[4] Leibniz's calculator was the first mechanical calculator in history capable of performing all four arithmetic operations.

[5] Mcculloch, W. S., & Pitts, W. (1943). *A Logical Calculus of the Ideas Immanent in Nervous Activity*. Amsterdam University Press.

connected artificial neurons. This model could compute any computable function in which simple net structures could implement all the logical connectives (and, or, not, etc.). They also suggested that properly defined networks could learn.

In 1950, Turing published the paper "Computing Machinery and Intelligence"[6], a turning point in AI history. He introduced the Turing Test: an examinator is separated from the person (or machine) by a teletype. If the interrogator cannot be sure whether he or she is communicating with a person or a machine, the machine can indeed be said to think. Turing also introduced the concept of machine learning, genetic algorithms, and reinforcement learning.

### *1.2.2 The birth of AI (1956)*

In 1956, some scientists, including J. McCarthy, M. Minsky, C. Shannon, N. Rochester, met at Dartmouth College. They organized a two-month workshop collaborating on a proposal to the Rockefeller Foundation, with the aim "to study the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it." The Dartmouth summer conference's concrete results were low, but the meeting gave Artificial Intelligence its name.

Moreover, two participants, Allen Newell and Herbert Simon, already had a reasoning program, the Logic Theorist (LT), described by them as "a computer program capable of thinking non-numerically" that solved the venerable mind-body problem. Soon after the workshop, the program solved a large number of mathematical theorems, also providing briefer proofs than former ones. The Dartmouth workshop did not lead to any breakthrough, but it did introduce all the significant figures to each other, people who dominated the field for the next 20 years.

### *1.2.3 Early years: enthusiasm and the first winter (1950-1980)*

The early years of AI were full of success, considering primitive computers and programming tools. Some successful programs were:

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[6] Turing, A. M. (1950). I. - Computing Machinery and Intelligence. *Mind*, *LIX*(236), 433–460.

- The General Problem Solver, or GPS, by Newell and Simons, a program designed to imitate human problem-solving protocols. Within the limited class of puzzles, it could handle considered goals, sub-goals and possible actions. It was similar to how humans approach problems. GPS was the first program to embody the “thinking humanly” approach.
- At IBM, the Geometry Theorem Prover proved theorems that many students of mathematics would find quite tricky; a series of programs for checkers that learned to play at a robust amateur level.
- The high-level language Lisp, defined by J. McCarthy at MIT, was about to become the dominant AI programming language for the next 30 years.
- The micro-worlds research, studied at MIT by M. Minsky and a group of students. They came out with programs that solved first-year college calculus integration problems, geometric analogy problems, or algebra story problems. The most famous microworld was the blocks world, consisting of a set of concrete blocks placed on a tabletop. A typical task in this world is to rearrange the blocks in a certain way, using a robot hand that can pick up one block at a time.

In the 1970s, AI was subject to many critiques and disinvestments. AI researchers were too optimistic in the early years, rising impossibly high expectations, while difficulties and fundamental limits emerged. The first problem was the limited memory and processing speed of the operating systems and languages. Moreover, many problems could be solved only in exponential time in the inputs' size, requiring an incredible amount of time in case of challenging problems. Other limitations were that programs needed an appropriate amount of information from the world in applications like vision or natural language. For example, early translator machines did not consider common language sayings, but they used simple syntactic transformations based on grammars and on-word replacement. Although computers could quickly solve theorems or geometry problems, they could not complete child-level tasks, such as visually distinguishing two objects.

### *1.2.4 The boom and the second winter (the 1980s)*

In the first decade of AI, researches' approaches are now called weak methods. These were based on the search mechanism intention of stringing together elementary reasoning steps to find complete solutions. The alternative to these methods is the expert system. This program answers questions or solves problems about a narrow domain of expertise, using reasoning steps derived from the experts' knowledge. The first example of this approach was the Denral program by E. Feigenbaum and other researchers. The Denral program began in 1965 and was capable of identifying organic molecular structure from the information provided by a mass spectrometer. In 1972, Feigenbaum and other researchers demonstrated the practicability of their approach developing the MYCIN, a program to diagnose blood infections, deducing about 450 rules from experts' interviews, textbooks, and direct cases.

The facility of building and modifying expert systems, joined to their fundamental utility in specific domains, helped in their diffusion. In 1980, the first successful commercial expert system, R1 (also called XCON), was used by the Digital Equipment Corporation. The program helped configure new computer systems orders, saving companies an estimated $40 million a year. Corporations around the world began to develop and use expert systems. By the end of the '80s, nearly every major U.S. corporation had its own AI group and was using or investigating expert systems.

The AI industry boomed from a few million dollars to billions. Hundreds of companies started building expert systems, vision systems, robots and software and hardware specialized for these purposes. Many companies failed to deliver their promises. Therefore, the perception of investors and governments regarding AI was that of a speculative bubble. Soon after, another "AI Winter" comes.

### *1.3.6 New approaches towards AI (1990-2010)*

In the late 1980s, several researchers advocated an entirely new AI approach based on robotics, going in the opposite direction from most of what AI had done since then. The new wave of AI researchers criticized their colleagues' thinking about intelligence. According to them, it was not only about symbolic integration, proving mathematical theorems or solving algebra problems. They believed that machines needed to have a body to perceive and move.

This new way of thinking brings the field of AI to come under the scientific method, in which the hypothesis must be subject to empirical experiments. AI began to be used throughout the technology industry, focusing on particular problems and approaches, being more successful than ever before.

A new paradigm called "intelligent agents" emerged during the 1990s. An intelligent agent system perceives its environment and takes actions to maximize its chances of success. The paradigm defines AI research as "the study of intelligent agents". AI was provided with a common language to describe problems and share solutions among AI scientists and non, such as control theory experts and economists.

The new paradigm, approaches and especially the evolution of computers hardware brought to one of the greatest successes of those years: IBMs Deep Blue[7]. On 11th May 1997, it became the first computer chess-playing system to beat the world chess champion, Gerry Kasparov. The computer was able to calculate up to 200 million possible chess positions per second.

## 1.3 THE AI LANDSCAPE TODAY

Rapid technological changes characterize today's landscape. Researchers and scientists refer to this phase of innovations as the Fourth Industrial Revolution. Klaus Schwab, Founder and Executive Chairman of the World Economic Forum, stated that "*advances in AI, robotics, the internet of things, autonomous vehicles, 3D printing, nanotechnology, biotechnology are changing the way we live, work and relate to one another*"[8].

AI is a buzzword in the current scenario since it is influencing every business and every sector. It has foundations in long-established fields such as sciences, engineering, mathematics, philosophy, psychology, linguistic and computer science. It is now creating tremendous value in the software industry. However, a large part of this potential value lies outside the software industry, in sectors such as retail, travel, transportation, automotive, materials and manufacturing (see figure 1.1). It is hard to think of an industry in which AI will not significantly impact in the next several years.

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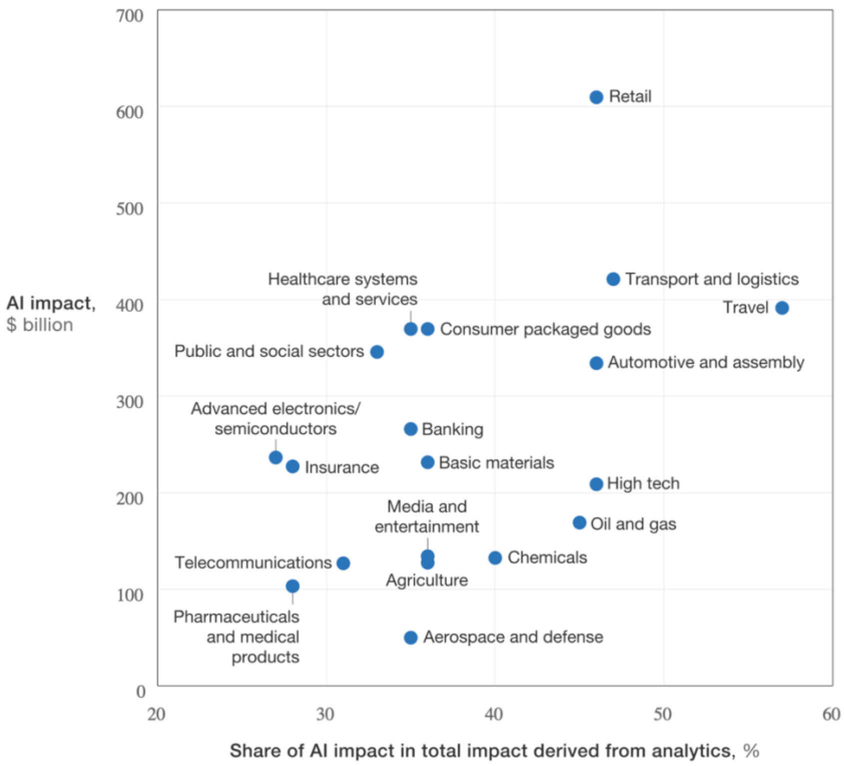
[7] IBM. (2011). *Deep Blue*.

[8] Schwab, K. (2017). *The Fourth Industrial Revolution* (Illustrated ed.). Currency.

**Figure 1.1**: Potential value created by AI across sectors




*Source: McKinsey Global Institute*

Although computer science's history began sixty years ago, the last decade has seen an incredible number of breakthroughs in AI technologies. This progress results from advancements in three main areas: the development in computers' power and capacity, the progress in algorithms and the explosion of data.

The advances in computers' power and capacity made in the last years allow firms to work on a large amount of data and develop AI solutions. Moreover, cloud solutions offer cheaper computing and storage services now accessible to companies without large capitals.

In the last sixty years, the techniques and algorithms at the AI base have been developed continuously. Recent progress in AI techniques has dramatically increased the accuracy of classification and prediction. While the emphasis was previously on the algorithm, now the tendency is to focus on access to large amounts of data, known as "big data". Today, an exceptional amount of data is created every day, feeding algorithms with the information needed to produce new insights. International Data Corporation estimates that there may be one trillion gigabytes of data by 2025[9], ten times the data generated ten years before. The immense quantity and variety of information require systems to organize and analyze these data, which represents a new opportunity to extract value from data that was not available in the past.

### *1.3.1 The adoption of AI among firms*

According to a McKinsey Global Institute study, 50 percent of companies interviewed have adopted AI in at least one business function in 2019. Two-thirds of them declared an increase in revenues resulting from the adoption of AI. Moreover, around 70 percent of companies are expected to adopt AI technologies by 2030[10].

Forecasting the economic impact of AI is highly speculative because of the large number of variables that have to be considered, such as technical feasibility, labor market characteristics, cost of developing or arranging technologies, regulatory and social environment. Despite these analytical obstacles, researches estimated that AI applications could deliver an additional $13 trillions of value annually by 2030. Such amount represents about 1.2 percent additional GDP growth per year, which was never seen before, considering that the impact from robots in the 90s is estimated to be around 0.4 percent and the spread of IT in the 2000s 0.6 percent[11].

The economic impact of AI is estimated not to be linear. Forecasts describe a slow start due to the costs and investments related to learning and deployment, followed by a rapid acceleration given by the cumulative effect of competition and improvement in complementary capabilities. Consequently, it is projected as an accelerating pace over time. In this way, early adopters will benefit from adopting these technologies in later years at the expense of firms with limited or no adoption. Figure 1.2 shows the predicted economic impact of AI depending on the rapidity of firms to adopt it. The research finds that front-runners could increase economic value by 122 percent by 2030. Given their advantage in resources such as talents, computing power, algorithms and data, big techs

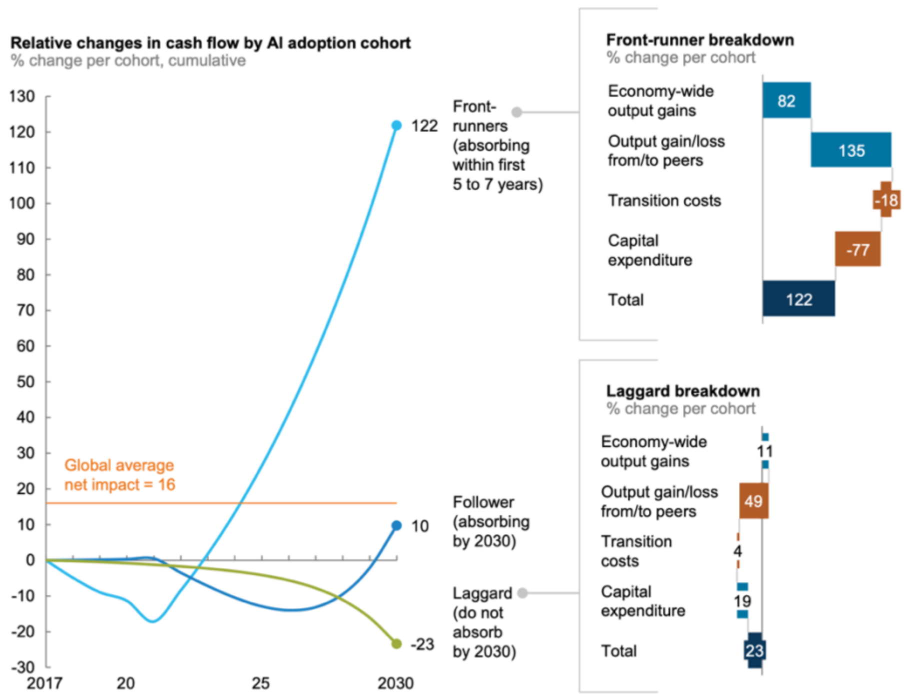
[9] Reinsel, D., Gantz, J., & Rydning, J. (2017). *Data Age 2025: The Evolution of Data to Life-Critical*.

[10] McKinsey Global Institute. (2020). *The state of AI in 2020*.

[11] McKinsey Global Institute. (2018). *Notes from the AI Frontier: Modeling the Impact of AI on the World Economy*.

providing AI technologies belong to the front-runner category. The followers' category, instead, comprises firms that are starting to adopt AI technologies. Further, researches expect cash flow will be modest compared to front-runners' one. The third group comprises laggards: firms that are not investing in AI seriously or do not adopt it whatsoever. The latest category comprises most firms, and forecasts see them lose around 23 percent of the current cash flow.

**Figure 1.2**: Predicted Economic Impact of AI




*Source: McKinsey Global Institute*

### *1.3.2 Different national approaches to AI*

The AI race is not limited to firms only. Nowadays, AI is a national priority, and it will widen gaps between countries, reinforcing the current digital divide. AI leaders could increase their lead in AI adoption over developing countries. Leading countries could generate 20 to 25 percent in net economic benefits while developing countries only about

5 to 15 percent[12]. Many of these countries are facing slow GDP growth, partly due to the ageing of their population. Although developing countries are obliged to push on AI innovation to capture higher productivity, they are less motivated. They tend to have other ways to improve their productivity, such as catching up with better practices or restructuring their industries. Investing in AI may offer them a smaller economic benefit than advanced economies' one. However, this does not mean that they will lose the race regardless. It merely means they will be able to build the foundations to support the acceleration of AI adoption.

The two countries currently leading the AI race are the US and China. These economies attract talent, lead investments and research activities such as patents and publications. Currently, the US leads the AI race due to technological leadership through the past several decades and, most recently, the last digital innovation wave. Venture capital as a system was created here, and the result has been the foundation of tech giants like Amazon, Google, Facebook and Microsoft and thousands of others. Trillions of dollars have been invested in these firms, creating one of the world's most essential technology industries. Besides, the US has a highly specialized labor pool with academic and research institutions vigorously pushing AI innovation borders further. The US government plays a crucial role too. In fact, AI has been named the second-highest research and development priority after American people's security for the fiscal year 2020. Moreover, in the same year, the government launched the American AI Initiative and the AI.gov, intending to channel federal government resources towards AI and make it easier to access the governmental AI initiatives.

Unlike other technologies, AI is considered strategic by most governments, and several approaches have been taken. European Union countries, China and the United Kingdom have adopted approaches supervised by governments. The United States strategy, on the other hand, is self-regulated and dominated by big tech companies. The government only facilitate AI innovation. Moreover, while the US and European countries focus on substantial shareholders and creditors' protection, the Chinese model is characterized by an intense state of control on capital accessibility, investments decisions and stock market listing. Chinese government's efforts to become the first power in the world are not limited to the growth of domestic consumption or the development of the New Silk Road

[12] McKinsey Global Institute. (2018). *Notes from the AI Frontier: Modeling the Impact of AI on the World Economy*.

initiative only. China also strives for excellence within the technological field, in which AI plays a central role. In 2017, the Chinese government announced the “Next Generation Artificial Intelligence Development Plan” to create a domestic market of 1 trillion renminbi ($150 billion) by 2020 and become the AI world leader by 2030[13]. To achieve this result, the Chinese government started to set up an "intelligence industry zone" near Tianjin to support the AI industry. Further, the government actively encourage AI-related innovations with financial incentives. The efforts of the Chinese government finally begun to bear fruit. China now has more than 2,000 AI companies, significantly reducing the gap with the US. In 2017, Chinese AI startups received 48 percent of global AI venture funding, overtaking the US for the first time.[14] Even more surprising is the data regarding the number of patents’ applications. China surpassed the US and now leads the world with more than 110,000 AI patents in 2019.[15] Like the US, China has its tech giants, such as Alibaba, Baidu, Tencent, and Huawei. All these are heavily investing in AI and work closely with the government. Another critical factor regards customer privacy, which China is not as concerned about as the rest of the world.

Internationally, several countries are capturing the benefits of AI, and international organizations such as the UN, OECD and Council of Europe have all formulated their own AI goals. Most countries worldwide have understood the importance of AI and how fundamental it is to ride the wave. Most of them have started programs for AI technologies’ development.

Japan has been a long-lasting leader in AI, especially in the development and adoption of robotics. In 2017, the Japanese government released the “Artificial Intelligence Technology Strategy”[16] that focused on R&D for AI and created a connected system between the industry, the government, and academic research. Another vital factor for the Japanese AI innovation is Softbank, an investor firm leader in the venture capital industry. However, at the moment, the firm's major investments are not focused on the Japanese own AI industry. Moreover, the country is facing demographic concerns due to the

[13] Department of International Cooperation Ministry of Science and Technology (MOST), P.R.China. (2017). *Next Generation Artificial Intelligence Development Plan.*

[14] Mckinsey Global Institute. (2017). *Digital China: Powering the Economy to Global Competitiveness*.

[15] Xue, Y. (2020). *China tops world in AI patent filings, surpassing the US for the first time*. South China Morning Post.

[16] Council of Europe. (2017). *CAHAI - Ad Hoc Committee on Artificial Intelligence*.

population ageing and the consequent workforce shortage, which will cause problems in the creation of dominant AI companies.

The South Korean governments is a strong supporter of AI innovation too. It is announcing investments to strengthen its AI research by creating AI schools to form AI engineers and support AI startups and businesses.

The European leader for AI is the United Kingdom. The English government, academic institutions and venture capital firms are investing in the development of AI-related projects. The UK seems determined to be one of the most important actors in AI innovation. This drive is probably due to the famous English computer scientist, Alan Turing, considered the AI father. Another reason the government's regret of declined AI investments.

In addition to the above, many countries are investing and adopting strategies to develop AI technologies, including Germany, France, Israel, Russia, Canada, and many others. The race for AI domination is fierce, and, at the moment, the US and China are in the lead, considering their amount of resources and the advantage of being the first-movers. However, the AI market does not support a winner take all approach. Many countries will reap the benefits of AI technologies, while those who have not taken actions will stay behind.

## 1.3 TYPES OF AI

### *1.3.1 Based on Capabilities*

There is much enthusiasm about AI, but also worrying. One reason for this is that AI represents two distinct ideas, coined in 1980 by John Searle[17], that have divided AI researchers and philosophers. He distinguished two hypotheses about artificial intelligence: weak AI and strong AI.

Almost all the progress we see in AI is artificial narrow intelligence (ANI), also known as weak AI. ANI supports the idea that intelligent behavior can be modelled and used by a computer to solve complex problems. These AIs rely on a specific operation, such as a

[17] Searle, J. R. (1980). Minds, brains, and programs. *Behavioral and Brain Sciences, 3*(3), 417–457.

smart speaker, autonomous car, or AI to search the web. Considering the above, some argue that just because a computer behaves intelligently, that does not prove that it is intelligent in the way humans are.

In contrast, the second concept of artificial general intelligence (AGI) - known as strong AI - can be described as "*the appropriately programmed computer with the right inputs and outputs*". Therefore, it "*would thereby have a mind in the same sense human beings have minds*". Many researchers also refer to artificial superintelligence (ASI), defined as a machine's ability to be super-intelligent and do even more things than any human can. The followers of strong AI believe in the possibility of creating computers or robots with emotions and real consciousness, but this is rarely considered a goal of AI.

The standard methods of distinguishing between strong AI and weak AI is to perform different professional tests:

- the coffee testing: an intelligent machine can enter a home and figure out how to make coffee, find coffee, add water, find a mug, and brew the coffee by pushing the proper buttons;
- the Turing test: whether an evaluator can distinguish a human from a machine by the nature of conversations between them;
- the robot college test: a machine can pass the enrollment tests to a university, pass the required classes as a real student would, and obtain a degree.

For now, there is extensive progress in weak AI and almost no progress in strong AI. That is because people perceive progress in weak AI as incredibly valuable, while they are still skeptical about strong AI. Overall, it will probably need new technological breakthroughs for its concrete development. Many public figures, like Stuart J. Russell, Bill Gates[18] and Stephen Hawking[19] have expressed concerns about the threats of strong AI to human existence.

[18] Rawlinson, B. K. (2015, January 29). *Microsoft's Bill Gates insists AI is a threat*. BBC News.

[19] Hawking, S. (2017, October 23). *Stephen Hawking: 'Are we taking Artificial Intelligence seriously*. The Independent.

### *1.3.2 Based on Functionalities*

Another classification subdivides AI on the base of the level of intelligence embedded into a machine. Arend Hintze[20] classifies AI based on functionalities: reactive machines, limited-memory machines, the theory of mind, and self-awareness.

1. **Reactive machines** are the simplest level of AI machine and probably one of the oldest categories. These AIs have no memory power of their own. They cannot work on previous data for better decision-making. They simply respond to a limited combination of inputs. Deep Blue, IBM'S chess-playing supercomputer, which, in 1997, beat the international grandmaster - Garry Kasparov - is a perfect example. It can identify the pieces on a chessboard and knows each possible piece move. It can predict what moves might be next for it and its opponent. It can also choose the optimal moves from all the possibilities. However, it does not have any concept of past experiences, so it cannot use previous information as inputs to determine future actions, so it cannot "learn". Deep Blue only looks at the chessboard pieces and chooses from a range of potential next moves. Similarly, Google's AlphaGo[21], which has beaten many Go Experts, can evaluate all the possible future moves. However, unlike Deep Blue, it uses a neural network to evaluate game development.
   These methods improve AI systems' ability to play games better, but they cannot be easily changed or applied to other situations. They cannot function beyond their specific tasks, and they can be easily tricked. They are useful as they ensure reliability yet no added value when engaging with the world.

2. **Limited Memory** class contains machines that can look into the past. Almost all current applications of AI fall into this category, from chatbots to virtual assistants. Another recurring example is autonomous cars. Observing other cars' speed and direction, they identify specific objects and monitor them over time.

[20] Hintze, A. (2016, November 14). *From Reactive Robots to Sentient Machines: The 4 Types of AI*. Livescience.com.

[21] DeepMind. (2015). AlphaGo is the first computer program to defeat a professional human Go player, the first to defeat a Go world champion, and is arguably the strongest Go player in history.

Moreover, these observations are added to the cars' preprogrammed representations of the world, including lane markings, road curves and traffic lights. This past information is only temporary, in any case. They do not get saved as part of the car’s library of experience that it can learn from. Therefore, it cannot be compared to human drivers’ experience.

3. **Theory of mind** AI is the next level of AI systems. Unlike the previous two types of AI, this is currently considered the kind of machines humans will build in the future. The term "theory of mind" comes from psychology. It represents these machine systems' ability to understand the entities they interact with by discerning their needs, emotions, beliefs, and thought processes.
   Future AI systems will probably understand humans' thoughts and feelings, make expectations about them, and adjust their behavior accordingly.

4. **Self-awareness** AI is probably the final stage or ultimate ambition of AI research and development. It involves AI systems that have evolved to the point where they could be compared to the human brain, meaning they have developed self-awareness.

# CHAPTER II. OVERVIEW OF ARTIFICIAL INTELLIGENCE

AI research aims to develop an intelligent and autonomous system that can interpret data and learn in various dimensions to make more accurate forecasts than humans. Although no machine has ever passed the Turing Test, the recent developments in AI have been astonishing. There are multiple subfields of AI. Essential AI technologies within the financial sector are machine learning, expert systems, natural language processing, speech machines, and machine vision. These technologies can work separately and mutually using various techniques such as artificial neural networks, cluster analysis, decision trees, evolutionary (genetic) algorithms, LASSO regressions, and support vector machines[22].

## 2.1 MACHINE LEARNING (ML)

The rise of AI has been driven mainly by a tool called machine learning (ML). Arthur Samuel[23] defined ML as the "*field of study that gives computers the ability to learn without being explicitly programmed*". It regards the development of computer programs that can interpret data and use it to learn for themselves. It can be considered closely related to computational statistics. The machine begins with the observation of data and given instructions or direct experience; it automatically learns and recreates the action that has to be taken without human intervention or assistance. Even though the primal ML technologies were developed in the 1950s, only from the 1980s, they started to flourish.

Under ML, three main types of problems are studied: supervised learning, unsupervised learning, and reinforcement learning.

[22] The study is focused on these techniques given their impact in the financial field.

[23] Samuel, A. L. (1959). Some Studies in Machine Learning Using the Game of Checkers. *IBM Journal of Research and Development*, *3*(3), 210–229.

- Supervised learning is the most common type of ML. An algorithm establishes a mathematical relation between the feature data (input) and the response data (output). Rather than explicitly programming the model, the learning algorithm starts with a set of training examples that have been correctly labeled. Then it learns the correct relationships from these examples, and it adjusts the model to minimize the prediction of an error on the training data. Once the model has been established, it can be used to infer a response to unlabeled data. The training process is iterative. It is adjusted based on the erroneous outputs. Over time, increasingly more accurate relations are produced until the best relation is found. The learning process is considered supervised as the training set of correctly classified response data is used to guide the learning.
- Unsupervised learning is used to identify unlabeled data. It concerns inputs only, not outputs. It can also divide groups of data points into clusters and learn which data points have similarities. This approach is functional, for example, in marketing, where customers can be separated into different groups, and different strategies can be developed for each group. In unsupervised learning, the computer teaches itself, while in supervised learning, the computer is taught by the data.
- Reinforcement learning is based on an agent (e.g., a program, a robot, a control system) that learns how to act appropriately in an environment based on reward or punishment signals. In each iteration, the agent observes the state of the environment, decides how to act, then receives a reward and information about the next state of the environment. An example of reinforcement learning technology is Google's AlphaGo Zero, an algorithm that learned to play the board game Go by repeatedly playing itself and defeated the best human players.

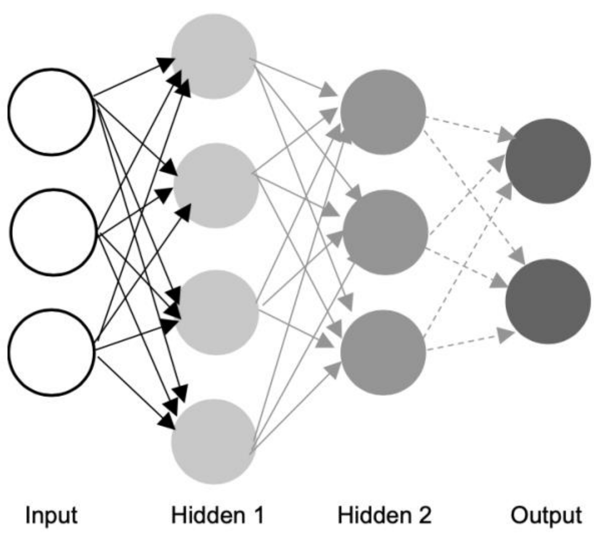
Predictive analytics is composed of various statistical techniques to estimate future outcomes. It has been around long before the birth of AI. Alan Turing utilized it to decode encrypted German messages (Enigma Code) during World War II. Now, its typical adopters are banks and Fintech industries. Predictive analytics and ML go together, as predictive models typically include a ML algorithm. These models can be trained over time to reply to new data or values, delivering results that businesses need. The most widely used predictive models are neural networks, decision trees, and regression.

Decision trees consist of a simple yet powerful form of multiple variable analysis. An algorithm identifies the various way of splitting data into segments or subsets based on categories of input variables. Regression analysis estimates the relationships among variables, finding key patterns in large and diverse data sets, and how they correlate to each other.

### *2.1.1 Artificial Neural Network and Deep Learning*

One of the most famous ML tools is the artificial neural network (ANN). It consists of a piece of software inspired by biological brains' structure and designed to replicate human intelligence. Similar to what occurs in biological neurons, an ANN is composed of connections nodes between artificial neurons. Some artificial neurons are inputs, hence, sources of information. They pass the information to intermediate neurons that process the information and change their internal states according to the input. Then the signal goes to the next neuron to produce an output. Artificial neurons are usually organized in layers. The architecture of neural networks is shown in the figure 2.1.
The ANN is essentially a big mathematical equation that tells how to compute the outputs, given the inputs. Commonly, the information flow between two neurons is a set of real numbers, and the output is calculated by a non-linear function of the sum of its inputs. It is an advantageous technique for learning input-output mappings.

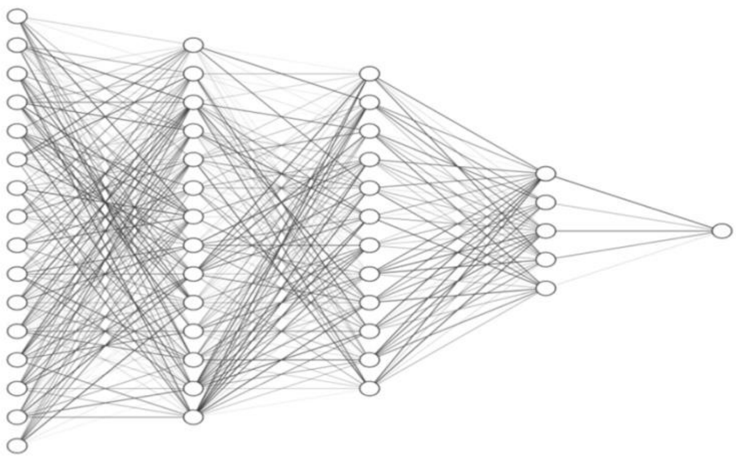
**Figure 2.1**: Artificial neural network architecture



A complex ANN that requires enormous amounts of structured or unstructured data to train is called deep learning (DL). It consists of an ANN with many hidden layers (see figure 2.2). This approach tries to model how the human brain processes light and sound into vision and hearing. It can establish correlations between two things and learn to associate them with each other, predicting what will happen next. It is applied in many fields, including computer vision, speech recognition, machine translation, and audio recognition. An example of deep learning application is face recognition systems such as Facebook's tagging feature or Apple's iPhone face-recognizing the same person with weight gain, weight loss, beard, without a beard, or new hairstyles. With the rise of the internet, the introduction of Big Data, and the technological developments of computers, deep learning systems are increasing considerably. Learning systems strictly depend on data.

Consequently, data is becoming the most valuable commodity. Data is messy, and having inappropriate data implies that the AI will learn inaccurate things. For example, data problems such as incorrect labels and missing values must be fixed or removed. AI teams are fundamental in studying data, even when they are observable types of unstructured data such as images, audio, or text.

**Figure 2.2**: Deep learning architecture



In the last years, it may seem that neural networks, deep learning, ML, and AI are all the same concepts, but each has its history and origins, and hierarchy. ML is a subset of AI, while ANN is a subset of ML, DL is essentially a complex ANN.

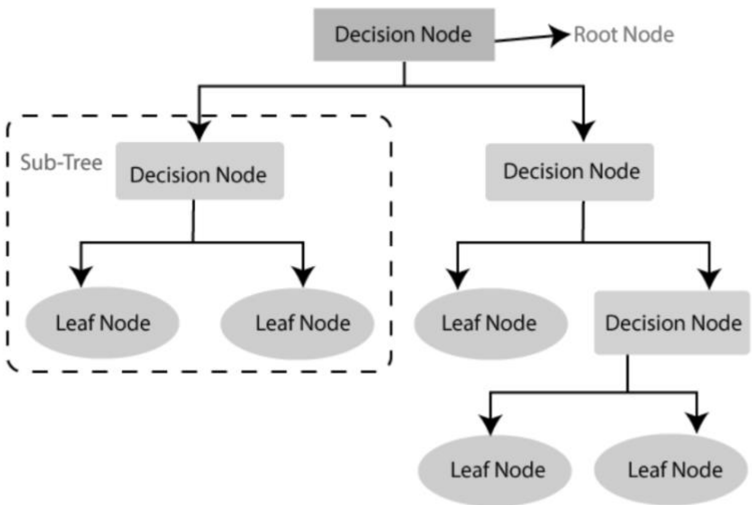
### *2.1.2 Decision Trees and Random Forests*

A Decision Tree is a supervised ML algorithm that can be used for both classification and regression models. A Decision Tree's primary goal is to create training models that can be used to forecast the class or value of a target variable by learning simple decision rules inferred from a set of training data.

It is constructed as a diagram starting from a root node (see figure 2.3), split into increasingly smaller nodes, called internal nodes, based on a single characteristic. The branches represent a range of values. The node ending the chain is called the "leaf" node, which represents a data item.

In Decision Trees, data is pre-determined and divided into classes based on its features. Data items are split according to the values of these features. The process is done recursively, and it terminates when all the data items in the subset belong to the same class.

**Figure 2.3**: A conceptual decision tree diagram

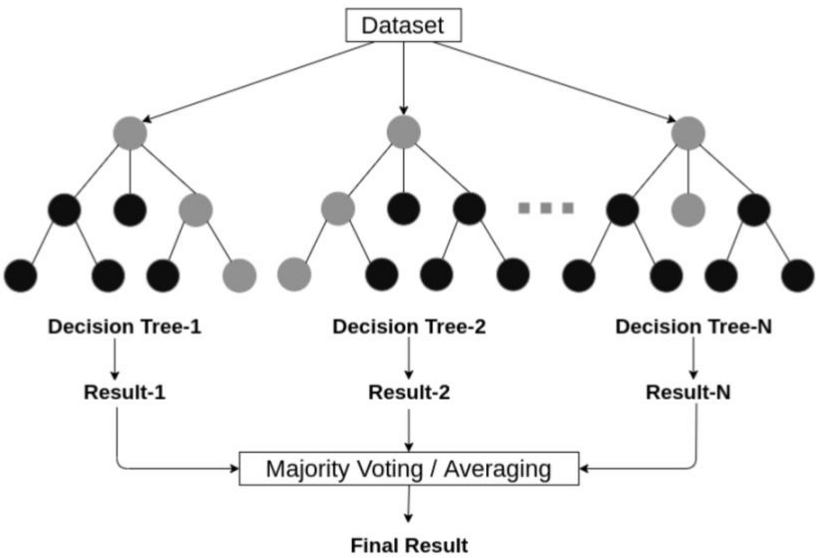



A Random Forest is a group of classification and regression methods consisting of many decision trees (see figure 2.4). Each Decision Tree is made from a random selection of samples of the training data. Furthermore, random subsets of attributes are considered when splitting nodes. The prediction is made by gathering all the forest's predictions. In the case of regression, they get averaged. In the case of classification, it considers the majority of votes. Random Forest represents an ensemble learning in which multiple ML algorithms are combined to predict performances better.

Decision Trees have a crucial advantage over other ML techniques because the rules they use to classify data are human-readable. Thus, we can easily trace the reasons underlying a particular classification. In the case of a Random Forest instead, the interpretability is sacrificed to favor the method's higher accuracy. To achieve both performance and interpretability, some model compression techniques transform a Random Forest into a "born-again" decision tree, reproducing the same decision function.

In finance, decision trees and random forests are beneficial in classification and decision making.

**Figure 2.4**: A conceptual decision tree diagram



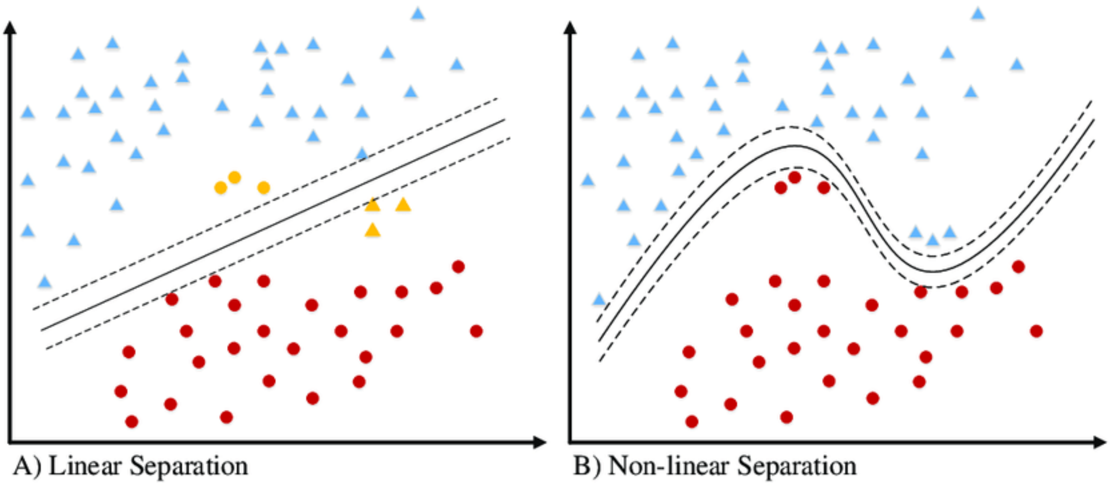

### *2.1.3 Support Vector Machines (SVMs)*

Support Vector Machines (SVMs) are supervised algorithms typically used for classification, regression, or outlier detections. They produce significant accuracy, as they do not require much computation power. These algorithms construct boundaries (hyperplanes) that divide the feature space into two or more classes and, once defined, they can be used to classify new data. The boundaries position and orientation are given by support vectors, which are the data points closest to the hyperplanes. They are the most challenging data to classify. Finding the ideal hyperplane is an optimization problem. It consists of the maximal margin of separation between the hyperplane and the closest data point, given a weight vector and bias. The inputs of these algorithms are sets of training samples (many inputs xi and one output y), while the outputs are a set of weights, one for each feature, whose linear combination predicts the value of y.

The significant advantages of SVMs are that they do not overfit training data. Secondly, they are helpful in high-dimensional spaces. Finally, they are versatile as different kernel functions SVM algorithms utilize a set of functions defined as the kernel. The function of the kernel is to take data as inputs and transform them into the required form. These functions can be linear, non-linear, polynomial, or radial basis functions and specified for the decision function.

Figure 2.5 presents an example of linear and non-linear training data. In the case of linear data, the separation of data has been chosen to maximize its distance from the nearest data point in each class. In non-linear data, kernel methods are used to find more complex separation boundaries.

**Figure 2.5**: SVM with linear and non-linear training data




*Source: Research Gate*

### *2.1.4 LASSO regression*

Linear regression is a common and relatively simple way to fit a model on data to make predictions or to estimate missing values. It seeks the coefficients of explanatory (predictor) variables contributing to the dependent (predicted) variable value. The most

common approach used in linear regression is the Ordinary Least Squares (OLS) regression. It minimizes the sum of square errors, which are the difference between observed values and the values predicted by the model. However, as the model complexity increases with the number of regressors, so do predictors' variability. A significant number of parameters could cause the model to overfit data.
The most common method to overcome regression models' overfitting is regularization. The main regularization techniques are the Ridge Regression and the Least Absolute Shrinkage and Selection Operator Regression (LASSO) method. The latter is widely diffused for ML applications.
The LASSO method encourages models with fewer parameters. It is appropriate for models that exhibit high multicollinearity levels and automate model selection procedures, like parameters elimination or selection. The procedure aims to set some of the model's estimated regression coefficients to zero, minimizing the coefficients' absolute sum. If there is a high correlation in a group of predictors, LASSO regression automatically identifies the most relevant one and shrinks the others to zero, producing easily interpretable models.
The main problem with LASSO regression is the coefficient's shrinking itself, which could lead to some information losses resulting in the model's low accuracy.
In finance, the main areas of applications are forecasting and robust regression analysis.

### *2.1.5 Genetic Algorithms*

The genetic algorithm is a search algorithm based on Charles Darwin's theory of evolution by natural selection. It exploits the principle of the "survival of the fittest" to figure out complex optimization problems.
The genetic algorithm starts with an initial search space, an initial population of candidate solutions that can be randomly generated or manually allocated and includes some individuals or solutions. Each individual, also called a chromosome, is a finite group of variables or parameters represented as genes. Genes are usually coded as a binary alphabet 0 or 1. Thus, a chromosome is composed of a set of binary alphabets.
The process requires three iterations: fitness selection, recombination, and mutation (see figure 2.6). The first step has the primary goal to determine which individuals have the highest fitness score based on an objective function. Those who pass the first step are

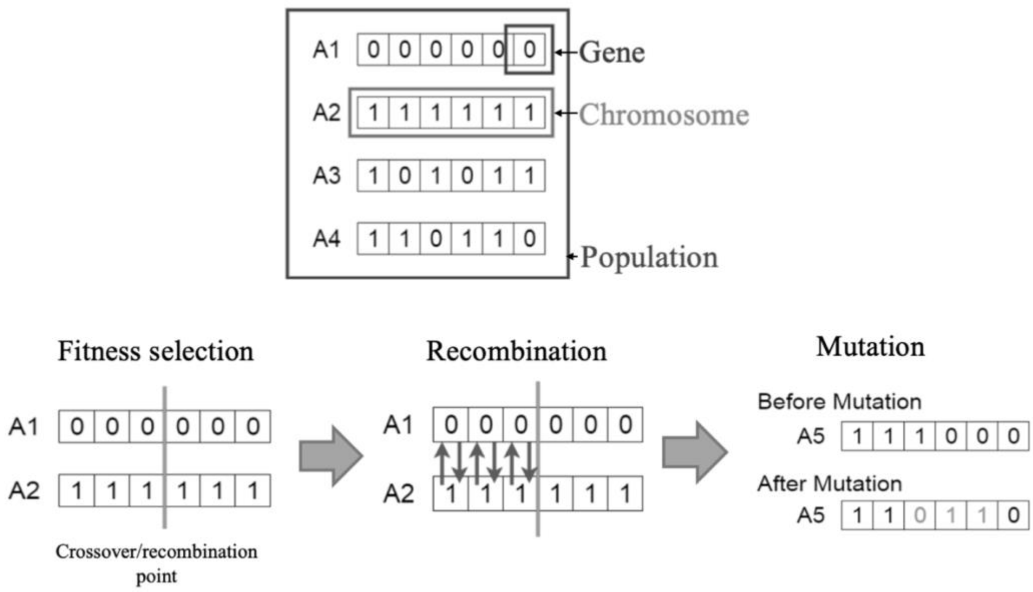
used in the recombination step. At this stage, new candidate solutions are created by selecting a couple of individuals and merging information to create a new unique solution. The third step starts with a new offspring who shares genes from the parents. However, small mutations are randomly introduced.

The new solutions iteratively replace worse-performing ones. The entire fitness selection process, recombination, and mutation are repeated to find better solutions over time. The algorithm terminates when the offspring produced are not significantly different from the previous generation or when the predefined conditions are met.

Evolutionary algorithms do not require a mathematical formulation of the problem and do not make assumptions such as convexity or linearity about the objective function. They can also be applied to complex problems in which other optimization algorithms fail. These algorithms are commonly used in quantitative financial applications, as portfolio optimization and trading.

Genetic algorithms have some limitations. For example, for the evaluation of complex problems, they may require expensive fitness function evaluations. Further, the solution found is "better" only compared to other solutions. Moreover, it can be considered a weak solution due to an inconsistent explanation of why it works.

**Figure 2.6**: Genetic Algorithm and its Evolution Process




*Source: Towards Data Science*

### *2.1.6 Cluster analysis*

Cluster analysis is an unsupervised learning technique that seeks to partition a dataset into groups or clusters. Clusters identification and labeling are proper to classify new data. The same data may yield many different possible sets of clusters, depending on the number of clusters desired, how data are distributed, and the clustering algorithm itself. The most straightforward and most used clustering algorithm is K-means clustering, which requires the user to specify the desired number of clusters, K. This method starts by randomly choosing some cluster centroids and allocating each data point to the closest centroid. It subsequently alternates between moving each centroid to the center of its data cluster and reassigning the data points. Applications in finance include cluster analysis of markets, companies, financial instruments, time series, and documents.

## 2.2 NATURAL LANGUAGE PROCESSING (NLP)

Natural language processing (NLP) began as a blend of AI and linguistics. This AI technique consists of a group of computational methods and applications that utilize natural language data to enable computers to learn, analyze, and manipulate human language. These systems can process both written text and speech.

The foundations of NLP lie in several disciplines, obviously in AI and robotics, but also in computer and information sciences, linguistics, mathematics, electrical and electronic engineering, and psychology. In NLP are frequently used ML techniques such as DL and SVMs. Applications of NLP include automatic summarization, speech recognition, social media analysis, and sentiment analysis. In finance, much attention is given to natural language financial forecasting, which extracts information such as sentiment from financial news or social media and incorporates it into models that predict financial data movement.

The most common use of NLP systems is translation. A computer automatically transforms one natural language into another while preserving the meaning. It is a difficult task even by artificial intelligence standards, as it requires knowledge of word order, sense, pronouns, tenses, and idioms, which all vary extensively across languages. In machine translation, the device scans words that humans have already translated to look for patterns. In the past, the system generally used for translation was the statistical machine translation: a data-driven approach that advocates probabilistic models to describe the translation process. An example of a service using this technique is Google Translate. In the last years, like in ML, machine translation has improved a lot by using DL-based models that allow it to learn patterns' recognition. This kind of machine translation has become a new paradigm for online translation.

Classification and clustering approaches can be applied to NLP. Text classification is a technique used for spam detection and sentiment analysis. The effect is assigned to a given set of texts being analyzed. Successful text classification, or document classification, happens when an algorithm takes text input and reliably predicts the text category. Document clustering can be done even without understanding or being fluent in the text input language because the algorithm learns statistical associations between inputs and the categories. The algorithm can extract information from a chunk of text. Information extraction means automatically extracts structured information from answers to questions asked in a natural language. This practice is frequently used in customer service chatbots to answer the most frequent or basic questions before passing the query to a real human if needed. These are different from bots, which are automated programs that look up a specific type of information on the internet.

A significant area of NLP application is speech-to-text, which is the process of converting audio and voice into a written text. It can support users who are visually or physically impaired and can improve safety with hands-free operation. Speech to text tasks use ML algorithms that learn from massive data sets of human voice samples. Data sets train speech to text systems to fit production-quality standards. Speech to text systems have value for businesses because they can aid in video or phone call transcriptions. Text to speech systems, instead, convert written text into audio files that sound like natural speech. These technologies can be used to serve individuals who have speech disabilities, for instance.

Speech recognition is a task where a system receives a speech through a microphone and checks against a vocabulary bank for pattern recognition. When a word or phrase is recognized, the system will respond with the associated verbal response or a specific task. Well-known speech recognition examples are Apple's Siri, Amazon's Alexa, Microsoft's Cortana, and Google's Google Assistant. These products need to recognize the speech input from a user and assign the correct speech output or action. Even more advanced are attempts to create a speech from brainwaves for those who lack or have lost the ability to speak.

## 2.3 EXPERT SYSTEM (ES)

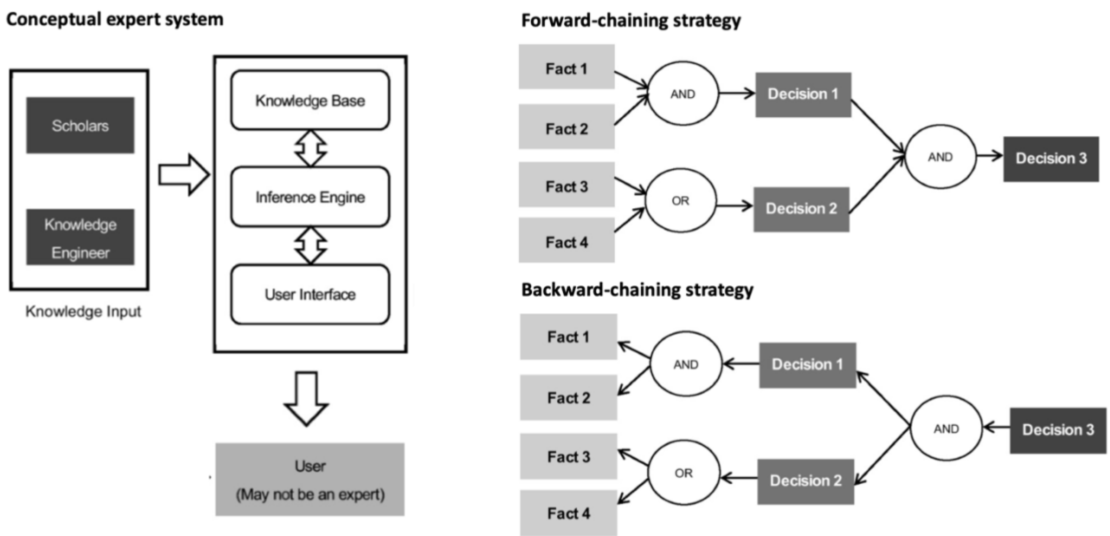
Expert system (ES) is a computer system that emulates the decision-making ability of a human. It has a knowledge base on a particular domain and an inference engine to solve problems that would typically require human intelligence.

An ES needs three fundamental components: a knowledge base, an inference engine, and a user interface. The knowledge base data must be complete, high-quality, and accurate for that specific domain. Thus, it should contain factual and heuristic knowledge. The first kind of knowledge consists of the information commonly diffused by scholars, engineers, and other experts. The second one, instead, comprises hypotheses, judgments, evaluations, and past experiences. The knowledge is obtained from various experts on the ES application field, and it is represented in the form of IF-THEN-ELSE statements.

The inference engine is a set of rules to apply the knowledge base and extract the solution for a specific problem. These rules are applied to the data repeatedly, continually adding new information to the knowledge base every time a solution is reached. The main strategies used in an inference engine are forward-chaining and backward chaining (see figure 2.7).

Forward-chaining consists of a data-driven strategy that deduces the solution, having considered specific facts and conditions. The second is aimed at finding causes or reasons for a specific result, given a well-defined problem.

**Figure 2.7**: Conceptual ES, Forward and Backward-chaining strategies



ES are commonly used in healthcare, telecommunications, financial services, and transportation. For example, an ES in traffic management can help design smart cities by acting as a "human operator" to relay traffic feedback to the appropriate routes. In the financial field, they can be used for fraud detection and transaction monitoring, trading, and investment advisory.

ES's consistency of solutions reduces human work, especially for repetitive tasks and processes, reducing risks and error rates. Moreover, unlike other AI techniques, such as ANN, they provide reasonable explanations and clarify the reasons behind conclusions. Other advantages regarding ES include their quick adaptation to new conditions and their low production costs.

Although the ES provide many significant advantages, these technologies lack self-awareness. They cannot replace human experts in decision-making as they are limited to the system's rules. They cannot make creative and innovative responses like humans do in unusual situations. Other limitations include high maintenance and development costs.

## 2.5 ROBOTIC PROCESS AUTOMATION (RPA)

Robotic Process Automation (RPA) is the science of software robots to mimic human actions. In contrast with the other AI techniques, which aim is to replicate human capacities to think and learn, RPA deals with a physical matter. It involves the construction and design of machines to accomplish a specific physical task that generally requires the capacity to recognize and adapt in an environment.

Mobile robots are usually composed of two main elements: locomotion and computer vision. They need locomotive mechanisms to move within their environment. This component can be of several types, for example, legged or wheeled. The other fundamental component is computer vision, which allows robots to recognize their environment.

For decades, Robotics applications have been used in several sectors, starting from the global manufacturing sector in the production assembly line and packaging to NASA robots for space exploration. Progress in AI technologies and innovations in hardware allowed the creation of collaborative robots. These are also called "cobots" designed to physically interact with humans in a shared workspace, helping to eliminate dirty, tedious, or dangerous tasks.

The primary idea of RPA is to make robots as autonomous as possible through learning. Although robots as intelligent as humans have not been created yet, some robots nowadays can learn decision-making by formulating associations between an action and the desired result. An example is Kismet, a robot created by MIT's Artificial Intelligence Lab, which is learning to recognize voices and body language to reply appropriately. Thanks to the developments in cloud computing, now humanoid robots can share learning and experiences. Hence, the next step seems to be direct communication between robots.

## 2.6 MACHINE VISION

Computer vision or image recognition is defined as computers obtaining a high-level of understanding from digital images or videos. It is a significant component of many IoT applications, such as household monitoring systems, drones, and car cameras and sensors. When the image recognition is integrated with a deep learning system, performance accuracy and versatility on object classification are optimized. An example of computer vision is Apple's Face ID that allows iPhones to recognize owners' faces to unlock the screen.

Machine vision is the science of making computers see. It takes computer vision one step further by combining vision algorithms with image capture systems to guide robot reasoning better. It captures and analyzes visual information using a camera. It converts analog data to digital, and then it works on digital signals, categorizing inputs. With training, machines' computer vision can learn to recognize inputs in different states, like humans. An example of an application is Microsoft Azure, an AI service that analyzes content in images and video for businesses to extract text, give spatial analysis and data.

Machine vision is one of the critical technologies in manufacturing due to the increasing demand for documentation quality and the products' traceability. Some of the standard machine vision systems' tasks are: object identification from various objects; robots and components' position detection; completeness checking, shape, and dimensional inspection; and surface inspection of finished products.

# CHAPTER III. AI AND FINANCIAL SERVICES

## 3.1 THE RISE OF FINTECH

In the last century, the importance of well-functioning financial institutions, their role in promoting and enabling capital accumulation and economic development have grown dramatically. The financial field is crucial for private sector development. It reduces risks and vulnerability. It increases households' ability to access essential services, such as health and education, directly impacting poverty reduction.

In history, technology as a tool has had three significant impacts on business and industry:

- It has allowed the automation of processes, replacing human workers with machines or algorithms.
- It has reduced the cost of information acquisition and made information more accessible to everyone, threatening any business whose primary reason for existence was information asymmetry.
- It has made manufacturing and distribution processes far more efficient, resulting in no more useless intermediaries.

Despite these revolutions, the financial services sector has not been affected by them until the last years, probably due to its profoundly regulated structure and countries influence. Since the Global Financial Crisis of 2008, the financial sector was characterized by many changes: financial regulation over the world has become more uniform; traditional financial actors have partially lost their reputations; communication and transaction developments have been facilitated by technology, customers' expectations changed, and their confidence with new technologies increased.

After the Global Financial Crisis, regulators aimed to improve the safety and robustness of the financial system. Therefore, regulatory burdens increased in established financial institutions. This way, they were forced to focus on essential risk management and compliance initiatives that caused a slowdown in product and process innovations. At the same time, several regulators helped the nontraditional competition development. Meager interest rates helped these nontraditional players to access funds, like venture capital.

Meanwhile, digital innovation was spreading all over the world. New digital businesses like WhatsApp, Facebook, WeChat, and Uber changed their sectors and customers' expectations for digital experience. They introduced customized, direct, and remote digital services that changed customers' expectations on financial services, which were considered outdated and unreliable. As emerged from the Global Fintech Report 2020[24], most millennial customers seek faster and easy-to-use financial services with low-cost offers and personalized products.

Rapid technological advancements required new approaches. Traditional institutions were deeply based on rigid, decades-long systems. Thus, a structural change would have involved extraordinarily challenging and costly operations. Companies investing more money in technologies, especially in AI, always include tech-giants such as Microsoft, Google, Apple, Alibaba, Baidu, Tencent, and others. Instead, banks or traditional financial services firms rarely push AI boundaries further. Nevertheless, remarkable are the technology investments in the financial sector that newcomers are making these days. These new players are called FinTech companies.

FinTech derives from the intersection between finance and technology. It identifies the newborn, hybrid sector of financial technology, son of the current digital revolution we are living in. At the moment, there is not a recognized univocal definition, and many definitions have been given. Generally, the term "FinTech" refers to an ensemble of societies developing activities based on new digital technologies applied to the financial field.

The Financial Stability Board[25] defines financial technology as "*technologically enabled financial innovations that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services*".

Fintech solutions that use AI, big data analytics, and blockchain technologies are currently introduced unprecedentedly in the last years. These new technologies are changing the financial industry's nature, creating many opportunities that offer more inclusive access to financial services. According to a McKinsey Global Institute[26] survey,

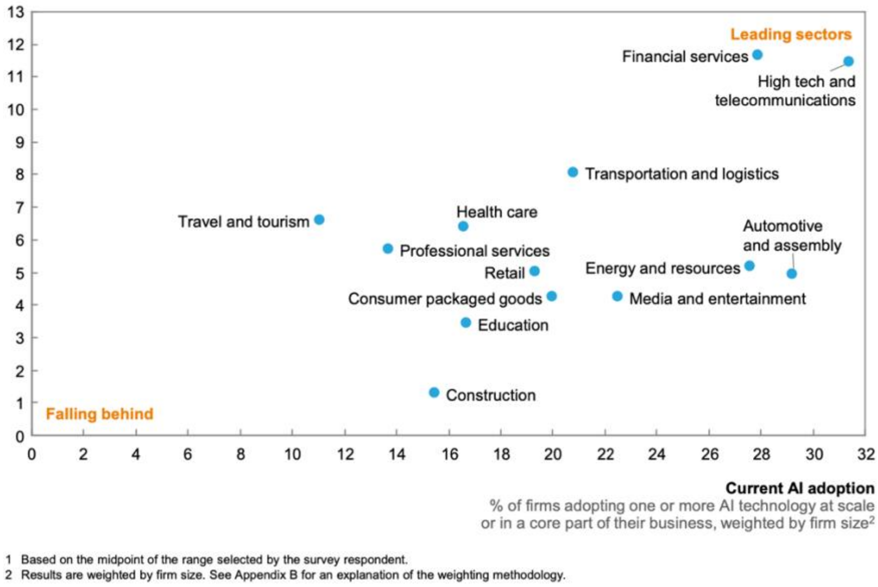
[24] Capgemini. (2020). *World FinTech Report 2020*.

[25] Financial Stability Board. (2017). *Financial Stability Implications from FinTech: Supervisory and Regulatory Issues that Merit Authorities' Attention*.

[26] McKinsey Global Institute. (2020a). *Global survey: The state of AI in 2020*.

FinTechs are leading technological investments, especially in AI, within the entire financial services industry (see figure 3.1).

**Figure 3.1**: Sectors leading in AI adoption




*Source: McKinsey Global Institute*

Moreover, FinTechs are building new business models, such as investment services that compete fiercely with established banking operations. In April 2017, according to the Financial Times[27], Ant Financial's money market fund (the so-called Yu'e Bao) had overtaken J.P. Morgan's US government fund with assets under management of $165.6 billion.

In 1994, Bill Gates stated that "*banking is necessary, banks are not*"[28]. This statement is now more accurate than ever. FinTechs have already won the first round of the innovation battle. In contrast, incumbents have started to update their business models to engage the FinTech ecosystem and compete in a challenging race to zero prices. Although it is not clear who the business beneficiary of the FinTech revolution is, whether incumbents or newcomers, it is evident that consumers certainly benefit from decreased cost and increased efficiency. Despite the advantages, FinTech solutions bring some risks and threaten consumers' protection and financial stability.

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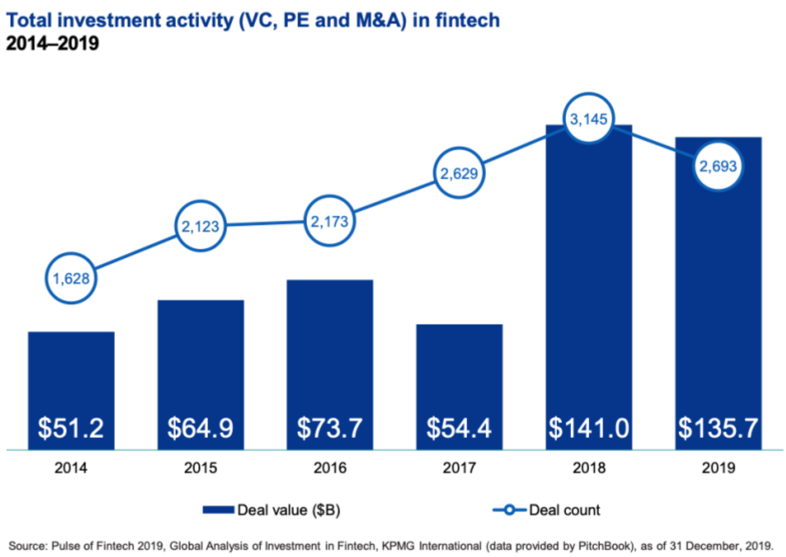
[27] Lucas, L. (2017, April 26). *Chinese money market fund becomes world's biggest*. Financial Times.
[28] Mohan, V. (2019). *"Banking is necessary; banks are not."* Business Times.

### *3.1.1 The Fintech Environment*

Based on a Statista survey[29], as of February 2021, there are more than 26,000 Fintech startups in the world. With 8,775 of them based in America, 7,385 in Europe, Middle East, and Africa, followed by 4,765 in the Asian Pacific region. The industry is expected to gradually grow in the following years and reach a market value of approximately $305 billions by 2025,[30] growing at a compound annual rate of 22.15 percent over the forecasted period 2020-2025.

KPMG's Pulse of Fintech 2019 report[31] indicates that global investments in Fintech through mergers and acquisitions, venture capitals, private equities hit $135.7 billion at the end of 2019, with more than 2,600 deals sealed (see figure 3.2). Moreover, tech giants are riding the FinTech wave with investments and acquisitions. As of 31st December 2019, Alphabet made 65 deals while Tencent Holdings 49 between 2014 and 2019.

**Figure 3.2**: Total investment in fintech




*Source: KPMG*

Big Techs' interest in the FinTech ecosystem dates back to 2011 when Alphabet launched Google Wallet (today is known as Google Pay). A service that allows consumers to transfer money to other users via PC or smartphone using their emails or phone numbers.

[29] Statista. (2021). *Number of Fintech startups worldwide from 2018 to February 2021, by region*.
[30] Market Data Forecast. (2020). *Global Fintech Market Research Report*.
[31] KPMG. (2020). *KPMG Pulse of Fintech 2019*.

In 2014, Apple launched its payments service too. Apple Pay permits consumers to pay online or in-store purchases using an Apple device, like an iPhone. Big Techs did not focus only on the payments area of FinTech. In 2011, Amazon launched a lending service for small and medium enterprises directly through its e-commerce platform.

Not only US Big Techs are riding the FinTech wave. Through their subsidiaries, Chinese Big Techs, such as Tencent, Baidu, and Alibaba, impacted every financial services area, from payments to wealth and asset management.

The European FinTech ecosystem is growing, mainly thanks to the developments and widespread digital banking. Among all European states, the UK has the leading role. Among the top 50 FinTechs in Europe, 25 are from the UK based on their valuation. Italy is following the European trend. At the end of 2019, there were 278 FinTechs, with 49 new companies compared to the previous year. These companies' total turnover reached €373 million in 2018, with a 40 percent growth in the previous year[32]. However, in the international context, the Italian Fintech ecosystem continues to be weak compared to other countries. According to the Global FinTech Index[33], Italy is ranked 24th globally. The Italian fund dedicated to FinTech is worth €93 million[34], a modest amount compared to IT modernization investments.

Emerging markets, especially in Asia and Africa, have experienced a healthy FinTech development too. Primarily thanks to government policies pursuing economic development. In Africa, the undeveloped nature of banking services and the widespread of mobile telephones have helped the birth of FinTechs, allowing customers to securely transfer funds, pay bills, and receive government payments. A successful example is M-Pesa[35], a FinTech company specialized in digital payments, which exceeded Kenya’s GDP by 43 percent in transactions made in five years from its launch.

The FinTech revolution has impacted every area of financial services, from the most innovative, such as cryptocurrencies and digital payments, to the traditional ones, such as lending and insurance. AI techniques are now commonly used by FinTech players and incumbents. The financial services macro-areas more impacted are lending, payments and transactions, wealth and asset management, trading, insurance (InsurTech), regulation, and compliance (RegTech).

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[32] PwC. (2020). *FinTech calls for fuel*.
[33] Findexable. (2020). *The Global Fintech Index 2020*.
[34] Bank of Italy. (2019). *Survey on the adoption of FinTech in the Italian financial system*.
[35] Runde, D. (2015, August 12). *M-Pesa And The Rise Of The Global Mobile Money Market*. Forbes.

## 3.2 LENDING

### *3.2.1 Lending and FinTechs*

Banking's core activities (deposit-taking and lending) have been around for hundreds of years. However, only recently, the sector has begun to evolve significantly. Lending is a massive business that touches the economy and almost everyone's life, directly and indirectly. According to the Federal Reserve Bank of New York[36], as of September 2020, mortgage debt in the United States was over $9.9 trillion. Credit card debts accounted for roughly $1 trillion. Student loans are around $1.55 trillion, and car loans around $1.3 trillion. The total household debt in the United States exceeded $14.3 trillion.

The lending environment was impacted by increased restrictions after the 2008 financial crisis. Several individuals and small businesses found themselves excluded from traditional sources of capital. As a result, a new opportunity turned up. New kinds of FinTech lenders were born.

These new entries have impacted the lending domain differently. In addition to exploring new financing mechanisms, as Peer-to-peer lending, they have explored new mechanisms of originating and underwriting loans. Especially with AI techniques, FinTechs lenders are now offering borrowers access to a faster loan application experience. They introduced new credit evaluation mechanisms, automated and efficient underwriting processes.

Old incumbents have now urgently to solve inefficiencies and optimize their product and service offerings to remain competitive and relevant in light of changing customers' expectations and environment. Considering that even a tiny improvement in the return of the loans or a market share increase would be worth a considerable amount of money, both established banks and FinTech companies are continually looking for ways to innovate.

In such an environment, AI is poised to be a game-changer. With numerous AI applications in the making, huge gains could be realized over the coming decade. Thanks to AI, the industry is expected to save more than $1 trillion by 2030[37].

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[36] Federal Reserve Bank of New York. (2020). *Quarterly report on household debt and credit (November, 2020).*

[37] The Financial Brand. (2018). *Artificial Intelligence and The Banking Industry's $1 Trillion Opportunity.*

Lending is essentially a big data problem. Therefore, it is naturally suited to ML. Part of the value of a loan is tied to the creditworthiness of an individual or business. So, the more data is collected about an individual borrower and how similar individuals have paid back debts in the past, the better their creditworthiness can be assessed.

AI techniques are used in many lending scenarios: user identification and customer screening, credit evaluation, underwriting, fraud prevention, and customer service.

### *3.2.2 User identification and biometric adoption*

The first step made by lenders is the identification of eligible customers and onboard them as potential borrowers. In the past, to identify and accept customer loan applications, lenders used to manually compare the relationship between the applicants and the documents held by them. Moreover, they had to prevent potential risks, like stakeholder collusion, during the client onboarding processes.

Financial institutions are still inefficient in manually screening high-risk customers. This method seriously affects regular customers' onboarding experience, demotivating them to apply for a loan, which will result in a loss of customer flow and business opportunities. Nowadays, assuming to have a knowledge base already arranged and an ML underwriting model already trained, a broader customer base and the first screening on various customer segments can be provided to market campaigns to offer borrowers personalized lending conditions. Once a potential borrower begins the onboarding procedure, APIs (application programming interfaces) can be used to integrate borrowers' data into KYC (know-your-customer) systems, which use ML models to verify customers' truthfulness. Formerly, to apply for a loan, customers had to physically present trusted identity documents such as passports, driver's licenses, and proof of address. Now, this process is moving digitally. KYC systems are supported by biometrics and facial recognition technologies using AI, which, combined with electronic documents, allow customers to remotely apply for a loan, save time and avoid human identification errors. Although the most accurate facial recognition method combines human and machine expertise, research shows that facial recognition technologies are more precise at identifying customers than humans. Other technologies that can improve the user identification process are eye and fingerprint recognition, document anti-counterfeiting, and text recognition.

### *3.2.3 Credit evaluation*

Machine learning methods have a significant impact on credit evaluation. These can streamline the process and reduce applications processing time from days or weeks to a few minutes.

The business of lending works on one essential information: credit scoring. This information is a critical measure that shows a person or organization's ability to repay a loan. Lenders' priority is to avoid or minimize the risk of borrowers defaulting, which is assessed by analyzing their repayment histories, implying that borrowers need to have one. Traditional credit evaluation methods utilize the FICO score. This credit score system uses statistical analysis models based on borrowers' information, such as payment history, the current level of indebtedness, borrowers' guarantees (e.g., car, home, business), and new credit accounts. The FICO scores[38] range from 300 to 850. Scores between 670 to 740 are considered "good" credit history. The priority of the FICO scoring is performed by the bank based on a judgmental view of credit experts, credit bureau, or credit groups.

This method, at first glance, seems reasonable, but numerous consumers cannot access credit due to inaccurate measures or lack of payment histories, consider immigrants, for example.

Credit scoring problems are generally seen as typical classification problems. Objects are categorized into one of the predefined groups or classes based on observed attributes related to that object. Different methods, such as linear discrimination analysis and logistic regression, have been suggested. Nowadays, FinTech lenders have entered the unsecured personal loan space to fill the unmet demand for credit. Using alternative data sources, big data, and AI technologies like ML algorithms, FinTech lenders could reduce credit decision-making and operating costs. This way, FinTech lenders would increase the number of borrowers to access credit. Nowadays, credit scoring is one of the most common AI applications in lending, and it is particularly crucial in the absence of any credit history. That would be the case of students, new businesses, and immigrants, for example.

In the last years, many researchers tried to incorporate AI technologies to build credit scoring models. These technologies include decision trees, genetic algorithms, ANNs,

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[38] *FICO® Score*. (2020). FICO.

SVMs, and combinations of them. ANNs could be arranged using the customers' characteristics and financial data as inputs and the payment histories or the credit analyst decisions as the desired outputs. Numerous researches about ANNs in credit scoring comparing them to different statistical methods or other AI techniques have been published. Most of them describe the ANNs as a successful algorithm for assessing credit evaluation. In the same way, all the other ML techniques seem to perform better than traditional statistical methods. Moreover, evidence proves that their hybridization often leads to even more accurate results than the unitary approach.

### *3.2.4 The use of alternative data*

AI techniques can merge and analyze data points from various sources to make a holistic decision. Therefore, alternative data are becoming more relevant in lending. Alternative data could reduce the number of nonperforming loans, including forward-looking indicators about a prospective borrower's ability to repay. Alternative data could also increase a lender's potential customers' pool when traditional credit scoring metrics are not available. As mentioned above, missing information is common for some categories like immigrants or emerging markets.

Alternative data used by FinTechs refers to any additional data point or real-time information collected to help lenders build a realistic and accurate picture of a borrower's profile. It can include:

- bank account and credit card transactions, recurring transactions;
- utilities or rent payments;
- consumers' occupations;
- internet footprints, which refers to customers' online presence (psychometric data from social networks);
- online shopping habits;
- investment choices; and
- consumers' use of mobile phones and related activities.

Nowadays, some lenders such as Amazon, PayPal, and Square, have access to some of this alternative information from their platforms.

By feeding ML models large quantities of alternative data from various sources, lending applications can foresee financial patterns and infer certain behaviors or psychological

traits that correlate positively with borrowers' attitudes towards loan repayment. This also leads to a rich knowledge base that gradually learns over time and adjusts its outputs.
In some cases, financial institutions will even develop new sources of data. For example, the Chinese lender Ping An will initiate video calls with some prospective borrowers and use AI-enabled micro-gesture facial recognition technology to evaluate the truthfulness of their responses to questions about how they intend to use the loan.

### *3.2.5 Underwriting*

Traditional underwriting requires skills such as organization, analytical abilities, and months of training. Furthermore, lenders are required to change the process to stay updated on regulatory and compliance standards, investor requirements, and customer demands. Manual underwriting is a long, paper-based process: loan applications files circulate within the financial institutions' departments, and the employees analyze a large amount of information. This process could lead to problems of inconsistency, inaccuracy, and biases.
Nowadays, once borrowers are onboarded and additional information about them is captured, they are inserted into ML models. Lenders can now predict the potential borrowers' risk and future repayment behavior. Additionally, they can further assess the customer segments that have been traditionally categorized as "at-risk" and reduce default rates significantly. The ML model could also augment human loan experts' capability to make the final judgments on affordability and risks.
When a loan is approved, a contract needs to be created, sent to borrowers to accept and sign before the funds are made available. RPA now automates this process.
In the last stage of the process, ML continuously monitors the borrower's financial behaviors and patterns to flag any future risk of potential default and proactively inform the customers and lenders in advance.

### *3.2.6 Peer to peer (P2P) lending*

New FinTech players are making the financial industry even more competitive, promoting Peer to Peer (P2P) lending. P2P lending was born as a brokerage platform matching investors and borrowers or small/medium enterprises (SMEs). Its objective was to remove banks as intermediaries between those who need capital and those with an excess of capital. However, this new kind of business needs to be monitored and regulated as it could lead to potential problems such as information asymmetry, moral hazard, and herding behaviors.

The most famous case of P2P lending is from America's LendingClub, which attracted significant attention due to some extent to a successful IPO in 2014. The prices of its shares jumped from $15 to $24.75[39],. The platform rapidly evolved into marketplace funding, in which large institutional investors such as hedge funds, pension funds, and other banks made loans. Their advantage was offering borrowers loans with lower interest rates and lenders a higher rate than traditional financial institutions and investments. At the end of 2015, the company announced that the total loan amount had reached more than $13.4 billion.

P2P lending business is developing, particularly in Asian countries such as South Korea, Indonesia, and China. The latter represents the market with the most P2P loan platforms globally, amounting to around 2,300 as of March 2017[40].

Developing a P2P lending business requires the same technological investment of an internet-based system, borrowers' data, historical default rates, and an ML system.

It is fundamental for P2P lending platforms to pay attention to individual characteristics to obtain adequate data, for example, through interviews, and to offer customers a high-quality easy to use service, ensuring privacy protection in the meantime. Collecting useful data is vital to train the ML system for risk evaluation and discrimination reduction. However, unlike banks, data collected by P2P lending usually come from third parties, and they include FICO scores and information verification databases.

Initially, P2P lending platforms had problems with the creditworthiness assessment. This led to moral hazard dangers, like failed or late payments or fraud attempts. Fortunately, credit scoring and fraud detection methods based on ML systems are making P2P lending increasingly safer and more efficient. Furthermore, advances in the RegTech field are helping businesses ensure they meet regulatory requirements and protect consumers. This matter will be discussed in more detail in chapter 3.7.

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[39] Alloway, T. (2014, December 12). *Lending Club banks 56 percent surge on debut*. Financial Times.

[40] Stern, C., Makinen, M., & Qian, Z. (2017). FinTechs in China – with a special focus on peer to peer lending. *Journal of Chinese Economic and Foreign Trade Studies*, *10*(3), 215–228.

### *3.2.7 Fraud in lending*

Lending is sensitive to scams in various ways, from personal details counterfeiting to fraudulent transactions and loan stacking. In the case of personal details counterfeiting, scammers provide false personal information or misrepresent their income or credit. This kind of fraud can be quickly detected using ML-based credit scoring systems.

Once lending operations are made, transaction monitoring and money management allow borrowers to stay updated about their finance. With the introduction of open banking, customers can now choose to share their financial information with other banks or regulated FinTech companies with banking licenses. This information includes their current saving accounts, existing financial products, regular payment, account transactions, and account features and benefits. This means that there is an excellent opportunity for lenders to aggregate this information to feed ML models in addition to the alternative data knowledge base. As a result, lenders would obtain more in-depth insights into their borrowers' financial behavior and patterns. Based on all the insight generated by ML, a personal virtual advisor can proactively provide customers with guidance on their finances. It can help them monitor their budget, make real-time spending adjustments, or provide early signals of moving to default or missing any payments.

ML systems can learn what type of transactions are fraudulent, predicting and preventing them. Factors that may affect the ML system effectiveness include transaction frequency, size, location, type, and types of merchants involved. This aspect will be analyzed in more detail in the section 3.3, dedicated to payments and transactions.

Another common cyber-crime in the lending business that ML systems can quickly eliminate is loan stacking. That consists of customers taking multiple loans from multiple lenders. ML systems can detect and flag customers having multiple loan apps installed on their smartphones from various lenders.

## 3.3 PAYMENTS

### *3.3.1 Payments and FinTechs*

The financial payments sector is continuously evolving, leading to an increased in the volume of digital payment transactions across the world. New payment forms include QR codes, contactless cards, and mobile wallets, which are increasingly spreading in people's daily lives. Both in developed and emerging economies, the use of cash is less frequent. In particular, in some advanced economies, this trend continues a digitalization process where accepting digital payments has become more straightforward and less expensive for merchants. In some European countries, digital payments have become so common that cash is disappearing. For example, as emerged from a Reuters Editorial article, the amount of cash in circulation in Sweden has halved from 112 billion Swedish Kronor to 50 billion ($6.14 billion)[41]. The most significant changes in the use of cash can be found in the Asian-Pacific regions, where the proliferation of mobile phones and the boom of e-commerce have driven a real digital payment revolution.

In fact, according to World Payments Report, digital payments in this area have grown by nearly 25 percent in 2019, surpassing Europe and North America and becoming the digital payments volume leader, with $243.6 billion[42]. The global widespread of e-commerce systems and the increased speed of shipments are the other two significant factors that helped the evolution of digital payments. Nowadays, goods and services are purchased from across the globe at any time: people are no longer bound by borders or time zone. Researches show that numerous people shop online at night-time.

Governments and regulators also play an indispensable role in the spreading of digital payments. For instance, in the European Union, the Second Payment Services Directive (PSD2) introduced a limit on interchange fees at 0.2 percent for debit cards and 0.3 percent for credit cards[43].

AI further increases the rise of digital transactions, old fraud-detection systems are no longer efficient, and AI can help provide real-time fraud detection to support the global and without time constraints payments sector. Humans alone cannot supervise and control

[41] Reuters Editorial. (2018, February 26). *Cash still king: Swedish central bank urges lawmakers to protect cash payments*. Reuters.

[42] Capgemini. (2020b). *World Payments Report*.

[43] European Commission. (2013). *Press corner*.

all transactions and prevent errors and fraud incidents. Here is where ML methods come into play, allowing the monitoring of activities and the early detection of anomalies to act on.

Moreover, as AI is transforming the payments industry, consumers want to make payments safely and quickly via their devices and platforms without experiencing frictions.

### *3.3.2 Frictionless and secure payments (authentication)*

The customers' main concern regarding payments is the ease of use, which reduces friction. For example, Amazon Go represents an evolution in how payments are handled at the point of sale, providing a revolutionary customer experience. Customers can enter the store, pick up any product and leave, knowing that they will get charged on their account. The payment is entirely invisible, and there is no need to use cash or cards. According to Juniper Research[44], hidden payments business models are expected to generate over $78 billion in annual transactions by 2022.

While the ease of use of payments is the primary concern for customers, payments providers' major concern is maintaining security and respecting regulatory burdens. Truly frictionless payments require advanced security systems that can authenticate a customer and their payment method without causing customer experience issues.

Security systems for payments are built around the concept of multifactor authentication. The user usually needs to combine different factors such as a PIN or password, with other factors as the card or device used for the payments; in some case, biometrics information is required. Contactless payments are an exception since only a card or device is required. To mitigate the risk, they are usually limited. On the other hand, e-wallets are very efficient in increasing security and reduce payment friction since they can be made by a device secured by biometrics. E-wallet payments have limitations too, inserting friction into payments, biometrics are vulnerable to theft or mimicking, and require a specific "authorization event" such as the facial scanner or the fingerprint reader.

[44] Juniper Research. (2017). *Smart Store Technologies to Generate Over $78 billion in Annual Transaction Revenue by 2022*.

Biometrics such as fingerprints or static passwords are called static authentications. These remember the user based on unchangeable biometrics, but to create a secure and frictionless payments channel, the biometrics needed is the dynamic or continuous authentication that focuses on identifying a user throughout the session while logged in.
The best example of dynamic authentication is behavioral biometrics, which is the measurement and use of human behavioral patterns as a means of identification and authorization. Information can take many forms, from the shape and flow of one's handwriting, or the pressure across a screen over time, or unique patterns of an individual way of walking, speech, or other features of one's general behavior.
The strength of behavioral biometrics comes from the continuous analysis of vast amounts of behavioral data, limited only by sensors used for the observation and by the algorithms working on this data. The complexity of the data makes behavioral biometrics extraordinarily secure and difficult to compromise by external agents.
The best tool for authentication based on behavioral biometrics is ML. It uses complex algorithms that cannot be per-trained to identify patterns, but they have to analyze the user specifically. In this way, behavioral biometric algorithms must continuously train on the same data they are using for identification.
A simple example of how a behavioral algorithm can work might look like this:

1. Behavior to analyze selection (e.g., typing data).
2. Division of a given behavior into parts (e.g., typing speed, key precisions, etc.), typically comprises a wide range of data).
3. Frequency/value determination for each factor for a specific user.
4. Creation of a user profile: unsupervised learning. The more the user interacts with the relevant device, the more the profile is trained.
5. Application of a similarity measure between the profile and the current behavior. A similarity measure algorithm is used, determining the operating margin of error.
6. Determination of the limit value for generating an alert.
7. Verification of the current user behavior against the profile. The verification of the user’s current behavior is unsupervised learning, but it differs from the user profile in which it is time-limited. Moreover, another algorithm used considers the margin of error that has been determined to create a probability of the user being correct, to determine if an alert should be generated.

Frictionless payments are still far from becoming the norm. However, with declining sensors costs and the widespread use of smart devices, we will assist in exponential behavioral data that can improve the authentication process.

### *3.3.3 Fraud detection in payments and transactions*

Businesses have realized that focusing on making their payments process life cycles efficient can be highly profitable. The boom in digital payments brings an enormous opportunity but also raises serious challenges. One of the main challenges for merchants and banks is increased fraudulent activities, growing proportionally with digital payments. According to the Nilson Report 2019[45], global losses from payment fraud have tripled from 2011 to 2020, reaching $28.65 billion, and it is forecasted to continue increasing.

AI could be part of the solution because ML algorithms can analyze millions of data to discover fraudulent transactions that would otherwise go unnoticed. Traditional rule-based and mostly manual fraud detection systems try to spot criminal activities by monitoring various variables, such as location, the seller, and the amount spent. For example, if a customer appears to be spending more than usual on a given item with an unfamiliar seller and at a different location, probably this purchase will be flagged as a potentially fraudulent transaction. Standard fraud detection systems rules are too rigid, leading to inaccuracies and causing either false positive or false negative. Moreover, rule-based systems often use legacy software that can hardly process the real-data streams that have a critical impact on the digital space. All these characteristics result in missed revenue opportunities, and it also frustrates customers and lower retention.

A financial institution that integrates ML systems into its payments can detect fraudulent activities in real-time and successfully recognize anomalies to distinguish and predict fraudulent transactions and reduce data processing and manual work time. In this way, ML not only protects against the loss of funds but also saves businesses additional costs for legal settlements, which can add up to above $3 for each dollar lost to scammers[46].

[45] Nilson Report. (2019). *Card Fraud Losses Reach $28.65 Billion*.

[46] LexisNexis Risk Solutions. (2019). *2019 True Cost of Fraud[SM] Study: E-commerceRetail*.

Standard scam methods include the creation of transactions close to originals or making a copy of a transaction. Traditional systems regularly fail to distinguish between errors or unusual transactions from real fraud. For example, a customer can accidentally push a submission button twice or simply buy twice more goods. While traditional methods fail to differentiate suspicious duplicates from human errors, ML approaches will increase accuracy in distinguishing them.

Different companies are now implementing AI systems to detect fraud. One of them is Mastercard, whose “Artificial Decision Intelligence” technology uses existing data to see patterns from their cards' historical use to establish standards of transactions and score them periodically. Furthermore, suppose a swindler is trying to use someone else's Mastercard by stealing personal data. In that case, the system will analyze the operation and send an immediate notification to the holder's email or smartphone, who can approve the operation in the case of false positive or block it in an attempted theft.

Nowadays, organized crime schemes are increasingly sophisticated, and they adapt rapidly. Defense strategies based on any single, one-size-fits-all analytic technique will not be efficient. So, as in Mastercard's "Artificial Decision Intelligence" technology, ML supervised and unsupervised models have to be used. An example of payment fraud detection based on ML is structured in this way:

- A supervised model trained on a large set of transactions tagged in “fraud” or “non-fraud”. The model is trained to work on a massive amount of tagged transactions to learn patterns that best reflect legitimate behaviors.
- An unsupervised model is designed to spot anomalous behavior if tagged transaction data is relatively thin or non-existent. A form of self-learning is employed to find patterns in the data that are invisible to other analytics tools. It is designed to discover outliers that represent previously unseen forms of fraud.

An optimal blend of supervised and unsupervised ML techniques means real-time behavioral profiles analysis and an adaptive analysis.

### *3.3.4 Payment optimization*

Payments systems integrated with AI technologies can use smart routing technology that calculates various parameters and routes transactions to specific acquirers to maximize approvals. To ensure no transaction loss, soft declined transactions like tech failure or time-out are automatically redirected. For businesses with more than one acquirer, transactions can be routed based on pricing or acceptance rates. ML can maximize card payment acceptance rates by ensuring that transactions go through the optimal route based on a merchant's payment preferences; efficiency is increasingly improved, and processing time for payments can be tangibly reduced.

Other frequent problems that customers could have during payment transactions are lags or connection problems that can disrupt the payment experience. To solve this, Visa announced a Smarter Stand-in Processing (Smarter STIP), a new capability that uses real-time AI to help financial institutions manage transaction authorizations when service disruptions occur. Using ML to analyze past transactions, Smarter STIP generates informed decisions to approve or decline transactions on behalf of the issuers if their systems go offline.

With ML, payments companies can search rapidly and efficiently through their payments data beyond the standard set of factors like time, speed, and amount. ML can predict customer’s behaviors and convert this knowledge into better customer segmentation. ML algorithms can analyze transaction data to find patterns, like seasonal dips in revenues. They can provide targeted marketing capabilities like reward programs and analytical dashboards to help business owners manage their inventory, capture new sales and optimize their businesses for each consumer.

As a whole, AI impact in payments provides more powerful payment products, driving customers and merchants to more digital commerce opportunities and creating a safer ecosystem. The potential of AI technologies and how they transform the payments process and the customer's experience will only grow in the coming years.

## 3.4 INSURTECH

### *3.4.1 FinTech and Insurance*

Insurance plays a fundamental role as a social protection mechanism. It provides financial security and peace of mind to individuals, households, and businesses. It also provides a long-term investment tool. FinTech applications have dramatically impacted the risk-averse and slow to change the insurance industry. While other financial services areas have tried to increase businesses' efficiency by modifying their delivery, pricing, and operations, FinTech applications in the insurance domain, also called InsurTech, have introduced fundamentally new products.

Traditional consumer insurance offerings are based on the notion of pooling risks across a large number of people. Standardized policies protect against a variety of undesirable events. They are offered for a fixed term and do not vary with new information. Traditional insurance products are not proactive. They do not seek to prevent undesirable events. They are limited to providing compensation if an unfortunate event occurs.

InsurTech startups are now a game-changer. For example, in 2016, Trōv created a direct-to-consumer mobile insurance platform where the user could insure a specific product (television, laptop, musical instrument, etc.) for a specific duration of time. Moreover, consumers could turn the protection on or off with a simple swipe. Many InsurTech startups are seeking opportunities to create new insurance products. Today there are several “pay-per-use” insurances for drivers.

Moreover, thanks to the tracking sensors' progress, InsurTech is developing new ways to prevent car accidents. They are lowering premiums for cautious drivers and penalizing risky behaviors. Sensors are becoming more and more common in houses, offices and everyday objects. Consequently, it is safe to assume that the number of insurance products will grow. For instance, Nest produces a range of “smart devices”, among which an intelligent smoke detector. They offer consumers the option to share the device information and communicate with the insurance company any problem or help request. Considering individual health, the company Vitality offers incentives for its policyholders based on their healthy lifestyle choices. They offer premium discounts or rewards by tracking users’ physical activity via wearable technologies such as a Fitbit or Apple Watch.

InsurTechs do not create new products only. They also aim to improve the customer's onboarding process. They strive to attract people that are usually not interested in insurance products, such as younger generations, and that is where AI technologies come into play.

### *3.4.2 AI applications in InsurTech*

One of the AI's most immense scopes within the insurance field regards an ensemble of automation techniques in claims processing. It aims to reducing costs and improving customer experience. For example, the InsurTech firm Lemonade[47], which specializes in home-owners and renters' insurance, aims to create a system that allows customers to get insured in less than 2 minutes. Moreover, they offered customers to submit claims via app by sending a simple message or a video processed and analyzed by an AI-enabled automated system. In 2017, Lemonade's AI claim agent set a record: it processed a claim in three seconds only. In China, several firms like Ping An, Ant Financial, Tencent, and SenseTime use machine vision and other AI techniques to assess automobile damages and estimated repair costs based on images uploaded by the policyholder.

Other AI-enabled tools are chatbots. They can be found in insurance processes and almost all the financial activities impacted by AI. They automate and carry out time-consuming operations of the insurance processes, such as customer onboarding and inquiries. Moreover, they can assist insurance agents in expanding commercial insurance policy sales. In the insurance incumbent case, Allstate developed a chatbot system that uses NLP to understand agents' questions and provide insurance products' quoting and issuance.

Speaking of the lending sector, insurance firms use AI techniques to improve their decision-making in the underwriting process, using ML systems and alternative data. For example, the InsurTech Zendrive[48] analyzes drivers' behavior associated with dangerous activities such as aggressive driving or phone use while driving. Nevertheless, Zendrive does not use these data for pricing practices, yet for delivering driver coaching to prevent road accidents.

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[47] Schreiber, D. (2019, July 29). *Lemonade Sets a New World Record*. Lemonade Blog.

[48] Zendrive. (2021). *How It Works*.

### *3.4.3 Fraud detection of insurance claims*

The insurance business is widely affected by scams. This represents a high cost for insurance players. In the US, the estimated revenue loss caused by insurance fraud in 2020 is between $80 and $100 billion[49].

AI techniques, like ML, are also used to automate fraud investigations. ML helps detect fake or rigged claims and inconsistencies in repair or reimbursement costs. For instance, ML can analyze files written by insurance agents, doctors, lawyers, and clients, search for inconsistencies and provide evidence. Moreover, it can uncover hidden correlations in claim records or individuals' suspicious behavior.

## 3.5 CHATBOTS AND ROBO-ADVISORY SERVICES

### *3.5.1 Chatbots*

A chatbot is a human-computer communication system relying on auditory or textual methods. Nowadays, chatbots are commonly used in our daily life and are developing rapidly. To give an example, WeChat's chatbot is commonly used to call a cab, make medical appointments, or check for a flight. Chatbots are based on ML algorithms, and advanced ones also use sophisticated NLP systems. Simple chatbots elaborate on users' inputs and give the most accurate answer found in the preset database.

Currently, more and more banks are using chatbots to manage some of their customer support services. Chatbots improve customer experience through human-like interactions and intuitive interfaces, reducing the friction that usually arises from multiple banking channels. Their ability to answer sophisticated questions improves every day thanks to the developments in graph-based question answering (KGQA). These systems are also highly convenient. According to Juniper Research[50], the operational cost savings from using chatbots, considering the banking field only, will globally reach $7.3 billion by 2023. Chatbots increase job satisfaction allowing former customer service personnel to

[49] Deloitte. (2021). *2021 Insurance M&A outlook*.

[50] Juniper Research. (2019). *AI in Fintech: Roboadvisors, Lending, Insuretech & Regtech 2019–2023*.

focus on higher-value and less tedious tasks. In some situations, they are more effective than human employees. They improve service efficiency and represent a great marketing channel to promote customers' engagement and acquisition. Moreover, chatbots continuously collect fundamental user's data, enabling forms of targeted marketing.

An example of the successful use of chatbots is Bank of America's virtual assistant "Erica"[51]. It allows seven million customers to lock or unlock their debit cards, schedule face-to-face meetings, dispute a charge. "Erica" can also remind them of bill payments or notify them in case of excessive expenses.

Chatbots have different functions. As a matter of fact, India's HDFC bank[52] has introduced a chatbot trained to understand and talk to rural customers with a regional language. Chatbots are often used to collect debts. It turned out they are more efficient than human collectors in simple scenarios, like informal and reminder phone calls. Debt collection chatbots work by steps: they initially upload a call list and group users. Subsequently, they set different strategies and wordings based on the different call groups. Finally, they make calls, and all feedbacks collected through customer calls are reported and stored.

### *3.5.2 Robo-advisors*

Paolo Sironi defines Robo-advisors as "*automated investment solutions which engage individuals with digital tools featuring advanced customer experience, to guide them through a self-assessment process and shape their investment behavior towards rudimentary goal-based decision-making, conveniently supported by portfolio rebalancing techniques using trading algorithms based on passive investments and diversification strategies*"[53].

Robo-Advisors are born within the FinTech ecosystem, characterized by digital businesses with automation and technology at their core. These programs have gained significant attention recently, becoming a global phenomenon with established players in

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[51] Fuscaldo, D. (2021, January 7). *Bank Of America's Virtual Assistant Now Has More Than 10 Million Users*. Forbes.

[52] Cio, E. T. (2017, September 8). *HDFC Bank's EVA becomes India's largest banking Chatbot*. ETCIO.Com.

[53] Sironi, P. (2016). *FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification (The Wiley Finance Series)* (1st ed.). Wiley.

the US, Europe, and Asia-Pacific. The US is their biggest market in terms of the number of players and assets under management. Their first appearance dates back between 2008 and 2010. In the following years, they spread globally due to a set of concomitant factors such as:

- the international regulations, whose goal was to foster investors' protection and favor fee-only advice. Examples of international regulations are the European Market in Financial Instruments Directive (MiFID II), the FINRA and DOL rules in the US;
- the incredible widespread of smartphones;
- their asset growth under management, favored by a period of the relative strength of the US stocks; and
- their recognition as valid instruments by wealthier customers, which previously trusted traditional advisory firms only.

In the Robo-Advisors ecosystem, copious actors with different business models are identifiable. Not all FinTechs addressing personal finance fall into this field, and not all actors are FinTechs. Nowadays, many other retail and private banks, asset managers, and platforms are riding the wave. Moreover, all these actors operate in different ways. They differ from the degree of passive management, diversification principles, investments in automation, assessment mechanisms, or customer segmentation.

One important Robo-Advisors' feature is their strong focus on simplicity and cost-efficiency compared to the alternatives. The everyday workflow of a Robo-Advisor can be segmented into five steps:

1. customer onboarding and strategic asset allocation;
2. investment advice;
3. order execution;
4. automating rebalancing; and
5. performance reporting.

### *3.5.3 Robo-advisors: customer onboarding and strategic asset allocation*

One of the significant work fields for Robo-Advisors is the personalization of the investment experience based on individual goals and personality. Nowadays, FinTechs and incumbents are investing a substantial amount in research and development to improve the dialogue with investors. A successful long-term investment is given by a robust and well-diversified asset allocation aligned with the investor's investment goals and risk profile. Brunel[54] has shown that goal-based investing helps find the strategic asset allocation that maximizes the probability of reaching a specific investment goal in a certain period.

Market regulation already imposes the creation of investors' risk profiles that have to be regularly updated. They need to be as accurate as possible to avoid investor's propensity to deviate from defined asset allocation. While traditional methods consist of paper questionnaires to document individual investors' characteristics, Robo-Advisors take advantage of digital technology to improve and speed up enrollment and enhance the customer experience. The difference lays in a more attractive process and in questionnaires that look less so, yet able to obtain and evaluate customer information such as age, attitude toward risk, financial goals, and amount invested. Moreover, customers' perception of their participation in the decision-making process is improved. This way, the model portfolio created after the self-assessment procedure will be perceived by investors as the most logical choice among their own opinions, instead of a third party's recommendation.

### *3.5.4 Robo-advisors: Investment advice and order execution*

Robo-Advisors systems are more likely to focus their investment advice on long-term model portfolios using simple passive ETF strategies. While active strategies have to outperform their benchmark, passive ETF strategies seek to replicate another benchmark's performance. That can be a broader equity market or a specific sector, a trend and have the advantage of being less expensive.

[54] Brunel, J. L. P. (2015). *Goals-Based Wealth Management: An Integrated and Practical Approach to Changing the Structure of Wealth Advisory Practices (Wiley Finance)* (1st ed.). Wiley.

To determine the long-term performance of an investment, two kinds of costs have to be considered: the investment advisor's fee and the investment product's cost. The latter can also be called the total expense ratio. It expresses the total cost of managing and operating an investment product or fund. It usually includes management, trading, legal and audit fees, and other operational expenses. For ETFs, the total expense ratio generally varies between a few basis points and 0.4 percent, while it can be much higher for active funds[55].
A wide range of ML techniques and NPL is used to incorporate textual data for market data analysis. Moreover, Robo-Advisors use big data to access large volumes of financial and non-financial data sources.
The key to this step is to account aggregation. Paolo Sironi[56] stated that investors prefer receiving self-directed Robo-advice of their total wealth allocation rather than their entire asset invested. Robo-Advisors systems focus on account aggregation and investments' advice presented intuitively and graphically to the investors, who can execute orders rapidly thanks to one-click options.
Furthermore, despite different jurisdictions having different taxation principles, capital gains taxes for active assets usually tend to be higher than Robo-Advisors passive investment and rebalancing techniques.

### *3.5.5 Robo-advisors: automating rebalancing and performance reporting*

Timing markets can be problematic for investors. During a negative phase, investors might decide to limit the loss and exit the market. At this stage, they do not know when to re-enter, ending up increasing the exposure to risky assets again. Moreover, empirical research has demonstrated that investors are inclined to behavioral biases when investing, such as loss aversion, regret, overconfidence, or media response, leading to emotional trading practices. To avoid this, there are two solutions: first, investors stop acting emotionally. Second, prevent them from basing their actions on behavioral biases. The first option is unrealistic. The second, instead, can be achieved thanks to Robo-Advisors'

[55] Uhl, M. W., & Rohner, P. (2018). Robo-Advisors versus Traditional Investment Advisors: An Unequal Game. *The Journal of Wealth Management, 21*(1), 44–50.

[56] Sironi, P. (2016). *FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification (The Wiley Finance Series)* (1st ed.). Wiley.

action of automated portfolio rebalancing. Rebalancing is a risk management technique that imposes the asset allocation to revert toward its desired long-term equilibrium.
Existing Robo-Advisors show different rebalancing rules, which are not always part of a fully automated process:

- discrete schedules (e.g., once a month);
- discretional decisions of fund managers (e.g., personal views on single asset classes);
- statistical triggers to avoid unnecessary trading and minimize costs (e.g., widening of tracking error volatility against a benchmark);
- re-optimization as new asset classes are made available, or the economic environment changes abruptly (e.g., a market crash or a fundamental shift in monetary policy).

Rebalancing is extremely helpful for the last step of Robo-Advisor workflow: performance reporting. Robo-advisors reporting improves performance and communications by being more interactive and graphically attractive compared to traditional report systems.

### 3.6 CAPITAL MARKETS

The advent of FinTechs and their emphasis on AI has revolutionized some of the core practices of asset and risk management, which is expected to suffer the most significant number of job cuts shortly. According to the 2019 FIS Readiness Report[57], asset managers embracing data and analytics are growing their revenue 2.2 times more quickly than the rest of financial services.
Many asset management companies are now employing AI and statistical models to run trading and investment platforms. The grown adoption of AI across a range of tasks in asset management calls for a more systematic investigation of the various techniques and applications involved and the concomitant opportunities and challenges they bring to the sector.

[57] FIS. (2019, June). *FIS Readiness Report*.

### *3.6.1 Portfolio management: expected return and variance*

Portfolio management involves making asset allocation decisions to create a portfolio with specific risk and return properties. AI techniques can contribute to this process by helping fundamental analysis through quantitative or textual data analysis. They can also optimize asset allocation in financial portfolios. Moreover, AI can be employed directly for asset allocation decisions to build portfolios that meet performance targets more closely than portfolios constructed using traditional methods.

Fundamental analysis is the study of macroeconomic factors, such as the economy and industry conditions, and microeconomic factors like its management's effectiveness. It can be considered the foundation of portfolio management and can be significantly facilitated by AI. Currently, fund managers and analysts are facing the 21st-century challenge of data overload and fake news. Consequently, they need to establish a systematic way to organize and analyze large quantities of data. Textual analysis, the study of how words and sentences affect human behaviors in economics and financial activities, is one of the most significant AI application fields beside a useful tool. During the last decade, sentiment textual analysis research has demonstrated the relation of positive or negative words to market reactions. Now NLP approaches can extract a large volume of economic information from various sources, such as corporate annual reports, industry research, news articles, and YouTube videos. However, unlike traditional textual analysis techniques, like dictionary-based approaches that extract information from individual words in the texts only, AI approaches can also interpret context and sentence structures.

LASSO regression can automatically select the most significant explanatory power factors for future returns from a large set of return-predictive signals documented in the literature. The LASSO framework can also be employed to find lead-lag relationships between asset groups or markets. For example, it can investigate which domestic industry or market returns are the most significant return predictors of them all.

Among AI techniques, it turned out that ANNs perform better for return prediction. As a matter of fact, out of ANN sample predictions with three hidden layers, almost 30 percent were more accurate than those generated by a gradient boosted regression tree, which is the second-best performing technique. The success of ANN, in this case, is attributed to its ability to capture complex nonlinear relationships. Moreover, they are highly versatile:

many functional forms and structures are available, allowing them to learn from data more effectively than other techniques.
ANNs are also famous for predicting stock returns, bond returns, and company fundamentals. However, recent studies[58] highlighted how SVMs could be better than ANNs at predicting the first two moments of asset returns, providing they are well set.
Today a hybrid approach is frequently implemented. Combining multiple AI techniques proved to produce better predictions than any individual AI technique.
Prediction and modeling of asset prices and optimal portfolio construction are complex challenges if derivatives are involved. Some difficulties are their undefined prices and payoffs, their reliance on other assets, and their benchmark. While conventional derivative approaches heavily rely on theoretical models, AI techniques can be beneficial. ANNs can be used for forecasting future option prices, for instance.
AI can also be used to improve estimates of variance-covariance matrices in the Markowitz framework[59]. The model, also called mean-variance, analyzes the various possible security portfolios based on their expected returns and variance. A hierarchical cluster analysis can replace the covariance structure of asset returns with a tree structure. This method uses all the information contained in the covariance matrix. However, it requires fewer estimates, and thus it leads to more stable and robust portfolio weights. By using simulated return observations, empirical evidence suggests that, given a minimum variance portfolio, this approach brings a 31,3 percent higher Sharpe ratio[60] than the classical Markowitz framework.
AI implementations are generally superior to traditional ones in-stock selection, factor investing, or asset allocation. AI implementations bring advantages such as their ability to capture nonlinearities, outweigh costs, and potential data issues like collinear variables. Many managers are starting to use AI techniques in investment strategies, and many others will follow suit in the near future. Despite all these pros, there are still some challenges, especially considering the lack of liquidity and efficiency in emerging markets. Another challenge is the selection of raw variables and their transformation into

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[58] Arrieta-ibarra, I., & Lobato, I. N. (2015). Testing for Predictability in Financial Returns Using Statistical Learning Procedures. *Journal of Time Series Analysis*, *36*(5), 672–686.

[59] Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77.

[60] López de Prado, M. (2016). Building Diversified Portfolios that Outperform Out of Sample. *The Journal of Portfolio Management*, *42*(4), 59–69.

appropriate formats for AI models (the so-called "feature engineering"), which constitutes an essential and time-consuming part of the process.

### *3.6.2 Porfolio management: optimization*

Portfolio managers' decisions involve allocating funds among a large set of assets to construct a target portfolio that satisfies an objective. This can be mimicking a benchmark index or maximizing the Sharpe ratio, the performance measure of an investment compared to a risk-free asset per unit of volatility or total risk. Usually, the foundation of this process is given by Markowitz's portfolio optimization model.

When it comes to practice, two main problems arise. The first is that the optimal asset weights are very sensitive to estimates of expected returns, which are often uncertain and that can yield to optimization with unstable weights that, in fact, perform poorly. The second problem arises in estimating the variance-covariance matrix of Markowitz's optimization model. It requires a significant amount of time series data and the assumption of a stable correlation among asset returns.

AI techniques address these challenges in two ways. They can estimate return and risk in a more accurate way than those traditional methods. These estimates can be used within traditional portfolio construction frameworks. Moreover, AI techniques can also provide alternative portfolio construction approaches to generate optimized portfolios with better out-of-sample performance than those built by traditional methods.

ANNs can be trained to execute asset allocation decisions subjected to complex constraints that are often not easily integrated into the traditional models. For example, ANNs can select portfolios according to a learning criterion that maximizes returns subjected to value-at-risk constraints. They can also solve multi-objective optimization problems, constructing an optimal portfolio quickly and efficiently. Moreover, ANNs can capture nonlinear relationships between assets without any prior knowledge about the underlying data structure. This last feature is incredibly useful in replicating a benchmark portfolio like an index by carrying a fraction of the constituents while minimizing tracking errors by matching some of the benchmark's risk factors. It can result in lower transaction, management, and monitoring costs. In this way, a portfolio can be constructed with the lowest costs and risks, and it can outperform the specific benchmark by 1 percent on an annual basis.

Another handy AI technique in portfolio construction is evolutionary algorithms. It has the flexibility to deal with more complicated asset allocation problems. For example, evolutionary algorithms can solve optimization problems under cardinality constraints, restricting the portfolio's number of assets and maximum or minimum holding thresholds. They can also incorporate additional objectives. For example, they are incorporating model risk into the optimization problem to reduce forecasting error. Optimal portfolios using this approach have Sharpe ratios better realized by approximately 10 percent than those that consider only volatility and return in their objective functions[61].

### *3.6.3 Portfolio risk management: market and credit risks*

AI techniques are also applied in risk management regarding both market risk and credit risk. Market risk refers to the probability of loss resulting from aggregate market fluctuation. In contrast, credit risk is the risk of a counterparty not fulfilling its contractual obligations, which results in a loss of value.

Market risk analysis includes modeling, estimating, and forecasting risk factors that affect the investment portfolio. AI can be helpful in different ways: using qualitative data for risk modeling, validating and backtesting risk models, and producing more accurate forecasts of aggregate financial or economic variables.

AI techniques in market risk management involve qualitative information extraction from textual or image data sources. These data sources include news, online articles, social media posts, financial contracts, satellite images, and bank reports and statements. These sources can be precious and are not usually captured by quantitative variables.

AI approaches that use textual data have been shown to produce better forecasts of market crashes, interest rates, and other macroeconomic outcomes than those using information from corporate disclosures to determine firms' systematic risk profile.

AI can also help risk managers validate and backtest risk models. Unsupervised AI techniques can detect anomalies in risk model outputs by evaluating all projections generated by the model and automatically identify irregularities. On the other hand, supervised AI techniques can generate benchmark forecasts for the model validation

[61] Skolpadungket, P., Dahal, K., & Harnpornchai, N. (2016). Handling Model Risk in Portfolio Selection Using Multi-Objective Genetic Algorithm. *Artificial Intelligence in Financial Markets*, 285–310.

practice. In this way, comparing model results and benchmark forecasts will indicate whether the risk model produces predictions that significantly differ from those generated by AI. A significant difference between AI forecasts and standard risk model outputs can highlight potential problems and bring to a deeper investigation.

In market risk analysis, modeling future financial or economic variables' future trends is vitally important because they can affect the portfolio's assets performance. ANNs are trendy tools in forecasting macroeconomic variables, such as interest rates and exchange rates, performing better than linear autoregressive approaches. However, the use of ANNs involves the risk of producing implausible forecasts in the long run.

Another exciting approach of AI tools, like ANNs and LASSO regression, regards the detection of systematic risk factors, capturing nonlinearities and covariates' interactions, including firm characteristics and macroeconomic variables. Determining these factors is helpful for risk awards and to distinguish between diversifiable and non-diversifiable risks. These models can select the most relevant systematic risk factors from a subset of factors or market indices.

AI techniques, especially those with the ability to capture nonlinear dynamics such as ANNs and SVMs, can be advantageous for predicting market volatility and financial crises. ANNs and SVMs techniques can predict market volatility directly. When they predict financial crises, they are also called "early warning systems". Nowadays, these techniques are used by almost all financial institutions to monitor systematic risk. They can efficiently predict currency crises, banking crises, and recessions. However, events like crises are rare financial events, and AI techniques require a sufficient number of events in the sample to provide reliable predictions.

Credit risk management's objective is to ensure that any counterparty failure in meeting its obligations does not harm the portfolio beyond definite limits. Asset managers need to control the credit risk of the entire portfolio and individual positions and transactions. This practice involves modeling the solvency risk linked to institutions issuing financial products, including equities, bonds, swaps, and options. There is an extensive range of credit risk modeling approaches, and AI techniques such as ANNs and SVMs are widely used. ANNs are used for mainstream bankruptcy modeling since the early 1990s, thanks to their higher capabilities and successes in forecasting bankruptcy and determining credit ratings compared to traditional techniques.

Nowadays, SVMs are preferred due to their better accuracy in bankruptcy forecasts and their lower propensity to have typical ANNs problems like overfitting. Many other AI techniques can be used for credit risk modeling. Each of these modeling techniques has its advantages and disadvantages. Therefore, nowadays, an ensemble technique that uses various approaches separately and later combines the resulting forecasts is used for achieving the best performance possible.

## 3.7 ALGORITHMIC TRADING

### *3.7.1 AI and trading*

AI algorithms affect the trading process too. The trading process can be divided into three steps, the pre-trade analysis, the trade execution, and the post-trade analysis. In the pre-trade analysis step, data are used to analyze financial assets performance and analyze future ones, considering risks and costs involved in trading them. This step can be manual, meaning that it involves an asset manager's supervision and considers pre-trade analysis with risk assessment and client preferences. Nowadays, in high-frequency or fully automated systems, this step no longer involves human intervention. The pre-trade analysis leads to trade execution. In this step, trades are implemented while ensuring low transaction costs. Actual trading outcomes are evaluated in the post-trade analysis. While the first two steps, particularly complex and time-consuming, are now mainly handled by algorithms, post-trade analysis often involves human supervision.

Algorithmic trading, also called "Automated Trading Systems", has become a dominant force in global financial markets. Algorithmic trading was born in the 1970s.

It can be defined as the implementation of trading rules into a program and the usage of this program for trading purposes. This approach involves using AI tools, particularly ML, that learns the structure of data and then tries to forecast what will happen.

Algorithm trading now involves using complex AI systems to make quick trading decisions and automate one or more stages of the trading process. Their use is exponentially increasing in asset management. Researchers estimated that their market share is close to 40 percent[62].

[62] Brummer, C., & Yadav, Y. (2017). The Fintech Trilemma. *SSRN Electronic Journal*, 17–46.

The reasons for their spread among the industry are attributable to many factors. First, significant developments in computing power, data science, communication technologies, and their impact on financial markets operations are worth mentioning. The second factor is represented by the breakthroughs in mathematical finance and ML that have provided financial analysis faster and more efficient tools to operate. Another important reason concerns the increasing complexity, scale, and speed of financial markets that made it impossible for humans to track markets simultaneously and make real-time trading decisions. At the same time, ML techniques implemented are close to real-time.

Algorithmic trading' benefits comprise:

- the ability of trades to be performed at the best possible prices;
- the increased accuracy and the reduced probability of errors;
- the ability to simultaneously and automatically  check various market conditions;
- the reduction of human errors caused by emotional or psychological conditions.

Nowadays, algorithmic trading is used mainly by the hedge, investment, pension and mutual funds, and the next generation market makers.

While fundamental analysis is commonly used in asset management to forecast expected returns and portfolio optimization, algorithmic trading strategies are often based on technical analysis. This kind of analysis is based on the study of historical prices and volumes to predict future asset returns.

Algorithmic trading systems make thousands of trades daily. This means that they commonly use high-frequency trading, and for this reason analyzing lower-frequency data such as firm fundamental is less effective. Researchers indicate that technical indicators dominate fundamental ones in generating profitable trading signals using AI tools. Moreover, technical analysis also incorporates information from other sources such as fund flows, investor trades and textual data from news or online sources implementing AI techniques such as NLP.

In the last years, researchers proved that high-frequency trading benefits are changing the traditional trading market, and AI techniques will continue developing and reinventing the sector. The benefits of algorithmic high-frequency trading systems have been explained by various researchers:

- they help with price discovery and efficiency by trading in the direction of permanent price changes and the opposite direction of pricing errors;

- they provide market stability;
- they improve market liquidity; and
- they reduce trading costs, such as bid-ask spreads.

Financial institutions do not openly reveal their AI strategies to trading for a proprietary reason. However, it is believed that ML techniques play a fundamental role in calibrating real-time trading decisions. The following are four common algorithmic trading strategies: signal processing, market sentiment, newsreader, and pattern recognition.

1. Signal processing is a mathematical expansion of technical analysis based on filtering to eliminate noises and discern trading patterns.
2. In the market sentiment strategy, the computer is entirely unaware of market activities until it is fed model market data flows. Then, the algorithm becomes aware of the market agitation and participants' activity. The objective is to provide the algorithm with the appropriate context to analyze and learn supply and demand's market psychology.
3. New reader strategy does not react to major political events unless it is taught how to read news headlines artificially.
4. Pattern recognition strategy enables machines to learn, adapt and react when patterns arise, creating revenue opportunities.

An example of the algorithmic trading in use is given by ING's Katana[63], a tool based on AI that uses predictive analysis to help traders decide what price to quote when buying or selling their clients' bonds, based on past and real-time data. Katana learns from the history of hundreds of thousands of trades and turns it into predictions or suggested decisions for the trader. This tool is designed to increase man-machine cooperation. It organizes and displays relevant data predictions that the trader can rapidly and easily examine. After six months of tests and trials, Katana led to cutting costs by 25 percent, while decisions are 90 percent faster[64]. ING's Katana is only one example of AI algorithms used in trading. Other investment banks such as UBS and JP Morgan have already introduced algorithmic trading tools, and they are investing millions of dollars in these technologies. Moreover, they are now investing and collaborating with FinTechs

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[63] KatanLabs. (2021). *More about Katana, the bond market trade discovery tool*. KatanaLabs.

[64] Noonan, L. (2017, December 12). *ING launches artificial intelligence bond trading tool Katana*. Financial Times.

such as Cloud9 Technologies that, for example, uses AI techniques to offer a service voice communication platform using cloud-based technology as an alternative to traditional communication methods for voice trading[65].

### *3.7.2 Transaction cost analysis*

In the pre-trade analysis, transaction costs must be computed to evaluate whether the transaction would generate profits or not. Transaction costs include brokers' commission and the bid-ask spread, which is the difference between the price paid for security by the dealer and the price the buyers pay. Other substantial transaction costs are the market impact costs, defined as the adverse effect of trade on market prices. The peculiarity of these costs is that they are not observable before the trade is initiated. This means that they require an estimation as accurate as possible, considering that they absorb roughly two-thirds of systematic funds' trading gains[66].

AI approaches are beneficial for predicting market impact, mainly thanks to their nonparametric structure and their ability to capture nonlinear inputs. The most performing technique in predicting a market order's market impact by 20 percent out of the sample are SVMs. On the other hand, well-defined and estimated ANNs perform well in forecasting the market impact.

Although AI nonparametric approaches perform well in estimating the market impact, they have two weaknesses. First, most have no economic intuition for price impact drivers, so they tend to capture noises rather than relevant information. Second, they cannot differentiate between permanent and temporary market impacts, which require additional factors, such as trade direction and liquidity.

To overcome these problems, parametric and nonparametric approaches are combined. LASSO regression is an example of a technique that can capture informative variables related to the order book and other sources, such as trade sign and market order size, to forecast the price's impact.

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[65] Khalil, K. (2020, June 5). *UBS Investment Bank leads $17.5 million investment in JP Morgan-backed communications FinTech Cloud9*. The TRADE.

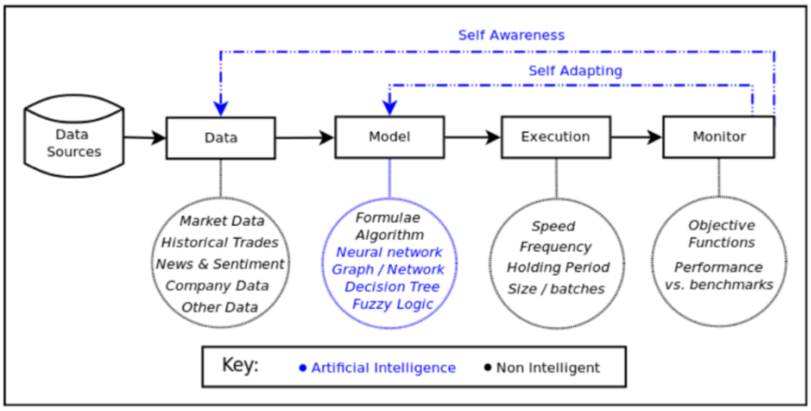
[66] Financial Stability Board. (2017a). *Artificial intelligence and machine learning in financial services*.

The cluster analysis approach is another helpful AI technique for estimating the market impact of trades in assets that do not have enough (or do not have) historical trading data. An example of how this approach works is Bloomberg's liquidity assessment,[67] which employs cluster analysis to identify comparable assets and provides a dynamic list of these securities. Further, a liquidity score is given, and it indicates the security level concerning the market impact. This process's significant advantages are that portfolio managers can gain consistent information about prices, volumes, and timing for specific securities, reducing transaction costs.

### *3.7.3 Model choice and use*

To better understand algorithmic trading systems, we can use a simple conceptual architecture made of three components that handle different aspects of the algorithmic trading system (see figure 3.3): data, strategy, and execution.

**Figure 3.3**: Conceptual Algorithmic Trading System




Conceptual Algorithmic Trading System

*Source: Turing Finance*

The data can be structured, unstructured, or both. In unstructured data like news and social media posts, ANNs and NPL tools are used to manage them.

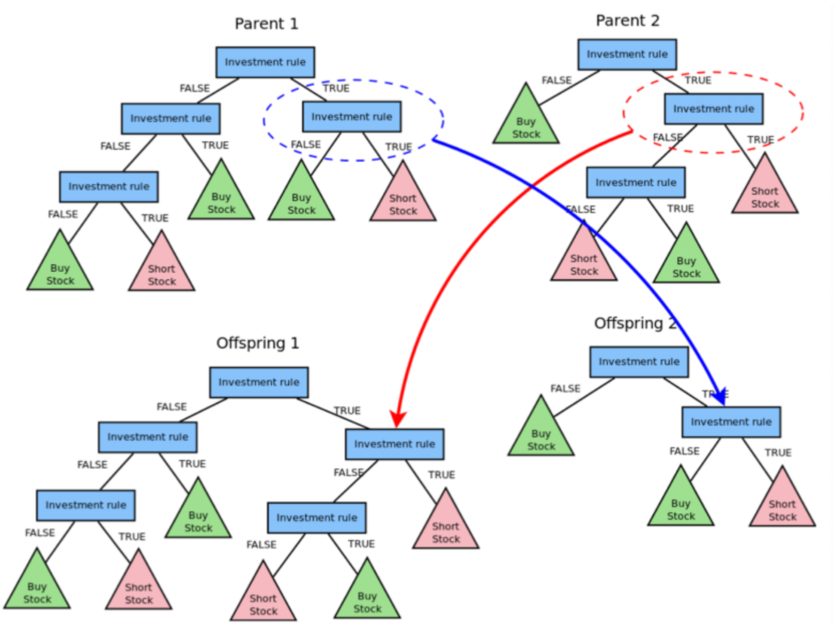
The model represents how the algorithmic trading system believes the markets work. The main goal is to use it to make inferences about the markets. Models can be structured

[67] Bloomberg. (2019). *Bloomberg Liquidity Assessment (LQA)*.

using different methods—for example, AI techniques of decision trees and ANNs. The main goal of different models is to reduce the system complexity to a manageable and quantifiable set of rules which describes the system behavior under different scenarios.

- Within decision tree models, each node represents a decision rule (or decision boundary). Each child node is either another decision boundary or a terminal node indicating the output, given a set of fundamental, statistical, or technical data (see figure 3.4). Decision trees can be divided into classification trees and regression trees. The firsts contain classes in their outputs, like "buy", "hold", or "sell". The seconds contain outcome values for a particular value (e.g. -3 percent, 0 percent, +3 percent). The nature of data determines what kind of decision tree is produced.

**Figure 3.4**: Conceptual crossover of two decision trees




*Source: Turing Finance*

- ANNs are one of the most popular techniques used for algorithmic trading. The input layer receives the normalized inputs, which are the factors expected to drive the assets' returns. On the other hand, the output layer could contain either buy, hold, sell classifications or forecasts of potential returns. Hidden layers adjust inputs and extract important salient features with more predictive power, minimizing ANNs error.

### *3.7.4 Trade execution*

The execution component is responsible for putting through the trades that the algorithmic model identifies. Many requirements, such as the execution speed, frequency of trades, the holding period, need to be met. Another problem regards the execution of large trades that often involves significant market impact costs. Bertisimas and Lo's[68] best execution model has been the dominant strategy in the last two decades to address this problem. This approach consists of splitting large trades into a sequence of smaller orders, easier and cheaper to execute. It requires a fixed time, smaller orders, and stochastic control techniques to determine an optimal execution strategy.

These classical models' problem is that they rely on restrictive assumptions regarding asset price dynamics and the functional form of market impact. On the other hand, AI approaches offer a more straightforward solution to facilitate and determine optimal trade execution strategies. The ML technique of reinforcement learning can be used to return optimal execution strategies receiving book variables as input orders. These variables can be bid-ask spread, volume imbalances between buyers and sellers, and signed transaction volume. The algorithm learns to map the combination of variables in order to give back trading actions that minimize transaction costs.

The advantage of AI approaches is that they rely on data rather than normative assumptions to determine market impact costs, price movements, and liquidity. Moreover, they have the advantage of being very flexible and adapt to market condition changes and new data availability. The disadvantages are represented by the difficulty of training and the intrinsic risk of following systematic events that affect the whole market.

### *3.7.5 Algorithmic trading issues*

The algorithmic trading practice raises skepticism, especially among traditional traders, who are dubious about the lack of transparency and the "black box" nature of AI algorithms, ANNs in particular. The "black box" nature of ANNs and DL algorithms entails that they can be viewed in terms of inputs and outputs, but without knowledge of their internal workings. ANNs essentially program themselves. They often learn arcane

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[68] Bertsimas, D., & Lo, A. W. (1998). Optimal control of execution costs. *Journal of Financial Markets*, *1*(1), 1–50.

rules that no human can fully understand. Many researchers expressed their doubts on algorithmic trading, stating that these algorithms risk not representing the world accurately. Especially concerning high-frequency trading, they stated that these models often mimic other trade operations without exploring the underlying real value of the companies' shares traded. Instability and market freeze could be created if trading strategies interact in unforeseen ways.

For example, high-frequency trading has been accused of the 6th May 2010 "Flash Card", when the Down Jones index experienced its most significant one-day point decline in the entire history. The stock prices of some of the world's largest companies traded at incomprehensible prices. For example, Accenture traded a share at a penny, while Apple traded at $100,000 per share[69]. The S&P500 fell more than 8 percent before quickly rebounding. This is described as the first market crash in the new era of algorithmic trading[70]. In 2016, there was a flash crash of the UK pound during the Brexit referendum by approximately 6 percent in two minutes[71].

Empirical researches indicate that algorithms' forecasts are more accurate than human ones. However, people often tend to be averse to algorithmic forecasters, even when they demonstrate to outperform humans. This is due to people losing confidence in algorithmic forecasts more quickly than humans' after seeing them make the same mistakes. On the other hand, people prefer algorithms, even if imperfect, as long as they can modify them. Moreover, researchers identified some issues related to or brought by algorithmic trading practices. These unintended consequences could be flash crashes, fire sales, careless IPOs, cybersecurity breaches, and catastrophic trading errors. Researchers' attention is now focused on new adaptive and systematic approaches to regulating these practices, where technological advances go hand in hand with protecting the most vulnerable and potentially damaged parts.

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69 Bartram, S. M., Branke, J., & Motahari, M. (2020). Artificial Intelligence in Asset Management. *SSRN Electronic Journal*, 2–39.

70 Kirilenko, A. A., & Lo, A. W. (2013). Moore's Law vs. Murphy's Law: Algorithmic Trading and Its Discontents.

71 Mullen, J. (2016, October 6). *U.K. pound plunges more than 6 percent in mysterious flash crash*. CNNMoney.

## 3.8 REGTECH

### *3.8.1 RegTech: regulation meet FinTech revolution*

RegTech could be considered a different sort of FinTech innovation. The Institute of International Finance defines it as "*the use of new technologies to solve regulatory and compliance burdens more effectively and efficiently*"[72].

Following the Global Financial Crisis of 2008, governments worldwide started to restructure their existing regulatory framework and introduce massive new regulations aiming to prevent future crises. As a result, there has been an exponential increase in the compliance burden on financial institutions on top of regulatory penalties' direct cost. According to CNBC[73], the latter amounted to $200 billion globally in the seven years after the financial crisis. In response to the new regulatory environment and the exponential growth of compliance costs, RegTech has emerged and developed into several regulatory contexts. It can represent the next evolution of financial services regulation. It should develop into a foundational base supporting the entire financial services sector.

The Institute of International Finance attributes the rise of RegTech to different factors. Supervised entities needed to manage and control a massive amount of data. Developments in data science and AI techniques allow them to structure unstructured data, continually monitor, predict and identify potential risks. On the other hand, new technologies dev financial institutions have been a natural solution to compliance requirements and regulatory fragmentation of different markets. In fact, despite policymakers trying to uniform reforms, they still differ between markets. RegTech can improve financial institutions' service, protect customers, and restore the trust lost after the global financial crisis.

On the other hand, the FinTech revolution has raised new challenges for regulators too. The country majorly impacted was China, where firms such as Alibaba, Baidu, and Tencent have entirely transformed the financial sector. Other countries, such as the US, the UK, Australia, and Singapore, have started developing new regulatory approaches for FinTech market dynamics in recent years.

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[72] Institute of International Finance. (2015). *Innovation - Regtech*.

[73] Cox, J. (2015, October 30). *Misbehaving banks have now paid $204B in fines*. CNBC.

Nowadays, RegTech represents an exciting field for investment. The focus on consumer protection and data security, the enrichment of the regulatory landscape in a different jurisdiction, and the digital transformation within financial institutions lead to a growth of investments. According to a KPMG analysis[74], global private investments in RegTech amounted to $2.5 billion in 2019.

### *3.8.2 RegTech differs from FinTech*

RegTech is considered a subcategory of FinTech. In fact, they are two different kinds of businesses that cooperate. The digitalization of the financial sector brought by the FinTech revolution has made the industry more vulnerable to cyber-attacks, thefts, and frauds from hackers. As we have seen in lending, payments, and insurance, we can safely state that cybersecurity is the clearest example of how FinTechs demand RegTech.
In addition to the obvious distinction between RegTech, focused on the regulatory, and FinTech, focused on the financial sector, other characteristics differentiate them. Unlike FinTech, which has both business-to-customer (B2C) and business-to-business (B2B) offerings, RegTech solutions address almost to established financial institutions exclusively. RegTech innovation is not seen as a threat by incumbents as it collaborates with them. This because compliance is seen as a cost for all industry players, and working together will reduce costs. Another difference is that RegTechs do not require regulatory licenses as FinTechs do, for example, in digital banking or P2P lending.
Regulators support the RegTech ecosystem, adopting RegTech solutions themselves. After the global financial crisis, they realized the increasing need to deal with masses of reports and data efficiently. Regulators need to develop systems to manage and analyze regulatory datasets appropriately. Among them, many have already started, while others are staying behind. The entire ecosystem will benefit from IT-enabled RegTech solutions to ensure financial stability and market integrity. Many countries are now developing regulatory responses as FinTech innovation continues to transform the field of financial services. For example, since 2015, after an initial laissez-faire approach, China has started implementing a complete regulatory framework for FinTech.

[74] KPMG. (2020). *KPMG Pulse of Fintech 2019*.

*3.8.3 The challenges to overcome*

The post-crises regulatory reforms that majorly impacted financial services include the anti-money laundering (AML) and the know-your-client (KYC) requirements. Financial institutions must control every client or potential client under the AML requirements. This process requires documentation of identity, income, source of income, and imposes continuous monitoring and identification of suspicious transactions. For large financial institutions with operations in different countries, this process must be implemented effectively inside the firm's risk management, compliance, and IT system. Moreover, these systems must be addressed to specific regulatory requirements of individual markets in which the firms operate. Today, this process is tremendously inaccurate, highly expensive, and almost totally manual. Up to 80 percent of costs are related to humans' work. Only in the US, financial institutions spend more than $50 billion per year on AML and KYC compliance. Instead, global money laundering transactions are estimated to amount to approximately $1.5 trillion a year, which is less than 1 percent of them seized by authorities[75].

Other areas of challenge for RegTechs regard:

- the macroprudential regulation (Dodd-Frank Act, Basel III, Basel IV), which increased financial industry reporting requirements in order to mitigate the systematic risk;
- the capital assessment and stress testing (CCAR, AQR), which require to observe specific rules of capital, leverage, and liquidity, and to monitor firms' financial stability periodically with reviews and "stress tests"; and
- trading reporting requirements on exchange-traded activities (Volcker rule, MiFID II).

RegTech services need to overcome all the above, which justifies the billions of dollars invested in the sector.

Robust IT systems and AI techniques combined with alternative data are the means to address AML and KYC requirements. For example, the RegTech startup Tookitaki, collaborating with the United Overseas Bank of Singapore, has developed an ML solution

[75] Bannerjee, P. (2011). *UNODC estimates that criminals may have laundered US$ 1.6 trillion in 2009*. United Nations : Office on Drugs and Crime.

to prevent money laundering in the bank's systems. Once the solution is fed with suspicious activity data, it will identify similar patterns for future alerts.

To address other challenges, both established institutions and RegTech startups are building strategic platforms to aggregate the near-real-data needed to comply with stress testing requirements and evaluate thousands of variables impacting financial institutions. ML algorithms can control transactions and trading practices.

### *3.8.4 Regulating the AI in the financial industry*

Nowadays, both regulators and industry players like financial institutions, tech firms, and FinTechs, have understood the importance of AI applications. The next step is to establish customers' trust and confidence in AI. Commonly AI applications are seen with fear since it is believed that it will take away human labor. This is partially true. However, at the current stage of AI developments, it is evident that human work is required in the input, training, and learning of AI algorithms.

Regulators worldwide, especially where FinTech and AI-enabled systems are widespread, have started to regulate how technologies' developments are used. Regulators aim to prevent biased outcomes to ensure an appropriate degree of consumers' protection and financial systems' integrity.

Regulatory sandboxes represent a significant element of these new regulatory approaches. A sandbox represents a virtual environment where businesses can test their innovative products, services, and business models in a live market environment with regular feedback. This way, they can test whether their products and services fulfill consumer protection measures.

The leading example of this new kind of regulatory approach comes from the UK. It was launched in 2016 by the Financial Conduct Authority (FCA)[76]. Other jurisdictions have followed the example by implementing their regulatory sandboxes. That is the case of China, the US, Australia, and Canada, while others have expressed their intention to set up similar initiatives.

The FCA has reserved the participation only to firms that show a new solution to support the financial services industry, which offers a benefit to consumers and needs to be tested

[76] *Financial Conduct Authority's regulatory sandbox opens to applications*. (2016, May 9). FCA.

within a sandbox framework. Further, the business needs to show appropriate investments and resources to develop and understand the applicable regulations and mitigate the risks. Sandboxes give FinTech startups valuable feedbacks allowing them to review and modify their models. Some of them also have the chance of securing funding through and after the testing phase. Considering Robo-Advice systems, consumer risks are minimized in two ways during the test. Firstly, qualified financial advisers are used to check the automated advice. Secondly, they will receive notifications to act after consumers have received suitability reports. In this way, consumers are ensured to receive only suitable advice. Moreover, firms under the sandbox are strictly supervised by the FCA, which can also stop the business in standard violations. Further, firms need to have sufficient capital to compensate clients in the event of losses arising from unsuitable advice.

Despite AI regulation being considered difficult due to ML algorithms' "opaque" nature, regulatory approaches like sandboxes permit to build consumers' trust and confidence in AI. Developers in financial institutions and FinTechs have to receive regular training on fair treatment of customers, data protection, and equality laws. Moreover, continuous monitoring and testing of algorithmic programs are mandatory. Eventual problems need to be solved as soon as possible. Many examples of regulation of AI systems already exist. One of them is the Quantitative Input Influence method that detects potential bias in machine learning using an iterative process of tests on the algorithm and decides which inputs influence the outputs majorly.

RegTech innovations also help build consumers' trust and confidence in AI. The collaboration between FinTechs and regulators increases customer protection. For example, the FCA working with FinTechs brought the development of ML and NLP-enabled regulatory assistant and advisers to provide help with the authorization processes, the automatic compliance practices, as well as the regulations' interpretation.

It can be said that the future of the regulatory world seems to be an interdisciplinary approach. The trend that is emerging is that the complexity of the FinTech ecosystem, driven by AI and other new technologies, requires:

- governments collecting and storing large amounts of data;
- continuous collaboration between regulators and financial players;
- the application and integration of AI systems for regulatory compliance;
- a global sandbox, such as collaboration and sharing of ideas, information, and best practices between regulators. An example is the Global Financial Innovation

Network (GFIN)[77], a network of 38 organizations committed to support financial innovation.

In this way, a practical regulatory approach, the protection of consumers, the promotion of innovations and the elimination of regulatory arbitrage opportunities can be achieved.

[77] Global Financial Innovation Network. (2021). *Global Financial Innovation Network (GFIN)*.

# CHAPTER IV. ANT GROUP CASE STUDY

## 4.1 INTRODUCTION

Headquartered in Hangzhou, Ant Group expanded only a few years ago and is actually the most successful fintech globally. Ant Financial has established over time an ecosystem centering on Internet Finance with 1.3 billion active users and more than 80 million merchants in 2020[78]. Since its birth as Alipay, the company was immediately considered a fintech "unicorn", a private company valued at $1 billion or more. As of June 2020, Ant announced it made $3 billion (21.2 billion yuan) in net profit for the first half of the year, on revenue of $10.5 billion (72.5 billion yuan) and an annual payments volume of about $17.5 trillion (118 trillion yuan)[79].

In October 2020, the company was ready to raise $34.5 billion in its initial public offering (IPO) in the dual Shanghai and Hong Kong listing, making it the largest IPO of all time. Ant's valuation would have amounted to $313.37 billion based on its pricing[80], more significant than some of the US's most prominent banks (figure 4.1). However, the IPO was stopped by the President of the People's Republic of China, Xi Jinping.

**Figure 4.1**: Ant Group market value 2020


*Source: Forbes*

[78] Liao, R. (2020, July 14). *Jack Ma's fintech giant tops 1.3 billion users globally*.
[79] Xie, S. Y., & Yang, J. (2020, August 25). *Inside Ant Group's Giant Valuation: One Billion Alipay Users and Big Profit Margins*. WSJ.
[80] Kharpal, A. (2020, October 26). *Ant Group to raise $34.5 billion, valuing it at over $313 billion, in biggest IPO of all time*. CNBC.

The company's fintech empire has operations in mobile and online payments, wealth management, money market funds, digital banking, credit scoring, cloud technology, and insurance services. Ant Financial's success lies in leveraging data to learn about users' needs to respond with digital services to address them.

## 4.2 THE CHINESE FINTECH INDUSTRY

### *4.2.1. The Chinese traditional banking industry*

In the first decade of the 2000s, the Chinese traditional banking industry's outlook was creating concerns. The majority of established financial institutions were state-owned, and capital flows were directly addressed to large state-owned companies. Lending by banks was directly toward politically driven objectives, resulting in the propagation of "zombie enterprises", which consisted in loss-making companies impossible to shut down. Domestic banks' loans might be made under government directives, allocating capital according to its strategic priorities to improve economic stability.

This situation left out of credit a multitude of SMEs, which necessarily needed credit. SMEs were facing obstacles in securing essential financing, and the circumstances were worsening since they lacked the channels to fundraise from the capital markets directly.

Established financial services relied profoundly on the build-out of physical branches, with high overhead and personnel expenses, and most importantly, they were directed on market segments offering the highest margins. Small or micro businesses and the rural population were largely unserved.

The financial sector's problems were further intensified by the lack of an efficient credit profiling system, an essential basis for banks to manage risk accurately and create a healthy economy. The country's credit profiling system was handled by China's Reference Center, which collected the majority of citizens essential information, such as names and identification data, but only less than a third of the population had credit records.

Another problem of the Chinese finance industry of the time was inclusiveness. The majority of adults were financially illiterate and not covered by traditional credit reporting systems. Furthermore, loans in rural areas accounted for only 23 percent of the total loan balance[81].

### *4.2.2 The Fintech revolution*

As we have seen in the third chapter, the financial industry has observed the so-called "fintech revolution" in recent years. The evolution of information technologies such as cloud computing, blockchain, big data, and AI has wholly transformed the financial industry. The interaction between finance and technology has resulted in various new forms of financial services and products, like digital banking, P2P lending, InsurTech, mobile wallets, and new payments services.

China has become a significant driving force and market for global fintech development. Despite a late start, the country is currently enjoying a late-mover advantage in the fintech environment, with an unrivaled growth level. According to the EY global fintech adoption rates index 2019[82], Chinese consumers had the highest level of fintech adoption rate at 87 percent, at the same level as India. Digital payments are the most frequently used fintech services by consumers, with 95 percent of Chinese consumers using them.

Some local governments, including Beijing, Shenzhen, and Hangzhou, have facilitated the development of fintech in China, supporting FinTechs with talent training, infrastructure promotion, and capitals. Moreover, the People's Bank of China has created the Fintech Committee to assist the "fintech revolution ", strengthen the research, improve its application, and push the financial industry's innovations.

It has always been a challenge for Small and Medium-Sized Enterprises (SMEs) to obtain assets and finance access in China. Around 90 percent of the organizations and firms in China belong to SMEs, creating almost 80 percent of the employment opportunities, which acts as an essential contribution to China's economy[83]. However, it is seen that only 30 percent of these businesses have been able to get access to loans from the banks.

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[81] Chen, L. (2016). From Fintech to Finlife: the case of Fintech Development in China. *China Economic Journal, 9*(3), 225–239.

[82] EY Global. (2019). *EY global fintech adoption rates index (2019)*.

[83] Ping An Digital Economic Research Center. (2020). *China's SMEs Amid the Pandemic*.

The development of internet services and the rapid economic growth favored a high mobile internet penetration. Statista[84] estimated that in 2020 more than 980 million people in China have access to mobile internet facilities, which gives them power and opportunities to explore online services and get assets for their small business. Small firms in China are now increasingly offering online solutions to their customers, usually underbanked and unbanked. The giant e-commerce ecosystem enables companies to access big data to reduce information asymmetry and control risks. Because of these facilities, the business is growing, leading to the betterment of the economy.

At the core of the Chinese fintech ecosystem there are big techs, also known as the "BAT" (Baidu, Alibaba, and Tencent). These companies, successfully leveraging the more extensive user base in their online ecosystems, have reached the fintech growth wave much faster than traditional financial institutions. For example, Alibaba has more than 780 million users[85], which provide the company with behavioral data for years. The number is much higher than that of traditional banks, so traditional financial institutions have started strategic cooperation agreements with "BAT" subsidiaries in recent years. The financial services sector has emerged for the big-tech triumvirate as an adjacent market, but now they are present everywhere: payments, lending, banking, insurance, and investments.

Establishing a regulatory framework for the fintech sector is a priority for governments worldwide. China, which is seeing incredible growth in the fintech environment, is not an exception. The Chinese government has been working on FinTech regulation for years to create a framework that balances innovation, growth, and financial stability. Such a regulatory framework is still in a nascent phase, as many subsectors remain underregulated and others still unregulated.

[84] Statista. (2020). *Number of internet users in China from December 2008 to December 2020*.

[85] Business Wire. (2020). *Alibaba Group Announces March Quarter and Full Fiscal Year 2020 Results*.

## 4.3 ANT GROUP HISTORY

Ant Group represents the evolution of Alipay, an affiliate company of the Chinese e-commerce giant Alibaba. Alibaba was founded in 1999 by Jack Ma and partners, raising the next year $25 million in funding by the Japanese Softbank, Goldman Sachs, Fidelity Investments, and others[86]. Alibaba is one of the most prominent e-commerce companies, providing B2B, B2C, and C2C services.

In 2003, the company launched Alipay, an online payment platform. The country's social and economic background in the early 2000s helps us understand why mobile payments in China and Alipay developed at such a rapid speed. One of the primary reasons why the banks in China did not have much technology was that the financial sector was entirely ruled by the Government, which even led to a lower number of credit card penetration across the country. However, China was rising from a central planning system to a free-market economy, and Alipay provided the solution to this change, going hand-in-hand with the development of a new kind of market, e-commerce.

Alipay was initially created to act as an effective payment tool to assist another Alibaba subsidiary, Taobao.com, an eBay-like consumer-to-consumer online retail marketplace, which was growing. However, Taobao.com was facing tough competition in the Chinese market, so in order to increase safety during online shopping and transactions, Alibaba introduced Alipay, which kept the money as a security deposit until the delivery of the products or services. At the 2016 Honour International Symposium in Singapore, Jack Ma stated: *"The lack of development in Chinese e-commerce was due to one missing piece: a mechanism that could facilitate trust between people. I believe that Alipay is the mechanism that can fulfill this gap"*.[87]

In December 2004, Alipay was separated from Taobao.com, emerging as an independent payment system. The company began providing its online payment services to many other companies and enterprises apart from the Alibaba group, pushed by the weak consumer protection laws and worsening consumer confidence in C2C and B2C quality control. The main aim of Alipay from 2004-2008 was to focus on the internal market, given the advantage of being the first movers. Moreover, Alipay processed almost 50 percent of the

[86] Epstein, G. (2011, April 5). *Alibaba's Jack Ma Fights To Win Back Trust*. Forbes.

[87] Ma, J. (2016). *Honour International Symposium 2016*. YouTube.

total transaction of Alibaba. The e-commerce giant and Alipay were synergistic and mutually reinforcing.

The Chinese government was a business partner beneficial for the growth of Alibaba. The government in those years started a strict internet control within the country, effectively locking out US e-commerce giants like Amazon out of the Chinese market and leaving that market wide open for Alibaba to prosper.

In 2007, Alibaba was listed on the Hong Kong stock exchange, and in 2008, the company started exploring foreign markets. It came into partnerships which many foreign companies and expanded and grew outside China, in countries like Singapore, the US, France, and many more.

Through its services and policies, the company wanted to revolutionize finance management and wanted to make the life of the Chinese people much more comfortable. With the increase in smartphone usage by the people in 2008, the number of internet users in China increased rapidly, ultimately helping Alipay get its popularity and usage widespread. With the company's immense growth, it even started to provide financial services in terms of loans and additional paper money, in which the client could borrow up to $15.000 (100,000 yuan) to grow their business. Alipay further started working in the travel booking industry and collaborated with the three most renowned travel agencies: Ctrip, Elong, and Mango. It even came into the insurance sector. With these strategies, Alipay users increased up to 200 million in 2010, which led to a 100 percent growth rate compared to the previous year[88].

With the excellent growing path of Taobao in the e-commerce sector, Alipay became a fintech company in 2010. The company even collaborated with UnionPay and introduced 'Instant Pay,' a payment service that helped credit cardholders make payments online without opening any online banking accounts. To achieve it, Alipay had to get a third–party online payment license from the People's Bank of China for this service.

Further improvement was seen in 2011 when Alipay even developed the "Barcode Pay". It allowed the expansion from online to offline, permitting the company to target the traditional retail market and e-commerce both.. The expansion of the company's financial services helped to gain a large number of customers, which could rely on a unique service provider for different situations.

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[88] Zhang, X., & Choi, M. C. (2019). Study on the Development Strategy of Ant Financial. *International Journal of Financial Research*, *10*(5), 262.

In May 2012, the company got a payment license for serving the investment fund companies in the investment field, which helped people invest their money safely and efficiently. In June 2013, they entered the asset management market directly, releasing Yu’e Bao, a mobile wealth management platform.

In September 2014, Alipay got the China Regulatory Commission's (CBRC) license to start its online banking business: MyBank. In the same period, Alipay got replaced by Ant Group, also called formally Ant Financial. The name reflected the company vision: "*Bring small and beautiful changes to the world*". With the concept of "ant" symbolizing smallness, the company focused its services on the myriad entrepreneurs and merchants who sold goods through Alibaba. Ant Group offered financial services to both consumers and SMEs, serving the market segments unserved by traditional banks. The company now offers all its clients an enormous amount of financial services, from wealth management to credit, but the e-payment sector was and still is the reason for its rise. Indeed, at the time of Ant Financial's founding, while a quarter of western banks' income derives from payments, it accounts for only 5 percent of Chinese ones' income[89].

## 4.4 KEY PRODUCTS AND SERVICES

The fintech empire of Ant Group initially prospered by addressing on financial inclusiveness, offering a comprehensive set of products to unserved consumers and businesses in China. Ant Financial progressively expanded to the entire fintech sector and now operates in:

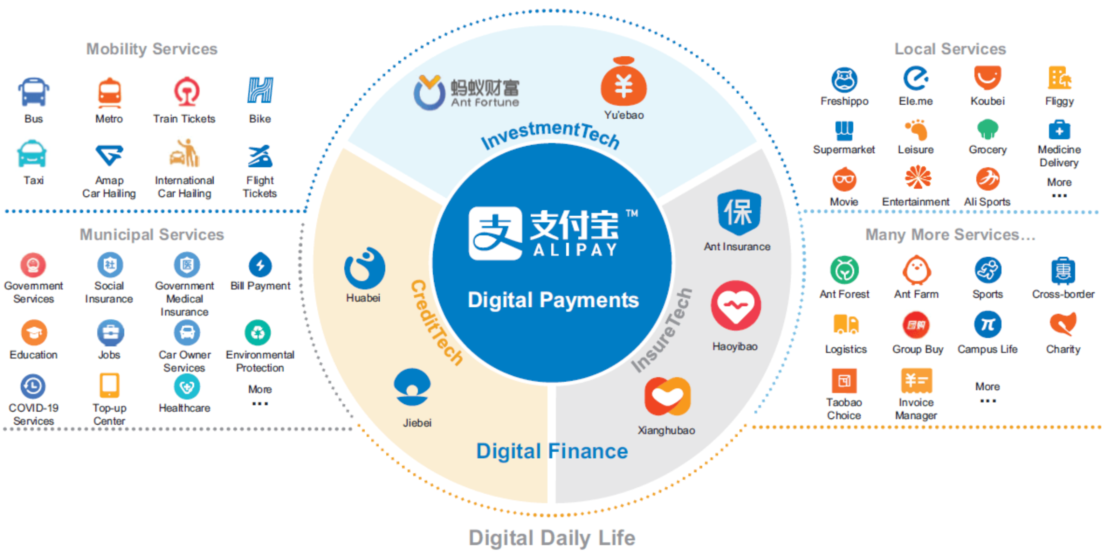
- mobile and online payment (Alipay);
- money market funds (Yu'e Bao);
- comprehensive wealth management (Ant Fortune);
- digital banking (MYbank);
- credit scoring (Zhima Credit);
- consumer credit portals (Huabei or Ant Credit Pay);
- insurance services (Ant Insurance Services); and
- identity verifications (ZOLOZ).

[89] Guo J. (2016, January 18). *Has Ant Financial Entered Its Golden Age?* TMTpost.

### *4.4.1 Alipay*

Alipay is essentially the Chinese answer to PayPal and now is the world's largest third-party mobile and online payment platform. It initially provided payment and escrow for the commercial business of Alibaba, but it quickly extended well beyond the Alibaba e-commerce ecosystem, starting to be used for products and services in-store or online. Over the years, the Alipay app was transformed from a simple digital wallet to a lifestyle enabler. Alipay now incorporates a broad range of advanced location-based services, including the possibility of booking a hotel, booking a medical examination, paying utility bills, buying movie tickers, and much more directly within the app. Alipay allows for direct integration with the other Ant Financial's services (see figure 4.2). According to the 2020 Q1 Chinese Third-party Mobile Payments Market Report[90], Alipay is the sector Chinese market leader, with a 55.4 percent market share. It widens the gap with Tencent's Tenpay, which comes in second with a market share of 38.8 percent.

**Figure 4.2**: Alipay App services



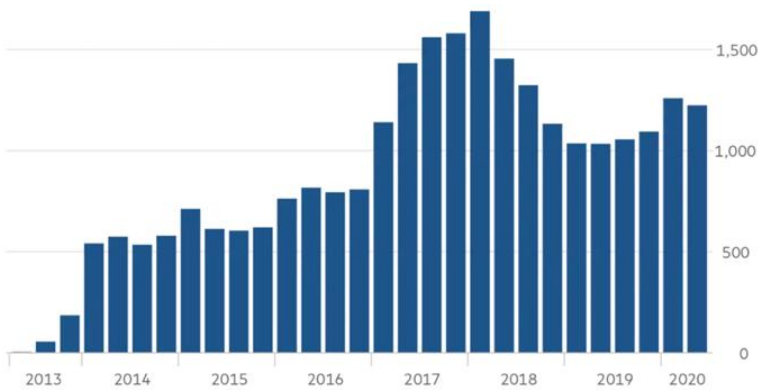

*Source: Alipay*

[90] iResearch. (2020). *2020 China's Third-party Payment Industry Report*.

### *4.4.2 Yu'e Bao and Ant Fortune*

Yu'e Bao is a cash management service founded in 2013, while Ant Fortune is a comprehensive wealth management platform. Both of them can be found in the Alipay app. When customers transfer money to the platform, it will be put into a money market fund managed by a partner asset management firm. Yu'e Bao generates returns for users, which can have access to liquidity for online or offline purchases at any moment. The platform now accounts for over 600 million users, who can also receive financial news feeds, personalized investment recommendations, updates on stock markets, and join a community of investors. For years its Tianhong Asset Management subsidiary invested the money, and it ranked as the world's largest money market fund. Given the rapid growth of Yu'e Bao's popularity, traditional asset managers responded by launching new offerings. For example, China Asset Management, which the Ant Group overtook as the nation's largest fund manager, launched its money market funds, collaborating with another tech giant, Baidu. Moreover, traditional banks increasingly started to pressure China's central bank to slow down the growth pace of fintech companies. Tighten regulations came in 2017 and took away the Yu'e Bao primacy, gradually pushing Tianhong to shrink each user's investment amount, reducing the total assets under management (figure 4.3). Chloe Qu[91], an analyst at Morningstar, stated that regulators intervened when they believed the Yu'E Bao fund had grown so large that a flow of withdrawals could potentially generate a systemic risk to the entire financial system.

**Figure 4.3**: Yu'e Bao assets under management (Rmb bn)




*Source: Wind Financial*

[91] McMorrow, R. (2020, August 26). *The transformation of Ant Financial*. Financial Times.

#### *4.4.3 MYbank*

In 2014, Ant Financial obtained regulatory approval to create its online internet bank service, MYbank. The online bank was one of the first private banks to receive approval from the Chinese Regulatory Commission and the first bank with no physical branches. MYbank provides loans with low rates or, in some cases, also interest-free loans to small and micro businesses, for example, in the case of companies operating inside the Alibaba business ecosystem. The company's focus was on providing inclusive finance to consumers, rural people, and SMEs, particularly in the e-commerce sector. Furthermore, the company developed the "3-1-0 lending model", consisting of a system without human intervention, enabling borrowers to complete loan demands online in three minutes and obtain approval in one second.

As of June 2020, MYbank and its partners have served 29 million small and micro businesses and individual entrepreneurs, with an average loan size of approximately $5,000 (36,000 yuan). The 80 percent of SMEs served by MYbank had previously never received business loans from a bank[92].

#### *4.4.4 Zhima Credit*

Zhima Credit is a credit score system addressed to Chinese consumers to access credit services such as microloans. Ant Group developed a credit rating system ranging from 350 to 950 determined by five factors based on data acquired from reliable sources; a higher score indicates a better credit. The five credit profiling factors are:

- credit and payment history: reflecting user's past payment history and indebtedness;
- behavior and preferences: showing user's online behavior, including the product that usually purchase or the online activity;
- fulfillment capacity: consisting of user's ability to adhering to contracts of loan, financial, and insurance products;
- identity characteristics: which rates the extent and accuracy of user's base personal information; and

[92] Business Wire. (2020b, April 27). *MYbank Served Over 20 Million SMEs as of 2019, Further Spurring the Growth of China's Small and Micro Businesses*.

- social relationships: consisting of the user's influence within or to his network of relationships.

Given Ant's strong ecosystem integration, a good credit score could yield benefits in Chinese people's daily life. For example, documents as visa might be released only to people that met a specific credit score level. Moreover, people with a good credit score could also benefit from other advantages, like renting a car or book a hotel without reservation fees or up-front deposits.

#### *4.4.5 Huabei (or Ant Credit Pay)*

Huabei is a consumer credit platform offering loans in small amounts to individual users, mainly for daily life consumption. The platform supports the recent trend of "buy now and pay later". Indeed, users can enjoy up to 40 days of delayed re-payment free of charge and 12-month installment services. The service fundamentally leverages the capital from financial institutions and other institutional investors.

#### *4.4.6 Ant Insurance Services*

Ant Insurance Services is a marketplace with more than 80 insurance companies offering thousands of products to more than 400 million users[93]. While competitors stroke-on partnerships to offer their clients personalized solutions, Ant Financial preferred to allow users to compare prices and solutions offered by a wide range of insurers.
However, the company introduced Xiang Hu Bao within the Alipay app, an online mutual aid platform. It provides an essential health plan for 100 kinds of critical illnesses. Users share the risk of critical illnesses and bear the related expenses collectively. The new service is not considered a health insurance product, but it aims to complement the other insurance offerings.

[93] CB Insights. (2020, July 6). *What The Largest Global Fintech Can Teach Us About What's Next In Financial Services*. CB Insights Research.

## 4.5 THE REGULATORY ENVIRONMENT

The development of the Chinese fintech ecosystem, thus including Ant Group, was pushed by the regulator, at least initially. This growth factor was the repressed Chinese financial system, which discriminated against SMEs and low-income households in their access to financial services. As explained in paragraph 4.3, Ant Group's Alipay initially addressed those unserved by traditional financial institutions, favored by some regulations voids. Furthermore, the Chinese government made massive investments in information and communication infrastructure, pushing the rapid adoption of digital technologies, like AI, big data, and cloud computing.

The critical factor of Chinese Fintech sector development was the accommodative regulatory environment. For years, a regulation was absent for many FinTechs, like Alipay, which obtained an official license by the government only seven years after its birth. Another example concerns the first P2P platform, FinVolutionGroup, which was born in 2007 and grew at an incredible pace for the following years. Nevertheless, regulatory standards came out only in 2016. There are probably two reasons behind the lack of regulation for FinTechs. One regards the laissez-faire approach of many government officials aimed at supporting financial innovation. In contrast, the other reason concerns the Chinese regulatory framework's focus on the traditional financial institutions, leaving the responsibility of regulation on the licenses. In this way, FinTechs fell into a gap area without any specific regulations.

The absence of regulation is a double-edged sword. FinTechs were able to leverage such arbitrage to develop new business models and services, sometimes resulting in illegal practices. For example, the P2P lending platform Ezubao[94], which raised more than $9 billion (59 billion yuan), was proved to be a Ponzi scheme, making it the most significant financial fraud case in Chinese history. The entire P2P sector has recently assisted in many closures by P2P companies since the 2016 regulation: over 60 percent of the more than 5,000 online P2P platforms have closed because they found themselves unable to comply with the new standards.

Chinese authorities discovered many other cases of fraudulent activity in all financial sectors and concerning data privacy. Such incidents created growing concerns about

[94] Reuters Editorial. (2017, September 12). *Leader of China's $9 billion Ezubao online scam gets life; 26 jailed*. Reuters.

fintech practices' legitimacy, pushing policymakers to incorporate fintech into the regulatory framework. From 2016, the regulators released several policy documents in order to reduce fraud, ensure customer protection and product transparency. Undoubtedly, if the regulator had imposed clear standards from the start, past years industry's chaos could have been avoided.

Regulation has helped enormously the rise of Ant Group, encouraging innovation and the development of more inclusive financial products. But, especially in the last years, it has also negatively affected the company's growth. In 2018, Chinese regulators new licensing and minimum capital requirements rules imposed a limit of 100,000 yuan of capital per individual in the Yu'e Bao money market fund, ten times lower than previously. Moreover, the platform had to lower its daily withdrawal limit from 50,000 to 10,000 yuan. The new rules led to a decrease of the fund asset under management from $266 billion to $157 billion at the end of 2019[95].

The same year, Ant Group's credit system Zhima was punished for enrolling users automatically, forcing them to stop the service for unlicensed financial businesses, including specific banks and consumer finance companies. The credit system is now used mainly for non-financial purposes, as for deposit-free rentals of cars and bicycles.

In the last years, Ant Group decided to reposition itself as a "techfin" company, a term coined by Jack Ma referring to technology firms enabling partners to improve their financial services offerings to consumers and small businesses. The company's repositioning has three main reasons:

- to emphasize its focus on developing technologies;
- to escape the closer scrutiny of financial regulators; and
- to benefit from the richer valuations the market provides to tech firms than to financial institutions for its IPO.

At the end of 2020, Chinese authorities stopped Ant Group's world's biggest IPO of $34,4 billion just two days before. Chinese authorities imposed the company a restructure plan to shift to a financial holding company structure, making it subject to rules and capital requirements similar to those for banks.

[95] Detrixhe, J. (2020, January 28). *Ant Financial's Yu'e Bao is no longer the world's biggest money market fund*.

Ant's restructuring is part of a broader central government campaign to increase the fintech and technology sectors' oversight. The Chinese authorities consider fintech a potentially cause of systematic risk, given last years' issues related to these activities.

## 4.6 DIGITAL INNOVATION TO RESHAPE BUSINESS AND OPERATING MODELS

### *4.6.1 Digitalization for market expansion*

Ant Financial is designing a new paradigm for the twenty-first-century company based on AI and sustainable and inclusive financial services. The firm deploys an operating model that leverages digital scale, scope, and learning that is disrupting the financial services sector.

The massive adoption of its services in China and the rest of the world allows Ant Group to collect an enormous amount of data, which is restructured and integrated into a platform using AI to improve functions such as application processing, credit scoring, loan approval, and fraud detection. The company's operating model's efficiency allows it to offer more than 1 billion customers an extensive range of services, employing less than ten thousand people. By comparison, Bank of America, now valued less than Ant Group, employs 170,000 people serving about 66 million consumers[96].

Digital technologies, based on software and data-driven algorithms, replace labor limitations in operating activities, driving business model innovation by remodeling operating models and eliminating traditional operation constraints.

Ant Group's success has not come only in recent years but lies in the initial business model of Alipay. Value creation was related to proposing a substitute for trust as an escrow-based payment service that facilitates transactions between buyers and merchants. This system alleviated consumers' distrust of online shopping. Moreover, it created value for two categories of customers: buyers and sellers. Value capture occurs through a 0.6

[96] Bank of America. (2021). *Bank of America Company Overview*.

percent transaction fee charged only to merchants, while did not charge consumers for using the service.
At this stage, the company decided to amplify the value created by trust in the service, increasing both the intensive margin of transactions, how many transactions a user makes, and the extensive margin of transactions, the number of consumers using the platform. Alipay quickly made its service available outside Alibaba's e-commerce platform to all individuals and businesses in the country. Consequently, it generated a positive network effect since more buyers attracted more sellers and vice versa, achieving higher returns to scale.
For a successful operating model, continuous improvement and the development of new products and services are necessary. Modern corporations look to innovation and learning as fundamentals factors to remain competitive, explore new opportunities and protect themselves from potential threats. Looking at the number of financial services offered, Ant Financial always seems to stay one step ahead in innovation and exploration of new opportunities. For example, in 2011, Alipay perceived the incredible boom in smartphone use in China as an additional income source, and decided to remove the high friction in the off-line commerce, giving customers the capability to purchase in-store products using their smartphones. The credit card system in China was not as developed as in western economies. Hence, the QR code established technology was incorporated in the Alipay app to remove this friction and facilitate transactions. In this way, users could use it for everyday expenses, such as buying coffee, splitting the bill at a restaurant, or even donating to a street performer.
Ant Group has continued to identify high friction services and focused on helping the customers by offering more straightforward solutions. In this way, the company reduces transaction costs for its users. The network effect combined with a service reducing frictions accelerated the growth of the platform. Once it achieved a critical mass of users, the company expanded the service offering, moving to adjacent financial services markets. To further improve the network effect, Ant Group decided to offer all these services as part of the Alipay App, creating a super app.
The fundamentals of digital operating models lie in bypassing human intervention on the product or service delivery process. Employees still essential in determining strategies, developing algorithms, coding software, and designing user interfaces, the process to drive customer value are now totally digitalized. The marginal costs of serving additional users concern only small incremental costs of computing capacity. On the other hand, the

digital operating model is easy to scale, and growth constraints are exclusively dependent on humans.

### *4.6.2 Digitalization to create partnerships*

A digital operating model can completely change the company's architecture. Ant Group's vital principle is creating an open platform to offer tech services to various partners, like banks, asset managers, and insurers.

Unlike consumers, financial institutions may offer the company higher revenue margins. Moreover, the promotion of new technologies and collaboration to these players ensure that they view Ant Group as a strategic partner rather than a rival. The company offers them technological services, including a secure transaction system, data privacy, and customer engagement tools. One example of this was Ant Group's decision to permit various market funds operated by external parties to offer services inside Alipay App, enabling them to have access to analytics to target customers as well as AI-based services. Another example came from the insurance industry. Ant Group offers insurers to operate in its marketplace, allowing them to access new AI tools like image recognition for assessing car damages and car insurance tools that quantify car owners' risk analysis into a numerical score. As of March 2019, Ant Financial has produced more than 100 technology products and services for digitalization, collaborating with more than 200 partners, including banks, insurers, and wealth management companies[97].

Over the long term, Ant Group aims at developing a globalization strategy to accelerate the adoption of its technology in other countries. It aims at creating a network of partners that enable its users to make purchases and transfer funds globally. As of February 2021, the company has invested in 96 enterprises worldwide, with 54 of them as lead investments[98]. Ant Group initially focused its attention on the countries around it, like India and Korea. In India, it has invested in Zomato, a food delivery service, while in Korea, in Kakao Pay, a payment service of its dominant messaging service Kakao.

Moreover, the company has acquired five organizations, including the English international money transfer company WorldFirst, for approximately $700 million.

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[97] Detrixhe, J. (2019, March 15). *Ant Financial's Alipay is expanding rapidly outside of China*. Quartz.

[98] Crunchbase. (2021). *List of top Ant Group Portfolio Companies*.

### 4.6.3 Digitalization to enhance the inclusiveness of rural areas

In the last years, Ant Group and Alibaba have worked closely to assist people living in rural areas in purchasing and gaining access to products and services similar to those available in metropolitan areas. This market's potential is enormous, considering that China's rural regions' population amounts to more than 550 thousand people.

The low population density renders traditional forms of payment inconvenient. Villagers and farmers have to walk long distances in order to deposit or withdraw money. Moreover, the agricultural sector's profitability is relatively low, forcing farmers to abuse loans and invest in high-risk opportunities for higher profits, resulting in higher default rates for rural lending. Exploiting the benefit of Alibaba's e-commerce services for rural areas, Ant Group provided farmers and villagers with financial services such as electronic payments and line of credit tailored for the rural market, as MYbank's Ant Rural Loan.

To reduce high default rates of rural lendings, Ant Group also made use of supply chain finance, lending to farmers via Alipay working capital restricted to the procurement of production tools and accessories on Alibaba's sites.

### 4.6.4 Digitalization for Chinese tourists abroad

As if the internal market wasn't big enough, Ant Group decided to serve also Chinese tourists when they travel. The potential revenues from these spendings are immense, since Chinese tourists, in 2019, spent about $254 billion while traveling abroad[99]. Ant Group relied on the fact that tourists are more relaxed in using a platform they already know instead of changing money into another currency. Currently, Alipay is supported in 110 countries[100], and in-store payments cover hundreds of thousands of retail stores. To use Alipay for payments and transactions, foreign merchants need only to provide their bank information to Ant Group, who will convert and credit the funds in the respective foreign currency.

[99] Statista. (2020b, December 15). *International tourism spending of Chinese tourists 2008–2019*.

[100] Alipay. (2021). *Alipay*.

## 4.7 AI-ENABLED TECHNOLOGIES

Ant Financial considers AI as one of the core driving forces of inclusive finance. For this reason, the core of the company's operating model is a sophisticated, integrated data platform using AI. Finance and AI support each other. AI provides financial services with better risk control, efficiency, improving user experience, and reducing information asymmetry. Financial services offer AI with new scenarios for new uses or developments.

AI is fundamental for a company with the scale and scope of business activities as Ant Financial, especially in managing the risks related to KYC, AML, credit, liquidity, security, data privacy, and particularly fraud detection. Indeed, over 50 patent applications in the field have been made by the company, which has also developed several AI technologies based on ML, image recognition, facial recognition, and NLP[101].

Ant Financial has built two crucial learning platforms: the Ant Graph Intelligence Platform and the Ant Intelligence Sharing Platform. The first consists of a ML system of billions of nodes that support graph data reasoning to help enterprises profile risks for loans. The second consists of a ML system capable of modeling millions of financial samples in few seconds to bring together reliable data of various parties, protecting these parties' data privacy. This second platform aims to build a system of cooperation between different financial institutions to strengthen risk control.

### *4.7.1 Big Data analytics*

With millions of users and billions of transactions every day, the company accumulates data on everything users do, from their financial habits, like how much they spend or save, to their life habits, like their preferred stores and restaurants. The primary sources of data used by Ant Financial are:

- the internal consumer behavior statistics, for example, payment records;
- transaction data from sellers on Alibaba's platforms;
- government data, as criminal records or academic profiles; and
- data from partners, as merchants and rental partners.

[101] Qi, A. (2019, December). *Ant Financial Applies AI in Financial Sector*. Alibaba Cloud.

Data are fundamental to feed an AI-enabled platform that runs hundreds of experiments daily, enabling the company to learn and understand the potential risks and opportunities provided by new features and products. Ant Financial strictly relies on scenario-based prototyping. In other words, use cases on the development, test, and improve applications and fintech solutions, while attracting a critical mass of users mainstreaming the technology gradually. Long Chen, Chief Strategic Officer of Ant Group, considers the "scenarization" and agile teams' ability to develop new financial services as the foundation of success within the fintech space.

Leveraging Ant Financial's "scenario-driven" advantage and AI techniques, Zhima Credit does not provide only credit scoring but also accurately predictions on users' repayment behavior. Data analytics and AI permit the company to stay one step ahead of the competition, identify consumer trends and preferences, and make inferences based on purchases. In this way, the company can better address its customers' financial needs and achieve its inclusive finance vision. Furthermore, the advantages of the amount of data held, combined with AI techniques, gave Ant Financial the capacity to enter new industries and develop faster than incumbents or new entrants.

#### *4.7.2 Cloud Computing*

Big data analytics and AI techniques permit Ant Financial to deliver timely and intelligent customer service. The company uses an advanced financial cloud technology platform to manage the incredible amount of data, which allowed it, since its birth, to keep each transaction's cost under $0,015 (0,1 yuan).

Ant Financial cloud architecture is superior to traditional ones for many factors. First, it helps to process Alipay's functions of accounting and payment non-stop. On November 11 Festival in 2017, it witnessed an unprecedented 256,000 peak transactions per second[102]. Second, the system works with low-cost PC server clusters to replace conventional database servers, decreasing the overall hardware expenses. Third, the system's performance and capacity are increased by adding more service, thanks to elastic computing. Lastly, Ant Financial cloud is 99.99 percent uptime, thanks to multiple synchronized data replicas on different servers in various locations.

[102] Alibaba Group. (2017, November). *Alibaba Group Generated US$25.3 Billion (RMB168.2 Billion) of GMV During the 2017 11.11 Global Shopping Festival*.

Client profiling and the efficient cloud architecture enable Ant Financial's MYbank to manage and approve small loans every hour and every day. Furthermore, data analytics and AI permit the subsidiary to operate on the completely automatized '3-1-0' system.

### 4.7.3 Risk control technology

Risk control is one of Ant Financial's top priorities since its foundation. Its computer network dedicated to the treatment, analysis and monitoring of risk control involves more than 2,000 servers. Moreover, more than 20 percent of the entire company's workforce is addressed to risk control functions[103].

The firm is committed to promoting research and exploring intelligent risk control, data security, and biometric identification. Eight security laboratories are addressed on security defense system research to improve users' capital and data security. To this end, the company collaborates with research laboratories, universities, and other companies or financial institutions.

AlphaRisk is the intelligent risk control engine developed by the company and one of the most advanced fraud detection systems worldwide. It uses AI techniques to analyze fraud attempts and patterns, adjusting risk profiles. It enables the company to implement effective transaction control measures, verifications, and user authentication in a fraction of a second. Under its protection, the fraud loss rate of Alipay transactions is less than 0.64 per ten million, far lower than similar systems.

### 4.7.4 AI systems to improve inclusiveness

Enhancing inclusivity is one of Ant Group's vision's root principles, which created an AI-based platform to address it. More than 100 million people have registered to the mutual aid platform XiangHuBao, which aims to improve inclusiveness helping users in the case of illness. The platform does not require upfront payment or admission fees, and it is accessible to people between 30 days and 59 years of age who meet essential health and risk criteria. The process of filing a claim takes two minutes, the user has to upload information with supporting evidence through the Alipay app, the process takes two

[103] Ant Group. (2021). *Ant Group*

minutes. Hence the request is processed and reviewed in more or less one second by the system. The system recognizes unstructured texts and elaborates the information through NLP and health knowledge graphs. After the data is extracted, verified, and the decision is made. In two hours, the user receives the payment for a maximum of approximately $43,000 (300,000 yuan)[104].

Traditionally, online mutual aid platforms in China have not the required technological capacities to reduce the risk of fraud, impacting their users' trust and failing to help those who genuinely need assistance.

#### *4.7.5 AI systems for eco-sustainability*

One of Ant Group's long-term goals is to reduce carbon emissions by promoting inclusive, sustainable financial services by using AI.

In 2017, the company developed Ant Forest, a platform inside the Alipay app, which encourages users to adopt low-carbon activities in their daily routines, such as using cashless payments or alternative means of transport as buses and bicycles instead of cars. Users' behavior is monitored by the platform and converted into "green energy points" that accumulate to grow a virtual tree. With a certain amount of energy points, a real tree is planted by Alipay and its partners in desertified areas that need reforesting.

By August 2019, Ant Forest has attracted over 500 million users, resulting in 122 million trees planted and the avoidance of 7.9 million tons of carbon emission[105]. This green initiative has been awarded the United Nation's highest environmental honor: the "UN Champions of the Earth" award.

Another green initiative made by Ant Group is the AI garbage classification application. This application identifies images, voices, and texts with over 90 percent accuracy, recognizing and classifying over 20,000 items[106]. The company is also working to spread AI-based intelligent garbage classification technologies across the entire garbage processing industry. If well implemented, the system could reduce carbon emissions in the carbage processing stage by 20 percent by 2025.

[104] Business Wire. (2019, November 27). *Alipay's Xiang Hu Bao Online Mutual Aid Platform Attracts 100 Million Participants in One Year*.

[105] Business Wire. (2019a, September 19). *Alipay Ant Forest Named UN Champion of the Earth, the United Nation's Highest Environmental Honor*.

[106] Qi, A. (2019, December). *Ant Financial Applies AI in Financial Sector*. Alibaba Cloud.

## 4.8 CONCLUSION

The purpose of the case study was to highlight how fintech, driven by new technological innovations, is revolutionizing the financial sector. The findings show how technological breakthroughs led to product and service innovation, resulting in new business and operating models.

Ant Group, since its birth, deviated from the traditional product-centered logic of established financial institutions, building a customer-oriented logic. The creation of value for customers is the foundation of the company's successful network effect. This approach allows the development of an enormous amount of services. Moreover, the study highlights how technological innovations could be used to encourage and support social inclusion and eco-sustainability.

New technologies like AI, data analytics, and cloud computing are essential for managing millions of customers and bringing them intuitive, simple, and tailored services. Furthermore, as demonstrated by Ant Group, they are fundamental in building partnerships. The study also shows how relevant the regulator's role is since it can facilitate companies' growth, slow it down, or even stop it.

Ant Group fully represents a new model of doing business, an evolution of the entire Fintech sector toward Finlife, a more sophisticated stage where people's whole financial lives are powered by technology.

# CHAPTER V. THE FUTURE OF AI AND FINTECH, TRUST AND ETHICAL CONCERNS

## 5.1 THE FUTURE OF FINTECH AND AI

### *5.1.1 The digitalization and platformization of financial services*

The financial services sector is changing rapidly. FinTechs are playing an important role and they are leading the industry on the path of innovation, forcing incumbents to partner with them or transform their business models and go in the same direction. At the same time, tech giants are threatening to enter the business or, as in the case of Ant Group, they are already part of it. But the transformation of the industry is not given only by the competition between these forces. New technological innovations, such as AI, big data, blockchain, and IoT, are changing the structure of the financial ecosystem, from the services and products offered, to the way in which they are built, bought and delivered.

Until few years ago, the success of financial institutions was given by the expansion of their branch network, in order to acquire new deposits and to build a relationship with consumers. Today the story has changed, customers are shifting away from traditional banking in favor of digital channels, in fact, banks in developed markets have achieved 25 percent less branch use per customer. Moreover, the COVID-19 pandemic has dramatically impacted the sector and accelerated the shift to digital, increasing the digital-only customers by another 10 to 15 percent[107].

Looking to the future, financial institutions are developing new ways to improve the digital interaction in different ways: via voice channels, developing integrations with "smart speakers" devices such as Amazon Alexa or Google Home; via chatbots, introducing click-to-call functionality to avoid manual identification and verification steps; and using AI for live coaching of agents or to check script compliance. This trend will probably damage incumbents with expensive and superfluous structures and human capital. An analysis from the National Community Reinvestment Coalition (NCRC) highlights a loss of branch in the US of more than 5 percent (nearly 4,500 branches) from

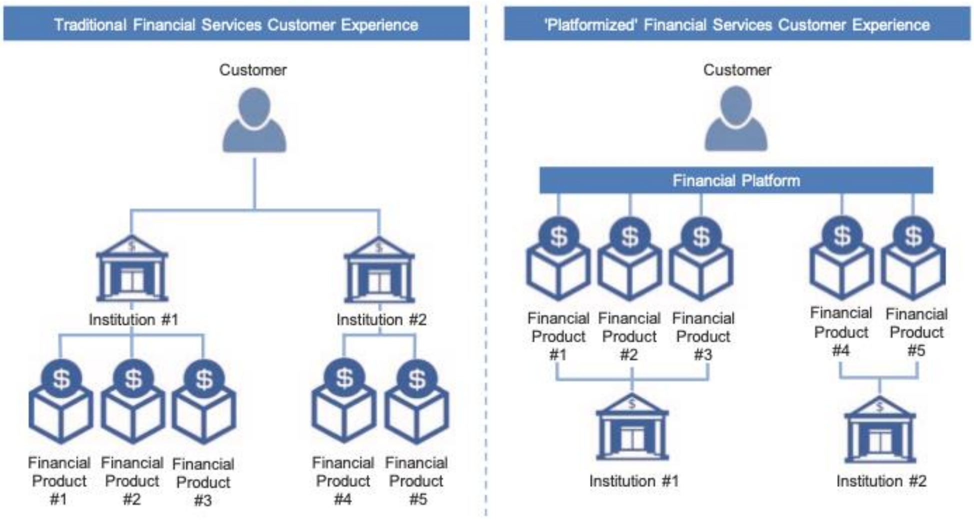
[107] Mckinsey Global Institute. (2020, December). *McKinsey's Global Banking Annual Review*.

2017 to the third quarter of 2020, underlining also that the total number of branches closed since the great financial crises amount to more than 13,000 in the US[108].

The e-commerce widespread has changed the approach to customers experience and this trend is affecting the financial services sector too. Nowadays, customer can choose between a range of different financial services, such as credit card products or funds in which they can invest. However, while in an e-commerce platform they can choose a different range of products offered by different merchants, in the field of financial products, the only way to access to products of different institutions is to sign up as a client of that firm. The increasing support by regulators towards "open banking" systems force financial institutions to provide secure channels for customers to share their financial data with third parties and in some cases to move their funds too. Many jurisdictions are going in that direction such as the European Union, UK, US, Canada, Japan and Australia.

In the next future, this shift of the customer experience could bring to the entering in scene of platform-based financial services, in which the provider may be not the producer of all products, but it will focus on offering a 360-degree service of products from many financial institutions, providing a personalized customer experience and tailored financial advices (see figure 5.1).

**Figure 5.1**: Traditional vs. "Platformized" Financial Services Customer Experience

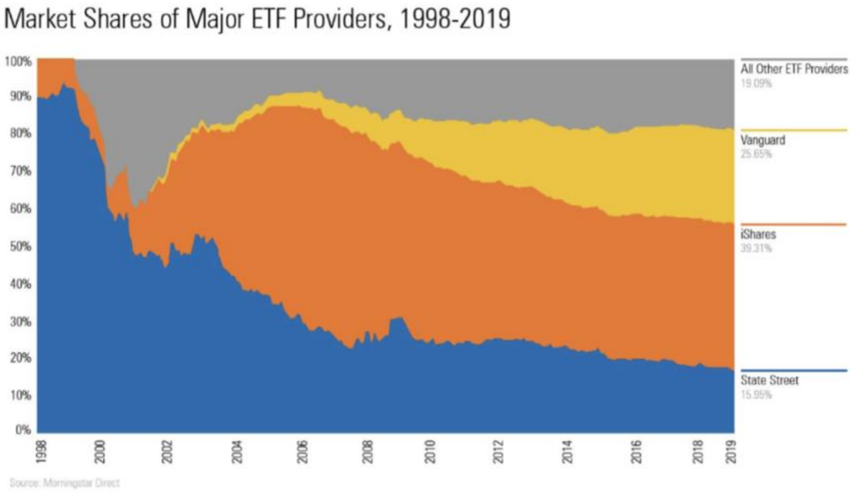



*Source: Arslanian and Fischer (2019)*

[108] National Community Reinvestment Coalition. (2020, December 14). *Bank Branch Closure Update (2017 – 2020)*.

Creating such a platform it would be very challenging and only few firms have the means, these are tech giants such as Amazon, Apple or Alphabet. These firms have the technological resources to manage a system with different partners, to provide automated recommendations using AI techniques and tools, and to move between different regulations, even if are the regulations themselves that are going in the same direction.
In this way, US tech giants would disrupt the financial services system without building their own financial structures, taking a different path from that of Chinese technological firms, like Alibaba and Tencent, that have built their own financial services.
Moreover, with the platformization of financial services, new FinTech banks, such as N26 and Revolut, will have the opportunity to enhance their customers base and to increase their partnerships with other FinTechs or incumbents.
In this context incumbents seems to be the most disadvantaged, but many of them, as ING and BBVA are looking to build a platform of their own. To have success, they have to make the right choices in how to invest in new technologies and how to reorganize their models for a new way of doing business. Many financial institutions are looking at the cloud as a mean to increase the efficiency of their organizations, adopting standardized exchange tools called application program interfaces (API) in order to outsource and integrate into their operations service providers like RegTechs. On the other hand, the advantage they have over tech giants is that they operate in a familiar sector, they already have a base of customers, and a major knowledge of the regulatory field.
The evolution brought by technological innovations and FinTechs will not only affect customer experience and financial institutions structures, but also financial products. With digital platforms, a quite good product will not ensure anymore strong performance since customers will have no more problems to switch to another product. In an environment like that, success can be obtained in two different ways: the first is given by delivering low-margins and highly-standardized financial products, the second is delivering a unique and customized product addressing to single individuals or organizations.
This path drives the market toward a situation in which there are big few players in producing highly-standardized products and many small niche players competing on the base of the uniqueness, the new features or the highly customization of their product.
The first situation is well represented by exchange traded funds (ETFs), in which costs decrease with the growth of assets under management. In fact, in the ETF market, the 80 percent of ETF assets globally is managed by three large players (see figure 5.2).

**Figure 5.2**: Market Shares of Major Providers, 1998-2019




*Source: Morning Star Direct*

## 5.2 THE FUTURE OF AI, RISKS AND ETHICAL ISSUES

### *5.2.1 Predictions on AI*

While the FinTech ecosystem seems to go towards digitalization and platformization, with all the changes they bring to the financial services sector, predicting AI applications' future seems to be more challenging, as demonstrated by the too optimistic predictions in the 1970s.

The most widespread prediction regarding AI among economists, scientists, and engineers, is that AI technologies will eliminate millions of jobs in the coming decades, leading to various social issues. While in the past, the implementation of AI techniques required the need to hire specialists or to carry out intensive and expensive R&D campaigns, currently, it is no more necessary. The spread of AI services allows firms to reduce the cost of technological investment outsourcing. For example, Google provides application programming interfaces (API) integration enabling firms to access unstructured data via NLP or providing access to machine vision algorithms.

Firms are also facilitated by the rise of new tools to build elementary AI applications that fit their needs. An example of these new tools is given by open-source code repositories offered by Google, Amazon, and Microsoft, which help even relatively small firms develop new solutions by assembling various plug-and-play components that require simple coding skills. Moreover, they exist services that offer access to AI tools without programming skills. For example, IBM's Watson Analytics[109] enables firms to upload data and integrate alternative sources of data to elaborate queries employing natural language instead of codes. The significant advantage of these tools, in addition to the significant reduction in costs, is that individuals highly specialized in their businesses have the means to solve AI problems that AI specialists were not even aware of. These developments will undoubtedly enhance the access to AI tools for those firms with few capabilities.

On the other hand, they will not impact companies who seek to innovate the AI sector and their necessity for highly-specialized talents. According to the World Economic Forum report "Future of Jobs Survey 2020"[110], in the first three places of the most demanded jobs, there are AI and data specialists or analysts. However, it seems that AI and robotics automation are creating a "job polarization" in the labor market. While the demand for highly skilled technical jobs is increasing, at the same time, mid-qualification jobs in factories and offices are facing automation pressure. According to a 2017 McKinsey Global Institute's report[111] estimated that up to 30 percent of current jobs would be displaced due to technological development as AI and automation by 2030, meaning that between 400 million and 800 million individuals worldwide need to find new jobs by 2030.

In the article "The Seven Deadly Sins of Predicting AI"[112], Rodney Brooks stated that long-term forecasts concerning AI and robotics have no absolute evidence. Hence, job loss estimations by AI, automation, and digitalization processes must be considered only as conjectures. Moreover, predicting AI's future impacts is challenging because of its irregular pace of research progress. As seen in Chapter 1, progress in AI research did not follow a linear development, but it alternated periods of rapid progress with long "winters", making the prediction much tricky in the long term.

[109] IBM. (2020). *IBM Watson Studio - Panoramica*.

[110] World Economic Forum. (2020). *Future of Jobs Survey 2020*.

[111] Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., & Sanghvi, S. (2019, May 11). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*. McKinsey Global Institute.

[112] Brooks, R. (2020, April 2). *The Seven Deadly Sins of AI Predictions*. MIT Technology Review.

### *5.2.2 Risks and ethical issues*

As always, the development of a new technology raises new concerns of different kinds. Many such concerns turn out to be wrong, for example, telephones did not destroy personal communication; some are correct, for example, the internet destroyed the video-rental industry. Some technological innovations, like nuclear power, have generated political and ethical discussions, and AI is not an exception. Many issues are related to the use and development of AI techniques and related robotic systems.

In the last few years, there has been a lot of talk about the privacy of data. Nowadays, all data collection and storage is digital, and people's lives are increasingly digital. We need only think about, for example, social media and online gaming, which attract an enormous mass of people. AI technologies enable the generation of unstructured data about the non-digital aspects of people's lives, the collection, and the analysis of this kind of data. For example, face recognition systems in photos or videos facilitate the identification and profiling of individuals. Data collection and its trade are now a foundation of the internet companies' business models. On the other hand, data privacy regulation has not been a primary necessity for regulators for years. Only after the Facebook–Cambridge Analytica data scandal, it seems that policymakers have begun to take action in this regard.

The long-term consequences of AI in the data privacy field are still uncertain. In the book Homo Deus, Yuval Noah Harari asks: "*What will happen to society, politics, and daily life when non-conscious but highly intelligent algorithms know us better than we know ourselves?"*[113].

The question leads to AI ethical issues that go beyond data collection and privacy, including the use of data to manipulate people's behavior. Behavior manipulation efforts are old, but now individuals or small groups may be targeted and influenced by AI algorithms. Many sellers, advertisers, and marketers base their business models on behavioral manipulation, as in the gaming and gambling industries. Now, this kind of practice is expanding to other sectors, as the low-cost airline industry.

While in the EU, policymakers have increased privacy protection with the General Data Protection Regulation of 2016, other countries, like China, prefer to develop with less regulation, aiming to obtain a competitive advantage in the data field. Without policies in

[113] Harari, Y. N. (2018). *Homo Deus: A Brief History of Tomorrow* (Illustrated ed.). Harper Perennial.

the interest of the whole community, businesses exploiting AI technologies will continue to invade people's privacy and manipulate their behavior.

AI systems for automated decision support, as in credit scoring, and predictive analytics, raise opacity and bias concerns. A system is opaque to a person when it is impossible to know how the decision came out. Moreover, ML systems are typically not transparent even for the expert that does not know how the pattern is identified. In this way, this opacity aggravates the likelihood of biases in decision systems.

While it is relatively simple to adopt a chatbot for customer service, deploying it for critical financial services is more challenging. For example, rejections in loan applications have to be free from bias based on gender, race, etc. The decisions should be based on the parameters established for approval or rejection of loan, and the ML decision-making process should be transparent.

Nowadays, several technical activities aim to reduce biases in the "black box" nature of AI systems, such as the Defense and Research Project Agency (DARPA), which seeks to teach ML programs constantly to justify decision-making end-user can easily understand it. Furthermore, the mentioned above EU GDPR 2016 has taken into account these kinds of issues, providing consumers with a legal "right to explanation" when faced with a decision based on data processing.

The elimination of AI-related risks and ethical issues is not the job of a single regulatory authority or industry. AI has now penetrated every aspect of people's daily lives, including financial activities. It needs that all parts come together and formulate a strategy and ethical codes structure encompassing its design and implementation, to prevent issues to individuals' privacy or discriminations.

### *5.2.3 The risk of singularity*

One of the most discussed considerations when predicting future AI developments is the possible advent of strong, or general, AI. The technological singularity is the possibility of achieving a general AI that surpasses human intelligence, whose development is out of human control and is not predictable. Many entrepreneurs and contemporary geniuses have expressed their fears about the possible development of a singularity. For example, Elon Musk considered it "*more dangerous than nuclear weapons*"[114], while Steven Hawking considered it as "*either the best or the worst event in the history of our civilization*"[115]. We are theoretically still far from developing a strong AI, but the discussion divides the experts. Indeed, many scholars have estimated the arrival of the singularity in the coming decades. Kurzweil[116] stated that the computing power has been increasing exponentially, doubling every two years, and estimating that by 2045 the singularity will occur. More recently, Amodei and Hernandez[117] estimated that in the years between 2012 and 2018, the computing power doubled every 3.4 months. Emphasizing how in recent years, the progress towards a singularity exceeded every expectation. How soon the singularity will arrive still unknown.

Kurzweil stated that the creation of a superintelligence does not involve only a computing power increase, but also the human brain's full emulation on a computer, the human biological paths, as well as networks and organizations.

Scholars are divided about the risk of singularity: many do not believe it will ever exist, while others believe that it can pose an existential risk for humanity. What seems clear to everyone is that AI technologies should be closely supervised in order to catch the new technological and social issues early or prevent them.

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[114] Clifford, C. (2018, March 14). *Elon Musk: 'Mark my words — A.I. is far more dangerous than nukes.'* CNBC.

[115] Kharpal, A. (2017, November 6). *Stephen Hawking says A.I. could be "worst event in the history of our civilization."* CNBC.

[116] Kurzweil, R. (2012). *How to Create a Mind*. Van Haren Publishing.

[117] Amodei, D., & Hernandez, D. (2018). *AI and Compute*. OpenAI.

# CONCLUSION

The current digital revolution is having an impact on every aspect of people's lives. It is modifying companies' structures, our daily habits and the way we all work. AI is one of the technologies that is having the most relevant impact on these digitalization processes. Firstly, the object of this work has been to analyze the AI applications within the financial field. Second, it aimed to provide a real example of how this technology influences and modifies the whole financial services sector through the Ant Group case study. Based on documents qualitative analysis, we can state that the AI application represents a crucial element in the XXI century society's progress.

The AI application development goes along with the digitalization process we are witnessing nowadays. This process, within the financial field, is well represented by FinTech. These societies have made the most out of AI technologies to create a competitive advantage over traditional financial institutions that had to face consumers' trust issues after the 2008 global financial crisis. However, even traditional financial institutions seem to have understood AI technologies' importance. Therefore, they started digitalizing their operation processes, editing their business plans and renewing their obsolete organizational structures, firmly based on physical branches and human work.

Several of these institutions have started to consider FinTech as potential partners rather than competitors, establishing collaborations.

AI technologies usage allows the creation of new services within every financial field, from lending to algorithmic trading, guaranteeing customers a tailored, efficient and quick service. Further, AI techniques help identify and prevent possible frauds. This way, they improve transactions' security.

As emerged from the Ant Group case study, the future trend for the financial services offer seems to put the services on platforms. This way, multiple tailored services are safely and digitally offered to the consumer via smartphone on one platform only.

Compared to traditional methods, these new techniques allow FinTech and financial institutions to reach far more clients and limit human work. This factor can bring additional benefits to the collectivity. For example, it further includes minorities like immigrants, rural areas inhabitants and small businesses, allowing them to access fundamental financial services like microcredit.

Despite all these advantages, AI development in the financial field brings risks and threats as well. Withing the workplace, AI could take away numerous unqualified jobs. Simultaneously, several other professional figures in the financial sector will have to adapt to the change and significantly depend on it. Furthermore, AI puts data privacy at risk. The regulatory represents another issue as well. Digital systems are making financial services management and legislation increasingly harder. The experts are working closely with regulators to set guidelines and better practices to support the innovation sector and protect consumers' privacy rights. Unfortunately, as emerged in this work, the new digital financial services' regulations on data privacy are highly diversified on a national basis.
Considering the digitalization processes' global and multisector entity, a closer and proper collaboration between regulators, FinTech and RegTech is recommended.

The main limit of the research is that the collected data are secondary data from published sources. Although the information is more than enough to understand the AI technologies' applications within the financial field, further information could be gathered through primary data analysis. These can be obtained through observations, interviews with financial companies that use AI technologies.

Another element to consider is that AI impact on financial services evidence could only be verified in the future, as the application within this field is exceptionally recent and in constant evolution. It may be concluded that implementing AI applications into operational models is necessary for all companies to remain competitive nowadays, especially within the financial field.

From my perspective, supported by the study conducted for this work, AI not only has the potential to improve the offer and the accessibility of financial services. It can also, provided good management, bring benefits to our lifestyle and health. It can bring inclusion into our ecosystem, avoiding discriminations and waste through more efficient data management. The most considerable risk that AI could bring is challenging data privacy management and potential behavior manipulation. However, thanks to regulations and cybersecurity, I am confident that, thanks to regulations and cybersecurity, these threats will fade away and AI will bring and increase progress and prosperity into our lives.

# LIST OF FIGURES

# REFERENCES


Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications*, *2,* 100006. https://doi.org/10.1016/j.mlwa.2020.100006

Aggarwal, C. C. (2018). *Neural Networks and Deep Learning: A Textbook* (1st ed. 2018 ed.). Springer.

Alhawiti, K. M. (2015). Advances in Artificial Intelligence Using Speech Recognition. *World Academy of Science, Engineering and Technology, International Journal of Computer and Information Engineering,* 1432–1435. https://doi.org/10.5281/zenodo.1106879

Alibaba Group. (2017, November). *Alibaba Group Generated US$25.3 Billion (RMB168.2 Billion) of GMV During the 2017 11.11 Global Shopping Festival*. https://www.alibabagroup.com/en/news/article?news=p171112

Alipay. (2021). *Alipay*. https://intl.alipay.com/home/about/buy.htm

Alloway, T. (2014, December 12). *Lending Club banks 56% surge on debut*. Financial Times. https://www.ft.com/content/0a25d3e8-8148-11e4-896c-00144feabdc0

Alpaydin, E. (2012). *Introduction to Machine Learning*. MIT press.

Altexsoft. (2020, February 27). *Fraud Detection: How Machine Learning Systems Help Reveal Scams in Fintech, Healthcare, and eCommerce*. https://www.altexsoft.com/whitepapers/fraud-detection-how-machine-learning-systems-help-reveal-scams-in-fintech-healthcare-and-ecommerce/

Alzubaidi, A., & Kalita, J. (2016). Authentication of Smartphone Users Using Behavioral Biometrics. *IEEE Communications Surveys & Tutorials*, *18*(3), 1998–2026. https://doi.org/10.1109/comst.2016.2537748

Amodei, D., & Hernandez, D. (2018). *AI and Compute*. OpenAI. https://openai.com/blog/ai-and-compute/

An., A. (2021, February 11). *Pechino cambia il futuro di Ant Group: da fintech a holding finanziaria*. Il Sole 24 ORE. https://www.ilsole24ore.com/art/pechino-cambia-futuro-ant-group-fintech-holding-finanziaria-AD3HHVHB

Ant Group. (2021). *Ant Group*. https://www.antgroup.com

Arner, D. W., Barberis, J., & Buckley, R. P. (2017). *FinTech and RegTech in a Nutshell, and the Future in a Sandbox (Research Foundation Briefs)*. CFA Institute Research Foundation.

Arner, D. W., Zetzsche, D. A., Buckley, R. P., & Barberis, J. N. (2017). Fintech and Regtech: Enabling Innovation While Preserving Financial Stability. *SSRN Electronic Journal*, 371–413. https://doi.org/10.2139/ssrn.3211708

Arrieta-ibarra, I., & Lobato, I. N. (2015). Testing for Predictability in Financial Returns Using Statistical Learning Procedures. *Journal of Time Series Analysis*, *36*(5), 672–686. https://doi.org/10.1111/jtsa.12120

Arslanian, H., & Fischer, F. (2019). *The Future of Finance: The Impact of FinTech, AI, and Crypto on Financial Services* (1st ed. 2019 ed.). Springer.

Bahrammirzaee, A. (2010). A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems. *Neural Computing and Applications*, *19*(8), 1165–1195. https://doi.org/10.1007/s00521-010-0362-z

Banerjee, S. P., & Woodard, D. (2012). Biometric Authentication and Identification Using Keystroke Dynamics: A Survey. *Journal of Pattern Recognition Research*, *7*(1), 116–139. https://doi.org/10.13176/11.427

Bank of America. (2021). *Bank of America Company Overview*. https://newsroom.bankofamerica.com/companyoverview

Bank of Italy. (2019). *Survey on the adoption of FinTech in the Italian financial system*. https://www.bancaditalia.it/media/notizia/survey-on-the-adoption-of-fintech-in-the-italian-financial-system/?com.dotmarketing.htmlpage.language=1

Bannerjee, P. (2011). *UNODC estimates that criminals may have laundered US$ 1.6 trillion in 2009*. United Nations : Office on Drugs and Crime. https://www.unodc.org/unodc/en/press/releases/2011/October/unodc-estimates-that-criminals-may-have-laundered-usdollar-1.6-trillion-in-2009.html

Bartram, S. M., Branke, J., & Motahari, M. (2020). Artificial Intelligence in Asset Management. *SSRN Electronic Journal*, 2–39. https://doi.org/10.2139/ssrn.3692805

Bertsimas, D., & Lo, A. W. (1998). Optimal control of execution costs. *Journal of Financial Markets*, *1*(1), 1–50. https://doi.org/10.1016/s1386-4181(97)00012-8

Bhat, S. (2021, March 15). *Expert Systems in Artificial Intelligence (AI)*. GreatLearning Blog: Free Resources What Matters to Shape Your Career! https://www.mygreatlearning.com/blog/expert-systems-in-artificial-intelligence/

Bloomberg. (2019). *Bloomberg Liquidity Assessment (LQA)*. https://data.bloomberglp.com/professional/sites/10/LQA-Fact-Sheet.pdf

Bocconi Students Fintech Society. (2020, April 15). *Ant Financial - History of how the “Ant” has become a giant*. Medium. https://bsfs.medium.com/ant-financial-f07eba73cb8d

Boobier, T. (2020). *AI and the Future of Banking*. Wiley.

Brooks, R. (2020, April 2). *The Seven Deadly Sins of AI Predictions*. MIT Technology Review. https://www.technologyreview.com/2017/10/06/241837/the-seven-deadly-sins-of-ai-predictions/

Browdie, B. (2015, February 26). *Can Alternative Data Determine a Borrower's Ability to Repay?* American Banker. https://www.americanbanker.com/news/can-alternative-data-determine-a-borrowers-ability-to-repay

Brummer, C., & Yadav, Y. (2017). The Fintech Trilemma. *SSRN Electronic Journal*, 17–46. https://doi.org/10.2139/ssrn.3054770

Brunel, J. L. P. (2015). *Goals-Based Wealth Management: An Integrated and Practical Approach to Changing the Structure of Wealth Advisory Practices (Wiley Finance)* (1st ed.). Wiley.

Buchanan, B. G. (2005). A (Very) Brief History of Artificial Intelligence. *AI Magazine, 26(4)*, 53–60. https://doi.org/10.1609/aimag.v26i4.1848

Buchanan, B. G. (2019, April). *Artificial intelligence in finance*. https://doi.org/10.5281/zenodo.2626454

Bughin, J., & Hazan, E. (2019). *Can artificial intelligence help society as much as it helps business?* The McKinsey Quarterly.

Business Wire. (2019a, September 19). *Alipay Ant Forest Named UN Champion of the Earth, the United Nation's Highest Environmental Honor*. https://www.businesswire.com/news/home/20190918006096/en/Alipay-Ant-Forest-Named-UN-Champion-of-the-Earth-the-United-Nation%E2%80%99s-Highest-Environmental-Honor

Business Wire. (2019b, November 27). *Alipay's Xiang Hu Bao Online Mutual Aid Platform Attracts 100 Million Participants in One Year*. https://www.businesswire.com/news/home/20191126005952/en/Alipay%E2%80%99s-Xiang-Hu-Bao-Online-Mutual-Aid-Platform-Attracts-100-Million-Participants-in-One-Year

Business Wire. (2020a). *Alibaba Group Announces March Quarter and Full Fiscal Year 2020 Results*. https://www.businesswire.com/news/home/20200522005178/en/Alibaba-Group-Announces-March-Quarter-and-Full-Fiscal-Year-2020-Results

Business Wire. (2020b, April 27). *MYbank Served Over 20 Million SMEs as of 2019, Further Spurring the Growth of China's Small and Micro Businesses*. https://www.businesswire.com/news/home/20200427005353/en/MYbank-Served-Over-20-Million-SMEs-as-of-2019-Further-Spurring-the-Growth-of-China%E2%80%99s-Small-and-Micro-Businesses

Capgemini. (2020a). *World FinTech Report 2020*. https://www.capgemini.com/it-it/news/world-fintech-report-2020/

Capgemini. (2020b). *World Payments Report*. http://www.worldpaymentsreport.com

CB Insights. (2020, July 6). *What The Largest Global Fintech Can Teach Us About What's Next In Financial Services*. CB Insights Research. https://www.cbinsights.com/research/ant-financial-alipay-fintech/

Chen, B., Zeng, W., & Lin, Y. (2014). Applications of artificial intelligence technologies in credit scoring: A survey of literature. *2014 10th International Conference on Natural Computation (ICNC)*, 658–664. https://doi.org/10.1109/icnc.2014.6975914

Chen, L. (2016). From Fintech to Finlife: the case of Fintech Development in China. *China Economic Journal*, *9*(3), 225–239. https://doi.org/10.1080/17538963.2016.1215057

Cheng, E. (2020, November 7). *With Ant's IPO on hold, China calls for fintech regulation*. CNBC. https://www.cnbc.com/2020/11/06/with-ants-ipo-on-hold-china-emphasizes-need-for-fintech-regulation.html

Chishti, S., Bartoletti, I., Leslie, A., & Millie, S. M. (2020). *The AI Book: The Artificial Intelligence Handbook for Investors, Entrepreneurs and FinTech Visionaries* (1st ed.). Wiley.

Cio, E. T. (2017, September 8). *HDFC Bank's EVA becomes India's largest banking Chatbot*. ETCIO.Com. https://cio.economictimes.indiatimes.com/news/strategy-and-management/hdfc-banks-eva-becomes-indias-largest-banking-chatbot/60421681

Clifford, C. (2018, March 14). *Elon Musk: 'Mark my words — A.I. is far more dangerous than nukes.'* CNBC. https://www.cnbc.com/2018/03/13/elon-musk-at-sxsw-a-i-is-more-dangerous-than-nuclear-weapons.html

Coppin, B. (2004). *Artificial Intelligence Illuminated (Jones and Bartlett Illuminated)* (Computer ed.). Jones & Bartlett Learning.

Corea, F. (2018). *Applied Artificial Intelligence: Where AI Can Be Used In Business (Understanding Complex Systems)* (1st ed. 2019 ed.). Springer.

Cortes, C., & Vapnik, V. (1995). *Support-vector Networks*. Springer.

Council of Europe. (2017). *CAHAI - Ad Hoc Committee on Artificial Intelligence*. https://rm.coe.int/leaflet-cahai-en-june-2020/16809ed7fd

Cox, J. (2015, October 30). *Misbehaving banks have now paid $204B in fines*. CNBC. https://www.cnbc.com/2015/10/30/misbehaving-banks-have-now-paid-204b-in-fines.html

Crunchbase. (2021). *List of top Ant Group Portfolio Companies*. https://www.crunchbase.com/hub/ant-group-portfolio-companies

DeepMind. (2015). *AlphaGo is the first computer program to defeat a professional human Go player, the first to defeat a Go world champion, and is arguably the strongest Go player in history.* https://deepmind.com/research/case-studies/alphago-the-story-so-far

Deloitte. (2021). *2021 Insurance M&A outlook*. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/financial-services/2021-insurance-ma-outlook.pdf

Department of International Cooperation Ministry of Science and Technology (MOST), P.R.China. (2017). *Next Generation Artificial Intelligence Development Plan*. http://fi.china-embassy.org/eng/kxjs/P020171025789108009001.pdf

Detrixhe, J. (2019, March 15). *Ant Financial's Alipay is expanding rapidly outside of China*. Quartz. https://qz.com/1570052/ant-financials-alipay-is-expanding-rapidly-outside-of-china/

Detrixhe, J. (2020, January 28). *Ant Financial's Yu'e Bao is no longer the world's biggest money market fund*. Quartz. https://qz.com/1791778/ant-financials-yue-bao-is-no-longer-the-worlds-biggest-money-market-fund/

Divine, J. (2020). *Artificial Intelligence Stocks: The 10 Best AI Companies*. Www.Money.Com. https://money.usnews.com/investing/stock-market-news/slideshows/artificial-intelligence-stocks-the-10-best-ai-companies?slide=9

Eiben, A. E., & Smith, J. E. (2015). *Introduction to Evolutionary Computing (Natural Computing Series)* (2nd ed. 2015 ed.). Springer.

Epstein, G. (2011, April 5). *Alibaba's Jack Ma Fights To Win Back Trust*. Forbes. https://www.forbes.com/forbes/2011/0411/features-jack-ma-alibaba-e-commerce-scandal-face-of-china.html?sh=5c1ea24c4af5

European Commission. (2013). *Press corner*. https://ec.europa.eu/commission/presscorner/detail/it/MEMO_13_719

EY Global. (2019). *EY global fintech adoption rates index (2019)*. https://www.ey.com/en_by/ey-global-fintech-adoption-index

FCA. (2016, May 9). *Financial Conduct Authority's regulatory sandbox opens to applications*. https://www.fca.org.uk/news/press-releases/financial-conduct-authority%E2%80%99s-regulatory-sandbox-opens-applications

Federal Reserve Bank of New York. (2020). *Quarterly report on household debt and credit (November, 2020)*. https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC_2020Q3.pdf

*FICO® Score*. (2020). FICO. https://www.fico.com/en/products/fico-score

Financial Stability Board. (2017a). *Artificial intelligence and machine learning in financial services*. https://www.fsb.org/wp-content/uploads/P011117.pdf

Financial Stability Board. (2017b). *Financial Stability Implications from FinTech: Supervisory and Regulatory Issues that Merit Authorities' Attention*. https://www.fsb.org/wp-content/uploads/R270617.pdf

Findexable. (2020). *The Global Fintech Index 2020*. https://findexable.com/wp-content/uploads/2019/12/Findexable_Global-Fintech-Rankings-2020exSFA.pdf

FIS. (2019, June). *FIS Readiness Report*. https://www.fisglobal.com/en/insights/what-we-think/2019/june/2019-readiness-report-invest-smarter-grow-faster

Fuscaldo, D. (2021, January 7). *Bank Of America's Virtual Assistant Now Has More Than 10 Million Users*. Forbes. https://www.forbes.com/sites/donnafuscaldo/2019/12/11/bank-of-americas-virtual-assistant-now-has-more-than-10-million-users/?sh=3c1a4652f69b

Giudici, P. (2018). Fintech Risk Management: A Research Challenge for Artificial Intelligence in Finance. *Frontiers in Artificial Intelligence, 1*, 1–6. https://doi.org/10.3389/frai.2018.00001

Global Financial Innovation Network. (2021). *Global Financial Innovation Network (GFIN)*. https://www.thegfin.com

Goode, A. (2018). Biometrics for banking: best practices and barriers to adoption. *Biometric Technology Today*, *2018*(10), 5–7. https://doi.org/10.1016/s0969-4765(18)30156-5

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning (Adaptive Computation and Machine Learning series)* (Illustrated ed.). The MIT Press.

Grover, R. (2019). *Deep Learning - Overview, Practical Examples, Popular Algorithms*. Analytics Step. https://www.analyticssteps.com/blogs/deep-learning-overview-practical-examples-popular-algorithms

Gu, S., Kelly, B. T., & Xiu, D. (2018). Empirical Asset Pricing via Machine Learning. *SSRN Electronic Journal*, 2223–2273. https://doi.org/10.2139/ssrn.3281018

Guo J. (2016, January 18). *Has Ant Financial Entered Its Golden Age?* TMTpost. https://www.tmtpost.com/1499061.html

Gupta, P., & Tham, M. T. (2018). *Fintech: The New DNA of Financial Services*. De|G Press.

Harari, Y. N. (2018). *Homo Deus: A Brief History of Tomorrow* (Illustrated ed.). Harper Perennial.

Hassani, H., Silva, E. S., Unger, S., TajMazinani, M., & Mac Feely, S. (2020). Artificial Intelligence (AI) or Intelligence Augmentation (IA): What Is the Future? *AI*, *1*(2), 143–155. https://doi.org/10.3390/ai1020008

Hawking, S. (2017, October 23). *Stephen Hawking: 'Are we taking Artificial Intelligence seriously*. The Independent. https://www.independent.co.uk/news/science/stephen-hawking-transcendence-looks-implications-artificial-intelligence-are-we-taking-ai-seriously-enough-9313474.html

Hendrik, L. R. (2018, June 5). *Why rule-based fraud management doesn't work*. Payvision. https://www.payvision.com/payment-insights/e-commerce/why-rule-based-fraud-managements-doesnt-work/#:%7E:text=The%20traditional%20approach%20to%20fraud%20management%20is%20based,detection%2C%20causing%20either%20false%20positives%20or%20false%20negatives.

Hintze, A. (2016, November 14). *From Reactive Robots to Sentient Machines: The 4 Types of AI*. Livescience.Com. https://www.livescience.com/56858-4-types-artificial-intelligence.html

Horan. (2020). *5 Keys to Using AI and Machine Learning in Fraud Detection*. FICO. https://www.fico.com/blogs/5-keys-using-ai-and-machine-learning-fraud-detection

Iansiti, M., & Lakhani, K. R. (2020). *Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World* (Illustrated ed.). Harvard Business Review Press.

IBM. (2011). *Deep Blue*. https://www.ibm.com/ibm/history/ibm100/us/en/icons/deepblue/

IBM. (2020). *IBM Watson Studio - Panoramica*. https://www.ibm.com/it-it/cloud/watson-studio

Institute of International Finance. (2015). *Innovation - Regtech*. https://www.iif.com/Innovation/Regtech

iResearch. (2020). *2020 China's Third-party Payment Industry Report*. https://www.iresearch.com.cn/Detail/report?id=3601&isfree=0

Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. *Financial Management*, *48*(4), 1009–1029. https://doi.org/10.1111/fima.12295

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning: with Applications in R (Springer Texts in Statistics)* (1st ed. 2013, Corr. 7th printing 2017 ed.). Springer.

Juniper Research. (2017). *Smart Store Technologies to Generate Over $78 billion in Annual Transaction Revenue by 2022*. https://www.juniperresearch.com/press/press-releases/smart-store-technologies-generate-over-78bn-2022

Juniper Research. (2019). *AI in Fintech: Roboadvisors, Lending, Insuretech & Regtech 2019–2023*. https://www.juniperresearch.com/researchstore/fintech-payments/ai-in-fintech-research-report

Kamath, U., Liu, J., & Whitaker, J. (2019). *Deep Learning for NLP and Speech Recognition* (1st ed. 2019 ed.). Springer.

KatanLabs. (2021). *More about Katana, the bond market trade discovery tool*. KatanaLabs. https://www.katanalabs.io/about

Kearney, C., & Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, *33*, 171–185. https://doi.org/10.1016/j.irfa.2014.02.006

Khalil, K. (2020, June 5). *UBS Investment Bank leads $17.5 million investment in JP Morgan-backed communications FinTech Cloud9*. The TRADE. https://www.thetradenews.com/ubs-leads-17-5-million-investment-in-jp-morgan-backed-communications-fintech-cloud9/

Kharpal, A. (2017, November 6). *Stephen Hawking says A.I. could be "worst event in the history of our civilization."* CNBC. https://www.cnbc.com/2017/11/06/stephen-hawking-ai-could-be-worst-event-in-civilization.html

Kharpal, A. (2020, October 26). *Ant Group to raise $34.5 billion, valuing it at over $313 billion, in biggest IPO of all time*. CNBC. https://www.cnbc.com/2020/10/26/ant-group-to-raise-tktk-billion-in-biggest-ipo-of-all-time.html

King, B. (2018). *Bank 4.0: Banking Everywhere, Never at a Bank* (1st ed.). Wiley.

Kirilenko, A. A., & Lo, A. W. (2013). Moore's Law vs. Murphy's Law: Algorithmic Trading and Its Discontents. *SSRN Electronic Journal*, 51–72. https://doi.org/10.2139/ssrn.2235963

KPMG. (2020). *KPMG Pulse of Fintech 2019*. https://home.kpmg/it/it/home/insights/2017/11/the-pulse-of-fintech.html

Kurzweil, R. (2012). *How to Create a Mind*. Van Haren Publishing.

LexisNexis Risk Solutions. (2019). *2019 True Cost of Fraud<sup>SM* Study: E-commerceRetail</i>. https://risk.lexisnexis.com/insights-resources/research/2019-true-cost-of-fraud-study-e-commerce-retail-edition

Liao, R. (2020, July 14). *Jack Ma's fintech giant tops 1.3 billion users globally*. Techcrunch. https://techcrunch.com/2020/07/14/ant-alibaba-1-3-billion-users/

López de Prado, M. (2016). Building Diversified Portfolios that Outperform Out of Sample. *The Journal of Portfolio Management, 42*(4), 59–69. https://doi.org/10.3905/jpm.2016.42.4.059

Lucas, L. (2017, April 26). *Chinese money market fund becomes world's biggest*. Financial Times. https://www.ft.com/content/28d4e100-2a6d-11e7-bc4b-5528796fe35c

Ma, J. (2016). *Honour International Symposium 2016*. YouTube. https://www.youtube.com/watch?v=n1s8I2xREZs

Maimon, O., & Rokach, L. (2010). *Data Mining and Knowledge Discovery Handbook (Springer series in solid-state sciences)* (2nd ed. 2010 ed.). Springer.

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., & Sanghvi, S. (2019, May 11). *Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages*. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

Market Data Forecast. (2020). *Global Fintech Market Research Report*. https://www.marketdataforecast.com/market-reports/fintech-market

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77. https://doi.org/10.2307/2975974

Marsans, M. (2021). *China's Fintech Revolution*. Center for Strategic and International Studies. https://www.csis.org/blogs/new-perspectives-asia/chinas-fintech-revolution

Mary-Ann Russon, B. (2019, September 10). *Why are people shopping online late at night?* BBC News. https://www.bbc.com/news/business-49633006

McCorduck, P. (2004). *Machines Who Think* (2nd ed.). Routledge.

Mcculloch, W. S., & Pitts, W. (1943). *A Logical Calculus of the Ideas Immanent in Nervous Activity*. Amsterdam University Press.

Mckinsey Global Institute. (2017). *Digital China: Powering the Economy to Global Competitiveness*. https://www.mckinsey.com/~/media/McKinsey/Industries/Technology%20Media%20and%20Telecommunications/High%20Tech/Our%20Insights/Digital%20China%20Powering%20the%20economy%20to%20global%20competitiveness/MGI_Digital-China_Report_Dec-2017.pdf

McKinsey Global Institute. (2019). *Notes from the AI Frontier: Modeling the Impact of AI on the World Economy*. https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20frontier%20Modeling%20the%20impact%20of%20AI%20on%20the%20world%20economy/MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018.ashx

McKinsey Global Institute. (2020a). *Global survey: The state of AI in 2020*. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020

McKinsey Global Institute. (2020b). *The state of AI in 2020*. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020

Mckinsey Global Institute. (2020, December). *McKinsey's Global Banking Annual Review*. https://www.mckinsey.com/industries/financial-services/our-insights/global-banking-annual-review

McMorrow, R. (2020, August 26). *The transformation of Ant Financial*. Financial Times. https://www.ft.com/content/c636a22e-dd3f-403e-a72d-c3ffb375459c

Mitkov, R. (2005). *The Oxford Handbook of Computational Linguistics (Oxford Handbooks)* (1st ed.). Oxford University Press.

Mohan, V. (2019). *"Banking is necessary; banks are not."* Business Times. https://www.businesstimes.com.sg/opinion/banking-is-necessary-banks-are-not

Moloi, T., & Marwala, T. (2020). *Artificial Intelligence in Economics and Finance Theories*. Springer International Publishing.

Morningstar, Inc. (2019, August 1). *ETF Market Share: The Competitive Landscape of the Top Three Firms*. https://www.morningstar.com/insights/2019/08/01/etf-market-share

Mullen, J. (2016, October 6). *U.K. pound plunges more than 6% in mysterious flash crash*. CNNMoney. https://money.cnn.com/2016/10/06/investing/pound-flash-crash-currency-brexit/index.html

Murphy, K. P. (2012). *Machine Learning: A Probabilistic Perspective*. The MIT Press.

National Community Reinvestment Coalition. (2020, December 14). *Bank Branch Closure Update (2017 – 2020)*. NCRC. https://ncrc.org/research-brief-bank-branch-closure-update-2017-2020/

Nilson Report. (2019). *Card Fraud Losses Reach $28.65 Billion*. https://nilsonreport.com/mention/1313/1link/

Noonan, L. (2017, December 12). *ING launches artificial intelligence bond trading tool Katana*. Financial Times. https://www.ft.com/content/1c63c498-de79-11e7-a8a4-0a1e63a52f9c

Oliver Wyman. (2017). *Fintech in China: Hitting the Moving Target*. https://www.oliverwyman.com/our-expertise/insights/2017/aug/fintech-in-china-hitting-the-moving-target.html

Oliver Wyman. (2019). *Artificial Intelligence Applications in Financial Services*. https://www.oliverwyman.com/content/dam/oliver-wyman/v2/publications/2019/dec/ai-app-in-fs.pdf

Phillips, P. J., Yates, A. N., Hu, Y., Hahn, C. A., Noyes, E., Jackson, K., Cavazos, J. G., Jeckeln, G., Ranjan, R., Sankaranarayanan, S., Chen, J.-C., Castillo, C. D., Chellappa, R., White, D., & O'Toole, A. J. (2018). Face recognition accuracy of forensic examiners, superrecognizers, and face recognition algorithms. *Proceedings of the National Academy of Sciences*, *115*(24), 6171–6176. https://doi.org/10.1073/pnas.1721355115

Ping An Digital Economic Research Center. (2020). *China's SMEs Amid the Pandemic*. http://www.pingan.cn/app_upload/file/official/SMEReport2020.pdf

PwC. (2020). *FinTech calls for fuel*. https://www.pwc.com/it/it/industries/fintech/docs/PwC-FinTech-2020.pdf

Qi, A. (2019, December). *Ant Financial Applies AI in Financial Sector*. Alibaba Cloud. https://www.alibabacloud.com/blog/ant-financial-applies-ai-in-financial-sector_595687

Ralph, O. (2018, October 28). *Chinese banks start scanning borrowers' facial movements*. Financial Times. https://www.ft.com/content/4c3ac2d4-d865-11e8-ab8e-6be0dcf18713

Rawlinson, B. K. (2015, January 29). *Microsoft's Bill Gates insists AI is a threat*. BBC News. https://www.bbc.com/news/31047780

Reinsel, D., Gantz, J., & Rydning, J. (2017). *Data Age 2025: The Evolution of Data to Life-Critical*. https://www.import.io/wp-content/uploads/2017/04/Seagate-WP-DataAge2025-March-2017.pdf

Reuters Editorial. (2017, September 12). *Leader of China's $9 billion Ezubao online scam gets life; 26 jailed*. Reuters. https://www.reuters.com/article/us-china-fraud-idUSKCN1BN0J6

Reuters Editorial. (2018, February 26). *Cash still king: Swedish central bank urges lawmakers to protect cash payments*. Reuters. https://www.reuters.com/article/sweden-cenbank-cash-idUSL8N1QG79Y

Reynolds, P. (2020). *Chinese Fintech Is Pushing Trillions From Savings Into Capital Markets*. Oliver Wyman. https://www.oliverwyman.com/our-expertise/insights/2020/aug/chinese-fintech-is-pushing-trillions-from-savings-into-capital-markets.html

Runde, D. (2015, August 12). *M-Pesa And The Rise Of The Global Mobile Money Market*. Forbes. https://www.forbes.com/sites/danielrunde/2015/08/12/m-pesa-and-the-rise-of-the-global-mobile-money-market/

Russell, S., & Norvig, P. (2011). *Artificial Intelligence: A Modern Approach* (3rd ed.). Pearson.

Samuel, A. L. (1959). Some Studies in Machine Learning Using the Game of Checkers. *IBM Journal of Research and Development*, *3*(3), 210–229. https://doi.org/10.1147/rd.33.0210

Schreiber, D. (2019, July 29). *Lemonade Sets a New World Record*. Lemonade Blog. https://www.lemonade.com/blog/lemonade-sets-new-world-record/

Schueffel, P. (2016). Taming the Beast: A Scientific Definition of Fintech. *SSRN Electronic Journal*, 31–54. https://doi.org/10.2139/ssrn.3097312

Schwab, K. (2017). *The Fourth Industrial Revolution* (Illustrated ed.). Currency.

Searle, J. R. (1980). Minds, brains, and programs. *Behavioral and Brain Sciences*, *3*(3), 417–457. https://doi.org/10.1017/s0140525x00005756

Sharma, G. (2019, December 31). *"Why China is the FinTech Capital of the World?"—50 Point Summary*. Medium. https://medium.com/@gaurav.sharma/why-china-is-the-fintech-capital-of-the-world-50-points-summary-6f3a66159196

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., Chen, Y., Lillicrap, T., Hui, F., Sifre, L., van den

Driessche, G., Graepel, T., & Hassabis, D. (2017). Mastering the game of Go without human knowledge. *Nature*, *550*(7676), 354–359. https://doi.org/10.1038/nature24270

Simon, J. P. (2019). Artificial intelligence: scope, players, markets and geography. *Digital Policy, Regulation and Governance*, *21*(3), 208–237. https://doi.org/10.1108/dprg-08-2018-0039

Singh, R. (2019). *Artificial Intelligence In Banking & Finance: How AI is Impacting the Dynamics of Financial Services*. Adhyyan Books.

Sironi, P. (2016). *FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification (The Wiley Finance Series)* (1st ed.). Wiley.

Skolpadungket, P., Dahal, K., & Harnpornchai, N. (2016). Handling Model Risk in Portfolio Selection Using Multi-Objective Genetic Algorithm. *Artificial Intelligence in Financial Markets*, 285–310. https://doi.org/10.1057/978-1-137-48880-0_10

Stanford Education. (2020). Ethics of Artificial Intelligence and Robotics. *Stanford Encyclopedia of Philosophy*, 2–38. https://plato.stanford.edu/entries/ethics-ai/#Refle

Statista. (2020a). *Number of internet users in China from December 2008 to December 2020*. https://www.statista.com/statistics/265140/number-of-internet-users-in-china/

Statista. (2020b, December 15). *International tourism spending of Chinese tourists 2008–2019*. https://www.statista.com/statistics/249702/international-tourism-expenditure-of-chinese-tourists/

Statista. (2021). *Number of Fintech startups worldwide from 2018 to February 2021, by region*. https://www.statista.com/statistics/893954/number-fintech-startups-by-region/

Steger, C., Ulrich, M., & Wiedemann, C. (2018). *Machine Vision Algorithms and Applications* (2nd ed.). Wiley-VCH.

Stern, C., Makinen, M., & Qian, Z. (2017). FinTechs in China – with a special focus on peer to peer lending. *Journal of Chinese Economic and Foreign Trade Studies*, *10*(3), 215–228. https://doi.org/10.1108/jcefts-06-2017-0015

Strategic Council for AI Technology. (2017). *Artificial Intelligence Technology Strategy*. https://ai-japan.s3-ap-northeast-1.amazonaws.com/7116/0377/5269/Artificial_Intelligence_Technology_StrategyMarch2017.pdf

Teh, P. S., Zhang, N., Teoh, A. B. J., & Chen, K. (2016). A survey on touch dynamics authentication in mobile devices. *Computers & Security*, *59*, 210–235. https://doi.org/10.1016/j.cose.2016.03.003

The Financial Brand. (2018). *Artificial Intelligence and The Banking Industry's $1 Trillion Opportunity*. https://thefinancialbrand.com/72653/artificial-intelligence-trends-banking-industry/

Turing, A. M. (1950). I. - Computing Machinery and Intelligence. *Mind*, *LIX*(236), 433–460. https://doi.org/10.1093/mind/lix.236.433

Uhl, M. W., & Rohner, P. (2018). Robo-Advisors versus Traditional Investment Advisors: An Unequal Game. *The Journal of Wealth Management*, *21*(1), 44–50. https://doi.org/10.3905/jwm.2018.21.1.044

Visa Inc. (2020). *Visa Harnesses Real-Time Deep Learning to Enhance Transaction Processing*. https://investor.visa.com/news/news-details/2020/Visa-Harnesses-Real-Time-Deep-Learning-to-Enhance-Transaction-Processing/default.aspx

Wakefield, K. (2020). *Predictive analytics and machine learning*. SAS UK. https://www.sas.com/en_gb/insights/articles/analytics/a-guide-to-predictive-analytics-and-machine-learning.html

Walch, K. (2020, February 8). *Why The Race For AI Dominance Is More Global Than You Think*. Forbes. https://www.forbes.com/sites/cognitiveworld/2020/02/09/why-the-race-for-ai-dominance-is-more-global-than-you-think/

World Economic Forum. (2020). *Future of Jobs Survey 2020*. http://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf

Xie, S. Y., & Yang, J. (2020, August 25). *Inside Ant Group's Giant Valuation: One Billion Alipay Users and Big Profit Margins*. WSJ. https://www.wsj.com/articles/jack-mas-ant-group-files-ipo-listing-documents-11598349802

Xing, F. Z., Cambria, E., & Welsch, R. E. (2017). Natural language based financial forecasting: a survey. *Artificial Intelligence Review*, *50*(1), 49–73. https://doi.org/10.1007/s10462-017-9588-9

Xue, Y. (2020). *China tops world in AI patent filings, surpassing the US for the first time*. South China Morning Post. https://www.scmp.com/tech/innovation/article/3111510/china-tops-world-ai-patent-filings-surpassing-us-first-time

Yang, Y. C. L. (2020, November 3). *Analysis: Fin or tech? China's Ant, biggest-ever IPO, says it's a tech firm not a bank*. U.S. https://www.reuters.com/article/us-ant-group-ipo-analysis-idUSKBN27I2TY

Yao, J., Li, Y., & Tan, C. L. (2000). Option price forecasting using neural networks. *Omega*, *28*(4), 455–466. https://doi.org/10.1016/s0305-0483(99)00066-3

Zendrive. (2021). *How It Works*. https://zendrive.com/how-it-works/

Zhang, X., & Choi, M. C. (2019). Study on the Development Strategy of Ant Financial. *International Journal of Financial Research*, *10*(5), 262. https://doi.org/10.5430/ijfr.v10n5p262

Zhang-Zhang, Y., Rohlfer, S., & Rajasekera, J. (2020). An Eco-Systematic View of Cross-Sector Fintech: The Case of Alibaba and Tencent. *Sustainability*, *12*(21), 8907. https://doi.org/10.3390/su12218907

Zhu, F., Zhang, Y., Palepu, K. G., Woo, A. K., & Dai, N. H. (2019). Ant Financial (A). *Harvard Business School Case*, 1–30. https://www.hbs.edu/faculty/Pages/item.aspx?num=52493