
Artificial Intelligence in the Financial Sector



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Open Innovation and Ethical Commitment

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Ai

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Executive Summary

Our intelligence is what makes us human, and artificial intelligence is an extension of that quality.

Yann LeCun, Chief AI Scientist at Facebook

If Alan Turing could see us now, he would certainly be in for a surprise. Renowned as the forefather of artificial intelligence, in the 1950s his talent and early foresight laid the vital foundations of the discipline. Nonetheless, Turing never could have foreseen the extraordinary strides that would be made after his time in areas such as automatic driving, image recognition, robotics and algorithmic trading. Thanks to these advancements, artificial intelligence has revolutionized countless sectors of the economy—transportation, healthcare, marketing, agriculture, logistics, distribution, education, and leisure, among others—and is not showing any signs of slowing down in the coming years.

The finance sector (and banking in particular) is one of the industries with the greatest possibility for both potential and real applications of AI. Its capacity to generate information, its heavy volume of transactions and the quantitative character of industrial activity mean it is fertile land for cultivating all the possible benefits of AI methods. This is especially true of machine learning, the paramount technology of the AI world. This report will explain how AI facilitates the development of a strategic framework for value creation, with six opportunities for improvement. The framework is based on both internal transformation (operational competitiveness, organizational advantage and innovation) and business methods (new

models, new products and services, and customer experience).

In this framework, one of the most promising trends on the business frontline is collaborative innovation, which will likely set the pace for the finance industry. Intense competition requires banks to reinvent themselves and remain open to flexible formulas for innovation—not only by utilizing their own resources, but also by making use of external sources (academic institutions, experts, customers, or even competitors) to take full advantage of the talent on the market. In this area, there are several different lines of action. One of these is crowdsourcing, which is based on the outsourcing of micro-tasks. When carried out on a mass scale, this generates value for the financial institution and accelerates the process of innovation. In addition, financial institutions are increasingly calling upon corporate operations to bring in the expertise of specialized organizations through different kinds of acquisitions, mergers or alliances with fintech and bigtech companies. By the same token, a complementary strategy is to participate in entrepreneurial projects or enterprise incubation.

The growing importance of artificial intelligence in the financial sector is attributable to the fact it has multiple applications, while the tools it offers can

be used to optimize every part of the value chain—from client interactions to market analysis, processing functions, and risk control and monitoring.

In this landscape, it is relevant to ask how financial institutions can capitalize on the value-generating opportunities AI has to offer, and to what extent are they opting to integrate this technology into their processes. While the applications of AI are focused on a select few banking operations (customer relations, fraud detection and risk management, above all), its technological maturity and high degree of market competitiveness are catalyzing its adoption across every area of business.

This report compiles a series of use cases with specific examples of what banks are doing across six areas (risk management, regulatory compliance, operations, commercial banking, asset management, and corporate banking) and their corresponding applications in key business processes such as credit rating and granting, the prevention of money laundering, customer experience and portfolio management.

In recent months, the outbreak of the coronavirus pandemic has caused unprecedented economic upheaval, and its impact on the development of AI is very difficult to determine. At the same time, however, the crisis has opened the door to new developments and opportunities for the applied use of AI. Focusing on the financial industry, we can see that its use has a renewed relevance in key sector areas such as risk management. Faced with the prospect of a drop-off in solvent demand for credit and a considerable increase in defaults, machine learning techniques can be of great help for gaging customer risk and even helping them to cope with the situation through debt relief. In addition, it has an increased

utility for addressing the changing liquidity and regulatory capital needs of financial institutions caused by Covid-19. AI is also a valuable tool for dealing with the reported rise in incidents of fraud that has been documented throughout the pandemic.

If Alan Turing did not envision many of the advantages and opportunities that AI would offer, nor did he suspect that it would pose some risks. Today, we know that the misuse of AI can lead to discrimination, infringements on privacy (facial recognition, for example, is very controversial), produce outcomes we cannot explain, create insecurity... the list goes on. Alongside certain dystopian fables that warn of replacing humans with machines, these risks have engendered a public opinion that views AI as something negative, or at the very least suspicious.

The best way to confront these risks is to be aware of them, taking them into account and acting responsibly to ensure they do not cause harm to individuals and society in general. This report proposes an ethical framework that aims to address these drawbacks. The framework combines four areas of strategic action—AI algorithms and systems, governance, organization, and society—each entailing different management axes or levers.

One of the key concepts of AI ethics is algorithmic bias. Without the necessary supervision and control, automated decisions can discriminate against certain population groups. A typical example of this would be an algorithm that offers biased recommendations because the model was trained with historical data lacking representation of a certain segment, whether differentiated based on ethnic, social or other features, excluding this group from access to credit, for example. Artificial intelligence biases can affect any industry or sector of business. This is

what happened in 2014 with the algorithm governing Amazon's recruitment process for technical programmers. When processing the stored information on hiring (which overwhelmingly favored men), the algorithm penalized those resumes that made any mention of the word "women." It is necessary to guarantee that automated decisions do not generate unfair discrimination, in other words, discrimination having a negative impact on people based on race, ethnic origin, religion, gender, sexual orientation, functional diversity or any other personal feature.

Transparency is another of the pillars that form the ethical foundation of artificial intelligence. In the finance sector, there is a growing sensitivity among clients and users about understanding the decisions of AI systems, insofar as they condition significant aspects of their relationship with credit or investment. In this context, the idea of "explainability" is particularly important, which is the ability to explain the results of an algorithm in a way that is easily understandable. Some models are so complex that they act like black boxes, making it very difficult to deduce why certain information (usually a huge volume of data) produces certain results. Organizations with an ethical commitment need to ensure they avoid this kind of ambiguity in their processes, instead working with systems that can be well interpreted and understood. In this sense, simply arguing that "those are the results of the algorithm" is unacceptable. If results have unwanted consequences, doing research into the life cycle of the algorithm (the kind of data it was trained with, how variable selection worked, the teams that were involved, etc.) should enable organizations to clearly identify the responsible factors.

In summary, the report that follows is an invitation to financial institutions to consider the benefits of using artificial intelligence. Today, AI is undoubtedly the leading-edge

technology that shows the most promise for use in the industry, even amid the exceptional current circumstances brought about by the Covid-19 pandemic. Its advantages are evident from both the perspective of enhancing operational efficiency, as well as the benefits it offers for improving products, services and the customer experience. Furthermore, when managed with ethical and responsible criteria (so-called "trustworthy AI"), artificial intelligence is an opportunity to bring additional value to companies and contribute to the well-being of citizens and society as a whole.



1. Fundamentals

Keys for understanding
what is happening now and
what is to come

Definition.

Sand through our fingers

HAL 9000, the computer from Stanley Kubrick's celebrated film, *2001: A Space Odyssey*, is probably the first depiction that many people associated with artificial intelligence (AI). HAL, the brainchild of the film's imaginative co-writer Arthur C. Clarke, was what we would now regard as a prototypical image of artificial intelligence: he could speak and understand, recognize faces, reason, read lips and give anyone a good game of chess. He could even feel emotions—"I'm scared," he says, when the ship's commander begins to disconnect his memory units—which is still far from the capabilities that today's artificial intelligence devices offer us. Nonetheless, as the enduring image of the 1968 film, HAL provides us with an early reference to the concept of AI.

If HAL works as a visual reference, it becomes much more complex when we try to capture the idea of AI in a universally accepted definition. Some say AI can be defined as system based on computer-powered calculations, where it is widely accepted that its behavior requires intelligence. Others would define it as a system capable of solving problems or making rational decisions in order to achieve objectives in any real-world scenario. However, it is clear that these definitions are either too generic, imprecise or oversimplified. So why is it so difficult to describe? Why does the definition elude us like sand slipping through our fingers?

Firstly, this is because we also lack a clear definition of what intelligence is, which often depends on context or on individual interpretation.

Moreover, notions of what is and what is not AI in the public imagination is changeable over time. This is what is known as the AI effect: if artificial intelligence makes a big breakthrough or solves a new challenge, there is a tendency to think about it as consequence of technical progress rather than a result of real intelligence. For example, when the supercomputer Deep Blue succeeded in defeating world chess champion Gary Kasparov in 1997, many people denied that it was truly intelligent because it had succeeded by using the force of its computational power, allowing it to calculate 200 million movements per second. Just thirty years earlier, the idea of a machine that could play chess so well as this was aligned with the concept of artificial intelligence. It is likely that the AI effect is a way for people to believe that intelligence is a quality unique to human beings.

Additionally, the meaning of AI is clouded by the culture of exaggeration that sometimes comes with it, which can also give rise to overstatements about advancements that are just simple evolutions from other disciplines.

Finally, confusion and complexity around the concept of AI also stem from the fact that, as a discipline, it has very varied objectives that are not necessarily related to each other. Such a myriad of objectives means that those working within the field may not only disagree about the best solutions to the problems they are addressing—which is common in many scientific activities—but also when it comes to determining what the problem actually is, a much rarer dilemma.

We can, however, lean on institutional definitions so the sand does not slip through our fingers so quickly. The most succinct one comes from the Financial Stability Board (FSB), an international body created by the G-20. In this definition, AI is described as “the theory and development of computer systems able to perform tasks that traditionally have required human intelligence.” A more exhaustive one is provided by experts from the European Commission: “Systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal.”

The academic definition is another way to approach the concept. This describes AI as a field of research that integrates multiple scientific disciplines, aiming to advance computers so that they have functionalities traditionally attributed to human beings exclusively, such as intelligence, awareness, emotion, or capacity to learn and develop long-term strategies. These disciplines are based on heavy application of mathematics, advancement towards models that use data to draw their own conclusions, and the creation of systems that are capable of interpreting and interacting with their environment.

From the perspective of business, perhaps more interesting is the definition of artificial intelligence based on its capabilities. In operational terms, AI can be explained as a set of techniques that equip computer systems with three basic capabilities:

Gathering and processing data with a predefined objective, in order to extract the maximum possible value from it.

Learning from data to reason and make decisions.

Interacting and adapting to an environment.

Within this conceptual framework, any initiative aimed at implementing an AI project must take into account the cross-sectional perspective of ethical and regulatory compliance. On this point, which will be expanded at length throughout this report, it is necessary to establish the importance of explaining and justifying results, controlling algorithms to curb the dangers of discriminatory bias, ensuring data security, and respecting the principles of privacy and confidentiality.

History.

Is winter coming?

To younger generations, AI might seem like the latest among new technologies. But in reality, it is a discipline with more than 70 years of history already behind it. In fact, it was the middle of the 20th century when research from this new branch of computer science first started getting published. Alan Turing, the British scientist who played a decisive role in deciphering German messages during World War II, laid the initial foundations in 1950 with his seminal essay *Computing Machinery and Intelligence*, predicting that in fifty years time “one will be able to speak of machines thinking.” Five years later, American mathematician John McCarthy coined the term “artificial intelligence” to refer to the discipline in its nascent form.

Since then, AI has come a long way, but its evolution has been far from linear. In fact, this seventy-year history is marked by an irregular timeline in which phases of enthusiasm and great progress have been followed by others of indifference. These periods of skepticism and lackluster investment have been called the winters of artificial intelligence (see Figure 1).

We can see in detail how the seasons have changed throughout the development of AI.

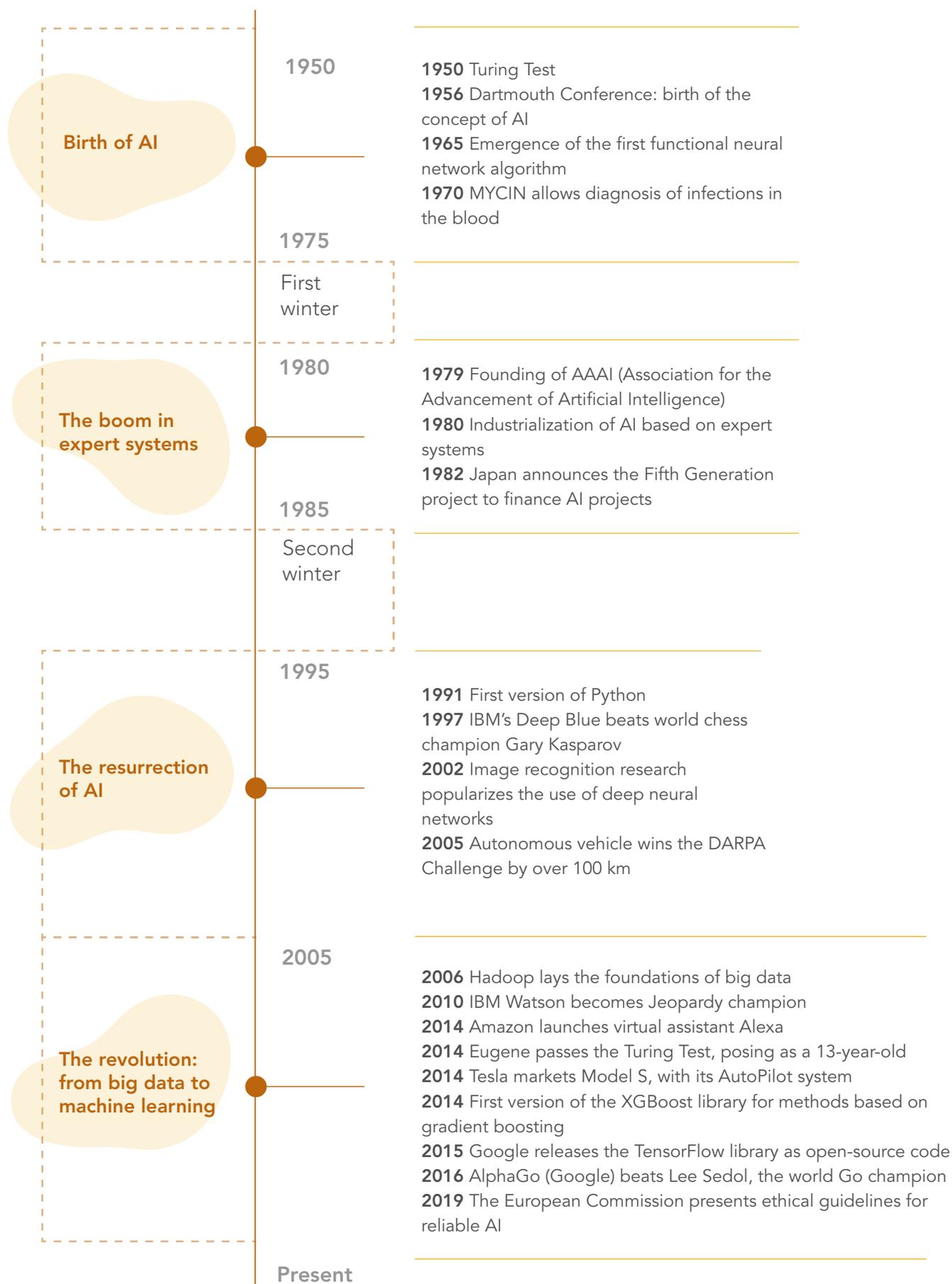
1950—1975. Beginnings: First sparks and moments of glory

Alan Turing’s essay published by *Mind* magazine in 1950 (*Computing Machinery and Intelligence*) raised the big question: can machines think? Understanding the difficulty

of defining what characterizes a machine and what is considered “thinking,” Turing avoids answering this question directly. Instead, he replaces the original question with an imitation game, which would later come to be known as the Turing test. This method measures the human intelligence level of a mechanical device that has now been used for many years. The game involves three participants: one person who asks questions and two people who answer. After a five-minute conversation, the interrogator must decide which of their two conversation partners is a person, and which is a machine. The machine passes the test if it manages to deceive the interrogator, proving that it thinks—or at least behaves—like a human under those conditions.

Many experts consider the Turing test to be first spark of the new discipline, although its theoretical foundations were not laid until several years later in 1956 at Dartmouth University in New Hampshire. There, some of the best experts in neural networks, automation and intelligence met at a summer seminar organized by professor John McCarthy. The discussions held began from the hypothesis that any aspect of learning or intelligence can be precisely defined, meaning that a machine could simulate it. Their aim was to determine whether machines could solve problems that had historically been limited to humans, and learn to improve their performance.

Figure 1. The timeline of AI



Source: everis, using public information

Despite the limited computing capabilities of the time, numerous advances were made during the 1960s and 1970s. Among them were the first functional chatbot and networks with “backpropagation,” as well as a bubble of expectations that was arising around the possibility of machine translation. Wide press coverage and the generosity of the U.S. Defense Advanced Research Projects Agency (DARPA), which granted \$2.2 million in funding for such projects in 1963, were also responsible for creating an atmosphere of great excitement, ushering in a golden era for the scientific community working on AI. It was what Professor McCarthy referred to as the “Look ma, no hands!” era.

1975—1980. The first winter

Disappointments in areas such as machine translation—which had built high expectations as a potentially useful tool in the Cold War—as well as difficulties using basic artificial neural networks known as “perceptrons” caused the AI bubble to deflate. In turn, public funding was reduced or disappeared entirely, meaning projects began to stall. The final straw came with the 1973 publication of the Lighthill report in the UK, which concluded that “in no part of the field have the discoveries made so far produced the major impact that was [then] promised.”

1980—1985. The boom in expert systems

The immediate future of AI was marked by a brief but intense period. From 1980 onwards, efforts were focused on creating commercial products through area-specific research into expert systems. It was in this way that the discipline arrived at a historical turning point. In the early phases, projects were geared towards what was known as “general” or

“strong” AI, which seeks to replicate human intelligence and can therefore be used in multiple activities. Faced with the difficulty of this objective, in the 1980s focus shifted towards “narrow” or “weak” AI, which looked to implement applications and systems in specialized areas such as financial planning, medical diagnosis, artificial vision, geological exploration and microelectronic circuit design.

This change in direction initiated a second wave of interest in AI among global authorities, stimulating the sector once again with the introduction of subsidies. In 1981, Japan announced the Fifth Generation project, a ten-year plan for building the next set of intelligent computers. In response, the United States created the Microelectronics and Computer Technology Corporation (MCC), a research consortium whose objective was to reinforce the competitiveness of the national economy. Although tarnished by the Lighthill report, the reputation of the discipline in Britain was restored in 1982 with the publication of the Alvey report, which proposed a five-year program to mobilize the technical capacities of the British economy. The peak of this investment scheme saw hundreds of new AI companies appear, as well as the emergence of adjacent industries.

1985—1995. A second winter

Just like the first winter, the second phase of inertia in research and investment was precipitated by the disappointing results of programs launched in different countries around the world. As many companies went bankrupt, the expert systems that had been developed began to receive criticism from specialists. The most notable was that of the mathematician who gave the discipline its name, John McCarthy. When warning against possible instances of malpractice, he gave the example of a medical assistance system that

would allow the killing of bacteria, but not save the patient's life.

1995—2005. The resurrection

Towards the end of the century, thanks to the application of specific engineering methods and a significant increase in computing power, we saw major advances in the development of sophisticated research tools.

For example, in 1997, Deep Blue—the chess computer developed by IBM—became the first machine to beat the Russian player Garry Kasparov, who was the World Chess Champion at the time. This had a great impact on the opinion of the public worldwide. That same year, two 20-year-olds from Stanford University in California created Google, which would revolutionize the world of AI in the years to follow. Another milestone was the Grand Challenge, a self-driving car race organized by DARPA in 2005, in which five vehicles successfully completed the 132-mile course.

In addition to these advances, it was also a successful time for the tools that have proven to be indispensable for the development of AI. One of these tools was the programming language Python, named after the British comedy group Monty Python. The first version of NumPy, an open-source numerical calculation library, was also released. These tools lay the foundation for the algorithms that AI uses today.

2005—Present. The revolution: from big data to machine learning

In 2004, Google published an article that popularized program modeling and inspired the creation of Hadoop in 2006. Hadoop is an open-source system that allows for the

distribution of data over multiple computers in order to solve problems that require the analysis of massive amounts of data. It makes it possible to manage large quantities of information in an efficient and cost-effective way. This is how big data was born.

Access to massive amounts of data, reduction in system costs, and improved computer capacity are three key factors that mark the turning point in the explosive development of the field over the last fifteen years. When combined, these three factors facilitated the industrialization of advanced machine-learning techniques, as well as the use of increasingly complex neural networks.

This led us to reach certain technological milestones throughout the century, such as machines based on weak AI. Among those include: IBM Watson, a supercomputer who reads and understands natural language to an extent that allowed him to win a TV game show in 2011; a supercomputer who passed the Turing test simulating a 13-year-old boy in 2014; the rise of virtual reality; and the launch of Amazon's virtual assistant, Alexa, in 2014.

Additionally, thanks to the growth of open-source software, libraries such as TensorFlow and XGBoost allow the capabilities of machine-learning algorithms to be used to the fullest. This is how data science communities, like Kaggle, gained popularity. These communities offer a place to share data in order to train automatic learning machines, and to compete against other data scientists to find the best algorithms to solve use cases, often financed by companies.

In this rich breeding ground, market solutions with extraordinary potential have appeared for the feasible development of various AI systems, such as self-driving cars, facial recognition, or virtual assistants.

In recent years, the implementation of case studies in the industry has led to a keen interest in the ethical, regulatory, and social responsibility aspects associated with the use of AI. This will be further analyzed in Section 2 of this report.

as humanity. It's more profound than fire or electricity." Is this fact or an exaggeration?

Maybe a bit of both.

The future: Will the cold return?

AI is more popular than ever before, and not just as a tool for specialists. It has come into our lives and is here to stay, especially because it is used in many of our day-to-day applications. In this global pandemic we are facing as a society—and as an economy—the use of AI in the public and private sectors is bound to make a significant contribution on the road to the “new normal.” AI can be used in the fight against the virus, whether it be by accelerating research for treatment and vaccines, or developing machines to detect the spread of the pandemic. AI can also be helpful in the recovery process, by helping companies act more efficiently during the crisis. However, under the current circumstances, and in the midst of unprecedented economic turmoil, it is quite difficult to know if a third winter for AI is coming. What is quite clear, though, are the high expectations AI generates today. The statement that Sundar Pichai—CEO of Alphabet Inc. and its subsidiary, Google—made at the World Economic Forum in Davos 2020 is more relevant than ever: “AI is one of the most profound things we’re working on



The history of AI in banking: delayed, but intense

AI did not arrive to the financial sector until the 1980s. In the 30 years leading up to this, the focus of the field was on the development of AI's basic functions, such as neural networks or its use of algorithms, as well as on solving algebraic or linguistic problems.

However, the boom of expert systems—which refocused AI towards specific areas known as weak AI—caused researchers to begin to look into the financial industry. In 1982, for example, Apex created PlanPower, an AI program for tax and financial advice offered to clients with incomes of over \$75,000.

That same year, famous mathematician James Simons developed Renaissance: a hedge fund that pioneered quantitative investing. Renaissance uses a combination of mathematical and computer-based systems to execute stock market trades.

In 1987, Chase Lincoln First Bank (now part of JP Morgan Chase), launched the Personal Financial Planning System. Shortly after, in 1989, FICO Score, a credit scoring formula based on a similar algorithm used by banks today, was released.

In the 1990s, the use of AI to detect fraud piqued great interest. In 1993, the United States Department of the Treasury sponsored the implementation of the FAIS system. FAIS has the ability to predict and identify potential money laundering incidents by processing up to 200,000 transactions a week.

The use of AI in the financial market has also had its upsets. The tampering with an automated program caused an extraordinarily sharp, albeit momentary, drop in the New York Stock Exchange, known as the flash crash

of 2010.

In the 21st century, the use of AI has skyrocketed. For more than a decade now, banks have been using machine-learning techniques to detect credit card fraud. In 2014, the British fund manager, Man Group, began using AI to invest its clients' money. In 2016, Bank of America launched its chatbot Erica, which was considered a milestone in customer interaction. In 2018, various institutions announced the development of recommendation systems.

Sub-fields and techniques

The dream of strong AI, and the reality of machine learning

AI is a broad discipline that integrates varied sub-fields and techniques. Among the most important are: machine learning, deep learning, robotics, natural language processing (NLP), knowledge representation, and computer vision. However, these are not isolated branches—they often overlap and interact with each other.

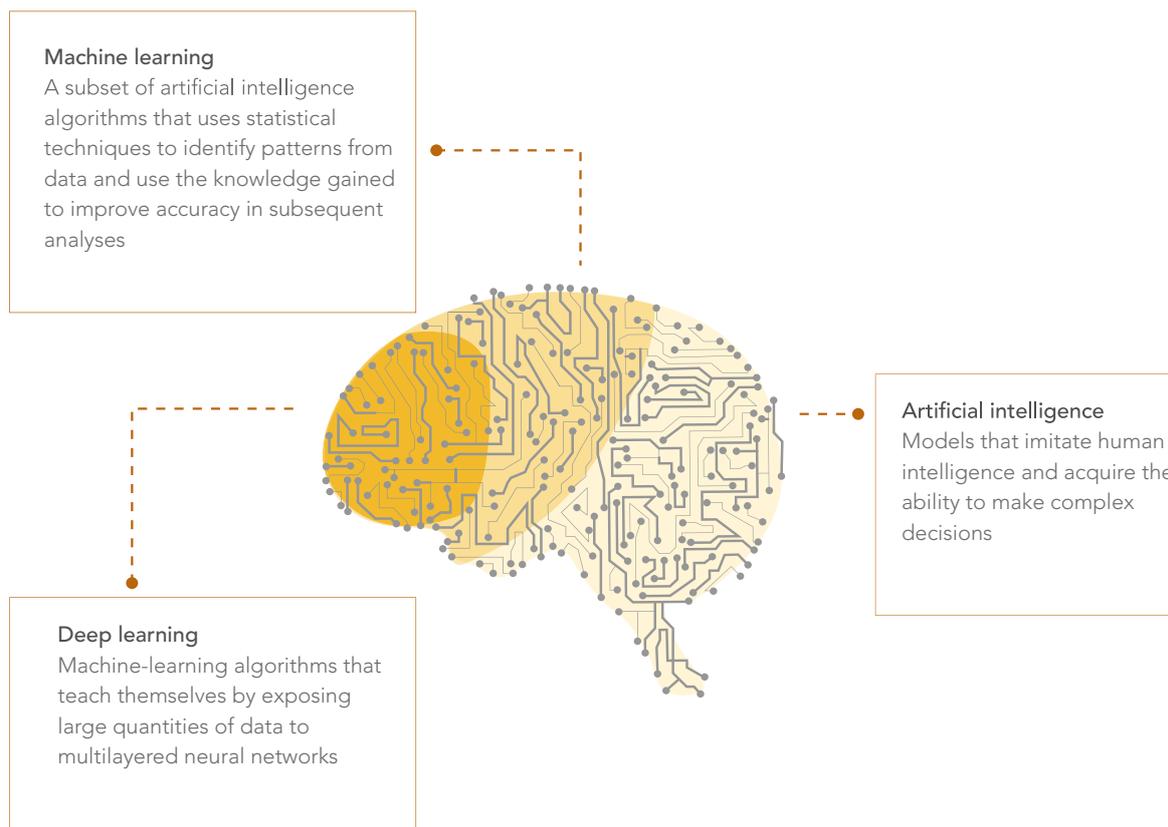
First, though, there is a distinction that showcases the complex geography of AI. This distinction is established between what is known as “general” or “strong” AI, and “narrow” or “weak” AI. General or strong AI (AGI) successfully reproduces the intelligence of a human being, and is therefore able to solve problems presented to it in various fields of activity. Weak AI, on the other hand, focuses on one particular field, such as chess, math, facial recognition, spacial vision, or any other specific activity.

Strong AI is more of a dream than a reality. Machines with the ability to learn, reason, communicate, and make decisions exactly like a human being do not exist. In fact, the closest machine to strong AI that exists is found in the movies, with robots like the BB-8 droid found in *Star Wars*. Weak AI, on the other hand, has been experiencing a major boost in its development in recent years. Its applications in certain fields far exceed the skills of human beings, offering extraordinary performance when solving specific problems.

In the field of weak AI, machine learning is the dominating technology. It is a process through which algorithms—the sequence

of instructions or rules that allow a problem to be solved—use statistical techniques to identify patterns from a large volume of data and employ the acquired knowledge to refine subsequent analyses. The more evidence available, the better the results, and this is all done with little to no human intervention. Common examples of this are spam filtering and banking fraud detection. Spam filtering is the observation of a large number of emails marked as spam which then allows the system to identify certain new messages as such. Fraud detection consists of data-based analysis of complex patterns that trigger alarms when an anomaly is detected.

Figure 2. Machine learning and deep learning as sub-fields of AI



Source: everis

There are different types of machine learning, in terms of the type of learning used:

- **Supervised learning.** This learning process is based on a set of known data previously tagged by an expert whose analysis helps define the new information.

A way to do this is through classification, which allows new data to be assigned to different categories. An example of classification is the identification of certain objects, such as a truck, car, or bicycle, in an image.

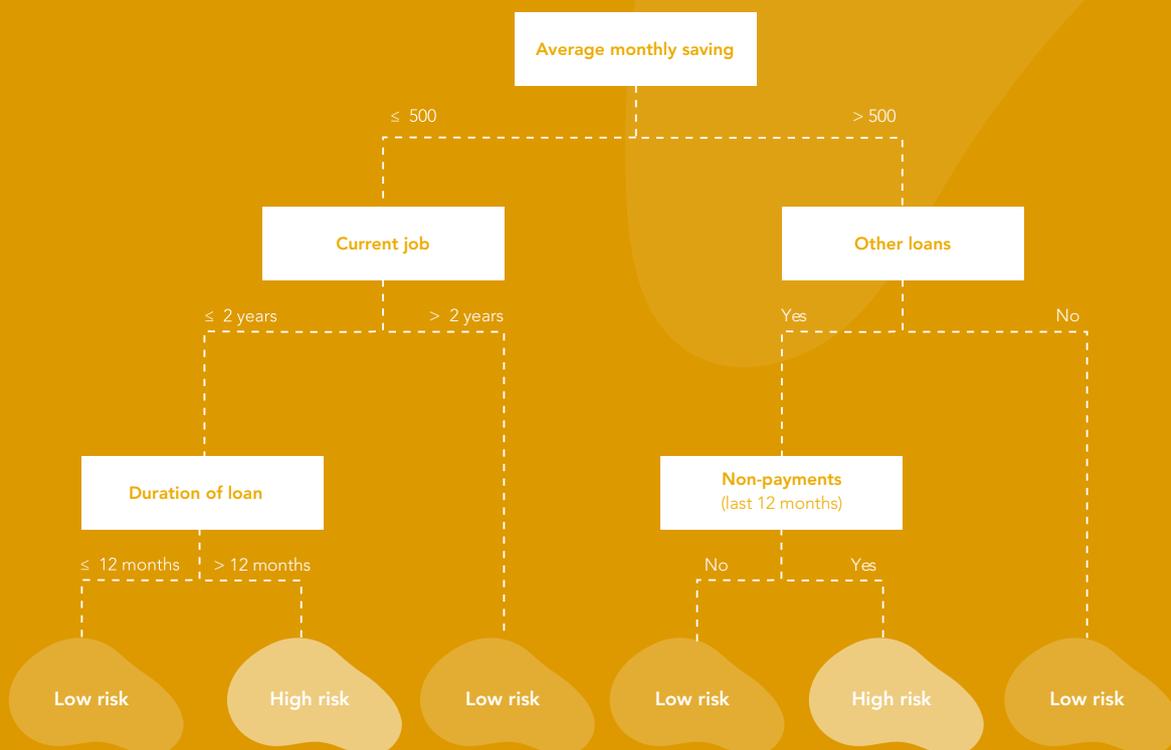
Another method is regression, which relies on known information to predict certain behaviors or outcomes. An example of regression is the estimation of the future sales of a product based on a series of available data including: previous sales, consumer trust, advertising effort, or even the weather.

Both the regression and classification methods can be developed through decision trees. A decision tree is a graphic representation of the events that could occur in response to certain sequential resolutions. Decision trees help us make the best decision possible (see Figure 3). Several combined decision trees, known as the ensemble method, are used to refine results and increase the quality of the model's predictions. The boosting method is a variant of the ensemble method. It reinforces the consistency of results and is used to predict outcomes. For example, it uses banks' accounting and financial information to predict future problems.

A tree that predicts risk

Decision trees, which were first presented as a machine-learning algorithm in 1975, are used in the banking sector as a predictive tool to determine a given client's credit risk. Below is a basic example in which factors such as bank account balance, loan duration, time spent at current job, and credit history are considered to be the defining criteria for creditworthiness.

Figure 3. Example of a simple decision tree for credit-risk analysis



Source: everis

- **Unsupervised learning.** This process uses unlabeled data, meaning no target variable is set and the structure is unknown. The aim here is to extract patterns by analyzing the structure of the information.

A subcategory of this is clustering, which consists of organizing the available information into groups (“clusters”) with differential meanings. A frequently used algorithm is “K-means” clustering, which establishes a fixed number of groups in a data set and assigns the information to each of them according to their proximity on a graphical representation. An example of learning by clustering is the creation of a set of consumer segments based on individual data, such as demographics, preferences, or purchasing behavior.

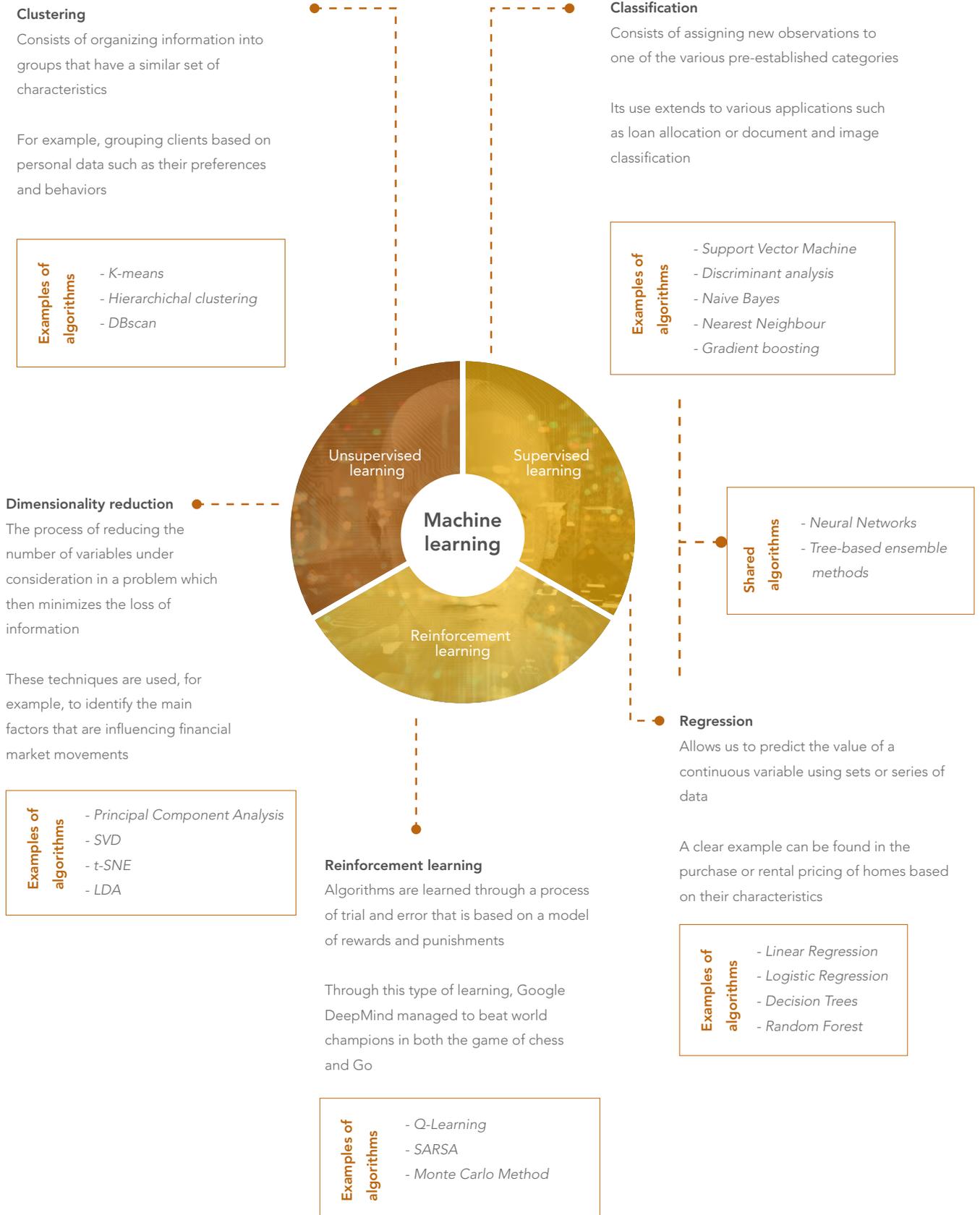
Another procedure is dimensionality reduction, which limits the number of input variables or dimensions of the feature set. Principal Component Analysis (PCA) is an algorithm used to remove non-relevant variables. A practical example of dimensionality reduction with PCA can be seen in models that predict the price of housing in a specific area. If the model contains information about three characteristics related to space (surface in

square meters, number of bathrooms, and number of bedrooms), PCA decides which one is the most representative of said space. PCA is also used to eliminate non-relevant variables in many areas of quantitative finance. Consultants use it to decide on investments between different types of assets and to develop algorithms for buying and selling shares. This simplifies processes and decreases computing and data-storage costs.

- **Reinforcement learning.** In this learning method, the algorithm learns by interacting with its environment through the process of trial and error. It receives information, through sensors and other sources, and makes decisions that are classified as positive or negative. This training is based on a model of rewards, when an action is positive, and punishments, when an action is negative. An example of reinforcement learning is the development of board games and videogame systems. It is also used to manage stock investment portfolios, whose actions generate either profit (reward) or loss (punishment). This serves as training to improve decision-making.



Figure 4. Machine learning problems and algorithms according to learning types



Source: everis

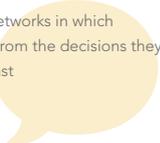
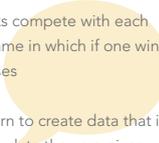
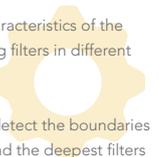
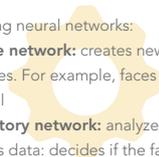
In addition to machine learning, there are other sub-fields and techniques. In many cases, these are derived from machine learning itself, and allow for important advances in AI.

This is the case with deep learning, which has become one of the most powerful AI tools out there. Deep learning uses machine learning algorithms based on artificial neural networks that mimic the structure and functioning of the human brain. The system consists of a set nodes (neurons) that are structured in layers and interact with each other to process information. Network behavior evolves over time through learning processes that may or may not be monitored. In this way, deep learning architectures allow complex, non-linear problems to be solved, as well as the adaptation of the system to changes in the environment. Deep learning is used to create credit-rating models that allow loan applications to be evaluated according to the applicants' characteristics. It is also used to

identify people in pictures on social networks based on their position in the picture, their expressions, or even the way they dress.

One technical variant of deep learning is a deep neural network, which is a network that has a couple of basic layers and many (from tens to thousands) hidden layers. Their complicated structure brings these systems closer to the concept of black boxes, i.e. systems whose decision-making methods are so intricate that it is difficult, even for the designers themselves, to explain the reasoning behind any given action. There are different types of deep neural networks, including: recurrent, convolutional, and generative adversarial (see Figure 5).

Figure 5. Deep learning algorithms

	Recurrent neural networks	Convolutional neural networks	Generative adversarial network
DESCRIPTION	Multilayered networks in which neurons learn from the decisions they made in the past 	Networks inspired by the eye's visual cortex that identify features in the input data in a similar way to how we identify objects visually 	Two networks compete with each other in a game in which if one wins the other loses They can learn to create data that is similar to the data they are given 
FUNCTION	The network has a limited memory which it can use in its analysis of data it has seen previously 	They detect characteristics of the data by applying filters in different phases The first filters detect the boundaries of the figures and the deepest filters detect complex forms 	Two opposing neural networks: - Generative network: creates new data instances. For example, faces that look real - Discriminatory network: analyzes and classifies data: decides if the face is real or not 
APPLICATIONS	Used mainly in natural language processing tasks - Text generation - Time series analysis - Language modeling - Classification 	Used in image analysis and artificial vision: - Detection of objects - Image labeling 	- Text and image generation - Increase image resolution - Frame prediction in videos 

Source: everis

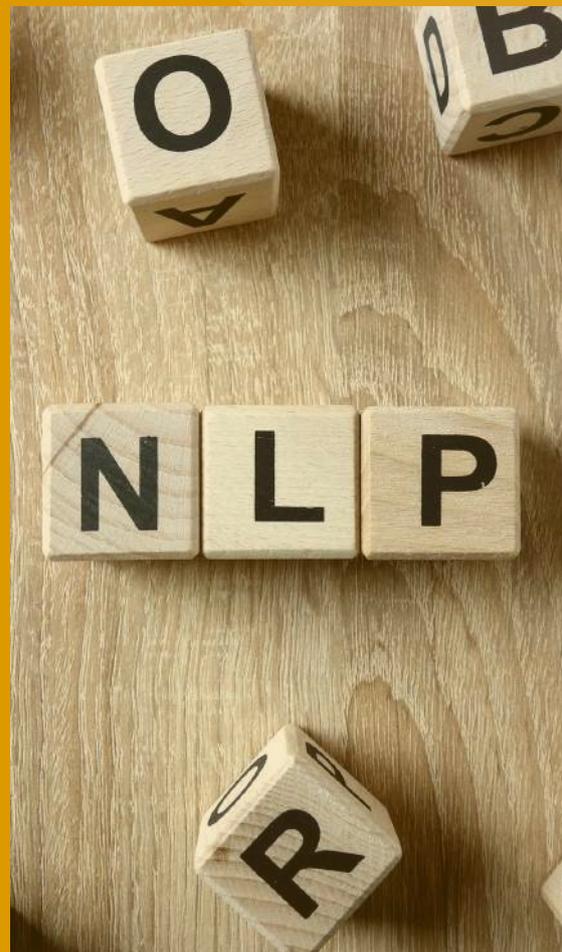
NLP: The natural ally of banking

A highly developed branch of artificial intelligence is natural language processing (NLP). NLP combines computer science, linguistics, and machine learning to enable machines to understand and interact with people's verbal or textual language. NLP has applications in industries varying from text translation, to automotive, aeronautics, smartphones, and healthcare. NLP has proven to be particularly useful for automating and optimizing routine tasks in the banking sector. It is used in three main fields:

- **Intelligent Document Analysis (IDA).** NLP makes it possible to automatically recognize important information and extract it from thousands of documents, such as trade agreements or credit contracts. It is used for legal, compliance, financial, and KYC matters.
- **Investment analysis.** Banks' investment departments are using NLP techniques to analyze financial documentation and find the relevant information—among the mountain of data provided by companies—to make decisions. In other words, NLP helps them find the needle in the haystack. It is also used to identify the market sentiment based on a company's results or a given investment situation.
- **Customer service.** Some U.S. banks have incorporated conversational devices, known as chatbots, to vocally assist customers to check their account balances, make transfers or search their transaction history.

NLP is often combined with other AI sub-fields, such as deep learning or optical character recognition (OCR). Two well-known NLP models are Bag of Words, which counts words and compares documents to draw conclusions about their main ideas, and

Word2vec, which is a two-layer neural network that sorts text to determine its meaning.





2. The situation as it stands

Cutting-edge banking trends and strategies

A framework for creating value

Six opportunities to boost competitiveness

AI is driving a profound transformation in financial services. AI strategy and data culture have become vital in shaping new business models and generating a differential relationship model. The model transcends the traditional concept of focusing on the customer's relationship to the brand, graduating to a higher level of connection: providing comprehensive service to people.

In this sense, it is essential to develop a strategy that revolves around the development of AI, known as AI First. This strategy takes into account the needs of the business and the culture of each financial institution, as well as the ethical and social impact of its use.

Within this strategic framework of value generation (see Figure 6), AI techniques promote six opportunities for improvement. Each is based on internal transformation, such as operational competitiveness, organizational advantage, or innovation, as well as business transformation, such as new models, products, or services and customer experience. These six windows of opportunity are detailed below:

1. Operational competitiveness. The capabilities of AI not only generate efficiency, but also extend its influence to the business model of financial institutions. This model is increasingly oriented towards personalized and agile customer service, and therefore, constitutes a fundamental element of market competitiveness. The entry of fintech (small companies specializing in financial

technology) and bigtech (the tech giants) into the banking world has highlighted the need to strengthen the role of the business model to generate outstanding customer experiences. This is because these two new competitors, especially bigtech, have a natural advantage over traditional banks. AI helps reduce that barrier.

2. Organizational advantage. From an organizational point of view, the transformation inherent to the use of AI technology means rethinking the way human beings and machines interact with each other in the work place. To maximize the organizational benefits of AI, banks must systematically extend their tools to all business processes and diligently engage and train all their workers. Furthermore, the AI strategy must be clearly aligned with the organizational culture of the institution. Otherwise, a major risk emerges: as famous business management expert Peter Drucker said, "Culture eats strategy for breakfast."

3. Open innovation. The intense competition in the financial services market requires banks to constantly reinvent themselves and be open to new, innovative ideas in order to generate opportunities and grow their business. Institutions looking to accelerate value generation are adopting flexible innovation models that incorporate external knowledge and resources to fully utilize the talent available on the market. And all of this is done at high speed. The proposed model is one of fast curiosity versus slow perfection. The volatility of the financial sector, including

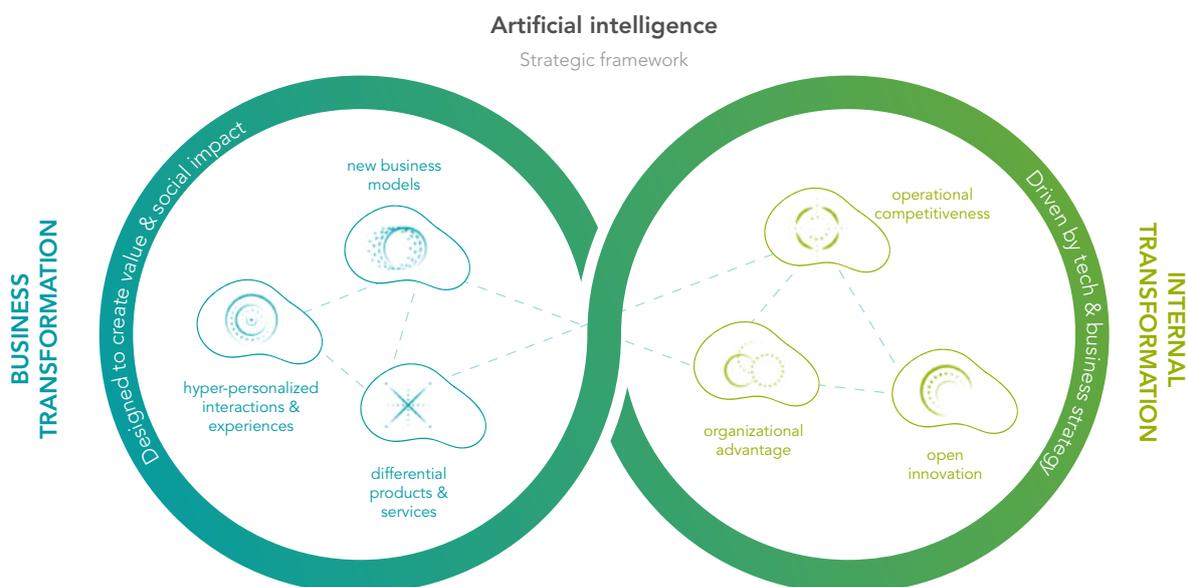
its competitors trying to take over the most profitable corners of the banking business, makes it necessary to configure ultra-connected, agile and decentralized innovation systems. These systems will allow the rapid launch of new products and services whose evolution will depend on their market impact.

4. New business models. The development of AI is a key factor in being competitive in a financial services market where traditional boundaries have become blurred. On the one hand, bigtech and fintech are taking full advantage of the market opening up and the explosion of new technologies to enter into competition in areas such as financing or the payment system, thus eroding the margins of the banking business. At the same time, the traditional or incumbent institutions strengthen their place in the digital ecosystem, exploring new business models (or new ways of making money) to add value to their offering. This is the case, for example, of so-called Banking-as-a-Service (BaaS), which allows institutions to provide financial services to fintech or non-banking companies, so they can in turn offer them to their clients. AI helps make customer knowledge profitable, and facilitates the development of new models.

5. Differential products and services. The large amount of information that credit institutions obtain from their clients, processed in accordance with the corresponding consent, is an excellent instrument for designing new differential products and services, personalized and adapted to people's needs. Understanding what's behind clients' decisions allows us to respond to individual expectations and apply new models of engagement with them. In this way, AI's capabilities restore customer confidence (a worsening reputation due to the economic-financial crisis is one of the main vulnerabilities of the sector) and can generate higher revenues.

6. Hyper-personalized interactions and experiences. AI is an essential tool for the personalization and improvement of the client experience. Consider, for example, recommendation algorithms, which compare the behavior of millions of customers to find similar patterns in consumer preferences and require a system of leveraging to connect the digital and physical worlds. The archetype is Amazon, but AI techniques are also applicable to the customer experience in financial services, through devices such as chatbots or virtual assistants, which facilitate interaction between the institution and the customer. Another example is biometric authentication, which cuts out cumbersome procedures. Experiences and interactions are increasingly focused on the customer.

Figure 6. Strategic framework for creating value through AI



Source: everis

The latest Trends shaping the future of AI in banking

Financial institutions frequently ask: which, among the avalanche of technological and organizational innovations that characterize the progress of AI, will be the trends that mark the pace of innovation in the financial industry. Among the main trends, the six listed below are the most promising.

1. Collaborative innovation

This is the tendency to complement one's own resources for innovation generation with the use of multiple external sources. These can include customer evaluations, the work of

academic institutions and expert communities, or even the experience of competitors. In this area, there are two lines of work that are compatible with each other:

- **Crowdsourcing.** This involves outsourcing micro tasks that, when undertaken on a large scale, generate value for the financial institution and catalyze the process of innovation. Three strategies stand out among the crowdsourcing mechanisms. In what are called "open challenges," banks search for innovative solutions to their problems through public platforms (Kaggle, founded in 2017 and acquired by Google in 2019, is

one of the most popular). On these platforms a community of experts compete to solve challenges as they arise. A second approach is to employ “bug bounty” programs, which credit institutions use to detect vulnerabilities in their systems. In these programs, hackers are invited to break into their systems and discover their security flaws, in exchange for payment. These practices are being adopted as part of the standard business operations of companies like Paypal, Dutch bank ABN Amro, and “neobank” N26. The best-known bug bounty platforms are HackerOne, Synack and BugCrowd. A third crowdsourcing strategy is the use of platforms or markets in which banks, especially smaller ones, lay out their AI needs and pay an agreed amount to those who solve them. Amazon Mechanical Turk (named after a 17th-century automaton that supposedly played chess) is one of the best-known platforms.

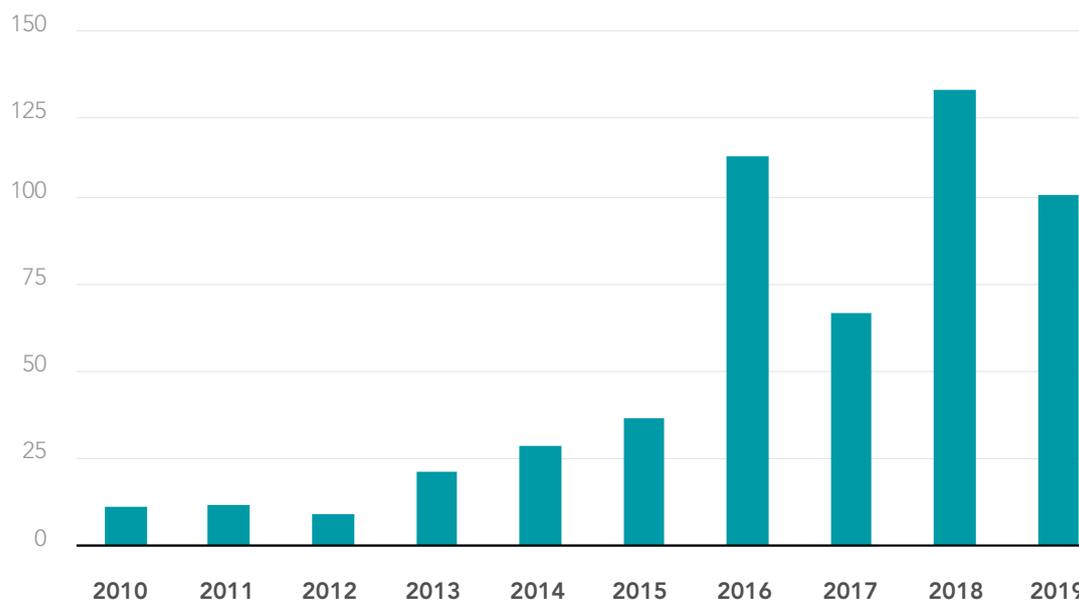
- **Mergers, acquisitions, alliances, and entrepreneurship and incubation projects.**

Financial institutions are aware that their internal capacities are insufficient to face the complexities of innovation, and they increasingly turn to corporate operations to integrate the knowledge of specialized organizations through purchases, mergers or alliances of a different nature. The clearest case is that of the operations of fintech and bigtech companies, whose experience in digital finance (payment systems and other services for private and business clients) and in customer relations is extremely useful for traditional banks. New competitors can also help improve operational efficiency and reduce costs. In the same vein, a complementary strategy is to participate in “corporate venturing” or business incubation to accelerate growth and take advantage of their experience in AI. And the interest is mutual, as new players also benefit from the financial strength and scale necessary to spread their ideas. As a result of this synergy,

numerous partnerships and operations have emerged between the two sides, producing a complex, innovative ecosystem. One of the most recent examples is Google's decision to launch checking accounts in 2020, in collaboration with the Citigroup banking group and a credit union at Stanford in California. Another notable initiative is the launch in the United States of the Apple credit card, in association with investment bank Goldman Sachs and Mastercard. Similarly, the bank JPMorgan Chase is offering an electronic wallet to large tech-based companies like Amazon and Airbnb. This collaborative trend between traditional banks and fintech has also led to multiple agreements.

The rich breeding ground for collaborative innovation is one of the reasons behind the strong growth in investment in AI. The funds raised for investment in companies in the sector exceeded \$100 billion in 2019 and, although the annual profile is irregular, this figure has increased dramatically in the last four years (see Figure 7).

Figure 7. Capital raised globally by big data, AI, and ML companies, in billions of dollars



Capital raised through private equity, venture capital and M&A for investment in the big data, AI and machine learning sector

Source: Pitchbook Data, 2019

2. New developments in machine learning

Machine learning is evolving towards specific developments that are primarily related to improvements in the operational and organizational aspects of financial institutions:

- **Automated Machine Learning (AutoML).** This is a tool for machine learning development models that automates repetitive tasks, enabling banks to build more efficient and productive models without compromising on quality. This way, the traditional banks boost competitiveness and reduce operational costs. Some credit institutions, such as ING, also offer this type of modeling to their clients to help them forecast product demand, and optimize their supply chain and financing. AutoML services are provided by tech giants like Google and Microsoft, among others.
- **Machine Learning Ops (MLOps).** This is a set of practices aimed at integrating machine learning models, operations development

and data to help manage the life cycle of a machine learning operation, which is usually quite complex. These processes facilitate both the creation of an AI governance model and progress towards an organizational culture based on data and digital applications. Mastercard is an example of a robust and well-defined AI system.

3. Edge AI

This is a computing technique that analyzes and processes data very close to its source ("on the edge"), such as a mobile phone. This avoids the need to send the data to remote, centralized locations (the cloud or large data centers), and the processing can be done in real time, without the need for a connection. Edge computing is still in its infancy, but expectations are high. This technology can help leverage the reach of AI, which will become part of everyday devices. In the case of banking, Edge AI is a trend with

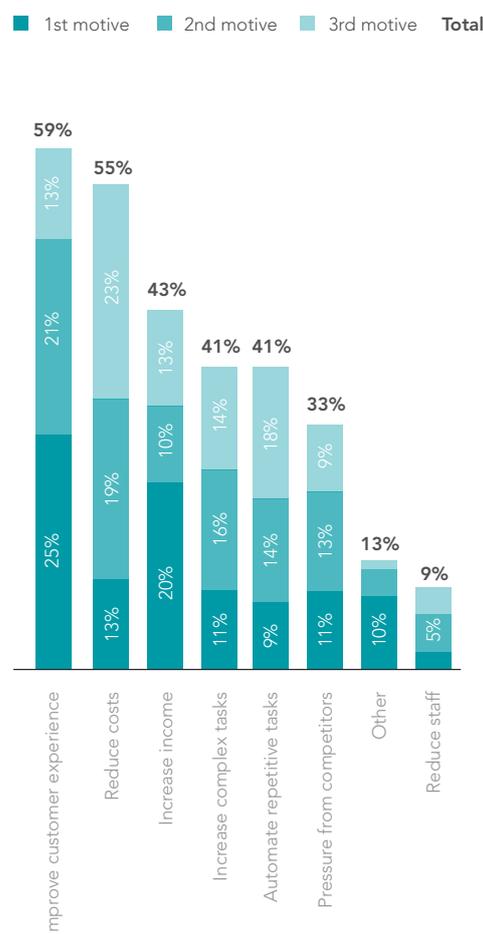
great possibilities, as it provides customer information in a matter of milliseconds, which helps to make it profitable. Especially promising is the combination of Edge AI with 5G mobile technology, which is beginning to take hold in Europe. 5G offers information in real time about the client's circumstances or characteristics (where they are, their spending, their interests, etc.) and opens the door to instant recommendations or new financial services based on AI programs. For example, an automated financial assistant could warn a client that a credit card payment would exceed their spending limit, or suggest ways of financing a purchase. The Commonwealth Bank of Australia has conducted trials with telecoms companies Telstra and Ericsson to explore the benefits of the convergence of 5G and Edge computing.

4. Strategic design of services by AI

Strategic service design is increasingly a catalyst for AI, creating new opportunities for customer experience improvement. Although AI provides the tools needed to create systems that facilitate a relationship tailored to each user, it is the design of the technology that allows differential interactions to be established. Through the use of user-centered strategic design, it is possible to improve the experience of using financial institutions' products and services. Digital banks in particular are making the most of these advantages to cultivate a loyal client base through the design of user-friendly processes and systems that put the customer at the center of the business model. In any case, the development of these systems requires the involvement of multidisciplinary teams throughout the entire process. According to a Gartner technology consultancy survey (see Figure 8), the trend to differentiate through more attractive and user-friendly design formulas is especially relevant when

considering that improving the customer experience is the number one motivation for companies to invest in AI.

Figure 8. Three fundamental reasons to invest in AI/ML (percentage of responses)



Source: Gartner, 2019

5. Contribution to sustainable development

The use of AI by financial institutions has a potentially positive effect on sustainable development, through the launch of new services that promote financial inclusion and education, or through data processing to support research. In general terms, an academic study (Vinuesa, R., Azizpour, H., Leite, I. *et al*) published in *Nature* magazine found evidence that AI could drive 128 of the 169 aims included in the 17 Sustainable Development Goals (SDGs), established by UN in its 2030 Agenda (see Figure 9).

In the social objectives section, AI is potentially beneficial for 65 aims (79.3% of that area), such as promoting the supply of food, water, energy and health services, promoting low-carbon systems and supporting smart cities. In the economic objectives section, the advantages affect 38 aims (some 63.3%), especially those related to efficiency, innovation and productivity. In the environmental SDGs, the benefits extend to 25 aims (92.6%). These include the promotion of renewable energy, pollution reduction and the preservation of plants.

Figure 9. Impact of AI on sustainable development objectives



Source: Vinuesa, R., Azizpour, H., Leite, I. and others (Nature, 2020)

It's important to note, however, that AI also has some potential contraindications for sustainable development, which are mainly derived from the inequalities it can generate between countries, and between social groups.

6. Extra attention to ethical problems

As we will discuss in the last chapter of this report, ethical issues and other undesired consequences which arise from the use of AI constitute one of the great challenges of its application. Banks, especially, are under public scrutiny for their responsibility in granting loans, in asset management and in how they handle their clients' confidential data, among other reasons. A report by the World Economic Forum underscores that there are several areas of concern about the use of AI in the financial industry:

- **Explainability.** The complexity of some AI systems makes it difficult to get a reasonable explanation as to why they produce certain results.

- **Bias and discrimination.** Using AI can exacerbate unfair bias in financial decision-making, and discriminate against clients based on factors other than risk such as race, gender, or social class.

- **Systemic risk.** The widespread adoption of AI can alter interactions between financial agents, generate shock in the markets and obstruct the system's risk management.

- **Advisory obligations.** There are doubts that AI systems are capable of fulfilling the fiduciary obligations that the provision of financial advice to clients entails (behaving with due diligence, loyalty and good faith).

- **Anticompetitive conduct.** The ability of AI systems to learn automatically poses the risk of them making decisions which are anticompetitive or breach market rules.



3. What the banks are doing

**AI as a Swiss Army knife:
Uses and applications along
the entire value chain**

The improvements made by AI in cost reduction, risk mitigation and the optimization of functions have encouraged financial institutions to invest in incorporating this technology into their processes. The trend is still new and, at the moment, focused on a few areas of banking operations. However, it is expected to become widespread in the next few years. According to a survey by the Association for Financial Markets in Europe, AI will be rolled out little by little, forming part of the typical day-to-day management of financial institutions within no more than four years.

The growing prominence of AI in the financial sector is no coincidence: its applications are varied and can be used for almost everything. It's like a Swiss Army knife whose tools can be used to perfect each part of its value chain: from client or market interaction tasks, to processing functions, and risk control and monitoring.

From frontier to frontier. The technological process, a spotlight in nonstop motion

The application of AI in the financial sector has various antecedents and technological developments that have overlapped over time and will continue to do so in the future.

A main forerunner (well known to financial institutions, which have used it for many years) is analytics. That is to say, a set of tools that facilitate data analysis for better decision making. In this technological phase, the raw material was data (organized, easily processed information). Analytics-based projects would process this data, use it as an instrument of analysis (typically a market solution) and, finally, produce a report as well as detail-rich visualization tools.

From this early ancestor came big data, a new discipline but one which, suitably enriched, picks up the baton from analytics. Big data brought in many advantages. We could now analyze not only structured data but also unstructured data. It could also handle a massive volume of information and had

much greater granularity. This represented a huge qualitative and quantitative leap, as it required the incorporation of much more complex structures in order to add, clean and prepare the data for processing. These days, storage capacity is skyrocketing, and costs are decreasing exponentially.

The next technological frontier, which stemmed from AI, is machine learning. With it, came the commonplace use of algorithms as fundamental elements, such as with techniques like Bayesian inference and decision trees. These concepts are nothing new, but are now being applied more frequently and intelligently. In any case, it is not too complicated a process, as it is auditable and explainable (via white box testing). A characteristic feature of this arena is the use of programming languages such as R and Python, or open libraries such as scikit-learn, which are used by many large financial institutions and which facilitate the use of machine learning.

The widespread use of ML is what ushered in the next technological chapter: deep learning. It uses machine learning algorithms, based on

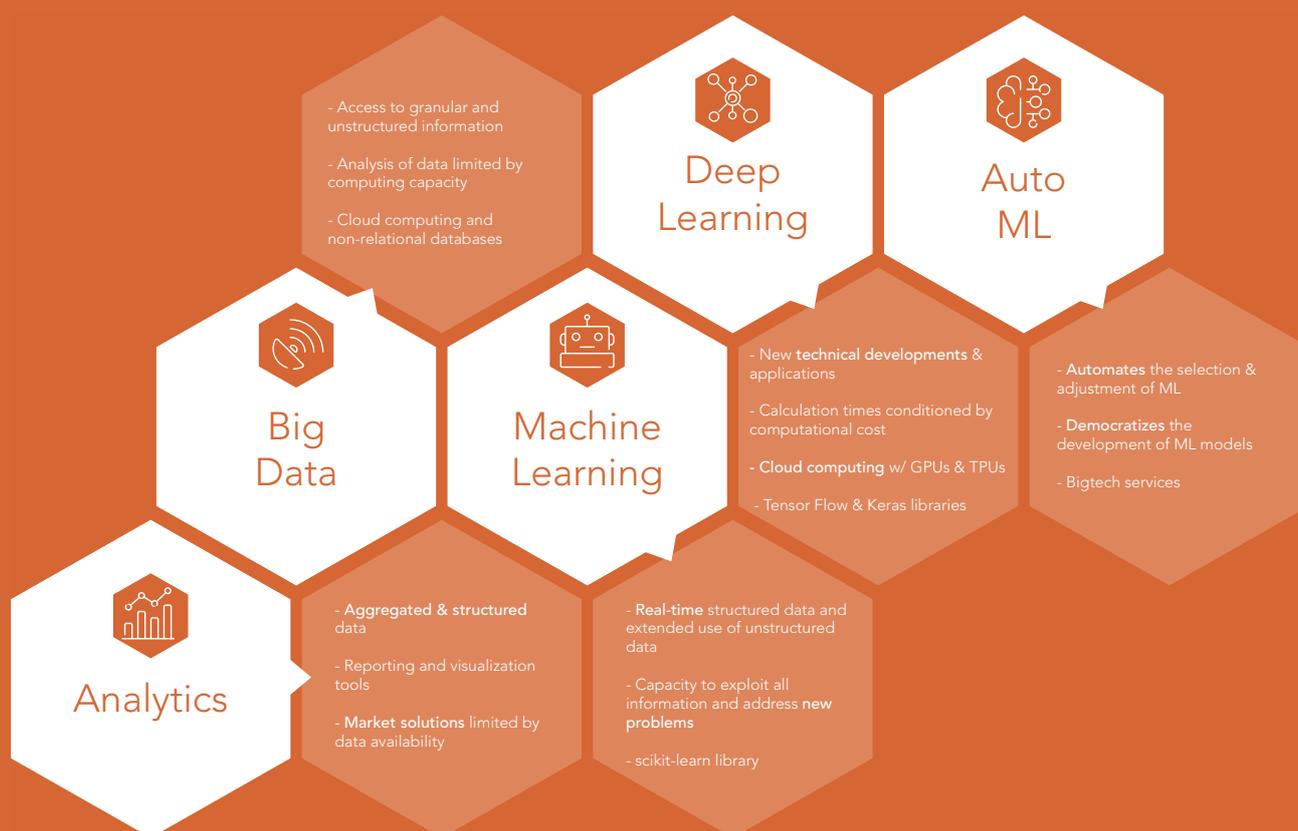
neural networks, that mimic the functioning of the human brain to solve complex problems. Because many more layers are incorporated, it sometimes becomes very difficult to understand the intermediate mechanisms that determine the final result, making it feel like some sort of “black box.” One of the most successful deep learning tools is the TensorFlow library, an open-code platform developed by Google. Different tools have been adapted around it, such as Graphics Processing Units (GPU) or Tensor Processing Units (TPU), which enhance its characteristics.

the development of machine learning and enables its users—regardless of their degree of experience—to use this technology, expanding its use to new applications and bringing productive solutions to the market faster.

The different stages of AI are therefore defined as a succession of techniques that intermingle and develop in a way that is not strictly linear, so the focus is in perpetual motion.

The final frontier in the development of AI solutions is automatic machine learning (AutoML). The development of machine learning models requires specialized knowledge that allows for the comparison of dozens of models to select and adjust the algorithm with greater precision. With new AutoML techniques, the models are selected, trained and adjusted automatically based on specific metrics. This advance democratizes

Figure 10. The evolution of advanced analytics techniques



Source: everis

What is being done and what is in store

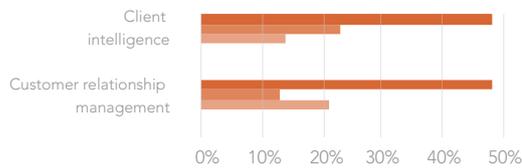
Client relations and risk management—right on target

What are financial institutions doing—or planning to do—in terms of AI? Recent experience shows that their main efforts so far are directed towards operations related to client relations (through the implementation of chatbots and new identification systems); fraud prevention (including processes related to the prevention of money laundering and terrorist financing); and risk management (with applications in credit rating, among other functions).

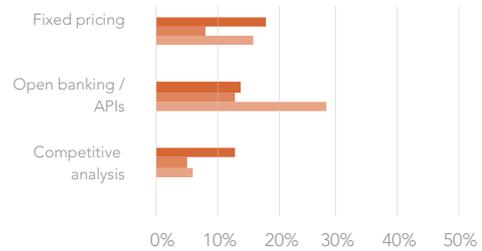
A 2019 survey conducted by the European Banking Authority (EBA) among 62 banks and 18 market analysts, points in this direction. The survey results (see Figure 11) are significant, and they provide us with a framework as to how European financial institutions are progressing with their AI projects.

Figure 11. What big data and advanced analytics solutions are the banks developing?

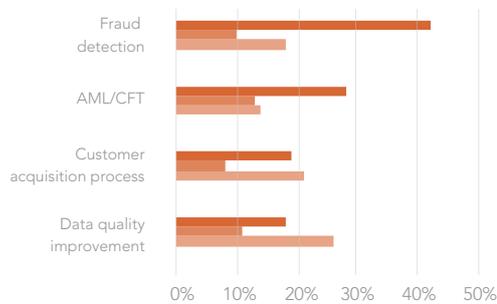
Commitment to the customer



Product processing



Process optimization



Risk management



■ In use ■ In pilot ■ In development

Source: EBA, 2019

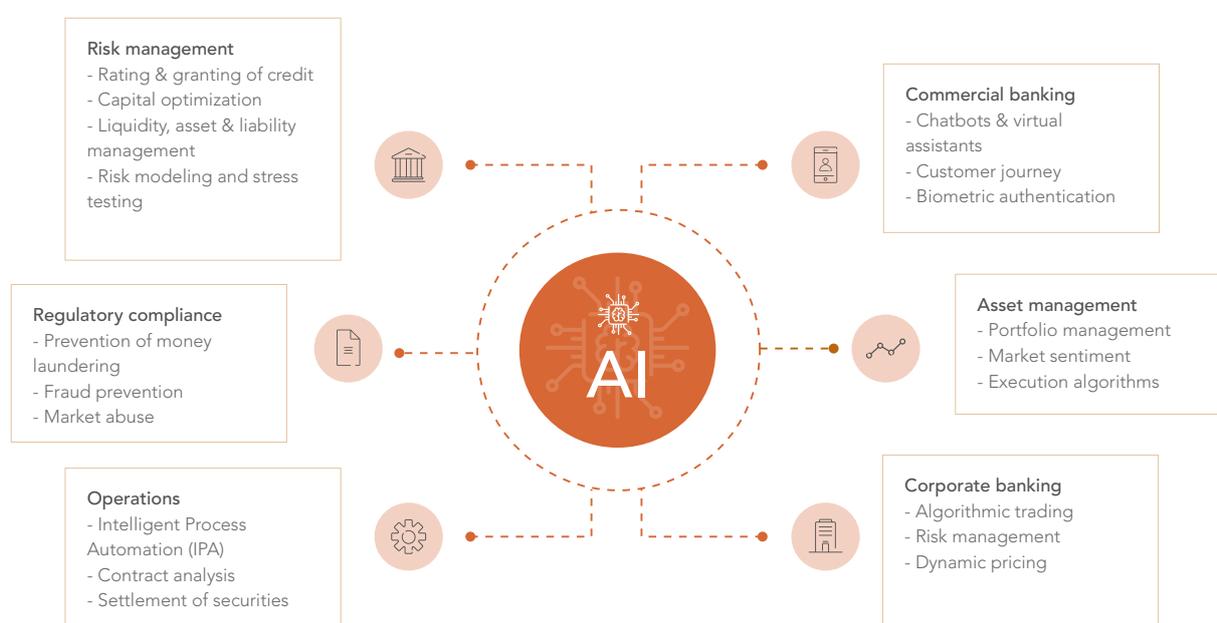
The applications

The most prominent uses of AI, from theory to practice

As we have seen, the applications of AI have great potential at every point in the value chain of credit institutions. But which of these have moved from theory into practice, from the possible to the concrete? This section explains the most prominent use cases in

the sector, divided into six blocks according to function: risk management, regulatory compliance, operations, commercial banking, asset management, and corporate banking.

Figure 12: AI applications in banking



Source: everis

1. Risk management

The ability of the different AI techniques to process large quantities of data quickly and extract hidden patterns at first glance greatly improves risk management, which is the heart of the business for financial institutions. Below, we discuss some of the applications with the greatest potential:

- **Rating and granting of credit.** This is a natural field of application for AI tools, since they offer great speed and efficiency in the gathering and processing of information from credit applicants, and in predicting their future behavior. The greater analytical capacity of AI improves credit evaluation, catalyzes the process and reduces concession costs compared to traditional scoring methods (FICO and others). In addition, the use of unstructured data, such as data from social

networks, may extend the scope of such concessions to customers with no credit history or with little available information. Traditional banking views this new approach with some suspicion (because, among other reasons, it requires massive use of resources to track millions of data on applicants' personal situations and payment histories) and prefers to rely on well-known rating systems. However, several fintech companies—in the United States, Europe, and China alike—are exploiting the opportunity that AI provides to use alternative and highly sophisticated credit rating models to assess the payment capacity of their clients, apparently successfully. Some of these new models are being analyzed by supervisors and regulators, as they are not tested during a full economic cycle (we do not know how they behave in a recession, for example) and may incorporate unwanted biases or lack transparency.

- **Capital optimization.** Maximizing return on equity is one of the basic objectives of any financial institution (especially in light of the increase in regulatory requirements in recent years), and its development relies on complex mathematical models. The use of AI increases the efficiency, rigor and speed of the process, and significant progress has been made in determining risk-weighted assets (RWA). Advances in RWA optimization facilitate the reduction of regulatory capital levels calibrated by traditional methods and increase confidence in certain conventional tools.

- **Liquidity, asset and liability management.** Liquidity problems are a major concern for financial institutions and supervisors, as historical experience shows that they pose a threat to their viability, both because of their potential impact on individual banks and because of the risk of propagation. Additionally, the coronavirus pandemic, which is causing the credit crunch and an increase in late payments, requires banks

to strengthen their liquidity levels in order to provide a sufficient cushion to cope with such exceptional circumstances. In recent years, Asset Liability Management (ALM) has become a strategic area within financial institutions when making investment and financing decisions that are consistent with the levels of profitability and risk that the bank is willing to assume. At both levels of risk management, machine-learning techniques (supervised, unsupervised, and reinforcement learning) make it possible to analyze highly complex factors that are related in a non-linear way. However, the experience of BlackRock, the world's largest fund manager, reveals some implementation issues. The firm experimented with neural network models to calculate liquidity risk, but encountered difficulties with explainability (the ability to explain the algorithm's decision-making process). For now, the company has opted to develop less complex and more interpretable systems, in order to better understand and manage them.

- **Risk modeling and stress testing.** Machine-learning techniques are being used to improve backtesting (a process based on historical data to evaluate whether a strategy or trading system works) and model validation, both of which are considered basic tools to check the effectiveness of risk management in financial institutions. Some investment banks employ unsupervised learning algorithms to validate equity-derivative models. Similarly, unsupervised learning is used to analyze the vast amount of information needed to build the models of financial institutions for the stress tests that supervisors carry out periodically. For example, it is used to analyze loss scenarios in case of non-payment or probability of non-payment.

2. Regulatory compliance

AI techniques facilitate regulatory compliance and allow for a more efficient and agile response to the requirements of financial supervisors. AI is particularly valuable for the development of the regtech (regulation and technology) sector, which brings together advanced technology companies that provide solutions to meet regulatory requirements, especially in the financial sector. Some of the main applications are listed below:

- **Prevention of money laundering.** The bank dedicates a large amount of resources to the prevention of money laundering and financing of terrorism (AML/CFT) since any failure or negligence in the control of these activities has a high cost, both in terms of the economy (because of the fines that are usually involved) and in terms of reputation. AI techniques are an important tool for monitoring transactions rapidly. They are also used to improve the customer knowledge process (KYC), which helps to investigate and verify the source of funds for each operation, as well as avoid unnecessary inconvenience for the clients themselves. Many institutions use machine-learning algorithms to reduce the number of alarms triggered by conventional methods of detecting suspicious transactions, and to increase their degree of reliability.

- **Fraud prevention.** Bank fraud mainly consists of the unauthorized use of credit and debit cards, both in person (when criminals manage to steal or replicate the card) and from a distance (when criminals obtain the card data and use it to make electronic payments). Fraud-prevention solutions need to be flexible and sophisticated enough not only to counteract criminals, but also to discredit false positives, which occur when an activity is erroneously detected as fraudulent, forcing

institutions to make additional screening efforts and causing client inconvenience. In this sense, machine-learning techniques make it easier to distinguish between legal and illegal operations. These machine-learning models also enable fast adaptation to new operations, therefore upgrading traditional systems that operate with rules and that degrade progressively with the development of different channels and fraud schemes. A good example of the use of AI is the PayPal payment platform, which uses machine-learning tools to study clients' purchase history and detect behavioral patterns. As a result, it has managed to reduce the fraud rate to 0.32%, compared to the industry average of 1.32%. The card company Mastercard uses a similar system to identify purchasing patterns and has managed to both increase fraud detection by 40% and to reduce false positives.

The outbreak of the COVID-19 pandemic has opened up a new frontier in fraud prevention. Banks are reporting strong growth in internal and external attacks and incidents as a result of, among other factors, remote-work practices and the increase in video conferencing, both of which have lowered security standards. In these circumstances, machine-learning techniques are particularly useful for identifying unusual transactions.

- **Market abuse.** European regulators have intensified their scrutiny of financial market transactions through initiatives such as the Market Abuse Regulation (MAR) and the second version of the Markets in Financial Instruments Directive (MiFID II). At the same time, operator behavior is changing and becoming increasingly sophisticated. This forces the supervisory bodies to increase their surveillance measures. AI helps markets and market participants process millions of transactions and optimizes their efforts to combat market-abuse practices, such

as disseminating misleading data, insider trading, or unlawful disclosure of non-public information. An example of the application of these techniques is that of the Monetary Authority of Singapore (MAS), which uses machine learning to investigate suspicious transactions and focuses its resources on the highest-risk operations. The Nasdaq market, on which the main U.S. technology companies are listed, also uses AI to detect anomalies in the purchase and sale of shares.

3. Operations

Financial institutions often face slow, inefficient, and costly internal processes in the areas related to operations (middle office and back office). AI techniques, which provide automation and speed in data processing, are able to solve some of these problems. The applications being used include the following:

- **Intelligent Process Automation (IPA).**

Dependency on manual processes is a source of inefficiency and errors that generates unnecessary expenses in financial institutions. For many years now, the implementation of robotic process automation (RPA) has minimized these inefficiencies and reduced costs in back office operations. However, the tools used are not flexible and are based on pre-defined scenarios. Intelligent process automation (IPA) enables robots with advanced AI capabilities to adapt to new situations. They use natural language processing (NLP) techniques to interpret and identify relevant content in complex text structures, as well as machine-learning tools, which assess their efficiency and effectiveness for learning-based improvement. A prominent case of the use of IPA is the global commerce area of the British bank HSBC which, through different techniques (OCR, robotics and text analysis), identifies and extracts key information from commercial documents

before incorporating them into the institution's transaction-processing systems.

- **Contract analysis.** The analysis and treatment of contractual documents is one of the most time-consuming functions of banking operations. This task can be simplified by the combined use of natural language processing (NLP) and machine learning. Within the financial sector, the use of NLP for document analysis has many applications. A potential use case is the study of the powers of attorney made by banking institutions which makes it possible to determine the extent, scope and limitations granted by society to its legal representatives. Similarly, the NLP is very useful in terms of analyzing contracts in order to, for example, detect specific clauses, such as the floor clause or the application of the Mortgage Loan Reference Index (IRPH). U.S. bank JP Morgan uses the program COIN (contract intelligence) to reduce and streamline the time-consuming task of reading and analyzing commercial documents. COIN uses machine learning to interpret, within a matter of seconds and with great accuracy, loan contracts that previously required approximately 360,000 hours of work by qualified professionals.

- **Settlement of securities.** This process, involving the purchase and sale or transfer of financial assets (shares, bonds and other securities), is very difficult given the increasing complexity of financial markets. In particular, financial institutions encounter processing difficulties when the transfer is blocked for some reason and must be managed manually by the support professionals in both the middle office and back office. In these cases, which require a large investment of resources, the machine-learning method is of great help in terms of resolving anomalies, as it allows the circumstances to be evaluated and managed in a fraction of the time required by a human. Additionally, AI tools can analyze

a large volume of historical-operation data, draw conclusions as to why failures have occurred, and propose solutions for the future.

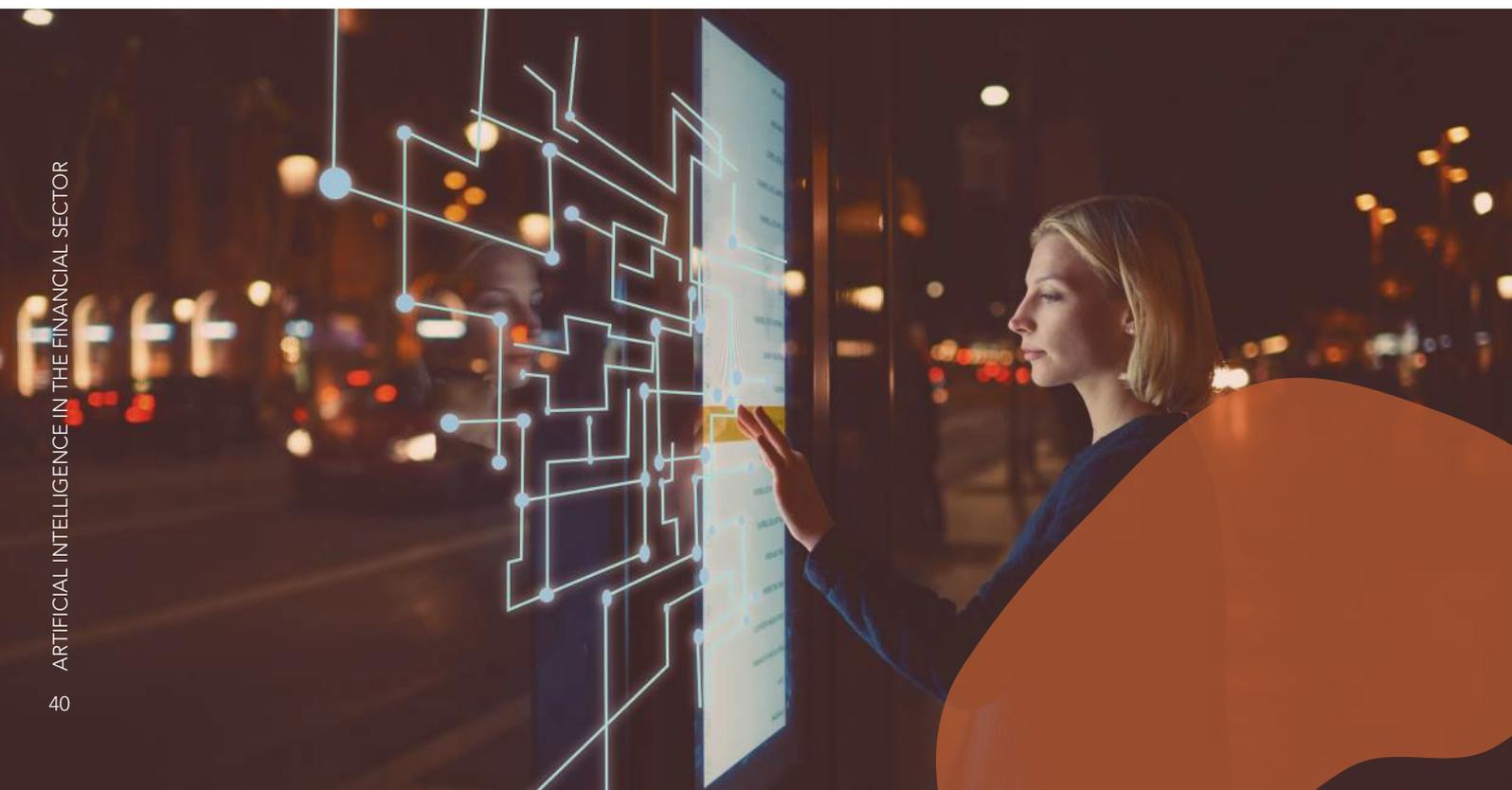
4. Commercial banking

Financial institutions are applying different AI tools for the part of their value chain that is directly related to the client and usually processed through commercial-banking channels. These are the most notable applications:

- **Chatbots and virtual assistants.** These are customer service tools, but can also be used among employees. These tools have certain differences (chatbots are more specific, while virtual assistants, such as Siri or Cortana, have a greater range of functions), but their purpose is similar: to communicate with users, either through voice or written text, in order to answer their questions or facilitate certain operations. These tools automate the relationship with clients, who can access them at any time. Additionally, chatbots and virtual assistants enable companies to

automatically collect and process information about interactions with users in order to know more about them. These tools are advantageous as they improve the customer experience, reduce costs and may even be used to increase sales. The use of chatbots is widespread across international banks: Bank of America has several devices that can understand text and voice messages and even make financial recommendations; Wells Fargo manages it through Facebook; Australia's Ubank helps its staff to answer client questions; and France's Crédit Mutuel uses an email analyzer. In Spain, several institutions have launched chatbots, with different degrees of development and focus (they are mainly used for customer service, but also for employees).

- **Customer journey.** It is vital for banks to be familiar with the entire customer experience process, from when a client opens an account (or even before, when they discover the brand) to when they start using the institution's app or contacting the call center to resolve a problem, encountering multiple



interactions along the way. An in-depth understanding of this process is the key to eliminating friction and improving customer service, which in turn allows institutions to differentiate themselves in a highly competitive environment. For this reason, banks dedicate large amounts of resources to optimizing the customer journey to identify which offers may be interesting (personalized products), through which channels they should be distributed, and at what specific moment. Currently, AI techniques (mainly machine learning) are used to segment and model clients, integrating geographic, telematic, and social information, or data based on the Internet of Things, among other sources. Based on this, algorithms are used to analyze consumer behavior, understand their preferences and define the next-best action or offer.

- **Biometric authentication.** AI offers valuable assistance in the development of biometric techniques to ensure authentication in banking operations. This ID system is particularly relevant in view of the entry into force of the enhanced authentication obligations established in the second version of the Payment Services Directive (PSD 2) for validating digital payments. The new regulations oblige companies to require at least two of the following three items from their clients: something the client knows (e.g. a password), something they have (e.g. a phone) and something unique to their person (e.g. their fingerprint). The most widely used authentication technique in banking is fingerprint recognition, which was first applied in banks such as the Royal Bank of Scotland, Barclays and the Bank of America. Fingerprint recognition is now widespread across mobile devices. Other technologies, such as retinal scanning (in initial phases at Wells Fargo and Bank of America) and palm print recognition, or voice and facial recognition (Citigroup), are in a more advanced state of development.

5. Asset management

The use of AI in asset management is nothing new, but advancements in technology have made it possible to broaden its scope and perform complex and intensive tasks that would be impossible with traditional methods. These are some of the main applications:

- **Portfolio management.** AI and machine learning are being used by some financial institutions to identify asset price signals and make better use of the vast amount of available data and market research, in order to make their portfolios more profitable. However, these tools are still seeing limited use. According to a 2019 survey carried out by the CFA Institute (an association of investment professionals) only 10% of managers around the world had used AI in the past 12 months to improve their investment processes. The rest of them were stuck in their old ways, using traditional tools such as Excel or other computer programs. The report attributes this limited expansion of AI to problems related to cost, training, leadership, technology and time.

- **Market sentiment.** Investors continually aspire to predict movements in the stock market. One of the ways in which they anticipate these changes is through market sentiment analysis, which consists of gathering and evaluating unstructured data that reflects investors' intuition. The problem here is that it requires a lot of effort to be put into collecting and analyzing an enormous amount of information from different sources—social media, financial analysts, communications to markets, corporate reports, mass media and more—that are constantly being updated. Artificial intelligence can play a major role in this environment in which so much information is constantly flowing. Bringing together techniques such as NLP and machine learning greatly increases the ability

Figure 13. Advancements made in developing virtual assistants in banking



Source: everis, using public information

to analyze market sentiment and to make investment decisions based on that analysis. Other aspects of AI, such as decision trees, neural networks, deep learning, ensemble methods, support vector machines, and more, are also being used to try to capture investor sentiment. Although, in some cases, these ideas are just academic proposals or projects that are still in the experimental phase. Examples of pioneers in the use of AI in this field include American hedge funds like the D.E. Shaw group, Two Sigma and Renaissance Technologies.

- **Execution algorithms.** Efficiently carrying out operations is a fundamental part of the investment strategies of financial institutions, whether it be regarding their own account or the accounts of their customers. To be efficient, these institutions must know how and when to complete a transaction to get the best price, while minimizing the cost of the transaction and reducing market impact. AI models can lend a hand to human middlemen in order to select the best way to execute an operation. The algorithms are able to analyze the transaction history and price history of a given market or counterparty. They also have to ability to make recommendations to ensure that the operation is carried out in the best way possible. For example, the investment management firm BlackRock uses machine learning to identify patterns in transaction costs to help improve their processes. However, not all firms and financial institutions are so comfortable with these technologies. Instead, some prefer to use tried-and-true models to carry out operations, since they generally deal with large-scale actions and any calculation error could be quite costly.

6. Corporate banking

Banks are beginning to use different AI tools to optimize their corporate banking activities,

such as management of financial operations and investments for large companies. In some institutions, these activities are an integral part of the business. These are the most noteworthy uses of AI in this sphere:

- **Algorithmic trading.** AI is now being incorporated into algorithmic trading. This practice is a method used in financial markets, and is based on automated rules and processes. It usually leads to instantaneous and concrete decision-making (“high-frequency trading”). Using machine learning algorithms allows for thousands of data sources to be more easily analyzed simultaneously, while helping to make better real-time, automated trade decisions regarding financial assets. That said, history shows us that complementing machine-learning algorithms with human operators is beneficial, as it avoids distortion and errors. J.P. Morgan and the Swiss bank UBS use machine learning in their algorithmic trading systems for deals in their foreign exchange markets.
- **Risk management.** Decisions regarding prices and portfolio hedging of spinoff products are paramount in the financial industry. AI has made it possible to create a new risk-management system called deep hedging. This technique allows conventional models that require simple hypotheses to be replaced, while focusing on a data approach supported by machine learning. J.P. Morgan uses this system, which was initially tested in an index option. It is predicted that in 2020 this system will be extended to specific shares as well as to asset pools. This project is part of a bigger plan with the goal of using machine learning in a variety of situations. This would allow for processes to be much quicker than if they were done manually, while saving costs in certain markets such as the raw materials market.

- **Dynamic pricing.** The dynamic pricing strategy for products and services allows for prices to be adjusted according to different, previously established parameters. In short, it is a strategy that primarily depends on customer segmentation. In the case of the banking industry, where prices should be transparent, the conditions (e.g. having a certain amount in a checking account) under which a certain price is applied should be perfectly clear and agreed upon by both parties. From the bank's point of view, deciding on a dynamic pricing system is a complicated process that requires financial components—such as the term structure of interest rates and credit spread—to be evaluated. It also means that regulatory components (cost of capital), customer behavior (financial history) and market components (competition) must be assessed. AI simplifies this process, as it analyzes data in real time to segment customers and to establish the settings of the price optimization models. This allows strategies to be adjusted to the conditions of the market.



4. The ethical dilemma

A question of trust

The benefits that AI has to offer are as obvious as they are extraordinary. Limiting ourselves to the financial sector, AI allows to optimize areas critical to its successful operation, such as risk management, which is the core of banking, fraud control or customer relations, which are improved with relevant and personalized real-time conversations, as we have seen in previous chapters.

At the same time, we know that applying artificial intelligence requires ethics principles allowing to ensure that it is used appropriately throughout an algorithm's lifecycle, in other words, from data selection and initial processing to large-scale use.

It comes down to trust, transparency and responsibility. In an algorithm supporting the decision of who gets a loan and who doesn't reliable? In this process properly supervised? Can we explain it to a customer in a simple way? How can we guarantee that discriminatory bias is not present in algorithms' activities? Can we trust a machine learning tool that decides to cancel a credit card due to a presumed fraud risk when the cardholder is going to pay in a restaurant? Is the information that a virtual assistant provides to a customer on the balance of their corporate line of credit reliable? Has the customer been informed that they are interacting with a virtual assistant and not a person?

These questions are particularly important, and make it necessary to develop artificial intelligence systems within a transparent governance framework allowing to monitor and explain the automated decision cycle. To face the challenge of defining trustworthy artificial intelligence, the European Commission's High-Level Expert Group on Artificial Intelligence believes that AI

must meet three generic requirements simultaneously during the entirety of a system's lifecycle: it must be lawful (in other words, compliant with legislation in force), ethical (guaranteeing respect for ethics principles) and robust (to avoid accidental damage). The ethics principles that must be acknowledged are respect for human autonomy, prevention of harm, fairness and explicability.

Combined with these general recommendations, the Expert Group has established seven specific and essential requirements for trustworthy AI, which were included in the *White Paper on Artificial Intelligence* published by the European Commission in February 2020. They are the following:

1. **Human agency and oversight.** Artificial intelligence systems must help people without conditioning their decision-making. To do so, guaranteeing human control and supervision through appropriate governance mechanisms is necessary.
2. **Technical robustness and safety.** Algorithms have to be trustworthy and robust during all phases of a system's lifecycle in order to minimize the risk of mistakes, reverse erroneous results and create contingency plans to manage potential unforeseen events in their operation.
3. **Privacy and data governance.** Data privacy and protection must be guaranteed, because of which it is essential for people to be able to be informed of the information being processed and to control it.
4. **Transparency.** The traceability of AI systems must be guaranteed and provide, to the extent possible, information explaining an algorithm's decision-making process.

5. Diversity, non-discrimination and fairness.

Biases must be avoided from start to finish in the development of AI systems, forewarning about the possibility of direct or indirect discrimination as an outcome.

6. Societal and environmental wellbeing. For AI to be trustworthy, it is necessary to take into account its impact on the environment and to encourage sustainability and ecological responsibility from the viewpoint of society as a whole.

7. Accountability. It is necessary to implement devices allowing to audit AI systems and their outputs. Specifically, potential negative impacts must be highlighted and evaluated in order to minimize them.

These key requirements for the development of artificial intelligence applications outline the principles of the difference between the European framework of AI requirements and the way that Asian powers (and China in particular) are addressing the issue.

For example, we can look at China's social credit system, which is a system that scores citizens and businesses by analyzing a variety of private data (their finances, interests, social media activity, purchases, images, travel, tax obligations, etc.). Its end goal is to assign a social score (a sort of trustworthiness rating) to all people and businesses, which allows or prevents them from engaging in certain activities, including access to certain services and jobs. While public information on the system is scarce, the way in which the boundaries between the public sphere and peoples' privacy are dissolving highlights the risks of the improper use of artificial intelligence in terms of discrimination, segregation and the violation of data or personal privacy.

However, the Asian model is not the only one

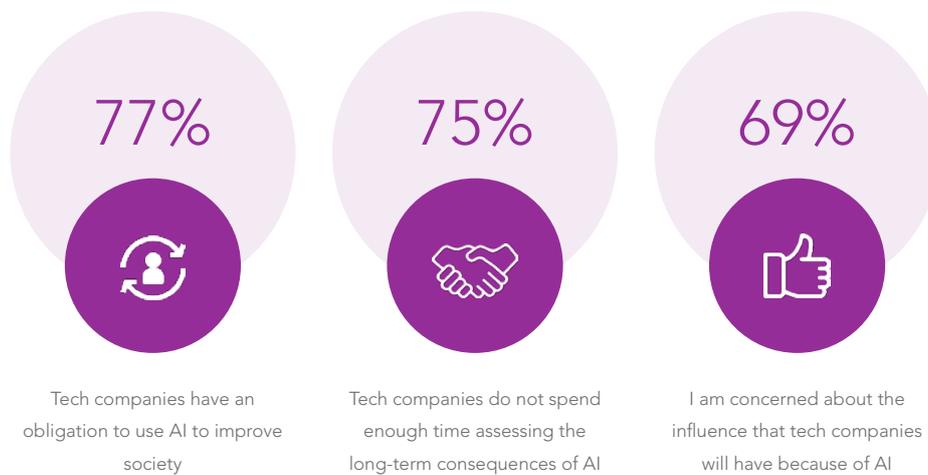
that comes with potential discrimination risks. Applecard, a credit card launched in August of 2019 managed by the investment bank Goldman Sachs, triggered a wide-reaching scandal around biases and explicability. On Twitter, one of the bank's customers claims that it had offered him a line of credit on his card that was 20 times greater than that of his wife, despite the fact that she had a better credit score than him and their finances and wealth were very similar. Steve Wozniak, Apple's cofounder, complained about something similar, later talking about the algorithm's discriminatory tendencies. The full complexity of the case, which is being investigated by the New York Department of Financial Services, came into light when Goldman Sachs revealed that not only was there no hidden intentionality in the processing of customer data, but also that the algorithm was completely unaware of her gender, in such a way that the discrimination in its decisions had to be related to the scoring or penalization of indirect variables, such as certain affinities or behaviors.

A less subtle example was the gender-based discrimination in Amazon's programmer hiring system, which in 2014 developed an artificial intelligence tool that penalized the resumes of female engineers. The program, which was ultimately canceled, was one of the first controversies around the need to supervise the automated decisions of algorithms.

However flashy these counterexamples may seem, they should not hide the fact that the ethical application of AI is an opportunity to provide additional value to companies. As argued by the European Commission's High-Level Expert Group, trustworthy AI stimulates reflection on the protection of individuals, and can contribute to achieving a fairer society, furthering citizen well-being and promoting equality through the distribution of social, economic and political opportunities.

A 2019 survey by the communication firm Edelman concludes (see Figure 14) that 77% of IT directors think that companies in the sector have the obligation to use AI to better society. The other side of the coin, though, is that 69% of them fear its potential influence.

Figure 14. Survey on the responsible use of AI

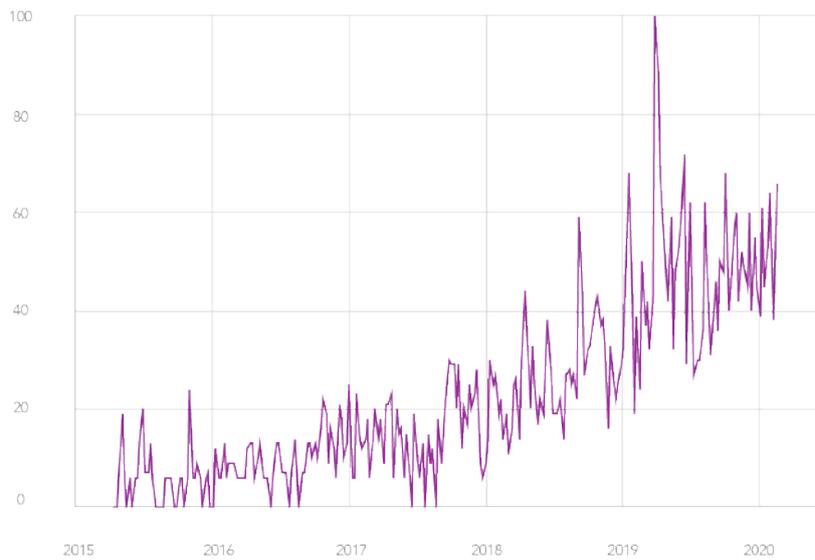


Source: Edelman, 2019

The ethics component is one of the features highlighted by the European Banking Authority (EBA) as one of the trends requiring an appropriate regulatory framework. Some large companies, such as Microsoft and Salesforce, have already hired ethics specialists to avoid potential discriminatory bias in their algorithms with regards to race, gender or any other undesired feature. Moreover, the consulting firm Gartner predicts that by 2023, more than 75% of large organizations will have hired AI specialists to reduce reputational risks.

The growing concern around the ethics aspects of artificial intelligence is conveyed by a graph of the percentage interest in Google searches for the term on the global level, which has clearly been experiencing an increasing trend over the past five years. The peak in interest was recorded during the first 15 days of April 2019, which coincided with the controversy around Google's AI Board (see information at the end of this chapter) and the publication of the European Commission's guidelines on ethics in artificial intelligence.

Figure 15. Evolution of global interest in AI Ethics (popularity in internet searches)



The results reflect the interest in the term “AI Ethics” as a function of the maximum number of searches recorded between April 2015 and February 2020, with 100 being the maximum popularity value

Source: In-house calculations based on Google Trends, 2020

Facial recognition: the public face of the controversy

The debate on the drawbacks of artificial intelligence tools is focused on areas in which the personal data being processed are particularly sensitive or more closely related to the right to privacy, as is the case of health, legal or financial data. Nonetheless, from the point of view of techniques, one of the most controversial is facial recognition, a variant of biometric identification, the indiscriminate use of which by some governments—and China in particular—has triggered protests among minorities and racial groups.

The European Commission has warned against using it in public areas unless this use is fully justified by essential reasons related to society’s well-being, stating the opinion that its application constitutes a serious risk to fundamental human rights. In addition,

the OECD has declared that it is in favor of the cautious use of facial recognition, and if possible, with people’s consent. Even the Vatican, in a rare statement on the dangers of artificial intelligence, has joined the ranks of the institutions warning against facial recognition.

Some governments have gone even further. In 2019, the San Francisco municipal government prohibited its use by the police and other municipal services. This controversy has made its way into the business world. Multinational corporations like Microsoft, Apple or Facebook have canceled or modified projects related to using it, and have refused to sell their facial recognition applications to the American police until a specific regulatory framework has been developed.

The global interest in ethical guidelines

In addition to the European Union, many other countries and institutions have expressed interest in the ethics framework of artificial intelligence, although almost always from the viewpoint of general stances and not regulatory enforceability. For example, in 2019, the Organization for Economic Cooperation and Development approved a document containing five recommendations or principles according to which AI must:

- Promote inclusive growth and sustainable development
- Respect the law, human rights and democratic values
- Be transparent and guarantee that its results can be understood
- Operate robustly and securely
- Guarantee accountability during all system phases

Furthermore, in 2020 the United States published a series of principles on artificial intelligence, including some related to its consequences, such as the need to guarantee justice, nondiscrimination, transparency and security.

Other national initiatives underway include the United Kingdom's guide on using AI in the public sector, the ethics framework being developed in Australia, the regulation approved in Canada to guarantee the transparency, lawfulness, accountability and fairness of automated decisions or the Monetary Authority of Singapore's (the country's central bank) 14 principles for the development of AI and data analysis in the financial sector.

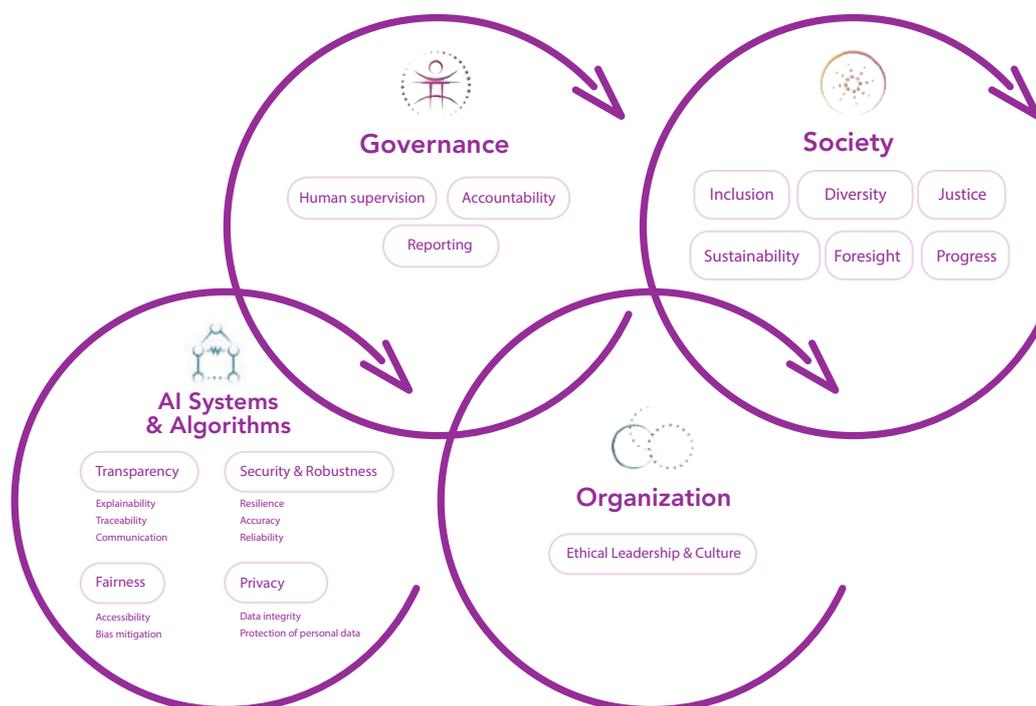
A strategic framework for every organization

Four areas addressing the ethical challenge of AI

The multiple ethical consequences of AI are generating a broad consensus around concepts (such as the bias or trustworthiness of algorithms), concerns (the fairness of results, transparency) and objectives (individual and societal well-being). These must be considered by financial institutions when designing and implementing their strategy for using data analysis and AI. This challenge implies the need to address the issue from a mixed and comprehensive viewpoint, encompassing both bottom-up

initiatives (all projects related to AI must consider their ethical implications) and a top-down approach (which analyzes their social impact and establishes an appropriate organizational strategy). The results of this dual course of action is a framework of operation that intertwines four spheres of strategic action (AI systems, governance, organization and society), each of which has different management pillars or levers.

Figure 16. Framework for an ethical AI



Source: everis

Algorithms and AI systems

The rapid development of technology in recent years—and its predicted acceleration in the immediate future—is resulting in exponential growth in AI’s capacity to transform processes and generate new business models, services and experiences. Leading organizations are already investing significant resources to ensure that the development and operationalization cycle of machine learning models (machine learning ops, or MLOps) meets market needs. Financial institutions need industry and data professionals to work together and use AI to generate new value proposals, allowing them to expand their reach. This implies the integration, development and continuous training of models that automate the process of making decisions quickly, accurately and

to scale—in other words, over a large volume of data. In this comprehensive approach, the challenge is to include ethics principles in all phases of the cycle, and for the agility of work models to be compatible with them.

In this sense, algorithm management needs ways to guarantee transparency (which includes explainability, traceability and reporting), fairness (accessibility and the mitigation of bias), security and robustness (resistance, rigor and reliability) and privacy (data integrity and privacy protection).

- **Transparency.** This is one of the most demanding aspects in terms of attention and resources, considering its importance for organizations and all of their interest groups (customers, employees, shareholders, etc.). In the finance sector, there is a

growing desire among clients and users to understand the decisions of AI systems, insofar as they condition significant aspects of their relationship with credit or investment. Transparency must also be a guiding principle for creators involved in development and approval processes; for legal specialists, who need to study the decision-making process in depth in the event of a dispute or accident; and for society in general, as its trust in technology will greatly depend on the ability of organizations and financial institutions to put forth a clear framework of action.

In this context, the concept of explainability is particularly important for developing and implementing an ethical AI process. In addition to attempting to explain the process behind the decisions of apparently inscrutable algorithms like neural networks, it also (and this is critical) attempts to explain this to different participants (business and communication departments, analytics departments and the institution's customers, shareholders, regulatory authorities or investors), especially if these decisions could have an impact on the financial exclusion of certain groups. To do so, the system must incorporate tools allow the algorithm to explain its actions or decisions to the person asking for this information (or even if nobody asks for it). It also must do this in a language and with a level of reasoning accessible to the majority of people, avoiding hard-to-understand technical details. Ultimately, the goal is not only to explain but for the explanation to be understandable and reach all sectors in which artificial intelligence has a significant impact on people's economic and social development.

In this sense, the idea that "the algorithm did it" is no longer an acceptable pretext. If the results of automation have undesired consequences, investigating an algorithm's lifecycle (the data used to train it, variable

selection criteria, the teams involved in development...) should guarantee the clear identification of events and responsibilities.

The ease with which AI techniques can be explained varies from one to the next. If we focus on machine learning families, decision trees, naive Bayes models or linear regression, they are generally characterized by their simplicity, which is associated with a greater degree of explainability. On the other hand, more complex techniques like deep learning—a variant of artificial neural networks which incorporates a large number of intermediate layers into the system—tend to make it difficult to explain results.

Currently, the requirement of explainability is a challenge in sectors like banking and insurance, which intensively use AI in processes with a direct impact on assessing people in order to grant them credit, financing or insurance. According to a survey conducted by the European Banking Authority (EBA), 35% of European financial institutions have already implemented AI initiatives related to risk scoring (for more information, refer back to Section 3 of this report).

Therefore, explainability has become a fundamental requirement for ensuring the fairness of AI systems and protecting citizens against discrimination and undesired biases. The European Union's General Data Protection Regulation (GDPR), which entered into force in 2018, states that all European citizens have the right to receive an explanation of any automated decisions made based on their personal data.

Another two aspects of the transparency factor are traceability and communication, which complement explainability.

Traceability requires all data collected and processed—as well as all of the steps taking

place from the selection of the algorithm to training, developing, implementing and monitoring it—to be perfectly documented in order to be identified at any time. Imagine the case of a small business whose loan has been denied based on an automated decision: the system must make it possible to identify the data used to train the algorithm that made the recommendation. Traceability is essential for more quickly detecting potential problems and reversing erroneous results.

Communication is another key to increasing transparency. Users must always be informed that they are interacting with AI systems.

- **Fairness.** The equality or fairness of an algorithm is another one of the fundamental pillars of ethical AI, and is also one of the most conflictive, especially with regards to aspects such as gender or racial discrimination, or elements related to people's personal life, such as religious beliefs or sexual orientation.

First of all, the system must guarantee accessibility for all people, regardless of age, gender, capabilities or other traits. In particular, it must guarantee accessibility for people with functional diversity. As a result, AI must maintain a flexible design focus, allowing the system to interact with a broad variety of users in order to encourage their access and participation.

Secondly, the model must be prepared to mitigate unfair or undesired biases that could discriminate against people based on race, ethnic origin, religion, gender, sexual orientation, disability or any other personal trait. It is necessary to recognize that discrimination can be introduced during any of the phases for implementing and developing the lifecycle of an AI system. As a result, it is necessary to ensure that:

- The data set is representative, relevant for the desired effects, rigorous and generalizable.
- The design does not include variables, features, processes or analytical structures (correlations, interactions and inferences) that could be considered unjustifiable or unreasonable.
- The results do not have a discriminatory effect on the lives of the people involved.
- The implementation is carried out by professionals with adequate training on how to make the system operate responsibly and without bias.

- **Security and robustness.** This is a very important factor, as potential security failures can seriously harm results and undermine the public's trust. It encompasses both the security of models with respect to error prevention as well as potential malicious attacks against systems, called data poisoning, which consist of providing poisoned data in order to corrupt results. This is what happened in 2016 in the case of Microsoft's chatbot Tay, which, as a result of being trained to learn from users' conversations, started to make xenophobic and racist statements. As virtual assistants become more present in interactions with customers, it is important to control this element, which can potentially have a big impact on an institution's brand image.

A system is considered secure when it is capable of maintaining the integrity of information and its operational dimensions even under adverse conditions. To guarantee that a system operates in accordance with security criteria, three objectives must be prioritized:

- **Resilience.** The system must be able to operate adequately in an environment that is hostile, whether due to a malicious intervention, the implementation of an error or the introduction of inappropriately biased

patterns.

- **Accuracy.** It must be calibrated using performance metrics showing the proportion of examples that generate a correct or incorrect output.
- **Reliability.** This element requires the system to behave in line with the expectations of its creators, even when unexpected changes, anomalies or disturbances take place.

All of this requires an exhaustive process of testing, validation and reevaluation. Furthermore, adequate supervision devices must be established to ensure that it operates properly in the real world.

To increase security and facilitate customer identification, some of the techniques used in the financial sector are biometrics, including facial recognition, which is used as a part of authorization or identity verification to access personal bank accounts. Although facial recognition is a controversial tool due to its potential for violating privacy (see the information attached at the beginning of this chapter), its use is not problematic in the financial sector so long as the person's

consent is obtained in advance and the scope of this use is limited to identity in the banking sphere.

One AI security concern is the increasing proliferation of deepfakes. Deepfakes are videos or audio tracks manipulated using artificial intelligence techniques (generally speaking, deep learning, hence their name) allowing the user to fabricate reality and attribute fictitious statements or behaviors to certain people. Deepfakes are becoming increasingly more believable and difficult to detect, thus constituting a risk for the security of many industries, including the financial sector.

- **Privacy.** Ethical AI sees the concept of privacy as a value to be defended and a right to be protected. It can be addressed from different viewpoints (including the technical, research and regulatory perspectives), but the common denominator of these is the obligation to preserve the protection and security of personal data. One concept to keep in mind is privacy by design, which refers to the need to guarantee—starting as of the



very first phases of creating a system—that privacy will be an inherent and fundamental component throughout its lifecycle. Obviously, the principle of privacy and data protection does not only apply to AI systems—it encompasses all of an organization’s operations. For this reason, the majority of companies have already implemented processes to ensure privacy, and possess the experience necessary to incorporate these processes into their AI systems.

Governance

Following the explosion of big data, over the past few years, we have witnessed a growth in the importance of data governance and the incorporation of regulatory principles to guarantee proper management. We are currently witnessing a similar process in AI governance, which aims to ensure that an algorithm’s lifecycle (design, development, implementation to scale and monitoring) takes place while incorporating ethical principles.

Therefore, the goal of AI governance is to incorporate and manage the ethics framework that guides an organization’s values and principles. This challenge highlights three main ideas:

- **Human supervision.** This is a fundamental line of action for uprooting some of the public’s persistent fears around the possibility that robots or machines will end up replacing humans and taking control of all activities. AI is designed to increase humans’ capabilities, not to replace them. This way of seeing things makes it necessary to develop a new way of looking at the interaction between both parties, in which human supervision is essential for increasing value and generating trust.

To address this collaboration model, which the technical literature refers to as human-machine interaction or augmented AI, we must start with the idea—mentioned at the beginning of this report—that so-called weak AI (which is applied in specific contexts) is not autonomous in itself. Instead, decision-making is carried out through a combination of human perspective and automated recommendations.

However, different degrees of supervision exist and are determined by governance devices that manage the automation levels of an AI system.

On the scale of human intervention from least to greatest, first comes highly automated systems (human on-the-loop) in which humans’ participation is limited to exceptions and overseeing its operation. This approach is used in certain applications in which automated decisions must be made practically in real time, such as suggesting financial products based on recommendation algorithms.

On the intermediate level are automated flexible systems (human-in-command), in which humans choose the situations in which AI processes apply. They also have the ability to ignore AI decisions. Therefore, we would be referring to nearly real-time contexts, where, for example, marketing campaigns for certain financial services target the customer segments identified as being more likely to purchase the products.

Last of all, the level with the most human intervention leads us to a less automated system (human in-the-loop) in which people are involved in every decision-making cycle and approve or reject each system proposal. This would be the case of AI applications in which processes do not have to operate in real time.

- **Accountability.** We must ensure that it is possible to audit systems and find out who is responsible throughout their lifecycle. In this sense, the goal of AI governance is to ensure compliance with ethics principles during each phase of the process. It also hands over the role of auditing systems to robust processes and tools, allowing us to trace and reproduce the steps of the decisions made to develop a model.

In this context, it is necessary to be aware that human judgment plays a crucial role in the “objective” decision-making system that designs AI. People participate in developing algorithms, making decisions on system use and in conditioning their results. Therefore, all of the professionals involved in the process (creators, designers, developers, etc.) are responsible for considering the impact of this, as are the companies investing in implementing them. Responsibility also goes hand-in-hand with the obligation of accountability when faced with potential errors or damages caused by the system.

- **Reporting.** The AI model must be prepared to report on the actions and decisions contributing to a specific system output,

as well as to address the consequences of this output. Identifying, evaluating, communicating and minimizing the potential harmful effects of AI systems is particularly relevant for those directly or indirectly affected by them.

In this sense, anonymous whistleblowers, NGOs and other organizations conveying legitimate concerns related to systems based on AI must be duly protected. Using impact assessments before and after the development, rollout and use of AI systems may be useful in reducing their harmful effects.

Organization

Companies must lead the way in creating internal awareness of the importance of AI and communicating the related ethics principles to the entire organization. Creating an appropriate business structure to convey these values and incorporate them into the company’s culture will facilitate the development of an AI policy that can be sustained over time. On the other hand, internal and external collaboration will make



it possible to find out the organization's needs and better meet them, as well as to promote having an adequate impact on society.

Moreover, developing and contrasting the values associated with AI is consistent with the growing trend among employees and consumers to see companies committed to ethics principles in a positive light. This commitment must be explicit and concrete, materializing in the form of a business structure that supports it.

One idea for implementing or strengthening business devices for the responsible use of AI is to create an ethics committee that evaluates and manages internal best practices, paying special attention to their impact on customers, employees and society.

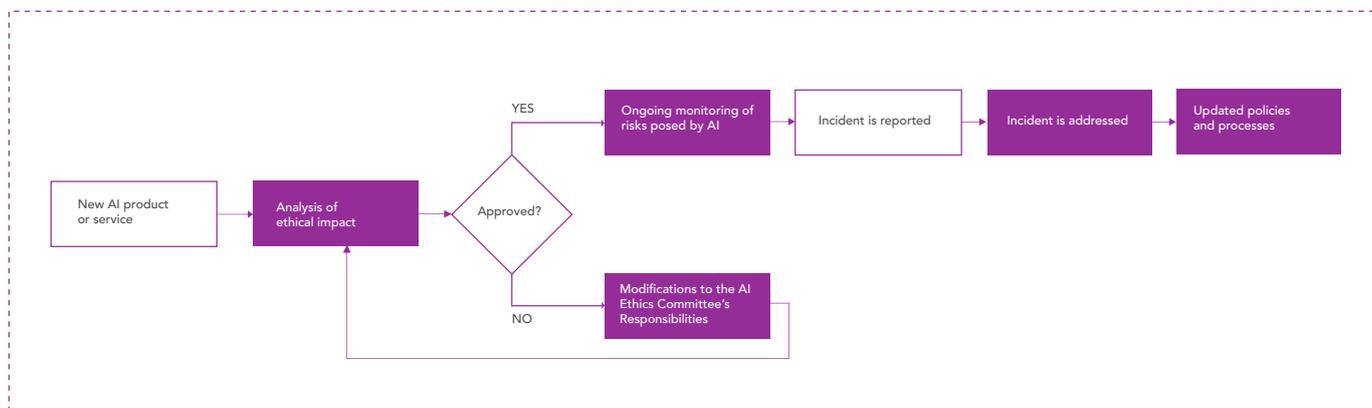
This AI ethics committee can play a dual role: both as a consulting and advising body and as the entity responsible for decision-making in certain matters. In this way, it can play a deterministic role in building an AI culture based on ethics principles while also helping to increase the transparency around these processes within the organization.

Diverse viewpoints and perspectives must be represented on the ethics committee, including independent experts and people from inside and outside of the organization and with different professional experience (specialized and nonspecialized). This includes data scientists, data protection regulations specialists, representatives of business management or the company's corporate social responsibility department. Appointing its members is a sensitive and crucial task in order for the committee to be able to properly fulfill its role, as Google is well aware. In 2019, the American giant set up an external committee of AI ethics advisors.

Nonetheless, it was forced to dissolve it ten days later, faced with the criticism of its own employees, who flocked to sign a letter protesting the appointment of the president of a conservative charity against immigrant rights and gender minorities.

The effectiveness of the ethics committee also depends on clearly defining the framework of its actions and review and communication processes, as well as its effect on the organization's policies, especially when launching a new product or service (see Figure 17).

Figure 17. Example of a process diagram for launching a new AI product or service



Source: everis

Society

AI designers and users must be aware that the technologies that they are using have huge transformative potential and can have long-term consequences for individuals and society. As a result, ethical AI must serve the community and must generate tangible benefits for citizens through the principles of inclusiveness, diversity, fairness, sustainability, foresight and progress.

In this sense, a system's supervisors must work in full awareness of their impact on the real world and anticipate the needs and problems that may result from its use, always safeguarding essential human values like empathy, free will or individual expression, and encouraging people's self-fulfillment and social cohesion.

AI's responsibility to have a positive social impact is becoming even more relevant in the context of the coronavirus pandemic. While the most common examples are mobility applications, contact tracing or confinement control, there is no denying that over the

medium term, we are facing a new data reality. The finances of millions of customers and businesses are being affected, and as a result, financial institutions have to constantly analyze the balance between risk and their ability to adapt AI decisions to new credit needs and the social context in which they emerge.

Last of all, organizations must guarantee that AI works properly, which is an ethics declaration in itself. If we already require financial institutions to ensure that their employees behave ethically and provide service to the community in accordance with certain action criteria, we likewise have to apply this logic to the development of AI and encourage the contribution of technology to the prosperity of society.

Benefits and fears: the two faces of artificial intelligence

How is artificial intelligence seen by the general public? To answer this question, everis DX Research Center, a member of everis Living Lab's technological innovation laboratory, held a discussion on the advantages and drawbacks of using AI. To do so, it created a focus group that consisted of nine people of different genders and ages with limited experience with advanced technology, with the main goal of understanding what people think about the impact of AI on their everyday life and how this opinion affects the use of products and services.

The debate gave rise to important concerns, which are likely influenced by the media, around the possibility that machines will replace human beings in many important decisions and will end up eliminating human-specific practices, such as empathy, emotional intelligence or personal interaction. In particular, participants fear what could happen in the future when new artificial intelligence capabilities—considered a limitless field of knowledge—are developed. On the positive side of the coin, the participants in the discussion considered the effects of the already-consolidated applications of AI that make up a part of their everyday lives, in particular those that improve security and health.

The debate's conclusions show that artificial intelligence projects should keep these perceptions in mind and emphasize the complementary nature of AI in human decisions, under all circumstances highlighting that people have the ability to take control of the process. In addition, it is necessary to be cautious with language, minimizing highly specialized terms. Moreover, functionalities

and products must be introduced gradually to facilitate the public's progressive familiarization with them.

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