LUISS

Degree Program in Management

Managerial Decision Making

THE INTEGRATION OF ARTIFICIAL INTELLIGENCE INTO CORPORATE DECISION-MAKING PROCESS. OPPORTUNITIES AND CHALLENGES.

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Accademico 2024/2025

Introduction

The topic of decision making has gained increasing importance over time, not only in economics and management studies, but also in the legal, political, and technological fields. The ability to make effective, rapid, and informed decisions is crucial to the functioning of complex organizations, be they businesses, public institutions, or states. The advent of Artificial Intelligence (AI) has made this issue even more central, introducing new tools capable of supporting, and potentially transforming, decision-making processes. This thesis addresses this topic in four chapters.

Chapter I is devoted to reconstructing the main theoretical approaches to decision making, with particular attention to the rational, behavioral, and organizational models that have shaped the evolution of the discipline. This analysis allows us to outline the interpretative categories necessary to understand the impact of emerging technologies on decision-making processes.

Chapter II addresses the convergence between Artificial Intelligence and decision-making, highlighting how machine learning algorithms, deep learning, and predictive analytics techniques are progressively complementing human activity in complex decisions. From this perspective, AI is not just an automation tool, but a force that redefines the dynamics of power, responsibility, and rationality within organizations.

Chapter III analyzes the sectoral applications of artificial intelligence, with particular reference to the fields of economics and finance, healthcare, law, and corporate governance. Through these concrete examples, the benefits of AI-assisted decision-making in terms of efficiency and accuracy are highlighted, as well as the risks associated with algorithmic opacity, discrimination, and accountability issues.

Finally, Chapter IV addresses the geopolitical dimension of the relationship between AI and decision-making, analyzing the TikTok case, which has become a battleground between the United States and China. This case demonstrates how control of digital platforms and their AI-driven algorithms is not just an economic or technological issue, but also a strategic stake in the global balance of power, directly impacting national security, digital sovereignty, and the definition of the future international order.

The thesis, as a whole, therefore aims to offer a critical reflection on the transformations underway, demonstrating how artificial intelligence, far from being a mere technical tool, is a structural factor of change in decision-making processes at the micro (organizations and businesses) and macro (institutions and geopolitics) levels.

CHAPTER I

DECISION MAKING THEORIES: THEORETICAL FOUNDATIONS

Premise

In the context of choice analysis, understanding the mechanisms underlying the decision-making process is essential to interpreting the behavior of agents and developing models capable of supporting effective choices under conditions of risk and uncertainty. *Decision making,* understood as the process by which individuals and organizations select between alternatives, has long attracted the interest of economists, psychologists, and organizational theorists, giving rise to a wide range of theoretical approaches and analytical models.
This first chapter aims to reconstruct the theoretical foundations of *decision making* with reference to the financial, administrative, healthcare context, etc., offering a critical overview of the main conceptual evolutions. The first section (1.1) introduces the definitional and methodological aspects of decision theory, clarifying the key concepts and basic assumptions. Section 1.2 analyses the transition from classical rationality, which presupposes fully rational agents, to bounded rationality, which takes into account cognitive and informational constraints. The third section (1.3) delves into the role of cognitive *biases* and decision heuristics, illustrating how these factors distort financial choices in real contexts. Finally, section 1.4 compares prescriptive, descriptive and normative models, highlighting

their theoretical differences, application purposes and implications for analysis.

Through this approach, the chapter aims to provide a theoretical basis for understanding financial, political, administrative decisions, etc., not only in ideal terms, but also in their concrete and behavioral dimensions, laying the foundations for the subsequent operational and empirical analyses of the thesis.

1.1 Decision making: defining aspects

The decision-making process is a crucial aspect of strategy definition and risk management. Decisions are strongly influenced not only by quantitative factors (think of the financial field, which is based on expected returns, cash flows, and capital structure), but also by qualitative and behavioral factors. Classical economic theory assumes rational agents capable of maximizing expected utility[1], but subsequent studies in behavioral analysis have highlighted how real-world decisions are often distorted by cognitive *biases* and heuristics. In particular, the [2]*framing effect, loss aversion, and overconfidence* are believed to significantly influence choices, sometimes leading to systematic deviations from theoretical predictions.

Decision-making in healthcare and public administration presents unique characteristics, linked to the complexity of the contexts, the multiplicity of actors involved, and the public nature of the interests at stake. Unlike the private sector, where decisions are often geared toward profit

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[1] Markowitz, H. (1952). Portfolio selection. *The Journal of Finance* 7(1), 77–91.

[2] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrics*, 47(2), 263–291.

maximization, in public and healthcare organizations the primary objective is to ensure equitable, effective, and sustainable services, within a framework of regulatory, financial, and social constraints.

In the healthcare sector, *decision-making* must take into account a wide range of clinical, economic, ethical, and organizational factors. Choices regarding resource management, funding allocation, the introduction of new technologies, or the definition of treatment protocols have a direct impact on citizens' health and require a balance between scientific evidence, professional expertise, and public responsibility. Furthermore, unpredictable events such as pandemics or health crises test the system's ability to respond promptly and consistently. Similarly, in public administration, the decision-making process is often influenced by multiple interests, political pressures, bureaucratic delays, and budgetary constraints.

In this context, decisions must be motivated by criteria of transparency, legality, and a focus on the common good, and not just economic efficiency. This makes the use of decision-making support tools that foster participation, traceability of choices, and analysis of alternatives particularly important.

In both areas, the introduction of structured approaches to *decision-making*, based on reliable data, impact assessments and control mechanisms, can help improve the quality of decisions, strengthening citizens' trust and the legitimacy of institutions.

In the finance sector, financial data analysis, using quantitative tools and predictive models, has assumed an increasingly important role in supporting *decision-making*, especially in environments characterized by

high volatility and uncertainty[3]. Therefore, an integrated understanding of analytical and behavioral dimensions is essential to improve the effectiveness of financial decisions in a dynamic and complex environment.
Decision-making is embedded within various decision-making fields (risk management, corporate finance, behavioral finance), contributing significantly to the way decisions are made.
Risk management is an essential strategic function within modern organizations, aimed at identifying, assessing, monitoring, and mitigating risks that could compromise the achievement of corporate objectives. According to the framework defined by the *Committee of Sponsoring Organizations of the Treadway Commission* (COSO, 2004), *risk management* is an integrated and systematic process that involves the entire structure required to make decisions and supports the creation of value through an informed approach to uncertainty. In the financial sector, *risk management* is particularly important in measuring and controlling exposures related to market, credit, liquidity, and operational risks. In particular, the adoption of quantitative tools such as *Value at Risk* (VaR), Monte Carlo simulations, and *stress testing models* allows companies and financial intermediaries to assess the potential impact of adverse events and implement hedging strategies *and* optimal capital allocation[4]. In addition to technical tools, effective risk management requires solid *governance*, a prevention-oriented organizational culture, and transparent risk communication to stakeholders. In this context, *risk management* is not only a defensive function, but also an enabling element for strategic decision-making,

[3] Damodaran, A. (2012). *Investment valuation: Tools and techniques for determining the value of any asset* (3rd ed.). Wiley.
[4] Jorion, P. (2007). *Value at Risk: The New Benchmark for Managing Financial Risk* (3rd ed.). McGraw-Hill.

capable of fostering the company's resilience and competitiveness in complex and turbulent markets [5].

Decision *making* within Corporate Finance is presented as a key discipline of business economics that refers to the financial decisions taken within the company, with the primary objective of maximising shareholder value (in this perspective it deals with the analysis of financing sources, management of the capital structure, evaluation of investments, distribution of dividends and liquidity management)[6]. One of the central concepts of Corporate Finance is the "valuation of capital" which sees companies having to choose between different investment opportunities using criteria such as the *Net Present Value* (NPV), the *Internal Rate of Return* (IRR) and the *Payback Period*. These tools allow for the comparison of expected returns with the cost of capital and the associated risk [7]and the correct allocation of resources towards projects with a high expected value represents one of the main levers of sustainable growth in the long term. Another fundamental theme of Corporate Finance concerns the capital structure, in this sense the theories of Modigliani and Miller (1958) deserve mention[8], as they were the first to lay the foundations for the study of the *trade-off* between debt and equity capital. Highlighting how in perfect markets, the financial structure does not influence the value of the firm. However, in the presence of market imperfections, represented by taxes, costs related to potential bankruptcy, and information asymmetries, the choice between *equity* and debt can have

[5] Lam, J. (2014). *Enterprise Risk Management: From Incentives to Controls* (2nd ed.). Wiley.
[6] Brealey, R. A., Myers, S. C., & Allen, F. (2020). *Principles of Corporate Finance* (13th ed.). McGraw-Hill Education, 98.
[7] Damodaran, A. (2012). *Investment Valuation: Tools and Techniques for Determining the Value of Any Asset,* cit., 88.
[8] Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporate finance and the theory of investment. *The American Economic Review,* 48(3), 261–297.

significant implications on the cost of capital and financial risk[9]. In recent years, Corporate Finance has evolved to include new challenges, including financial sustainability, ESG (*Environmental, Social, and Governance)* finance, and the impact of digital technologies on decision-making processes. Furthermore, growing pressure from institutional investors and civil society today calls for greater transparency and accountability in corporate decisions, pushing towards a finance that combines economic[10] *performance and social impact*. Therefore, today, Corporate Finance represents a dynamic and constantly evolving field, requiring an integrated approach between theory, practice, and innovation, in order to support companies in pursuing strategic objectives in increasingly competitive and regulated markets. Finally, the topic also brings into play the aforementioned Behavioral Finance, which represents an interdisciplinary field that combines economics, psychology, and social sciences. Cognitive and neuroscience to explain financial decisions that deviate from traditional rational models. Contrary to the assumption of perfect rationality and efficient markets, typical of the *Efficient Market Hypothesis*, behavioral finance highlights how individuals are subject to systematic errors of judgment, influenced by emotions, cognitive *biases*, and decision-making heuristics[11]. One of the discipline's fundamental contributions is Prospect Theory, according to which investors evaluate gains and losses in relative terms with respect to a reference point, showing a stronger aversion to losses than a propensity for gains. This leads to irrational choices, such as holding losing securities

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[9] Myers, S. C. (1984). The capital structure puzzle. *The Journal of Finance,* 39(3), 575–592.

[10] Giese, G., Lee, L. E., Melas, D., Nagy, Z., & Nishikawa, L. (2019). Foundations of ESG investing: How ESG affects equity valuation, risk, and performance. *The Journal of Portfolio Management,* 45(5), 69–83.

[11] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decisions under risk. *Econometrics*, 47(2), 263–291.

in a portfolio to avoid “realizing” a loss (the *disposition effect*) or seeking excessive risk in losing situations. Other relevant phenomena include overconfidence (overestimation of one's decision-making abilities), *confirmation bias* (the tendency to seek only information consistent with one's beliefs), and *herding behavior*, or the imitative behavior of investors, which can contribute to the formation of speculative bubbles[12]. As can be imagined, behavioral finance has significant implications not only for individual investors, but also for *policy makers*, investment funds, and regulators, who are called upon to design tools and regulations that take into account the cognitive limitations of economic agents[13]. In short, *behavioral finance* offers a more realistic and complete picture of the behavior of economic agents, transcending the purely rational approach and contributing to a better understanding of market anomalies and financial crises.

1.2 Classical rationality vs. bounded rationality

The evolution of the concept of “rationality” in economics represented a fundamental methodological turning point in the study of the behavior of economic agents. *Classical rationality,* which has its roots in the “expected utility” theory proposed by von Neumann & Morgenstern in 1944, presupposes perfectly informed agents, capable of processing all available alternatives and making optimal choices aimed at maximizing utility or profit.

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[12] These mechanisms often render the forecasts of traditional pricing models ineffective and require alternative approaches to analyzing risk and market dynamics.

[13] In particular, the so-called *nudging finance,* inspired by the work of Thaler and Sunstein (2008), proposes "gentle" interventions to orient financial decisions towards more rational outcomes, while preserving individual freedom of choice.

The maximum degree of utility will be defined in various ways depending on the context in which it is considered. Thus, if the choice concerns healthcare, it could involve maximum health protection, while if it concerns a public administration, it will concern maximizing the services enjoyed, in a company, maximum profit, and so on.

For decades, this vision has fueled models of neoclassical microeconomics and traditional finance, such as the *Efficient Market Hypothesis,* according to which prices fully reflect all available information. Since the 1950s, economists and cognitive psychologists have challenged the assumption of absolute rationality by introducing the concept of *bounded rationality,* which recognizes the cognitive, informational, and temporal limitations of agents[14]. According to this perspective, individuals do not aim to maximize, but rather settle for "satisficing" solutions *within* a context of imperfect information and limited computational resources. These observations paved the way for the emergence of the aforementioned "behavioral finance," which integrates concepts such as cognitive *biases,* emotions, and heuristic decision-making processes into the economic paradigm. Comparing the two approaches highlights a shift from a normative and idealized view of economic behavior to a more descriptive and realistic one. In economics, while classical rationality continues to provide a useful theoretical basis for modeling, bounded rationality can explain recurring empirical phenomena such as market anomalies, irrational investor behavior, and financial instability. In financial analysis, this has direct implications for forecasting models, the interpretation of market data, and the design of risk management tools that better reflect the reality of market

[14] Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics,* 69(1), 99–118.

participants' decision-making. The evolution of global financial markets has further challenged the hypothesis of classical rationality. Thus, the growing complexity of financial instruments, the speed of transactions, the digitalization of information, and the amplification of collective behavior through the media have accentuated the discrepancies between the model of rational *homo economicus* and the actual behavior of investors. Events such as the *dot-com bubble (1999–2000), the subprime mortgage* crisis (2007–2008), and the high market volatility during the COVID-19 pandemic demonstrate how markets are often governed by emotional dynamics, overreactions, and imitative behaviors, rather than decisions based on objective assessments of fundamentals. In response to these critical issues, behavioral finance and the Adaptive Markets Hypothesis (AMH*)* suggest[15] a dynamic approach, in which agents' rationality is considered subject to change over time, adapting to the competitive environment, learning, and evolving market conditions[16]. In this context, modern financial analysis must take into account not only historical data and quantitative assessments, but also the behavioral component and cognitive context in which economic choices occur. Recognizing the limits of classical rationality has led to a profound rethinking of forecasting models in financial analysis. Traditional models, based on assumptions of efficiency, normal return distributions, and risk neutrality, are often inadequate for anticipating extreme events or nonlinear market changes. Consequently, there has been a growing diffusion of alternative approaches, such as *agent-based* models and the use of *machine*

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[15] Lo, A. W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. *The Journal of Portfolio Management*, 30(5), 15–29.

[16] This vision allows us to integrate the traditional approach with elements drawn from evolutionary psychology, information theory, and neurofinance, offering a more realistic representation of financial decisions.

learning techniques to detect behavioral patterns and nonparametric forecasting models[17]. The operational implications are significant: in investment decisions, managers must consider the presence of cognitive *biases* and investors' nonlinear preferences; in risk management, models must be able to incorporate *stress scenarios* and behavioral dynamics; and in corporate valuation, distortions in the market's perception of value must be taken into account. Today, the increasing availability of granular data and the advancement of analytical technologies (e.g., artificial intelligence, *sentiment analysis*) offer new opportunities to develop predictive models that reflect the real complexity of financial behavior, overcoming the oversimplifications of neoclassical models.

1.3 Cognitive biases and heuristics

For every choice to be optimal, it should be able to count on the availability of all useful information so that it correctly reflects what is most appropriate.

Cognitive biases and heuristics represent fundamental psychological mechanisms for understanding the systematic deviations from rational behavior predicted by classical theory. Heuristics are mental shortcuts adopted by individuals to simplify complex decisions under conditions of uncertainty; while useful in many contexts, they can generate predictable and repetitive errors, known as *biases*[18]. Among the most relevant in finance is the aforementioned *overconfidence bias,* which leads investors to

[17] Hens, T., & Schenk-Hoppé, K. R. (2009). Handbook of Financial Markets: Dynamics and Evolution. Elsevier, 35.

[18]Among the first to describe them Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science,* 185(4157), 1124–1131.

overestimate their forecasting abilities, contributing to excessive trading and underestimation of risk. Another widely documented bias is *confirmation bias,* which leads individuals to seek and interpret information in a way that is consistent with their pre-existing beliefs, limiting the rational updating of expectations. The major problem lies in the fact that heuristics also influence the way investors assess probability and risk. The *availability heuristic,* for example, causes people to judge the probability of an event based on how easily they can recall similar examples, leading to overestimations of rare but salient events such as stock market crashes. The *anchoring effect,* on the other hand, refers to the fact that judgments are anchored to initial values, even if irrelevant, influencing *asset valuations*[19]. These phenomena have profound implications for the efficiency of markets and the reliability of financial forecasts, requiring the integration of behavioral models into decision-making processes. In this context, modern financial analysis faces the challenge of designing tools and methodologies capable of accounting for these cognitive distortions, to improve the quality of investment decisions and risk management. Recent history offers many examples of *biases* in the financial sector. During the tech bubble (1999-2000), many investors overestimated the future profitability of internet companies, often lacking real earnings. Overconfidence bias led analysts and investors to overestimate their ability to identify "future winners," while *herding* behavior generated a wave of widespread buying. Furthermore, *availability heuristics caused the few successes (e.g., Amazon,*

[19] The *anchoring effect* is a cognitive bias whereby people tend to base their decisions or estimates on an initial value—the "anchor"—even if that value is arbitrary or irrelevant. In finance, this can lead investors to overestimate or underestimate the true value of a security based on a previous reference price, such as the purchase price or a pre-existing *target price* .

Yahoo) to be perceived as representative of the entire sector, ignoring less solid companies. During the subprime mortgage crisis (which began in 2007), many investors, rating agencies, and *financial* institutions continued to view real estate as a safe, constantly growing *asset, anchoring themselves to historical data (e.g., the ten-year trend in real estate prices). The anchoring effect* prevented them from recognizing signs of a bubble. At the same time, *confirmation bias* led analysts and executives to ignore data that contradicted the dominant narrative, while the illusion of control led to underestimating the systemic risks posed by credit securitization. With the explosion of global COVID-19 cases in 2020, investors responded with mass selling. Loss *aversion* pushed many to liquidate their portfolios for fear of further declines, even in the absence of concrete information on the real economic implications while the *availability heuristic* Dramatic images and news stories became highly influential in risk perception. Furthermore, the negative *framing* of the media's presentation of the situation amplified panic and impulsive decisions. In 2021, the sudden *rally* in GameStop stocks, driven by retail users on Reddit (r/WallStreetBets), is an example of extreme *herd behavior,* fueled by viral dynamics rather than company fundamentals. Investors showed *overconfidence* in their strategies, often based on ideological or speculative motivations, and were strongly influenced by simplified narratives typical of *narrative bias.*

Table 1: Bias in financial crisis events

Event	Main biases	Demonstrations observed
GameStop meme -stock 2021	Herding, overconfidence, narrative bias, anchoring	Spectacular rally, coordinated trading, arbitrary targets
Bubble dot -com	Overconfidence, herding, availability heuristic	Tech overvaluation, mass imitation
Subprime crisis 2007–08	Anchoring, confirmation bias, illusion of control	Denial of real risk, selective attention to information

Source: Personal processing

Decision-making processes in fields other than finance raise the same challenges. For example, in healthcare and public administration, although guided by principles of rationality, transparency, and collective interest, decision makers are not immune to cognitive biases that can compromise the effectiveness and fairness of their decisions. In healthcare, for example, availability bias can lead doctors and managers to overestimate the likelihood of recent or emotionally significant clinical events, such as a pandemic or a critical case, at the expense of more statistically sound assessments. Decision-making requires a progressive approach, following steps, each of which should be supported by information.

Fig. 1: Decision making: steps

Source: umassd.edu

The anchoring heuristic, on the other hand, can influence diagnosis or treatment when professionals focus excessively on the first piece of information received (e.g., an initial suspicion), overlooking subsequent signals. These mechanisms, often unconscious, can also impact health policies, for example, in defining spending priorities or responding to health emergencies. In public administration, biases such as institutional conformity or the status quo effect can hinder the adoption of necessary reforms, encouraging the continuation of inefficient practices for fear of taking responsibility for change. Similarly, confirmation bias can lead public managers to select only information consistent with their initial hypotheses, reducing the objectivity of the decision-making process. Recognizing these cognitive limitations is increasingly important today, thanks also to the contribution of behavioral sciences and experimental economics. Targeted interventions, such as decision-making awareness training, structuring processes into transparent phases, or the introduction of behavioral nudges, can help mitigate the effect of biases and improve the quality of public and healthcare decisions.

1.4 Prescriptive, descriptive and normative models

Decision-making has traditionally been modeled through "prescriptive" approaches, which indicate how agents *should* behave to maximize expected outcomes, assuming rationality, consistency, and complete information. These models derive from expected utility theory (von Neumann & Morgenstern, 1944) and form the basis of many analytical tools used, especially in finance, such as optimal portfolio selection (Markowitz, 1952), real options valuation, and *asset pricing models* . The goal of these models is to provide a normative framework that guides decisions towards optimal outcomes under conditions of risk and uncertainty, through the application of quantitative criteria such as Net Present Value (NPV), Internal Rate of Return (IRR), or Value at Risk (VaR). However, the emergence of behavioral finance has highlighted the limitations of prescriptive models by recalling the aforementioned cognitive *biases,* emotions and informational limitations that compromise the efficiency of financial decisions. Consequently, a growing interest has developed in "descriptive" and "hybrid" approaches, capable of integrating prescriptive models with elements drawn from cognitive psychology and the observed behavior of market operators.

Unlike "prescriptive models," "descriptive models" aim to represent how financial decisions are actually made by individuals, taking into account cognitive limitations, emotions, and the real-world decision-making context. These models are based on empirical observation of investor behavior and assume that agents are not fully rational, but rather rationally bounded (*bounded rationality*), according to Simon's (1955) definition. From this perspective, decisions do not derive from the maximization of theoretical utility, but rather from simplified, heuristic, and adaptive strategies, often influenced by cognitive *biases* such as loss aversion, anchoring, or imitative behavior. This approach, although less normative, is essential for understanding real-world market dynamics, improving the quality of financial analysis, and designing decision support tools that are more in line with operational reality. "Normative models" represent an essential component of financial *decision-making* theory, as they establish ideal choice criteria based on economic rationality. They do not describe the actual behavior of agents, but rather outline how *they should* act to make optimal decisions, assuming logical coherence, complete information, and the ability to maximize expected utility (von Neumann & Morgenstern, 1944). In the financial field, normative models find direct application in numerous decision-making tools, such as cost-benefit analysis, the evaluation of investment projects (through indicators such as NPV, IRR), portfolio construction according to Markowitz's theory (1952), and risk measurement through metrics such as Value at Risk (VaR). The adoption of these models presupposes full and stable rationality on the part of agents, as well as an efficient market context, in which all relevant information is already incorporated into prices[20]. Although this approach provides a solid and formally rigorous theoretical basis for financial analysis, it has significant limitations in describing real-world decisions, especially in contexts of strong uncertainty or emotional pressure. For this reason, while

[20] Fama, E. F. (1970). Efficient capital markets: A review of theoretical and empirical work. *The Journal of Finance*, 25(2), 383–417.

normative models remain fundamental tools in managerial practice and financial engineering, they must be integrated with behavioral and adaptive approaches capable of capturing the complexity and irrationality typical of real markets. The discussion thus far provides a theoretical overview of financial *decision-making,* highlighting its conceptual evolution from classical rationality models to more recent behavioral approaches. Initially, economic theory described agents as perfectly rational subjects, capable of making optimal choices based on complete information and well-defined logical criteria. However, this normative vision has increasingly proven inadequate in describing the actual behavior of investors, especially in contexts characterized by high uncertainty and decision-making complexity. The introduction of bounded rationality and the development of behavioral finance have provided a better understanding of the cognitive dynamics that influence financial decisions. Cognitive *biases* and heuristics demonstrate how individuals tend to systematically deviate from the principles of pure rationality, giving rise to judgment errors, imitative behaviors, and emotional reactions. In this context, the comparison between prescriptive, descriptive, and normative models has highlighted the need to integrate different theoretical tools to effectively understand and manage the decision-making process (these elements form the theoretical foundation upon which modern financial analysis is based, increasingly attentive to the psychological and behavioral dimensions of decisions). With the aim of translating theory into operational practice in the following chapters, these concepts will be explored in greater depth through the analysis of the use of artificial intelligence, new application models, and quantitative tools used to support financial decisions. In healthcare and public administration, the quality of decision-making is essential to ensuring fairness, efficiency, and trust in institutions. Descriptive models focus on how decisions are actually made, taking into account cognitive limitations, environmental pressures, and actual organizational dynamics. In healthcare, for example, these models help understand why professionals may deviate from protocols, relying on intuition or habits. In public administration, they are useful for analyzing the behavior of public officials, which may be influenced by bureaucratic constraints, internal politics, or local interests. Normative models, on the other hand, represent the ideal vision of decision-making: they are based on logical, impartial, and fully informed criteria, with the aim of defining what would be "rationally correct" to do. They often form the basis of clinical guidelines or administrative directives and serve as a reference for designing fair and transparent public policies. However, these models tend to overlook practical complexities, such as resource scarcity or the uncertainty of outcomes. Finally, prescriptive models seek to bridge the gap between theory and reality by proposing tools and strategies that help decision makers concretely improve their performance. In healthcare, for example, they translate into triage algorithms, diagnostic support systems, or waiting list management procedures, while in public administration, they are expressed through simplified decision-making protocols, performance indicators, or cost-benefit analysis tools, aimed at guiding more informed choices[21].

[21] The integration of these three models allows for a more complete and realistic understanding of the public decision-making process: descriptive models reveal how decisions are made, normative models how decisions should be made, and prescriptive models indicate how decisions can be made better, taking into account available resources and real-world operating conditions.

CHAPTER II

CONVERGENCE BETWEEN AI AND DECISION MAKING

Premise

In recent years, technological evolution has profoundly transformed the way decisions are made within organizations, particularly in the financial sector but also in contexts such as large corporations or public institutions.
The growing availability of data, combined with the development of increasingly advanced analytical tools, has paved the way for a progressive convergence between artificial intelligence (AI) and decision-making, redefining not only operational methods, but also evaluation criteria, professional roles and levels of responsibility.
This chapter explores this convergence, critically analyzing the main tools and approaches that currently support or influence financial decisions. It begins with an overview of the most widespread AI models (such as *machine learning,* deep *learning,* and reinforcement learning) and then examines the role of expert systems and forms of symbolic reasoning, which represent the "logical" roots of automated decision-making.
Particular attention is paid to the recent development of generative technologies and large language models, which have seen rapid diffusion in the banking and financial sectors between 2023 and 2025. Their advantages, limitations, and implications for the analysis and forecasting of economic phenomena will be analyzed below.
The chapter then addresses the evolution of Decision Support Systems (DSS), highlighting the main typologies and their practical applications,

particularly in the financial context. On this basis, it delves into the emerging concept of Decision Intelligence, an approach that combines analysis, strategy, and continuous learning to build more robust, transparent, and adaptive decisions.

Finally, the organizational and value implications of introducing AI into the decision-making process are discussed, comparing fully automated models with those that retain a central role for humans (Human-in-the-Loop). The chapter concludes with a reflection on the key metrics for evaluating decision-making quality, such as accuracy, utility, and fairness, which are essential for guiding the responsible use of intelligent technologies.

2.1 Machine Learning, Deep Learning, Reinforcement Learning

In recent decades, the growing development of artificial intelligence has profoundly transformed the fields of financial, economic, administrative, healthcare, and other analysis, introducing new tools for data processing and interpretation. The origins of this transformation can be traced back to the mid-20th century, when scholars such as Alan Turing and later Marvin Minsky began to question the possibility of machines "thinking" and learning. However, it was only in the 1980s and 1990s that, thanks to increased computing power and the availability of vast amounts of data, the first applications of *machine learning began to spread* —systems capable of learning from past experiences to progressively improve their predictions. Over time, this first generation was joined by *deep learning,* an evolution of *machine learning* that draws inspiration from the workings of the human mind and uses models composed of multiple processing levels, capable of recognizing complex patterns in unstructured data, such as images, text, or market signals. The real turning point occurred in the decade following 2010, when the combined use of large *datasets* (*big data*) and multi-level architectures made these models particularly effective even in complex predictive fields such as finance. At the same time, *Reinforcement Learning developed,* a branch of artificial intelligence inspired by trial-and-error learning: an "agent" system interacts with an environment, learns through rewards and penalties, and refines its choices over time. This paradigm, originally studied in theory, has also found application in financial markets, for example in the construction of adaptive trading strategies or in automatic portfolio management. These technologies, while different in approach and purpose, share a fundamental characteristic: the ability to dynamically adapt to data, overcoming the limitations of traditional statistical models and offering new perspectives for predictive financial analysis, risk assessment, and strategic decision support.

Tab. 2: Comparison between Machine Learning, Deep Learning and Reinforcement Learning

Characteristic	Machine Learning	Deep Learning	Reinforcement Learning
Definition	Machine learning from historical data to make predictions	Learning through deep neural networks that simulate the human brain	Learning by trial and error through interaction with the environment
Origins	1980s-1990s	2010s (with data and computing power)	Theoretical concepts from the 1980s, recent applications
Data type	Structured (e.g. tables)	Unstructured (e.g. images, text, signs)	Sequential data from dynamic interactions
Objective	Predict outcomes or rank	Recognize complex patterns and abstractions	Maximizing rewards over time
Examples in finance	Risk models, credit scoring	Sentiment analysis, market forecasts	Algorithmic trading, automatic portfolio management

Source: Personal processing

In the healthcare sector, Machine Learning (ML) is used to analyze large amounts of clinical data and identify recurring patterns useful for early diagnosis. For example, ML algorithms are used to predict the risk of diabetes, heart failure or cancer recurrence, starting from blood tests, medical history data and lifestyle[22]. Deep Learning (DL), on the other hand, It finds application in the analysis of medical images, such as X-rays, MRIs or CT scans, where it is able to recognize anomalies (for example, lung nodules or brain lesions) with an accuracy comparable to or superior to that

[22] Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine*, 380(14), 1347–1358.

of specialists. Reinforcement Learning (RL) is used in personalized therapeutic treatment models, such as in the automatic adjustment of insulin doses for diabetic patients, where the system learns to improve clinical response over time based on the effectiveness of previous treatments. In the military and defense sector, Machine Learning (ML) is widely used today for the predictive analysis of operational scenarios, such as the recognition of recurring patterns in cyber threats or logistical movements, with the aim of anticipating attacks or optimizing resources. Deep Learning (DL) is used in the automatic recognition of objects and faces from satellite or drone images[23]. Reinforcement Learning (RL), on the other hand, is adopted in strategic simulation contexts, where autonomous systems learn to move or react in dynamic environments, such as in the control of drones, the navigation of autonomous vehicles, or the adaptive management of tactical resources in the field. These tools are also increasingly used in the administrative and public sectors; for example, Machine Learning (ML) is used to improve the management of requests and resources in public services[24]. Deep Learning (DL) is applied in the digitization and automatic classification of documents, such as in the case of administrative or legal archives, where it is able to read complex texts, extract relevant information, and prioritize urgent matters. Meanwhile, Reinforcement Learning (RL), still in its experimental phase, appears promising for the optimization of decision-making flows, for example in the

[23] For example, DL systems are capable of distinguishing military vehicles from civilian ones or identifying strategic structures in complex urban areas.
[24] For example, ML systems can predict the number of requests for building permits, social benefits, or documents in a given period, helping to deploy staff more efficiently.

automatic scheduling of urban maintenance interventions, where the system learns to balance costs, urgency, and impact on citizens[25].

2.2 Expert systems and symbolic reasoning

Before the emergence of machine learning-based approaches, artificial intelligence developed through paradigms based on "symbolic reasoning" also known as symbolic artificial intelligence . This approach, born between the 1950s and 1970s, is based on the explicit representation of knowledge in the form of logical rules and propositions, used by a system to deduce conclusions or recommendations. So-called "expert systems" are the best-known application: these are programs designed to emulate the decision-making process of a human expert in a specific domain, combining a knowledge base (made up of "if... then" rules) with an inference engine[26]. In the financial sector, "expert systems" were among the first attempts to automate complex decisions, such as credit assessment, accounting diagnosis, or portfolio analysis. A historical example is the XCON system developed in the 1980s for computer configuration, which inspired similar models in the banking sector for the automated provision of loans or investment recommendations. XCON (*eXpert CONfigurer*), developed by Digital Equipment Corporation (DEC) in collaboration with the Computer Science Department at Carnegie Mellon University, was designed to automate the technical configuration of VAX computers —that is, the consistent assembly of *hardware* and *software components* according to the

[25] European Commission (2022). *AI Watch: Artificial Intelligence in the Public Sector.* Publications Office of the EU. 23.
[26] Giarratano, J., & Riley, G. (2005). *Expert Systems: Principles and Programming* (4th ed.). Thomson. 101.

customer's specific requests. In a context where manual configuration was prone to frequent errors, slowdowns, and high costs, XCON proved to be a revolutionary tool, capable of drastically reducing human errors and improving operational efficiency. The system was based on a knowledge base of over 2,000 logical rules, built with the contribution of technical experts, and on an inference engine capable of deducing valid configurations in an autonomous and traceable manner.

The operational success of XCON represented a milestone in the development of symbolic artificial intelligence and demonstrated that expert systems could be effectively applied to real-world, complex business problems. This paradigm subsequently found application in non-technical fields as well, including, as mentioned, the banking and finance sector, where XCON-inspired models were adapted to support structured decision-making processes, such as granting credit, assessing risk, or recommending financial products. In these contexts, the added value of expert systems lay in their ability to codify the *know-how* of specialists into explicit rules, offering consistent, replicable, and transparent solutions.

Despite the effectiveness of these systems in stable and well-defined contexts, their structural rigidity and the difficulty in updating their knowledge base have limited their adaptability to more dynamic and complex environments, such as modern financial markets. However, the XCON case still represents an important historical reference in the transition to cognitive automation and provides the theoretical basis for subsequent hybrid developments between symbolic systems and machine learning techniques.

The strength of these systems lies in the transparency of the decision-making process, since each inferential step is traceable and interpretable.

However, the main limitations lie in the difficulty of updating the knowledge base, their rigidity with respect to dynamic contexts, and their inability to effectively manage uncertainty and ambiguity.

With the evolution of finance and the explosion of data, "expert systems" have gradually given way to statistical models and *machine learning*, capable of learning from large amounts of data and adapting to changing contexts[27]. However, in scenarios where explainability and transparency are required, such as financial regulation or *compliance*, symbolic reasoning still represents a useful resource today, especially when integrated with hybrid artificial intelligence approaches.

2.3 Generative AI and Large-Language Models (focus 2023-2025)

In recent years, generative artificial intelligence (*Generative AI*) has experienced unprecedented growth, establishing itself as one of the most significant innovations in financial technology. Unlike traditional systems based on rigid rules or statistical models, Generative AI is designed to create new and coherent content, such as text, images, forecasts, or simulations, starting from existing data. Its theoretical roots can be traced back to studies on the simulation of human learning and natural language, but it is only over the last decade that, thanks to rapid research progress and the growing availability of data, these systems have become concretely usable in the economic and financial fields[28]. In the context of analytics, Generative AI does more than simply replicate information: it can generate risk scenarios,

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[27] Turban, E., Aronson, J. E., Liang, T. P., & Sharda, R. (2005). *Decision Support and Business Intelligence Systems* (8th ed.). Pearson Education. 48.

[28] Brynjolfsson, E., & McAfee, A. (2017). *Machine, Platform, Crowd: Harnessing Our Digital Future,* W. W. Norton & Company. 88.

produce forecast reports, simulate market, sector, or scope responses, and even develop regulatory documentation or personalize communications with investors. These capabilities significantly expand the potential of decision-making tools, offering strategic support in both operational and management settings. Furthermore, Generative AI can facilitate greater accessibility of complex information by translating numerical data into natural language and making financial analysis more understandable even for non-experts. [29]However, this development also raises significant questions regarding the reliability, controllability, and accountability of automated decisions, especially in regulated contexts such as finance. In this context, the study of Generative AI is part of a broader reflection on the relationship between technology, human expertise, and *the governance* of decision-making processes in an era dominated by speed and information complexity.

Table 3: Generative AI: Advantages and Risks in Analysis

Advantages	**Risks**
Automatic generation of customized reports and analyses	Possible lack of transparency in decision-making processes
Simulation of alternative scenarios in real time	Risk of dissemination of incorrect or misleading content
Translating complex data into natural language	Difficulty in validating the reliability of forecasts
Support for strategic and operational decision making	Over-reliance on automated systems
Improving accessibility to information	Ethical and liability issues in case of errors

Source: Personal processing

[29] Kirkpatrick, K. (2023). The promise and peril of generative AI. *Communications of the ACM*, 66(3), 20–22.

In recent years, the development of Large Language Models (LLMs) has marked a turning point in the field of artificial intelligence applied to financial analysis. These are advanced systems trained on enormous amounts of text, capable of understanding, synthesizing, and producing human language fluently and coherently. Unlike early language models, which were limited to basic operations such as translation or automatic sentence completion, today's LLMs are capable of generating rich content, answering complex questions, drafting documents, and even analyzing financial texts in real time[30]. Their development has been made possible by the increasing availability of digital data and the evolution of machine learning methods, but their impact extends far beyond the technological realm. In business and finance, LLMs find application in a variety of areas: from automatically reading financial statements to producing market data summaries, from analyzing news and corporate press releases to monitoring regulations . These models offer, among other things, significant support in processing large volumes of textual information, reducing analysts' cognitive load and improving the timeliness of decisions. Furthermore, they can help increase data transparency and accessibility by translating technical concepts into language that even non-experts can understand[31]. However, the use of LLMs in the financial sector also raises questions related to the quality of sources, the possibility of misinterpretation, and the responsibility for the information generated,

[30] Bommasani, R., Hudson, D.A., Adeli, E., et al. (2021). *On the Opportunities and Risks of Foundation Models* . Stanford Center for Research on Foundation Models. https://crfm.stanford.edu/report.html

[31] Kozlowski, A. C., Taddy, M., & Evans, J. A. (2023). The language of prediction: Financial analysts and the emergence of automated interpretation. *Research Policy,* 52(2), 104669.

aspects that are especially critical in regulated or high-risk operational environments.
The rapid advancement of these tools suggests that LLMs are poised to become a structural component of analytical and decision-making activities in business and finance, offering new opportunities but also requiring appropriate skills and oversight to ensure their ethical and effective use.
In the two-year period 2023–2025, Generative AI and Large Language Models (LLMs) have experienced unprecedented growth and diffusion, establishing themselves as central tools not only in technological innovation but also in transforming decision-making practices across various fields. During this period, LLMs have become more accessible, precise, and capable of processing complex content with an increasingly human-like quality. Institutions, from large banking groups to *fintechs,* have begun integrating these technologies into their daily processes: from the automatic generation of financial reports to risk assessments, from the analysis of corporate communications to the interpretation of complex regulations.
The most significant aspect of this recent evolution lies not only in the power of the tools, but also in their ability to adapt to specific contexts, understand the nuances of industry jargon, and support analysts' work in synthesizing large volumes of information in real time. At the same time, awareness of potential risks has increased, including the spread of incorrect content, a lack of transparency in text generation processes, and excessive reliance on automated systems for high-impact decisions. For this reason, in recent times there has also been increased attention to model *governance,*

their regulation, and the need for responsible use, especially in regulated sectors such as finance[32].

In summary, between 2023 and 2025, Generative AI and LLMs have moved from experimental tools to structural components of financial analysis processes, helping to redefine the boundaries between automation, interpretation, and professional judgment.

2.4 Decision Support Systems (DSS)

Decision Support Systems (DSS) represent one of the first structured forms of integration between technology and the decision-making process, developing since the 1970s. Initially conceived as tools to assist *managers* in making strategic choices, DSS have evolved over time from simple models based on tabular data to complex tools capable of combining different information sources, alternative scenarios, and multiple evaluation criteria. The development of these systems has been strongly influenced by the growing need for organizations to make rapid and informed decisions in environments characterized by uncertainty, abundant data, and constantly evolving variables[33]. In the financial sector, DSS have found particularly fertile ground thanks to their ability to support complex decisions such as portfolio allocation, risk analysis, financial planning, and cost control.

Marketing sector, DSS help interpret consumer behavior, segment customers, and define pricing or promotional strategies. In logistics and

[32] IOSCO. (2024). *The Use of Artificial Intelligence and Machine Learning by Market Intermediaries and Asset Managers: Follow-up Report* . International Organization of Securities Commissions. 75.

[33] Keen, P. G. W., & Scott Morton, M. S. (1978). *Decision Support Systems: An Organizational Perspective* . Addison Wesley. 97.

manufacturing, they enable optimization of inventory levels, planning production capacity, and selecting suppliers based on multiple criteria. A distinctive feature of corporate DSS is their ability to integrate heterogeneous information sources (internal data, market indicators, economic forecasts, regulations) and transform them into decision-making tools. This is particularly important in highly variable and competitive environments, where decisions must be made quickly and based on solid evidence. However, the effectiveness of DSS depends not only on the technical quality of the tool, but also on the organizational capacity to interpret its results, adapt them to the specific context, and promote their critical use. In this sense, DSS do not replace the human role, but rather enhance it, offering a more structured analytical basis to guide complex and strategic choices.

Unlike automated systems that replace human judgment, DSSs are designed to support decision makers, improving the quality of assessments by structuring information, simulating scenarios, and visualizing key indicators. The value of these tools lies primarily in their flexibility, meaning the ability to adapt to specific user needs and the decision-making context, without imposing one-size-fits-all solutions.

In recent years, with the integration of more diverse data sources (texts, ESG indicators, market forecasts) and the growing focus on transparency in decision-making processes, DSS have returned to the forefront of regulatory and institutional attention. In this context, their continued evolution represents a concrete response to the need to empower financial decisions, without sacrificing the speed and analytical depth offered by technology. In the financial context, Decision Support Systems (DSS) can be classified into different types based on their structure and the primary function they perform. Below is a summary of the main categories:

Table 4: Types of Decision Support Systems (DSS) in the financial sector

DSS Type	Description	Examples in Business and Finance
Data-oriented DSS	Systems based on accessing, collecting, and analyzing large amounts of structured and historical data.	Financial dashboards, data warehouses, market monitoring systems.
Model-Oriented DSS	Systems that use mathematical, economic, or forecasting models to simulate scenarios and support decisions.	Risk assessment models, portfolio simulations, sensitivity analyses.
Communication-oriented DSS	Systems that facilitate collaboration and information exchange between decision makers within an organization.	Shared budgeting platforms, integrated financial planning systems.
Documentation-oriented DSS	Systems that provide access to documents, regulations, guidelines, and reports to support informed decisions.	Regulatory compliance management systems, regulatory databases.
Hybrid DSS	Systems that integrate multiple functions (e.g., data, models, communication) into a single platform.	Advanced financial ERP systems, integrated risk management solutions.

Source: Personal processing

Despite the numerous benefits brought by (DSS) in the financial sector, their use also involves a series of risks and critical issues that cannot be overlooked, including the excessive dependence on decision-making technologies, which can lead managers and analysts to completely delegate their critical judgment to the tools, reducing the capacity for autonomous evaluation, especially in situations not foreseen by the system[34]. Furthermore, the quality of decisions generated by a DSS depends largely on the quality and completeness of the input data (incorrect, obsolete or partial data can lead to distorted assessments and wrong financial decisions, with potentially significant economic impacts. A further risk concerns the lack of transparency of the criteria used by the system, which can make it difficult for users to understand the reason for a given recommendation, hindering the possibility of verifying its correctness or contesting it. This problem is accentuated in the more advanced or automated DSS, where the decision-making process can be opaque even for the operators themselves[35]. Finally, there is the risk that DSS contribute to consolidating rigid decision-making models, poorly responsive to changes in the external context or to non-formalisable intuitions. In a market characterised by volatility and increasing complexity, this can represent a strategic limit, for these reasons, it is essential that DSS are used as support tools and not as a replacement for human judgement, maintaining a balance between technology, analytical skills and critical sense. To obtain the maximum benefit from (DSS) while minimising their costs, To mitigate risks, it is essential to adopt a series of good organizational and operational practices. One of the first necessary conditions is to ensure the active involvement of end users in the design and maintenance of the system. This

[34] Turban, E., Sharda, R., & Delen, D. (2011). *Decision Support and Business Intelligence Systems* (9th ed.). Pearson Education. 115.
[35] In the financial sector, where decisions often have legal and regulatory implications, this can compromise traceability and accountability requirements.

allows us to ensure that the functionalities are truly consistent with specific decision-making needs, avoiding excessive automation and encouraging informed adoption of the tool[36]. Secondly, it is essential to pay attention to data quality, through rigorous processes of validation, updating and control of sources. The reliability of the DSS directly depends on the robustness of the information on which it is based: incomplete, outdated or distorted data can compromise the entire decision-making process. At the same time, it is recommended to ensure an adequate level of transparency, clearly documenting the criteria, models and logic that guide the system's analyses and recommendations[37]. This is particularly important in regulated contexts, where the traceability of decisions is often a regulatory requirement. Finally, one of the most effective practices is to promote a hybrid approach between man and machine, in which the DSS acts as a facilitator and not a substitute for human judgment.

The combination of analytical skills, professional experience and technological support allows us to better address the uncertainty and ambiguity of financial markets, maintaining the flexibility needed to adapt to new or unexpected scenarios. Continuous user training and the creation of a critical decision-making culture are, in facts, considered essential elements for the effective and responsible use of these tools in the long term. The evolution of Decision Support Systems (DSS) in recent years has led to a new generation of tools capable not only of organizing and presenting information, but also of learning from data, adapting to changes, and anticipating future scenarios. This transformation is made possible by the

[36] Turban, E., Sharda, R., & Delen, D. (2011). *Decision Support and Business Intelligence Systems*, cit.

[37] Id.

progressive integration of artificial intelligence within DSS, which enhances the systems' analytical and predictive capabilities while maintaining (or sometimes surpassing) the support functions of traditional models. In this context, modern intelligent systems combine heterogeneous data sources, forecasting models, machine learning techniques, and interfaces capable of interacting in natural language, offering more dynamic and personalized assistance to the decision-making process[38]. A concrete example of the evolution of Decision Support Systems (DSS) in the financial sector. This is illustrated by the experience of JPMorgan Chase, a leading global investment bank, which has integrated AI- based solutions into its credit risk assessment systems. Traditionally, this process relied on standardized models based on financial indicators, credit reports, and rigid quantitative parameters. With the introduction of intelligent systems, the bank has been able to enhance its DSS with predictive modules capable of learning from large volumes of historical data, text documents, and transaction behavior. Thanks to these systems, the institution can now anticipate signs of credit deterioration before they become evident, improving its risk prevention capabilities and personalizing decisions. For example, the automatic analysis of emails, company press releases, news, and cash flows has allowed it to identify “weak” signals that a traditional approach might have overlooked. The intelligent DSS does not make decisions autonomously, but provides updated risk scenarios in real time, which are evaluated by the *credit officer* for final approval[39].

[38] Sharda, R., Delen, D., & Turban, E. (2020). *Analytics, Data Science, & Artificial Intelligence: Systems for Decision Support* (11th ed.). Pearson, p. 102.
[39] JPMorgan Chase & Co. (2023). *AI and Data Strategy Report* . Internal publication and investor communications, p. 77.

This approach has led to significant improvements in decision timeliness, a reduction in the default rate for certain credit categories, and improved compliance with regulatory risk management requirements. JPMorgan Chase's experience demonstrates how AI-enhanced DSS can complement—not replace—human judgment, making decision-making more informed, adaptive, and proactive.

In the financial sector, these new AI-enhanced DSSs find application in highly complex areas, such as systemic risk management, fraud prevention, portfolio optimization, or real-time monitoring of global markets. However, the introduction of predictive and autonomous capabilities in decision-making systems requires rethinking traditional best practices, adapting them to a context in which operating logics are not always fully transparent or explainable. In this scenario, human control, the traceability of automated decisions, and the adoption of ethical and regulatory principles aimed at ensuring the reliability, neutrality, and accountability of the systems used become even more important. The transition from static DSSs to intelligent systems does not imply, as mentioned, replacing the human factor, but rather its requalification, in which the financial analyst is called upon to interpret and contextualize the results generated by the machine, avoiding both excessive trust and passive automation.

2.5 Decision intelligence

In recent years, the concept of Decision Intelligence has gained increasing relevance in the financial world, as a natural evolution of Decision Support Systems. It offers an integrated approach that combines analytical methods, human expertise, and machine learning logic to improve the quality, consistency, and impact of decisions in complex and dynamic contexts. Decision Intelligence stands out for its ability to structuredly connect data, forecasting models, qualitative assessments, and strategic objectives, with the aim of creating a more transparent, adaptive, and measurable decision-making system[40].

The Decision Intelligence *framework* is typically divided into three main components:

1. Decision context, which includes a clear definition of the problem, objectives and relevant variables;
2. Decision-making process, integrating analytical models, scenario simulations and multidimensional assessments;
3. Outcome and learning, which involves measuring the impact of decisions made and continuously improving future choices.

Decision Intelligence finds application in numerous sectors, from financial planning to operational management, from predictive marketing to risk assessment. Companies use DI to simulate alternative scenarios, quantify the impact of decisions before they are implemented, and adapt strategies in real time based on evolving markets or customer behavior. This approach allows them to move from a reactive logic to a proactive perspective, geared towards preventing problems and capitalizing on opportunities.

A distinctive element of Decision Intelligence is its focus not only on "what to decide," but also on "how" and "why" to decide in a certain way . In this sense, it promotes a culture of informed decision-making, based on transparency, traceability, and continuous learning (for example, a

[40] Lycett, M. (2023). Decision Intelligence: Towards a new discipline of decision making. *Journal of Decision Systems*, 32(1), 1–14.

company can use DI to analyze not only the results obtained, but also the causes that led to certain choices, with the aim of improving the quality of future decisions). In the financial sector, this approach allows us to overcome the limitations of static models and automated systems, promoting a systemic and iterative view of the decision-making process. For example, in portfolio management, Decision Intelligence allows us to combine risk analysis, macroeconomic inputs, and individual preferences, building more flexible and responsive strategies. Similarly, in credit or project evaluation, it promotes a more integrated interpretation of information, improving the overall quality of decisions made.

Decision Intelligence (DI) is rapidly establishing itself as an advanced decision support tool, thanks to its ability to integrate data, analytical models, expert knowledge, and organizational objectives into a coherent and adaptive decision-making framework. However, despite its innovative potential, the tool is not without risks and limitations that deserve careful consideration, especially in light of the strategic, operational, and regulatory implications associated with the adoption of automated decision-making systems.

One of the most significant risks is excessive reliance on models. The growing sophistication of DI systems, combined with their apparent objectivity, can lead decision makers to entirely delegate their judgment to the system, reducing human critical capacity and control over the decision-making process[41].

[41] This risk is amplified in highly complex financial environments, where models may not be able to capture all the qualitative and dynamic market variables. On the topic: Power, D.J. (2022). *Decision Support, Analytics, and Decision Intelligence* . Business Expert Press. 44.

A second critical issue concerns the lack of transparency and explainability of some DI solutions, especially when based on complex predictive models or logics that are difficult to interpret. In a regulated context like the financial one, for example, where traceability and *accountability* of decisions are fundamental requirements, a lack of clarity on the criteria underlying recommendations can be an obstacle to the responsible adoption of these technologies. Other risks arise from the quality of the data used: Decision Intelligence relies heavily on information, and the presence of incomplete, distorted, or obsolete data can compromise the reliability of the entire process. Furthermore, there is a risk that DI systems, once structured, consolidate decision-making models that are overly rigid and unresponsive to changing scenarios or unformalized insights; this limitation can be particularly critical in volatile and rapidly evolving financial markets. Finally, from an operational perspective, implementing DI systems requires significant investments in resources, training, and *governance,* making these solutions less accessible to small and medium-sized businesses or contexts where data culture is not yet established. Furthermore, the growing use of these tools raises ethical and regulatory questions, particularly regarding the liability of automated decisions, data protection, and the risk of implicit bias in the models.

In summary, Decision Intelligence offers concrete opportunities for innovation in the financial decision-making process, but its effectiveness depends strictly on the ability of organizations to manage its limitations, combining technological power with a conscious, transparent and critical use of the tools.

In conclusion, the evolution of Decision Intelligence can be considered an important step in the transformation of the decision-making process,

moving it from a purely technical or automatic logic to a more systemic, adaptive, and informed vision. However, as often happens with the introduction of powerful tools, its true value lies not in the technology itself, but in organizations' ability to adopt it critically and responsibly. The risk of blindly relying on models that promise precision and speed can lead to a loss of control and interpretative capacity, in areas such as finance or healthcare, where the margin of error can have significant consequences.
For this reason, reflection on Decision Intelligence cannot be limited to its operational dimension, but must also include a cultural and organizational assessment. A new type of decision-maker is needed, capable of understanding the potential of advanced systems without sacrificing critical thinking, expert judgment, and personal responsibility. Only through this balance will it be possible to transform Decision Intelligence from a simple analytical tool to a true strategic lever, capable of improving not only efficiency, but also the quality and ethics of decisions[42].

2.6 Human-in-the-Loop vs. Full automation

The increasing automation of decision-making processes has sparked a significant debate between two distinct approaches: on the one hand, the Human-in-the-Loop (HITL) model, which envisions active interaction between intelligent systems and human decision-makers; on the other, the Full Automation paradigm, in which decisions are entrusted entirely to automated systems, without direct human intervention. Both models have

[42] Power, D. J. (2022). *Decision Support, Analytics, and Decision Intelligence,* cit., 111.

advantages and limitations, which are particularly relevant in regulated and high-risk sectors.

In the Human-in-the-Loop model, technology acts as a support tool, not a replacement: systems generate analyses, suggestions, or scenarios, but the final decision remains the responsibility of the human operator. This approach is particularly appreciated in contexts where transparency, expert judgment, and qualitative assessment are required, such as granting credit, selecting strategic investments, healthcare decisions, or managing reputational risk (the presence of the human element allows for the integration of variables that elude analytical models, such as contextual, ethical, or relational factors). Full Automation, on the other hand, aims to maximize efficiency, speed, and standardization by completely automating the entire decision-making process. This model finds effective application in repetitive, large-scale tasks with a low margin of human error, such as managing high-frequency trading orders or optimizing daily cash flows. However, full automation also entails significant risks, including the opacity of decision-making criteria, the difficulty of assigning responsibility in the event of errors, and the loss of human control at critical moments.

The most widespread trend is not to adopt a pure model, but rather to integrate the two approaches, balancing automatic efficiency with human oversight. This balance is now central to discussions on the governance of automated decisions, especially in a context where the speed of innovation must necessarily be balanced with principles of accountability, transparency, and sustainability. In the field of corporate credit assessment, UniCredit has adopted a Human-in-the-Loop approach that combines automated analysis tools with strong human involvement in the final decision. The process begins with the automatic processing of balance sheet indicators, cash flows, sector ratings, and risk analyses. However, unlike fully automated models, the system provides customized risk scenarios that are reviewed by a specialized analyst, who is responsible for validating or modifying the system's recommendation[43].

This approach allows the bank to reduce processing times and standardize part of the process, without sacrificing the qualitative assessment of factors that are not immediately quantifiable, such as customer relationships, local knowledge, or the impact of extraordinary events. Incorporating human judgment has proven particularly useful during periods of significant economic uncertainty, such as the COVID-19 pandemic, when historical data was less reliable and the manager's experience carried greater weight in the final decision.

At the other extreme is ING 's approach to the digital *onboarding* process for *retail* customers, which has implemented a fully automated system for opening *online current accounts,* verifying identity, conducting preliminary risk assessments, and assessing financial suitability. Customers interact entirely with the digital interface, and the entire process (from application to approval) takes place without any human intervention, except in exceptional cases or anomalies flagged by the system.

This model allows ING to guarantee very fast activation times, drastically reduce operating costs and offer a smooth and uniform user experience. However, full automation also entails the need for continuous monitoring and periodic audits to verify that the criteria applied by the systems comply with regulations and do not produce unintended discriminatory effects, for example in the treatment of vulnerable or non-standardized customers.

[43]Source: Unicredit.it

Human-in-the-Loop and Full Automation models can coexist within the same industry, each with specific advantages and risks. The choice of the most suitable model depends on the nature of the process, the level of associated risk, the degree of standardization, and the need for customization. In a rapidly evolving context like banking, the primary challenge is not choosing between man or machine, but rather building effective collaboration models between automated intelligence and human responsibility[44]. In the context of advanced automation and the growing adoption of artificial intelligence in decision-making, the Human-in-the-Loop (HITL) model is not destined to disappear, but rather to evolve into more sophisticated and strategic forms. The idea that humans must remain "in the decision-making chain" responds to not only operational but also ethical, regulatory, and reputational needs, especially in fields like finance, where decisions can have significant impacts on individuals, businesses, and markets. In this scenario, the future of HITL is not as a resistance to automation, but as its critical complementarity[45].

In particular, it is believed that the human role will tend to shift from repetitive and technical operations to tasks of oversight, interpretation, and *governance* of automated decision-making. This implies a shift in the nature of the required skills: financial professionals will not only need to understand data and metrics, but also be able to interact with complex systems, recognize the limitations of predictive models, assess the impact of potential algorithmic *biases*, and ensure consistency with transparency

[44] Power, D. J. (2022). *Decision Support, Analytics, and Decision Intelligence,* cit.
[45] Power, D. J. (2022). *Decision Support, Analytics, and Decision Intelligence,* cit.

and accountability principles[46]. Furthermore, the future of HITL will be strongly influenced by emerging regulations on artificial intelligence, such as those promoted at the European and international levels, which emphasize the need to maintain significant human control over automated decisions. In finance, this will translate into a growing adoption of hybrid models, in which the system suggests but does not decide, and in which humans have the final say, especially in high-risk or highly discretionary cases.

Ultimately, the future of Human-in-the-Loop will not be defined by technology itself, but by organizations' ability to build resilient decision-making architectures, where AI supports, but does not replace, human responsibility and expertise.

2.7 Decision-making performance metrics (accuracy, utility, fairness)

In the context of Decision Intelligence, evaluating the effectiveness of a decision-making process cannot be limited to the technical accuracy of the outcome alone, but must include a broader set of qualitative and quantitative metrics. In the business and financial sectors, where decisions impact financial results, corporate reputation, and *stakeholder well-being,* the adoption of comprehensive evaluation criteria is essential to ensure not only efficiency, but also transparency and accountability. In the healthcare sector, the goal is to minimize diagnostic and treatment errors.

One of the first metrics to consider is "accuracy," or the consistency between the decision made and the observed outcome. In other words, a decision is

[46] In this logic, the Human-in-the-Loop will be called upon to play a role increasingly similar to that of an intelligent mediator between technology and the real decision-making context.

considered accurate if it produces results in line with rational expectations or established objectives[47]. In risk or credit management, for example, accuracy is measured by the ability to correctly predict a customer's creditworthiness or the probability of default. However, accuracy alone is not enough: a decision may be technically correct, but not necessarily useful in the context in which it is applied[48].

For this reason, " utility " represents a second central criterion, evaluating the concrete value generated by the decision for the organization or the customer, taking into account aspects such as timing, economic impact, reduction of uncertainty, or the quality of the excluded alternatives. In the economic-financial field, a decision can be useful even if not perfectly accurate, as long as it contributes to achieving a favorable long-term outcome or to containing an unforeseen risk[49].

Finally, an increasingly relevant metric is "*fairness*" that is, the equity of the decision-making process. In a regulatory and socially sensitive context such as the financial, military, or healthcare sectors, it is essential that decisions do not have discriminatory or unfair effects on certain categories of individuals. *Fairness* implies that criteria such as age, gender, geographic origin, or wealth status do not unduly influence the outcome of assessments, and that the same rules are applied consistently to all stakeholders. The three metrics should always be evaluated together, as some specific cases demonstrate.

Spanish bank BBVA adopted a decision support system based on predictive models to improve credit risk assessment in the retail and SME segments.

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[47] Power, D. J. (2022). *Decision Support, Analytics, and Decision Intelligence,* cit.

[48] Id.

[49] Id.

The key metric initially used was "predictive accuracy," or the system's ability to correctly predict defaults within 12 months. Although the models showed accuracy above 90%, the bank observed that highly accurate decisions did not always lead to improved operating profit.

For this reason, BBVA has also integrated utility metrics into its decision-making *framework,* evaluating the overall economic impact of decisions, including the opportunity costs associated with rejecting potentially profitable loans. This approach has made it possible to strike a balance between predictive rigor and generated value, optimizing risk-adjusted [50]profitability. In 2022, the Bank of Italy launched a review of automated counterparty selection models for market transactions, with a particular focus on compliance with *fairness.* The analysis highlighted that some selection algorithms used by banking institutions, while formally neutral, tended to penalize smaller, less visible, or non-standardized operators. The intervention led to the definition of a set of guiding principles on transparency and algorithmic fairness, promoting mandatory periodic audits, the possibility for excluded counterparties to submit a reasoned appeal, and the introduction of a human component for the review of *borderline cases*. This example highlights how fairness is not just an ethical value, but a necessary condition for ensuring legitimacy and trust in automated decision-making processes, especially in regulated environments. These cases demonstrate that the effectiveness of Decision Intelligence in the financial sector does not depend on a single metric, but on the ability to balance different criteria: accuracy for technical soundness,

[50] The case demonstrates that accuracy is necessary, but alone is not sufficient to ensure financially effective decisions.

utility for strategic value, and fairness for social and regulatory sustainability. Institutions that successfully integrate these dimensions are best positioned to address the challenges of an increasingly automated and complex environment. The integration of these three dimensions—accuracy, utility, and fairness—therefore represents a crucial challenge for the governance of Decision Intelligence: only by balancing technical precision, strategic value, and social equity can truly effective and sustainable decision-making processes be built over the long term.

CHAPTER III

SECTOR APPLICATIONS

Premise

The use of Artificial Intelligence in decision-making, as we've seen, represents one of the most significant transformations of our time, capable of impacting a wide range of sectors. Thanks to advanced data analysis, *machine learning algorithms,* and predictive models, Artificial Intelligence supports complex decisions by reducing uncertainty, response times, and human error. Automated analysis, combined with the ability to process large volumes of information in real time, not only optimizes operational and financial activities, but also improves the quality of healthcare services and makes public policies more effective and transparent. The following paragraphs will explore some of the main application sectors: Business & Operations, where AI optimizes *supply chains* and production processes; Finance & Risk Management, where intelligent systems support investment management and risk assessment; Healthcare & Life Sciences, where AI contributes to more accurate diagnoses and personalized treatment plans; and finally Public Administration & Policy, an area in which the use of AI can foster more inclusive, efficient and evidence-based decisions.

3.1 *Decision making* via AI in Business & Operations

Business *operations* represent the set of daily activities that allow an organization to function efficiently and generate value for its *stakeholders.* They include not only production and logistics processes, but also support functions that ensure the economic and organizational sustainability of the company. According to Porter (1985), the corporate value chain is made up of primary activities, such as logistics, production, and marketing, and support activities, including human resources, technology, and infrastructure. From this perspective, *operations* are not limited to the manufacturing dimension, but include an integrated approach that coordinates different functions to optimize the use of resources and improve competitiveness. Furthermore, technological evolution and the growing focus on sustainability have made *operations* a strategic lever for innovation, shifting the focus from mere internal efficiency to a model oriented towards the creation of shared value. In short, *business operations* can be considered the engine of the company, since through their coordination it is possible to transform inputs into outputs that effectively respond to market needs[51].

To outline *business operations,* the following summary can be used:

▯ *Operations and production*

- *Supply chain* management
- Production of goods or provision of services
- Quality control

◎ *Sales and Marketing*

- Market analysis and target definition
- Sales strategies and distribution channels
- Communication and promotion

◎ *Finance and Administration*

- Planning and management of financial resources

[51] Carullo, Gherardo (2021). Administrative decision-making and artificial intelligence. *INFORMATION AND COMPUTER LAW, 37* (3), 431-461.

- Accounting and management control
- Reporting and regulatory compliance

◎ *Human Resources (HR)*

- Staff selection, training and development
- Performance Management
- Corporate climate and organizational culture

◎ *Research and Development (R&D)*

- Product and process innovation
- Digitalization and new technologies
- Development of patents or know-how

Support and customer service

- After-sales customer support
- Complaints management and loyalty
- Customer experience

Below is an image that summarizes the functions described.

The application of Artificial Intelligence to *decision-making* in *operations* and manufacturing is radically transforming organizational models and business processes. First, in *supply chain management, machine learning* algorithms and predictive systems enable companies to anticipate demand, optimize inventory levels, and reduce the risk of supply chain disruption. Artificial intelligence (AI) is therefore increasingly being used by companies to forecast future demand for goods and services, enabling more informed decisions and optimized operational strategies. Its operation is based on advanced data analysis and the use of predictive models. AI integrates historical sales data, seasonality, market trends and internal information (inventories, production capacity), to which external data (economic trends, consumer behavior, weather, social media data or geopolitical events) are added, after which regression algorithms, neural networks and *deep learning* models are trained to identify complex *patterns* not easily detectable by traditional statistical methods [52].

AI provides not just a single estimate, but multiple possible scenarios (optimistic, pessimistic, realistic), with associated margins of uncertainty, allowing companies to prepare for different market conditions. The benefits for the company are varied, first and foremost, supply *chain* optimization, reducing inventory costs and preventing stock-outs; better resource allocation with more efficient production, logistics, and workforce planning; and the ability to make strategic decisions (supporting marketing, *pricing,* and investments).

These solutions, among other things, improve the resilience of global networks, enabling a proactive approach to managing market complexity and uncertainty. Secondly, in the *production of goods and the provision of services,* AI supports decision-making through intelligent production capacity planning, flexible automation, and predictive maintenance, which increase efficiency and reduce operating costs. Finally, in *quality control,* computer vision tools and *deep learning techniques* enable defect detection in real time, improving the accuracy of checks compared to traditional methods and accelerating the *feedback loop* to production processes[53]. Overall, the use of AI in these *operations* enables faster, data-driven, and highly adaptive decision-making, making companies more competitive and capable of generating value in dynamic and complex environments. As for the use of Artificial Intelligence in *sales and marketing functions,* is becoming

[52] The models self-update over time: the more data they receive, the more their forecasting ability improves.

[53]Lampen E.,Teuber J., Gaisbauer F., Bär T., Thies Pfeiffer b, Sven Wachsmuth (2019), *Combining Simulation and Augmented Reality Methods for Enhanced Worker Assistance in Manual Assembly,* Procedia CIRP, Vol. 81, 72.

central to the competitiveness of businesses in the digital age. Specifically, *machine learning algorithms* enable the analysis of large volumes of data from diverse sources (*online behavior,* social media, previous purchases) to segment customers and predict their future needs. This approach enables personalized *marketing strategies* and targeted communications, which increase conversion rates and improve the *customer experience. Furthermore, predictive analytics and recommendation* systems support sales by suggesting offers and products in real time, thus optimizing the *cross-selling* and *up-selling* [54]process.

Another area of application for Artificial Intelligence is represented by intelligent *chatbots* and virtual assistants, capable of managing immediate and continuous interactions with customers, reducing service costs and increasing overall satisfaction. In short, AI in sales and *marketing* not only automates operational tasks but is also becoming a *driver* for data-driven strategic decisions, guiding companies toward a more proactive, predictive, and customer-centric model. The adoption of Artificial Intelligence in corporate finance and administration processes is, among other things, significantly changing the role of administrative and accounting functions within companies, enabling an evolution from purely operational activities to strategic decision-making support functions. In particular, intelligent process automation (*Robotic Process Automation,* RPA) allows you to manage repetitive tasks such as invoice recording, account reconciliation and report generation, reducing operational times and eliminating much of the human

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[54]Thomas Davenport, Abhijit Guha, Dhruv Grewal & Timna Bressgott (2020), *How artificial intelligence will change the future of marketing,* Journal of the Academy of the Science of Marketing, Volume 48, 32.

error[55]. At the same time, *machine learning systems* applied to financial analysis allow you to improve cash flow forecasting, credit risk assessment and investment management, promoting faster decisions based on real-time data[56].

Artificial Intelligence cannot be considered a legal entity nor formally assume the role of director, due to legal requirements and the civil and criminal liabilities associated with the position. However, it can provide active, rather than merely instrumental, support to corporate bodies, reducing the burden of *compliance activities* and improving the quality of decisions through big data analysis and predictive capabilities. The use of AI, however, raises numerous critical issues, including decision-making transparency (the risk of "black box" scenarios), non-discrimination, privacy protection, the traceability of decisions, and director accountability. This highlights the need for an "AI use policy" that defines the scope, limits, and methods of its use, integrating it into corporate structures without transforming it into a delegated entity[57]. Looking ahead, artificial intelligence can help redefine corporate governance models, favoring smaller boards, more focused on strategic decisions, and supported by digital tools such as blockchain. However, the ultimate responsibility of human administrators remains essential, as they must retain the ability to monitor and make informed decisions.

Today, the use of anomaly detection algorithms helps strengthen internal control mechanisms and prevent fraud, a particularly sensitive area in

[55]Moll, J., & Yigitbasioglu, O. (2019). *The role of internet-related technologies in shaping the work of accountants: New directions for accounting research* . *The British Accounting Review, 51* (6), 1
[56]Id.
[57]Mosco, G.D. (2019), *Roboboard. Artificial Intelligence in Boards of Directors,* in Analisi Giuridica dell'Economia, 1/2019. 15.

corporate *governance.* In this way, AI is not only increasing the efficiency of administrative operations but is also becoming a strategic lever for improving the accuracy of financial decisions and increasing transparency towards stakeholders . As for the use of Artificial Intelligence in human resources (HR) management, it is revolutionizing the ways organizations attract, select, develop, and retain talent. First, AI is being applied to *recruitment* and selection processes through *resume screening systems* and predictive algorithms capable of analyzing large volumes of applications, identifying the profiles best suited to business needs and reducing *bias* and evaluation times. Second, *people analytics technologies* support decision-making in personnel management, offering insights into performance, engagement levels, and turnover risk, with the aim of adopting more effective *retention strategies. Furthermore, chatbot* -based tools and virtual assistants simplify the *employee experience,* providing instant answers to administrative questions and personalized support for training and professional development[58]. In short, AI applied to HR goes beyond automating operational functions, but is also a strategic tool for building a more competent, motivated workforce aligned with company goals.

Today, among other things, the application of Artificial Intelligence (AI) to Research and Development (R&D) represents one of the most significant levers for innovation and business competitiveness in the digital economy. Thanks to its ability to analyze large amounts of heterogeneous data, AI accelerates discovery, design, and testing processes, reducing the development times of new products and services. *Machine learning*

[58]Meijerink J., Boons M.,Keegan A., Marler J., (2021), Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM, *The International Journal of Human Resource Management* 32 (12), 44.

algorithms, in particular, are used to identify complex *patterns* in scientific and technological data, facilitating the generation of new knowledge and the identification of innovative solutions. Furthermore, *generative design tools* now support advanced design with excellent results, allowing thousands of design alternatives to be simulated and evaluated in a short time, significantly improving the quality and efficiency of prototypes. In the pharmaceutical and biotechnology sectors in particular, AI has proven crucial for *drug discovery,* drastically reducing the costs and duration of clinical trial processes[59]. In summary, the integration of AI in R&D not only optimizes operational activities, but constitutes a real enabling factor for the development of radical innovations and for strengthening the competitive capacity of companies in the long term, One of the main contributions is the ability to extract knowledge from large scientific and technological *datasets* . *Machine learning* and *deep learning algorithms* enable the identification of non-obvious correlations and the generation of innovative hypotheses that guide research in new directions. This approach is particularly useful in fields characterized by highly complex information, such as materials science and bioinformatics, where Artificial Intelligence significantly reduces analysis times while also increasing the accuracy of results. An emerging field is *generative design,* in which AI algorithms simulate and test thousands of design solutions in extremely short times, enabling companies to develop more efficient prototypes, improve the technical performance of

[59] One of the sectors benefiting most from the use of AI in R&D is the pharmaceutical and biotechnology sector. *Machine learning* applications are being used to identify new candidate molecules, predict their efficacy, and reduce clinical trial times. AI also allows for the modeling of complex biological interactions, increasing the likelihood of success in the drug development phase. This transformation has a direct impact not only on the efficiency of research processes but also on companies' ability to respond promptly to global health challenges (Vamathevan et al., 2019).

products, and reduce waste in production processes. The *data-driven approach,* based on the automatic exploration of design alternatives, not only accelerates incremental innovation but also paves the way for radically new solutions that would have been difficult to achieve using traditional methods. The use of Artificial Intelligence in Research and Development is not limited to supporting existing activities, but is able to redefine the innovation paradigm itself. Thanks to tools such as *machine learning, generative design* and applications in *drug discovery,* it is establishing itself as a strategic *driver* for the creation of sustainable competitive advantages[60].

Finally, the adoption of Artificial Intelligence (AI) in *customer service* has profoundly transformed the way companies and customers interact, introducing tools capable of ensuring continuous, personalized, and cost-effective assistance. Technologies such as the aforementioned intelligent *chatbots* and virtual assistants, based on *natural language processing* (NLP) algorithms, enable real-time management of requests and immediate responses even to complex questions, improving operational efficiency and customer satisfaction. Furthermore, *sentiment analysis systems* allow companies to automatically and rapidly monitor consumer opinions expressed on *social media* or in direct *feedback, providing valuable insights* for adapting products and services to market needs. Another area of application for Artificial Intelligence is *predictive systems,* which serve to anticipate customer needs, suggesting personalized solutions and fostering more effective loyalty strategies. In this context, AI doesn't just replace human intervention in repetitive tasks, but can also act as a strategic

[60] Companies that adopt these technologies not only optimize their development processes but also increase their ability to introduce radical innovations, consolidating their position in increasingly dynamic global markets.

support tool that strengthens customer relationships, increases service quality, and helps create a more seamless and engaging consumer experience.

3.1.1 (…continued) in Finance and Risk Management

In recent decades, the introduction of Artificial Intelligence in the financial sector has brought about a profound transformation of *business models*, decision-making processes, and risk management systems. First, *machine learning* and *big data analytics algorithms* are used in financial markets to develop algorithmic *trading* strategies that can process massive amounts of data in real time and identify *patterns* that would otherwise escape human analysis, increasing the speed and accuracy of investment decisions[61]. Second, Artificial Intelligence plays a central role in risk management and fraud prevention, thanks to predictive models and anomaly detection systems that allow monitoring of suspicious transactions, reducing exposure to potential losses. Furthermore, in everyday life, it is evident how the integration of *chatbots* and virtual assistants has improved banking *customer service*, offering personalized advice and ongoing support to *retail customers*, with a positive impact on satisfaction and loyalty. Overall, Artificial Intelligence not only increases the operational efficiency of the financial sector, but also helps strengthen its resilience and ability to generate value in a highly complex and volatile environment.

Risk management also represents one of the most significant innovations for contemporary business management, especially in highly complex sectors.

[61]Feng, G., He, J., & Polson, N. G. (2018). Deep learning for predicting asset returns. *Applied Stochastic Models in Business and Industry, 34* (1), 1–12

Thanks to *machine learning* and *data mining techniques*, we are now able to process enormous amounts of heterogeneous data, identifying risk *patterns* and predicting future scenarios with greater accuracy than traditional statistical models. A particularly relevant area is fraud prevention, where anomaly detection algorithms allow us to monitor suspicious transactions and behavior in real time, significantly reducing potential losses. At the same time, AI supports credit risk assessment. Through predictive models that analyze unstructured variables, such as behavioral data or *digital footprints*[62], financial institutions can expand their ability to assess customer creditworthiness. Furthermore, in operational management, AI is used for *stress testing* and scenario simulations, tools that help organizations improve resilience to unexpected events and develop more effective mitigation plans. In short, AI is a strategic ally for risk management, enabling organizations not only to respond to emerging risks but also to adopt a proactive and predictive approach to their management.

3.1.2 (continued) in Healthcare & Life Sciences

The use of Artificial Intelligence in healthcare today represents one of the most promising applications with a high social impact, as it improves the quality of diagnoses, optimizes treatment pathways, and streamlines hospital management. In the clinical setting, *machine learning* and *deep*

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[62]A *digital footprint* refers to the traces individuals and organizations leave online when using the internet and digital technologies. It includes both consciously generated data, such as posts, comments, or shared content, and data collected automatically and less visibly, such as through cookies, browsing history, or geolocation systems. A digital footprint contributes to one's online reputation and can have significant implications for privacy, security, and public image, making it essential to manage one's digital presence consciously and responsibly.

learning algorithms are used to analyze medical images (X-rays, CT scans, MRIs), ensuring greater diagnostic accuracy and supporting physicians in the early identification of complex pathologies such as tumors or cardiovascular diseases. Furthermore, AI finds application in personalized medicine, where the analysis of large genomic and clinical *datasets* allows for the development of treatments tailored to individual patients, improving the efficacy of therapies and reducing side effects. The use of Artificial Intelligence in medical diagnostic processes is revolutionizing clinical practice, providing tools capable of supporting healthcare professionals with levels of accuracy comparable, and in some cases superior, to those of humans. *Deep learning* algorithms, particularly convolutional neural networks (CNNs), have demonstrated remarkable capabilities in analyzing diagnostic images such as X-rays, MRIs, and CT scans, contributing to the early identification of pathologies such as tumors, cardiovascular diseases, and neurological disorders[63]. In the clinical field, AI is not limited to diagnostic imaging but also finds application in the analysis of clinical and genomic data, facilitating predictive and personalized medicine and enabling greater precision in therapeutic decisions. Furthermore, AI-based *decision support systems* can integrate data from electronic medical records, laboratory tests, and patient history, reducing the likelihood of diagnostic errors and increasing the timeliness of treatment. Artificial Intelligence does not replace the expertise of the physician, but acts as a complementary tool, capable of enhancing the quality of diagnoses and improving clinical outcomes for patients. One of

[63]steva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542* (7639), 115–118.

the most advanced areas of AI application is diagnostic imaging. In the interpretation of X-rays, MRIs, and CT scans, the aforementioned convolutional neural networks (CNNs) have demonstrated *performance* comparable to that of specialists. These tools are particularly effective in early detection of conditions such as skin cancers, lung lesions, or cardiovascular diseases, enabling more timely clinical interventions. Automated analysis also has the advantage of reducing reporting times and supporting radiologists in processing large volumes of data. Artificial Intelligence is also being applied to the analysis of clinical and genomic data, which are crucial for the development of predictive and personalized medicine. *Machine learning algorithms* can process electronic medical records, identifying hidden *patterns* that help predict the onset of chronic or rare diseases. Furthermore, the integration of genetic data allows for better targeted therapies, optimizing drug treatments based on each patient's unique characteristics, which are not overlooked by Artificial Intelligence (the approach described helps move beyond the standardized model of care, paving the way for more effective and sustainable healthcare). AI's further contribution to diagnosis is represented by Clinical Decision Support Systems (CDSS), tools that integrate data from diagnostic *tests*, medical history, and real-time monitoring, offering physicians *evidence-based suggestions* that reduce the likelihood of clinical errors. Through predictive systems, CDSS also help stratify patients based on risk, improving treatment planning and the allocation of hospital resources. In short, the use of Artificial Intelligence in medical diagnosis is a disruptive factor that is redefining traditional clinical practices, helping to improve diagnostic accuracy, personalize treatments, and reduce intervention times, fostering a more efficient and patient-focused healthcare system. The future

challenge will not be to replace the physician, but to integrate Artificial Intelligence into a collaborative model that combines AI with human experience and empathy.
Another area of development concerns decisions in the operational and administrative management of healthcare facilities, where predictive systems optimize resource planning, patient flow management, and waiting time reduction. In short, Artificial Intelligence, applied to healthcare, does not simply support the work of professionals, but helps build a more proactive, efficient, and patient-focused care model. In healthcare, Artificial Intelligence is not only used in the clinical setting, but is also playing an increasingly central role in hospital administration, helping to streamline the management and organizational processes of healthcare facilities by enabling rapid and effective decision-making. First, predictive algorithms and *machine learning systems* are used to optimize resource planning, improving the management of staff shifts, beds, and operating rooms, with the aim of reducing waiting times and overloads. Secondly, Artificial Intelligence enables more accurate management of patient flows through predictive models that estimate peak demand, allowing hospitals to adapt services flexibly and proactively. Furthermore, *natural language processing tools* facilitate the analysis of electronic medical records and administrative documents, automating diagnosis coding and healthcare billing, reducing errors and improving regulatory *compliance*. Finally, Artificial Intelligence systems also find application in financial management and cost control, supporting healthcare management in strategic resource allocation decisions. In short, Artificial Intelligence applied to hospital administrations not only increases organizational

efficiency but also contributes to building a more sustainable and patient-centered management model.

Specifically, it is used to optimize shift planning and healthcare personnel management, taking into account variables such as availability, specializations, and workloads. Similarly, predictive algorithms allow for better bed allocation and the organization of operating rooms, reducing waiting times and limiting overcrowding[64]. Through *machine learning* models, hospital administrations can address recurring problems and critical issues, predicting peaks in demand and proactively adjusting the provision of healthcare services. These tools allow them to anticipate the influx of patients in emergency rooms or specialist areas, improving the facilities' responsiveness and increasing the resilience of the healthcare system. *Natural language processing* (NLP) technologies are used in electronic medical records, diagnosis coding, and healthcare billing. Automating these tasks reduces the risk of bureaucratic errors, speeds up administrative processes, and ensures greater regulatory compliance, freeing up time and resources for higher-value activities. Artificial Intelligence also supports hospital management in financial management and cost control, thanks to predictive models that analyze spending trends and identify inefficiencies. In this way, it is becoming a tool to support *strategic decision-making,* allowing resources to be allocated in a more targeted and sustainable manner, contributing to improved healthcare [65]*governance*. Artificial

[64]Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine, 380* (14), 1347–1358

[65] In short, the use of Artificial Intelligence in hospital administrations not only increases operational efficiency but redefines the entire management approach. The integration of predictive and automated tools allows for improved planning, reduced costs, and more timely and personalized services. The future challenge will be to harmonize these innovations with the central role of healthcare professionals, building an administrative

Intelligence is taking on an increasingly important role also in the sector of *Life Sciences,* fostering significant advances in fields such as biology, biotechnology, pharmaceutical research, and genomics. *Life Sciences* refers to the set of scientific disciplines that study living systems, from their molecular and cellular structure to the organization of organisms and ecosystems. It is a multidisciplinary field that includes fields such as biology, biochemistry, genetics, medicine, biotechnology, pharmacology, neuroscience, agronomy, and environmental science. The primary goal of Life Sciences is to understand the fundamental mechanisms that regulate vital processes, with the aim of translating this knowledge into practical applications useful for improving human and animal health, and the environment (National Research Council, 2009). From an applied perspective, life sciences play a crucial role in various industrial sectors, particularly in healthcare, where they drive the development of new therapies and diagnostic tools; in biotechnology, with the design of innovative organisms and materials; and in agri-food, for crop optimization and food safety (OECD, 2021). In recent years, integration with Artificial Intelligence and digital technologies has further expanded the potential of life sciences, transforming them into an increasingly *data-driven field* oriented towards precision medicine.

Thanks to *machine learning* and *deep learning techniques,* it is possible to analyze enormous amounts of biological and clinical data, identifying complex [66]*patterns that support the discovery of new drugs and the understanding*

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model in which technology enhances decision-making and organizational capabilities without replacing human value.

[66]Zhavoronkov, A., Ivanenkov, Y. A., Aliper, A., Veselov, M. S., Aladinskiy, V. A., Aladinskaya, A. V. & Zholus, A. (2019). Deep learning enables rapid identification of potent DDR1 kinase inhibitors. *Nature Biotechnology, 37* (9), 1038–1040.

of the molecular mechanisms of diseases. In particular, AI is widely used in *drug discovery,* where it allows for the identification of promising molecules and the reduction of the time and costs of clinical trial processes. Among other things, the integration of Artificial Intelligence and genomics allows for the development of personalized medicine approaches, thanks to the analysis of genetic data and biomarkers that guide targeted and effective therapies. Furthermore, applications in biotechnology support the design of new enzymes and biological materials, accelerating innovation in fields such as agri-food and bioenergy. In this context, Artificial Intelligence does not simply improve the efficiency of research activities, but becomes a true catalyst for innovation, helping to transform *Life Sciences* into an increasingly *data-driven* and predictive discipline.

3.1.3 (continued) in Public Administration & Policy

The use of Artificial Intelligence in Public Administration is a key driver of the digitalization and innovation of public services. Through *machine learning tools, natural language processing,* and predictive systems, public administrations are improving data management, optimizing decision-making processes, and streamlining the delivery of services to citizens. Specifically, applications based on *chatbots* and virtual assistants enable automated management of user requests, ensuring continuous service and reducing response times. At the same time, predictive models are used to support resource planning and identify risks or anomalies in administrative procedures, contributing to fraud prevention and increased transparency. Another area of application is the analysis of *big data* to support public policies, allowing decisions to be guided by empirical evidence and improving the ability to respond to complex phenomena, such as health emergencies or climate change. However, the introduction of Artificial Intelligence in the Public Administration also raises issues related to algorithmic transparency, the accountability of automated decisions, and the protection of fundamental rights, which are subject to careful regulation and strong ethical oversight[67]. In short, while Artificial Intelligence represents a strategic opportunity to make the Public Administration more efficient, proactive, and citizen-oriented, it needs to be integrated with adequate guarantees of legality and *accountability*. The introduction of *chatbots* In Public Administration (PA), chatbots represent, among other things, one of the most significant developments in the digitalization of public services. Based on Artificial Intelligence algorithms and *natural language processing (NLP)* techniques, *chatbots* enable automated citizen interaction, providing real-time information and assistance. These tools, accessible through institutional portals or messaging apps, simplify access to services, reduce wait times, and ensure 24-hour service availability. In addition to their information function, *chatbots* are used to support citizens in filling out forms, booking appointments, or checking the status of administrative procedures, thus helping to reduce the workload of human operators and improve organizational efficiency. From a strategic perspective, the adoption of *chatbots strengthens the* citizen-centric digital administration model, fostering a more immediate and personalized relationship with users. However, their use also raises critical issues related to the need to ensure transparency, personal data protection, and inclusiveness so that these tools do not generate new forms of digital

[67]Galetta, D.-U., & Corvalán, J.G. (2019 *). Artificial intelligence for a Public Administration 4.0? Federalismi.it, 17* (4), 1–24.

exclusion or information asymmetries. Looking ahead, the evolution of *chatbots* toward increasingly intelligent systems integrated with *e-government platforms is believed* to represent a significant opportunity to make public administration more accessible, efficient, and responsive to the needs of the community.

The adoption of Artificial Intelligence in Public Administration offers undeniable benefits in terms of efficiency and innovation, but at the same time raises significant critical issues that must be carefully managed. A first risk concerns algorithmic transparency and opacity: automated decisions can be difficult to understand for citizens and public officials themselves, compromising the right to the justification and comprehensibility of administrative measures. A second critical aspect concerns legal liability. The use of automated systems raises questions about who is responsible in the event of an error, discrimination, or unlawful measure: the programmer, the administration that adopted the algorithm, or the official who failed to carry out a check?[68]Another significant risk is that of algorithmic *bias,* i.e., the possibility that Artificial Intelligence systems reproduce or amplify discrimination already present in the data used for training, with negative consequences for citizens' equality before the law. From an organizational point of view, there is also the risk of digital exclusion: less technologically literate citizens could have difficulty accessing public services managed through Artificial Intelligence, generating new forms of social inequality.

The question of the the digital *divide* refers to the inequality in access, skills, and opportunities related to digital technologies and the Internet. It's not

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[68]Galetta, D.-U., & Corvalán, J.G. (2019 *). Artificial intelligence for a Public Administration 4.0?* cit., 1–24.

just about the physical availability of devices or connections, but also the ability to use them effectively[69].

In Italy, AgID (Italian National Agency for the Development of Artificial Intelligence) published the Guidelines for the Adoption of Artificial Intelligence (AI) in Public Administration with Resolution No. 17/2025. Their purpose is to provide a regulatory and operational framework for the responsible and strategic integration of AI in the Italian public sector. These guidelines aim to guide public administration by offering principles and recommendations for the adoption of AI, ensuring regulatory compliance and respect for fundamental rights, as well as promoting its ethical and inclusive use, ensuring that its use does not discriminate and is accessible to all. The Guidelines also aim to ensure quality and reliability by ensuring that AI systems are accurate, reliable, and secure, and to encourage innovation and sustainability, using them to improve public services. Finally, the document aims to develop skills by training personnel for the effective use of AI. Structurally, the Guidelines are divided into five sections:

1. Compliance and Governance, defining a clear regulatory framework for the use of AI;
2. Ethics and Inclusion, promoting AI that respects fundamental rights;
3. Quality and Reliability, ensuring that AI systems are accurate and safe;
4. Innovation and Sustainability, encouraging the use of AI to improve public services;

[69]The *digital divide* has significant consequences, as it amplifies existing economic and social inequalities, hindering innovation and inclusive growth. For this reason, it is considered a central issue in public and corporate policies aimed at promoting equal access, training, and digital inclusion.

5. Training and Organization, developing the skills necessary for the effective use of AI.

Furthermore, the document includes technical annexes that provide practical tools for implementing AI in public administration. Furthermore, the public consultation, which remained open until March 20, 2025, provided an opportunity for citizens, experts, and stakeholders to contribute to defining the future of AI in public administration. In summary, the Guidelines aim to guide Italian Public Administrations towards the adoption of AI, ensuring that it is done responsibly, ethically, and geared towards improving public services, while constantly guaranteeing the protection of fundamental rights and regulatory compliance.

Finally, issues related to personal data protection and cybersecurity must not be overlooked, as the widespread use of sensitive information by public administrations exposes them to potential *privacy violations and cyber* attacks. In conclusion, where Artificial Intelligence is used in public administration, it must be accompanied by a clear regulatory framework, *accountability* mechanisms, and strong ethical oversight. So that technological innovation does not compromise the fundamental principles of legality, equality, and the protection of citizens' rights.

Finally, the use of Artificial Intelligence in public policy choices represents one of the most innovative and controversial frontiers in the relationship between technology and *governance*. Thanks to its ability to process enormous amounts of data rapidly, Artificial Intelligence can support policy makers in analyzing socioeconomic trends, forecasting future scenarios, and assessing the impact of legislative decisions[70]. Through *predictive analytics* and *machine learning tools,* it is possible to simulate the effectiveness of certain public policies, identify areas of greatest social and economic vulnerability, and better direct the distribution of resources. Artificial Intelligence can also facilitate democratic participation processes, for example through the analysis of *big data* from *social media,* which allows for real-time monitoring of public opinion and the integration of citizen input into decision-making processes. However, the use of these technologies also raises important ethical and political questions: the risk of algorithmic opacity and data *bias can compromise the legitimacy of decisions;* Excessive delegation to technology can reduce the critical role of democratic debate; finally, the political use of data can lead to surveillance and manipulation. In summary, AI is a powerful tool to support *evidence-based policymaking,* but it must be governed by principles of transparency, *accountability,* and inclusiveness to ensure that political choices are not only more informed and efficient, but also respectful of democratic values and fundamental rights.

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[70]Eggers, W. D., Schatsky, D., & Viechnicki, P. (2017). *AI-augmented government: Using cognitive technologies to redesign public sector work* . Deloitte University Press. 43.

CHAPTER IV

AI DECISION MAKING AND GEOPOLITICS. THE US CASE

Premise

This chapter aims to examine the AI algorithm that governs the TikTok platform as a paradigmatic expression of the tensions characterizing the strategic competition between the United States and China in the digital sphere. First, the analysis considers the US institutional and regulatory framework for safeguarding national security, with particular reference to the Committee on Foreign Investments in the United States (CFIUS), as an instrument responsible for vetting foreign investments that could impact the country's geopolitical interests. Subsequently, attention focuses on the nature and functioning of the TikTok algorithm, interpreted not only as a technology for profiling and distributing content, but also as a vehicle for a model of Chinese political capitalism, in which economic scale, state apparatus, and strategic goals are inextricably linked. From this perspective, the chapter then delves into the American interpretation of the so-called "TikTok case," presenting it as a genuine form of digital conflict, in which concerns about the protection of personal data and technological autonomy intertwine with broader geopolitical conflicts. The chapter concludes with some summary considerations, highlighting how the debate surrounding TikTok's algorithm transcends the merely commercial or technological dimension, instead emerging as a battleground between competing political-economic models and differing visions of the international digital order.

4.1 USA: National Security and Geopolitical Interest: The Committee on Foreign Investments in the US (CFIUS)

National security has always been a strategic priority for the United States, forming the cornerstone of major domestic and foreign policy decisions. After World War II, Washington progressively consolidated its role as a global power, building a system of military alliances (such as NATO) and an intelligence and defense apparatus capable of ensuring unprecedented international presence. US national security doctrine is not limited to border defense but extends to the protection of geopolitical and economic interests, including access to resources, market stability, and the maintenance of an international order favorable to the American balance of power. The concept of geopolitical interest for the United States translates into the ability to prevent or contain the influence of competing powers, ensure freedom of navigation on major trade routes, guarantee energy security, and support the spread of political and economic models consistent with its democratic values. International crises, terrorism, cyber threats, and technological competition have expanded the scope of national security, transforming it into an integrated set of policies that combine military defense, diplomacy, and technological innovation. In this framework, US national security appears closely intertwined with geopolitical interests, giving rise to a global strategy that aims not only to protect the country from direct threats but also to preserve its leadership on the international stage.

Within this framework lies the Committee on Foreign Investment in the United States (CFIUS), an interagency body of the U.S. government established in 1975, tasked with examining acquisitions, mergers, and foreign investments in American companies to assess their impact on national security. Composed of representatives from various departments[71], CFIUS has gained increasing importance in recent decades, particularly with the end of the Cold War and the rise of global economic powers. The regulatory framework is the Foreign Investment and National Security Act (FINSA) of 2007 and, more recently, the Foreign Investment Risk Review Modernization Act (FIRRMA) of 2018, which significantly expanded the Committee's powers. Specifically, FIRRMA expanded CFIUS's jurisdiction to include not only traditional mergers and acquisitions, but also minority investments and transactions involving sensitive technology sectors and critical personal data. Today, CFIUS's actions lie at the intersection of economic and geopolitical security, representing a tool with which the United States seeks to protect its critical infrastructure and technological *know-how* from the influence of foreign investors considered potentially hostile[72]. In recent years, the Committee's decisions have attracted international attention, as they often involve companies from China or other countries perceived as strategic competitors. In this sense, CFIUS is not only a technical investment review mechanism, but also a reflection of US foreign policy and global power dynamics.

4.2 Tiktok's strategic algorithm and Chinese political capitalism

Social media platform founded by the Chinese company ByteDance, initially launched in China under the name Douyin.

ByteDance Ltd. is a Chinese technology company founded in Beijing in 2012 by Zhang Yiming, which quickly established itself as a major player in the

[71] Including Treasury, Defense, Trade, Homeland Security, and Justice.
[72]Jackson, J. K. (2020). *The Committee on Foreign Investment in the United States (CFIUS)* . Congressional Research Service

global digital platform landscape. The company has become known for creating and developing applications based on artificial intelligence and machine learning systems, capable of sophisticatedly personalizing user experiences by processing large amounts of data. ByteDance's original product was Toutiao, a news aggregation platform that uses recommendation algorithms to select and propose personalized content, which immediately marked the company's innovative approach. However, global success was achieved with TikTok (in its Chinese version called Douyin), launched in 2016 and rapidly spreading internationally. From an organizational and financial standpoint, ByteDance is characterized as a formally independent private company, but operating within the Chinese political-economic system, in which the role of the Chinese Communist Party in corporate governance dynamics and content supervision is particularly significant. This has raised numerous questions at an international level regarding the protection of privacy, the protection of personal data and the potential geopolitical interference arising from the use of its platforms[73].

The app, designed for creating and sharing short videos accompanied by music and creative filters, was an immediate success in the domestic market, and in 2017,ByteDance decided to expand the format internationally, creating the global version known as TikTok. A crucial step in the platform's development was the 2017 acquisition of Musical.ly, a

[73] Today, ByteDance operates a diversified portfolio of applications ranging from entertainment to education, gaming to professional services, with a widespread presence in over 150 countries and hundreds of millions of daily active users. The company is considered one of China's leading technology "unicorns," playing a significant role in both the development of the global digital economy and the strategic competition between China and the United States.

highly popular app among young people in the United States and Europe specializing in synchronized music videos. In 2018, Musical.ly officially merged with TikTok, allowing the Chinese company to integrate an already established user base and strengthen its presence in Western markets. In just a few years, TikTok has become one of the most downloaded apps in the world, standing out for its recommendation algorithm, based on artificial intelligence techniques capable of personalizing the flow of content in real time. This mechanism has fostered a high level of *engagement,* transforming TikTok not only into an entertainment platform but also into a powerful tool for communication, marketing, and even social activism. Despite its success, TikTok's growth has been accompanied by controversies related to privacy, user data management, and its connection to China, which have led several governments, including the United States, to consider restrictions or bans on its use. These dynamics have made TikTok an emblematic case of the relationship between technological innovation, *soft power,* and geopolitical security. To understand this issue, we need to go back to one of the central elements of TikTok's success: its sophisticated Artificial Intelligence system, which powers the recommendation algorithm underlying the *"For You Page" (FYP) section*. Unlike traditional social networks, which rely largely on users' social connections (friends, *followers,* personal networks), TikTok prioritizes the analysis of individual behavior, offering a highly personalized feed. In summary, the functioning of TikTok's Artificial Intelligence algorithm is divided into several phases[74]:

[74]Cotter, K., & Reisdorf, B. C. (2020). *Algorithmic reframing in the TikTok ecosystem*. *Social Media + Society, 6* (4), pp. 1–12.

1. Behavioral data collection: The app records actions such as likes, comments, watch time, shares, and even the speed at which the user scrolls through content. Each interaction becomes a useful signal for shaping personal preferences.
2. Feature extraction: through *machine learning* and *deep learning* techniques, the system analyzes characteristics of both content (music, images, text, hashtags, trends) and user behavior.
3. Predictive recommendation: Based on this data, the algorithm predicts which content is most likely to generate engagement and delivers it in real time to the feed.
4. Continuous self-learning: As the user interacts with new videos, the algorithm constantly updates its model, refining its prediction ability.

The approach described allows TikTok to offer highly relevant content even to users without a pre-existing social network, reducing barriers to entry and accelerating loyalty. However, the same mechanism raises questions about algorithmic transparency, data privacy, and the potential for addiction, as optimizing *engagement* can encourage compulsive consumption.

These critical issues must be interpreted, among other things, considering the pervasive functioning of Chinese capitalism. The Chinese economic model, in fact, reflects a "socialism with Chinese characteristics," a formula that reflects the unique combination of centralized political leadership and selective openness to market mechanisms. Since President Deng Xiaoping's reforms in the 1980s, China has progressively integrated typical capitalist tools (such as competition, foreign investment, and private sector development) while maintaining strong state control over strategic areas of the economy. As is well known, in recent decades, China has established itself as a leading international economy, asserting its capitalism. Today, Chinese economic policy operates on multiple levels: on the one hand, the state promotes growth through multi-year development plans (such as the Five-Year Plans), which guide industrial and technological priorities; on the other, it supports strategic public and private enterprises by providing them with preferential access to credit, tax incentives, and direct support for research and innovation. In this context, the so-called *national champions,* leading Chinese companies in key sectors such as energy, telecommunications, and *high-tech,* take on particular importance. They enjoy government protection and support to compete globally. Political support is also evident in the management of relations with foreign economies. While China has encouraged the entry of foreign investment as a source of know-how and technology, it has also introduced control mechanisms (e.g., mandatory *joint ventures,* sectoral restrictions, and others) to ensure that technology transfer benefits domestic firms. At the same time, through initiatives such as the Belt and Road Initiative (BRI) [75], Beijing has extended its model of state capitalism beyond national borders, strengthening its economic and geopolitical influence. In this context, the policy supporting Chinese capitalism is configured as a synthesis of market and state, in which competitive dynamics do not develop in the absence of rules, but are guided by a broader political plan. This structure has allowed China to emerge as the world's second largest economy today, but it

[75]The Belt and Road Initiative (BRI), launched by China in 2013, is an international development and cooperation strategy aimed at promoting infrastructure, trade, and economic integration on a global scale. Divided into a land component (the "Silk Road Economic Belt") and a maritime component (the "21st Century Maritime Silk Road"), the initiative aims to strengthen connections between Asia, Europe, Africa, and beyond, while also serving as a tool for geopolitical projection and consolidating Chinese influence on the international stage.

continues to raise questions about the relationship between economic openness, political control, and compatibility with Western-style capitalist models. In this context, the AI algorithm adopted by TikTok represents a prime example of how digital platforms can be not only tools for global entertainment, but also the expression of a specific economic and political model. As mentioned, its suspicious algorithmic architecture, developed by its parent company ByteDance, is based on sophisticated AI systems that personalize content for each user in real time, maximizing engagement and time spent on the app. This capacity for *data-driven engagement* has transformed TikTok into a powerful player in the attention economy, capable of influencing social, cultural, and even political dynamics. This model, in fact, is not neutral, but is part of China's political capitalism, characterized, as described, by a profound intertwining of market logic and state control. Digital platforms like TikTok embody the strategy of combining technological innovation, global competition, and political governance. On the one hand, ByteDance operates as a private enterprise focused on growth and profit maximization; on the other, it remains subject to the rules and strategic objectives set by the Chinese government, which views digital data and algorithmic technologies as key *assets* for national security and the projection of international power. From this perspective, TikTok's algorithm cannot be considered merely a technical mechanism for recommending content, but a strategic device capable of collecting and analyzing enormous amounts of data, guiding cultural consumption, and channeling forms of Chinese [76]*soft power*. The TikTok case, with its geopolitical controversies over data management and national security,

[76] Testa, L. (2025). Trump v. TikTok: Freedom of Expression and National Security. *DPCE Online, 69* (1).

therefore highlights how Chinese political capitalism also manifests itself in the digital space, through Artificial Intelligence, posing crucial challenges to Western liberal models in terms of technological governance, economic competition, and information sovereignty.

4.3 The American interpretation of the TikTok case: the digital war

The term "digital warfare" refers to the set of tensions and conflicts developing in cyberspace, where data, technological infrastructure, and algorithms become true strategic weapons. Unlike traditional warfare, digital warfare is not fought on physical ground, but through the control of computer networks, the ability to conduct cyberattacks, the manipulation of information, and the management of global digital platforms. It is part of a context of growing technological interdependence, in which digital supremacy is an essential condition for economic and political hegemony. A central role in this scenario is played by Artificial Intelligence algorithms, tools that, as widely illustrated, are capable of analyzing enormous amounts of data and guiding decision-making processes in the military, economic, and social spheres. These algorithms not only fuel digital platforms and *social networks,* influencing the circulation of information and public opinion, but can also be used in cybersecurity, surveillance, predictive intelligence, and automation of military operations. The ability to develop and control such algorithms has therefore become a strategic resource, as it guarantees a competitive advantage in new forms of hybrid conflict.
In this sense, digital warfare and the use of Artificial Intelligence algorithms are not limited to the technical dimension, but involve geopolitical, ethical, and regulatory issues. States, like other countries, must balance the needs

of national security, data protection, and individual freedom, and they do so while competing to establish technological standards and governance models capable of determining the global balance of power of the future[77]. The TikTok case represents one of the most obvious manifestations of the tensions characterizing the so-called “digital warfare”, and has seen the United States and China as protagonists. From the United States' perspective, the ByteDance-owned platform is not just an entertainment social network, but a potential instrument of geopolitical influence and a national security risk. This accusation arises from assessments regarding the handling of US users' personal data and the possibility that such information could be accessed by the Chinese government under national legislation requiring local companies to cooperate with authorities.

The American interpretation of the TikTok phenomenon fits into a broader framework, in which digital infrastructure and algorithms are not perceived as neutral entities, but rather as strategic assets capable of influencing the economy, security, and even domestic political debate. From this perspective, potential Chinese control over an app so popular among young Americans poses a twofold risk: on the one hand, the possibility of external surveillance of citizens; on the other, the opportunity for Beijing to exert cultural *soft power* through the circulation of content.

For the US government, therefore, the TikTok case should be interpreted as part of a broader systemic competition, which is no longer being played out solely on commercial or military levels, but increasingly in the digital space. The so-called digital warfare manifests itself through technological restrictions, trade blockades, cybersecurity measures, and attempts to

[77] Testa, L. (2025). Trump v. TikTok: Freedom of Expression and National Security. *DPCE Online, 69* (1). 78.

reshape the global rules of the data economy[78]. The focus on TikTok, along with other measures against Chinese companies like Huawei, reflects the United States' desire to preserve its technological leadership and contain the expansion of Chinese political capitalism on the global stage, preventing the algorithms of these social networks from storing data suitable for subsequent manipulation.

The issue has been the subject of extensive debate that has extended the topic in a broader direction. Artificial intelligence, it has been said, is profoundly transforming the field of intelligence, redefining the ways in which information is collected, analyzed, and used, exposing it to the risk of espionage. Traditionally, espionage activities have relied on human methods (HUMINT), communications interception (SIGINT), and technical surveillance (TECHINT), but with the advent of artificial intelligence, these practices have evolved towards forms of automated and predictive analysis, capable of processing enormous volumes of data from open *-source intelligence, social media,* computer networks, and surveillance systems. Machine learning algorithms, *it is said,* allow us to identify hidden *patterns* and correlate fragmented information. In cyber espionage, Artificial Intelligence is used to detect vulnerabilities in computer systems, conduct targeted attacks, and even generate credible false content (*deepfakes*) for the purpose of spreading disinformation. Intelligence services are also leveraging Artificial Intelligence to strengthen their defense capabilities by automating intrusion detection systems and improving the security of critical infrastructure. This evolution has significant geopolitical and ethical implications. On the one hand, Artificial Intelligence amplifies state

[78] Testa, L. (2025). Trump v. TikTok: Freedom of Expression and National Security. *DPCE Online, 69* (1).

surveillance and industrial espionage capabilities, intensifying strategic competition between great powers; on the other, it raises questions about the protection of individual rights and the transparency of intelligence practices. In a context of growing digital interdependence, the use of Artificial Intelligence in espionage represents not only a technological advance but also a factor in redefining the global balance of power, and the TikTok case offers a pretext for reflection on these issues.

4.4 Considerations on the case

The Trump administration's "war" against TikTok in 2020 and 2021 was part of broader technological and trade tensions between the United States and China. After accusing the platform of posing a national security threat, alleging that US user data could be accessed by the Chinese government, Trump signed a series of executive orders in August 2020 [79]aimed at banning TikTok in the United States unless the company sold its US operations to an American company.

The executive orders were various and, above all, they resumed in 2025 with the new Trump presidency. Below is a table listing these orders.

[79]These are provisions issued by the President of the United States that guide the subsequent choices of the federal government.

Date	*Executive Order and Main Action*
Aug 6, 2020	Executive order 13942 – Ban on transactions with ByteDance
Aug 14, 2020	Definition order: sell or shut down Tik tok within 90 days
Jun 2021	Biden revokes Trump's orders
Jan 20, 2025	First order: suspension of Pafaca enforcement for 75 days
Apr 4, 2025	Second order: furthers suspension of 75 days
Jun 19, 2025	Third order: new suspension (90 days) until Sept 17, 2025

The acronym PAFACA shown in the table refers to the Protecting Americans from Foreign Adversary Controlled Applications Act, passed by the United States Congress in 2024. This law aims to ban or restrict the use in the United States of digital applications developed or controlled by foreign adversaries when deemed a threat to national security. It was primarily conceived in response to the TikTok/ByteDance case, but applies broadly to any app that collects sensitive data and is subject to potential foreign government interference. PAFACA grants the President of the United States the authority to impose restrictions, bans, or mandates divestment of controlling interests in such platforms and provides for the possibility of suspending or extending the application of bans through executive orders, as occurred in 2025 with the extensions signed by Trump for TikTok. In essence, PAFACA represents the legal framework through which Washington has sought to manage technological competition and data protection, using TikTok as a prime example of the conflict between national security, economic freedom, and digital geopolitics. Complex negotiations ensued with major corporations such as Microsoft, Oracle, and Walmart, but no definitive solution was reached. Lawsuits filed by

ByteDance and some users led several US federal courts to suspend the administration's actions, deeming the evidence of the alleged security risks insufficient. With the inauguration of the new President, Joe Biden, in January 2021, the incumbent administration decided to shelve Trump's coercive approach, revoking the executive orders and replacing them with a new regulatory approach based on a broader analysis of the risks associated with foreign digital applications. In essence, Trump's war on TikTok did not end with an actual ban, but rather set a political and legal precedent: the recognition of the strategic dimension of the Artificial Intelligence employed by Chinese digital platforms and the need for adequate institutional tools to balance innovation, free market, and national security[80].

The ensuing debate highlighted that, starting with espionage, Artificial Intelligence could also support military decision-making, thus identifying one of the most controversial frontiers. The ability of algorithms to analyze enormous amounts of data, recognize *patterns,* and make decisions very quickly makes Artificial Intelligence a potentially decisive tool for defense and warfare strategies. However, it was noted that its progressive integration into military policies raises significant ethical, legal, and geopolitical risks.

First, the automation of decision-making processes in warfare scenarios introduces the risk of loss of human control. Autonomous weapons systems, capable of selecting and striking targets without direct human intervention, raise questions about legal liability in the event of errors or violations of international humanitarian law. Second, Artificial Intelligence

[80] The incident marked the beginning of Washington's systematic attention to the so-called "digital warfare."

applied to cyberwarfare and surveillance can amplify espionage, disinformation, and cyberattack capabilities, with destabilizing consequences for international security[81]. These tools can be employed not only in declared conflicts, but also in forms of hybrid warfare, invisible and difficult to attribute, increasing strategic uncertainty. A further risk is linked to the technological arms race, as the military adoption of AI by major powers risks triggering a global competition without shared rules, in which the speed of innovation outstrips the capacity of international institutions to define norms and control mechanisms. This is a scenario that could lead to an erosion of strategic stability and an increased risk of unintentional conflict. Finally, the political-military use of Artificial Intelligence risks accentuating global inequalities, strengthening the position of technologically advanced states and marginalizing those lacking the resources to develop such capabilities. This creates a scenario in which Artificial Intelligence, from a tool for progress, could transform into a factor of geopolitical instability.

[81] Testa, L. (2025). Trump v. TikTok: Freedom of Expression and National Security. *DPCE Online, 69* (1). 11.

Conclusions

The analysis of the theoretical foundations of decision making has highlighted the complexity of a process that, far from being linear, is influenced by cognitive, organizational, and contextual variables.

First, the definition of decision making highlighted how it is not simply an act of choosing between alternatives, but a truly complex process involving information gathering and interpretation, risk assessment, prioritization, and accountability. Decision making involves choosing a process from which to draw a conclusion, and the amount of information it relies on is the primary variable determining the effectiveness of the decision itself.

The comparison between classical rationality and bounded rationality has shown the progressive overcoming of the ideal of the fully rational decision-maker, replaced by the model of bounded rationality, which is more in line with the reality of concrete decision-making processes, in which cognitive and informational capacities are inevitably finite.

This is the context for the study of cognitive biases and heuristics, which are simplifying mental mechanisms useful for reducing complexity, but also potentially leading to systematic errors. Psychological and behavioral research has shown how these factors impact both individual and collective and organizational decisions.

The analysis of prescriptive, descriptive, and normative models has also allowed us to distinguish the different perspectives from which the theory approaches decision making: from the prescription of optimal rules, to the description of actual behaviors, to the formulation of evaluation criteria to improve the quality of choices. Decision-making theory cannot, therefore, be reduced to a single paradigm, but must be understood as an interdisciplinary field, in constant dialogue between economics, psychology, sociology, and law. This plurality of approaches constitutes the essential basis for addressing the impact that artificial intelligence has on decision-making processes, both in terms of enhancing human cognitive capabilities and in relation to the risks and ethical, organizational, and geopolitical implications that arise from it. The convergence of artificial intelligence and decision-making processes represents one of the most significant directions of contemporary technological development. The analysis of different techniques and approaches has shown that AI does not simply provide automation tools, but profoundly impacts the very nature of decision-making, expanding its possibilities while simultaneously raising new issues.

The overview of machine learning, deep learning, and reinforcement learning has highlighted the ability of systems to learn from large amounts of data, identifying patterns and optimizing strategies in dynamic contexts. At the same time, expert systems and symbolic reasoning demonstrate how approaches based on rules and formal logic continue to maintain relevance, especially in sectors characterized by stringent regulatory constraints.

The evolution of Generative AI and Large Language Models have extended the role of AI far beyond classification or prediction, enabling the production of complex texts, images, and solutions, which have a direct impact on knowledge processing and sharing.

At the same time, decision support systems and the more recent notion of decision intelligence highlight a process of integration between computational capabilities and managerial rationality, in which AI becomes an integral part of organizational structures and operational strategies. In general, the dialectic between Human-in-the-Loop and Full Automation highlights how the current challenge is not only technical, but above all ethical and organizational: balancing the contribution of algorithmic autonomy with human oversight remains essential for the legitimacy of decisions.

Furthermore, reflection on decision-making performance metrics (accuracy, utility, fairness) shows that the value of AI is not measured solely in terms of efficiency, but must also be assessed against the fairness of its results and their social acceptability. In short, the convergence between AI and decision-making is producing a systemic transformation: AI is no longer merely a support tool, but a co-protagonist in decision-making processes. This makes it essential to address issues related to the sectoral and geopolitical implications of this interaction, assessing both the opportunities for innovation and the risks of concentration of power, opacity, and the reduction of human centrality in decisions.

Today, decision-making is benefiting from Artificial Intelligence in various fields: in the Business & Operations sector, the adoption of predictive algorithms and optimization systems is enabling more efficient resource management, more accurate supply chain planning, and greater ability to adapt to market changes. However, the risk of overreliance on algorithmic models and the need to ensure process transparency remain key issues.

In Finance and Risk Management, AI has demonstrated extraordinary potential in data analysis, complex scenario forecasting, and risk management. However, this also brings new vulnerabilities, both related to the opaqueness of algorithms and the potential for systemic effects in the event of errors or biases in models.

The application of Artificial Intelligence in healthcare and life sciences has demonstrated its ability to support early diagnosis, personalize therapies, and improve the efficiency of healthcare systems, as well as streamline administrative management. Despite the benefits described, ethical and legal questions are still emerging, particularly regarding the protection of sensitive data and the definition of professional responsibilities.

Finally, in the context of public administration and public policies, artificial intelligence offers tools to improve governance decisions, optimize services, and improve the relationship between the state and its citizens. In this context too, the use of automated systems in public decisions raises issues of transparency, democratic legitimacy, and the protection of fundamental rights. Generally, however, sectoral applications of AI in decision-making are not limited to increased operational efficiency, but raise broader questions of accountability, fairness, and governance. AI thus presents itself as a driver of systemic innovation, capable of redefining relationships between economic actors, institutions, and citizens, even anticipating geopolitical challenges. The analysis has shown how the TikTok case represents a unique laboratory for understanding the emerging dynamics of the relationship between artificial intelligence, decision-making, and geopolitics.

Through the Committee on Foreign Investments in the United States (CFIUS), the United States has progressively expanded its national security protection tools, assessing not only financial investments but also access to sensitive data and strategic technologies. From this perspective, the control of AI recommendation algorithms has become a security issue, as well as a market one.

Examining TikTok's algorithm has revealed its centrality within Chinese political capitalism, where technological innovation is intertwined with objectives of soft power, cultural influence, and the consolidation of state authority. The algorithm is therefore not simply a tool for entertainment, but a strategic resource capable of directing information flows and collective perceptions, being highly invasive and manipulative.

The US interpretation of the case has framed TikTok as a systemic threat, placing it within a full-blown "digital war" between the United States and China. In this scenario, technological competition has taken on the characteristics of a conflict for economic, political, and value supremacy in the contemporary international order.

The TikTok affair, which saw US President Trump demand that the Chinese social network cede its rights to US territory, transcends the individual company case, reflecting a broader transformation: digital platforms and their algorithms have become sites of geopolitical competition, where the boundaries between economy, security and sovereignty are being redefined. The case described led to the introduction of Pafaca, Protecting Americans from Foreign Adversary Controlled Applications Act, passed by the United States Congress in 2024. Pafaca represents one of the most significant legislative measures adopted by the United States in response to the growing concerns over digital security and foreign influence. The primary objective of the Act is to safeguard national security by restricting, or where necessary prohibiting, the use of digital applications that are owned or controlled by entities linked to so-called "foreign adversaries". Although the debate was triggered mainly by the case of TikTok and its parent company ByteDance, the scope of the Act is deliberately broader, allowing U.S. authorities to intervene against any platform considered capable of endangering sensitive personal data, enabling surveillance activities, or serving as a channel of disinformation. From a regulatory perspective, Pafaca confers extensive powers upon the President of the

United States, including the ability to impose outright bans, restrict transactions, or require the forced divestment of foreign ownership in companies operating within the American digital ecosystem. Importantly, the Act also provides flexibility in its enforcement: deadlines for compliance can be suspended or extended by means of executive orders, a mechanism that has already been used in the case of TikTok to grant additional time for negotiations and potential restructuring. While many commentators have welcomed the Act as a necessary instrument to counter new forms of digital vulnerability and algorithmic influence exercised by foreign states, others have expressed significant reservations. Critics point out that PAFACA risks fostering a form of digital protectionism, potentially conflicting with principles of free competition and even raising questions concerning freedom of expression. The debate therefore reflects a deeper tension between the need to ensure digital sovereignty and national security on the one hand, and the preservation of an open and globalized digital economy on the other.

The work has thus highlighted another aspect of decision-making through artificial intelligence. Especially in its applications related to machine learning and behavioral data processing, its algorithms possess the ability to influence and, in some cases, manipulate individuals' decision-making processes. By analyzing enormous amounts of personal data, algorithms are able to accurately derive individuals' preferences, habits, and vulnerabilities. This information can be used in a variety of ways, for example, to offer personalized content and targeted advertising, but also to shape political preferences.

Furthermore, the opaque nature of many AI systems prevents users from consciously recognizing the persuasion mechanisms to which they are exposed, increasing the risk of "externally induced" rather than truly autonomous decision-making. In short, Artificial Intelligence, far from being a simple technical tool, emerges as a global strategic factor, capable of influencing both the choices of individuals and the decisions of states. This requires considering algorithmic decision-making not only from an organizational or sectoral perspective, but also as a crucial issue of international order and global governance, including the military sphere, where Artificial Intelligence could dangerously replace human decisions.

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