



LUISS GUIDO CARLI

Department of Economics and Finance

Bachelor's degree in Economics and Business

Major in Finance

Financial Markets and Institutions

**The Applications of Artificial Intelligence by Financial
Institutions: An Analysis of Their Strategic Use**

SUPERVISOR

Prof.ssa Mirta Musolino

CANDIDATE

Leonardo Orsomando

Matr. 325151

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Chapter 1 - Foundations: AI in Financial Services

1.1 Defining artificial intelligence in finance

During recent years, AI services have reached almost all the main sectors of real life, from commercial activities to health and security systems, military defense, finance, and financial markets. Artificial Intelligence has emerged as a transformative force across the financial services landscape, fundamentally reshaping how institutions operate and deliver value to customers. To begin any discussion of AI, it is necessary to define the concept as it is interpreted in the contemporary context:

“‘AI system’ means a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.”¹

The definition emphasizes the primary features of modern AI systems: autonomous behavior, adaptive behavior, inferential output based on data, and generation of outputs, including predictions, recommendations, content, or decision-making. Artificial intelligence in finance does not refer to a single technology; it refers to an array of different technologies or computational approaches that differ in purposes and architectures within this field.

A major component of modern AI in finance is machine learning (ML), a collection of techniques that allow computers to learn patterns from data rather than follow explicit or hard-coded instructions to make predictions. These techniques make it possible to process and analyze large volumes of data drawn from heterogeneous and often unstructured sources.

¹ European commission, *Commission Guidelines on the definition of an artificial intelligence system established by Regulation (EU) 2024/1689 (AI Act)*, European Commission, 2025, 06 February https://digital-strategy.ec.europa.eu/en/library/commission-publishes-guidelines-ai-system-definition-facilitate-first-ai-acts-rules-application?utm_source=chatgpt.com

In the financial sector, these capabilities support a wide range of data-intensive functions. More broadly, AI systems rely on algorithms, that is, structured sets of computational rules used to process inputs and generate outputs. Typically, a problem is defined, a set of rules are formulated to solve it, and the solution is tested over a wide range of examples. In finance, we can observe the use of algorithms in algorithmic trading. It uses agent-based models to process information and to evolve the proposed solution.

Building on these methods, by the early 2020s, AI development accelerated markedly with the emergence of large-scale models and gen AI, particularly large language models (LLMs). Gen AI applications can take prompts as input and produce human-like output. This was facilitated by the development in 2017 of the so-called transformer architecture, which significantly improved neural networks' ability to handle natural language processing (NLP). Neural networks (NNs) connect inputs with outputs, but with hidden intermediate layers of neurons in between. Within these networks, interconnected units perform simple computations whose combined effect enables complex pattern recognition. The connections between units are associated with weights that are adjusted during training, allowing the network to improve its performance as it learns from data.²

1.2 Why AI emerged as a key tool in financial services

Financial institutions operate in environments characterized by a massive volume of data, high uncertainty, time-sensitive decisions, and a constant need to detect subtle patterns. For this reason, the technological conditions that made modern Artificial Intelligence viable in general also made it especially attractive for financial applications. AI has progressively emerged as a key tool in financial services because it enables institutions to process information more efficiently, improve internal operations, and deliver services that are increasingly accessible, personalized, and scalable.

² Milana C., Ashta., *Artificial intelligence techniques in finance and financial markets: A survey of the literature*, (Wiley Online Library), 2021, 10 May. https://onlinelibrary.wiley.com/doi/full/10.1002/jsc.2403?utm_source=chatgpt.com

From the customer's perspective, the benefits of AI mainly concern the enhancement of customer experience and the improvement of customer support.³:

- **Enhance Customer Experience:** Firms can use AI to synthesize massive amounts of data. This will include financial data (e.g. bank accounts, investment accounts and insurance policies) and other customer information. This will significantly improve the efficiency of most customers' interactions with their banks. It will also enable more relevant advice that helps customers plan their lives effectively.
- **Improve customer support:** AI systems can enhance personalization, streamline internal workflows, and support faster responses to client requests, without human intervention, providing quicker and more accurate solutions. These results can be delivered thanks to AI-powered chatbot and virtual assistants that handle routine customer inquiries, providing instant responses

Artificial intelligence emerged as a key tool in financial services not only because of its efficiency gains with customers, but also because of its capacity to reshape business models and improve strategic decision-making; however, there are common themes that frequently recur⁴:

- **Product innovation and revenue growth:** AI enables financial services firms to address market niches, such as mass-affluent advisory services, more effectively than was previously feasible. In addition to enhancing what is already offered, this will provide support for developing entirely new products and revenue streams using advanced data analysis and testing methods. The ability to analyze large volumes of

³ Bealeum A., Propson D., Parker D., *Artificial Intelligence in Financial Services*, World Economic Forum & Accenture, 2025, January. https://reports.weforum.org/docs/WEF_Artificial_Intelligence_in_Financial_Services_2025.pdf

⁴ Bealeum A., Propson D., Parker D., *Artificial Intelligence in Financial Services*, World Economic Forum & Accenture, 2025, January. https://reports.weforum.org/docs/WEF_Artificial_Intelligence_in_Financial_Services_2025.pdf

information can help institutions to find new cross-selling and up-selling opportunities. From automation of expense processing to simplify compliance tracking, AI-based applications allow for the handling of an increasing volume of transactions, with high levels of accuracy and consistency.

- **Data-driven decision-making:** Another reason why AI has become a key tool in financial services is its capacity to transform large and complex datasets into actionable insights. This strengthens investment decisions, improves risk assessment, and supports day-to-day managerial choices. Thanks to faster data analysis, AI tools can identify market trends and optimize financial and investment portfolios. These systems can provide actionable insights for both individual investors and institutional asset managers. Its scope can also be amplified to identify patterns in historical data and predict future outcomes. This capability is valuable for financial institutions seeking to anticipate risks and spot new opportunities.
- **Improved risk management, compliance, and security:** AI has also gained relevance because it significantly improves control functions within financial institutions. It is being used to constantly monitor for cybersecurity threats and to identify suspicious activity in real time. Its systems help with compliance by automating the monitoring of transactions and detecting suspicious activities. They also help in credit decisions by incorporating alternative data sources, such as utility payments, social media activity and geolocation patterns. This approach can improve access to credit for individuals who lack traditional credit histories.

In conclusion, AI technologies have emerged because they combine operational efficiency with strategic relevance. Its capacity to analyze large volumes of data in real time supports a wide range of functions, including customer interaction, portfolio management, risk control, compliance, and market forecasting. As a result, AI contributes not only to cost reduction and better resource allocation, but also to more accurate and timely decision-making across the financial sector.

1.3 Early evidence of AI and adoption in financial markets

Since the early days of the computer, when automated computations could perform only a few arithmetic operations in a single run of a program, the term “AI” has been used to describe correct logical operations. The idea that machines could reproduce forms of human reasoning attracted growing academic interest. The term Artificial Intelligence was officially coined in 1956, when Marvin Minsky and John McCarthy (a computer scientist at Stanford) hosted the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) at Dartmouth College in New Hampshire. This workshop reunited those who would later be considered as the founding fathers of AI. The decades that followed were marked by alternating phases of optimism and disappointment.

AI experienced an initial period of optimism and early successes, with programs such as ELIZA and the General Problem Solver showing the potential of machine intelligence. These achievements encouraged significant research funding, leading to heavy amounts of research money and speculation on the rapid emergence of intelligent machines capable of thinking and acting much like humans. However, the pace at which these innovations were made did not keep up with the excitement and predictions regarding future developments. The primary reason for this was due to how most of the early AI systems were based upon expert knowledge and formalized logic/rule structures, which worked well when applied to the highly structured domains for which they were designed; however, they had little success when attempting to tackle unstructured problems such as visual recognition, adapting through experiences. As a result, the field experienced periods of stagnation, often referred to as “AI winters,” during which enthusiasm declined, and investment slowed.

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through experiences⁵. This has been instrumental in changing AI's role from primarily an academic endeavor to a major player within our societies. The key difference from earlier decades is that contemporary AI is not built only on formal rules but increasingly relies on the ability of machines to learn from data, detect patterns, and adapt to new contexts. The current expansion of AI should not be interpreted as a sudden rupture with the past, but rather as the latest phase in a longer historical trajectory characterized by experimentation, limitations, and repeated redefinitions of what machine intelligence can realistically achieve, which is still a topic of discussion nowadays.

This shift is particularly important in the context of finance. The move from expert systems to machine learning and data-intensive AI has made artificial intelligence increasingly applicable to financial activities. More broadly, the growing interest in AI has also been reflected in investor behavior, including the expansion of AI-related securities and strong demand for investment products linked to the technology sector. Exchange Traded Funds (ETFs) of AI securities database, indicating that the annual returns average 43–48%, depending on whether the average is simple or weighted. These returns are far higher than those of any market index. Assets' total value is \$278 billion, indicating that there is a sizable attraction for this asset class. These results validate the importance of research on AI in general and the use of AI in finance and financial markets, in particular.⁶ The global AI in Finance market is projected to grow from USD 18.9 billion in 2024 to USD 78.6 billion by 2030, at a CAGR of 26.8% over the forecast period, driven by increasing demand for process automation among financial organizations,⁷ with projected investments across banking,

⁵ Haenlein M., Kaplan A., *A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence*, (Sage Journals), 2019, 17 July. https://journals.sagepub.com/doi/10.1177/0008125619864925?utm_source=chatgpt.com

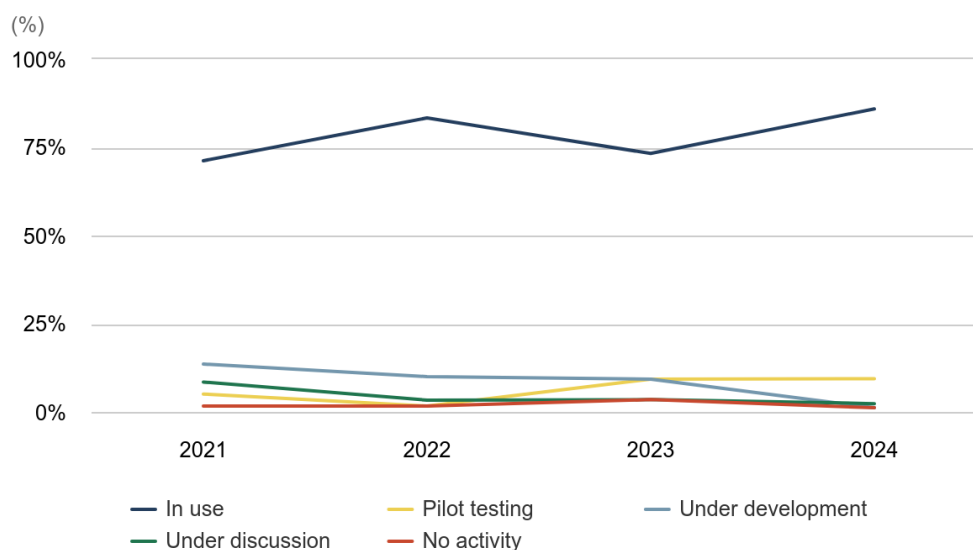
⁶ Milana C., Ashta., *Artificial intelligence techniques in finance and financial markets: A survey of the literature*, (Wiley Online Library), 2021, 10 May. https://onlinelibrary.wiley.com/doi/full/10.1002/jsc.2403?utm_source=chatgpt.com

⁷ Purwar P., *The Transformational Impact of AI Across Financial Services*, Northwestern University, USA, 2025, 6 April. <https://alkindipublisher.com/index.php/jcsts/article/view/9388>

insurance, capital markets and payments expected to reach USD 97 billion by 2027.⁸ This estimate suggests that AI is becoming a strategic tool for the financial sector, and that the ability to implement and understand it is increasingly becoming more of a necessity than a competitive advantage.

This technological revolution spans across various sectors, creating new paradigms for service delivery and customer engagement. According to Dr. Kostis Chlouverakis and Ajay Rawal's Global Financial Services AI survey, 85% of financial services companies already use AI, with 65% of the adopters considering it very to extremely important to their company's success, while having improved detection rates by 60%, reducing false positives by 50% compared to traditional methods.⁹ The rapid adoption of AI technologies reflects their proven ability to deliver measurable value across the financial services ecosystem.

Evolution and adoption of AI by EU banks. Source: EBA Risk Assessment Questionnaire



⁸ Belelieum A., Propson D., Parker D., *Artificial Intelligence in Financial Services*, World Economic Forum & Accenture, 2025, January. https://reports.weforum.org/docs/WEF_Artificial_Intelligence_in_Financial_Services_2025.pdf

⁹ Purwar P., *The Transformational Impact of AI Across Financial Services*, Northwestern University, USA, 2025, 6 April. <https://alkindipublisher.com/index.php/jcsts/article/view/9388>

As AI becomes central to technology strategies, executives must continually evaluate technology ecosystems to capture emerging opportunities, ensuring that AI investments are thoughtfully integrated into broader initiatives. Financial institutions have increasingly adopted complementary technologies such as mobile technologies, cloud computing, big data analytics, and social media infrastructures (Balakrishnan & Das, 2020), thereby creating an ecosystem in which AI can be deployed more effectively. This broader transformation has also facilitated the rise of fintech firms, which have challenged incumbent banks. In particular, the adoption of AI by financial intermediaries is driven primarily by generative artificial intelligence (GenAI), which accounts for more than half of new investment initiatives. GenAI is used mainly in operational activities, while in other areas, such as credit intermediation, predictive models based on machine learning techniques are more commonly employed.¹⁰

Overall, early evidence of AI adoption in financial markets and financial services suggests that the technology has moved beyond experimentation and has entered a phase of strategic implementation. Although its long-term implications remain subject to debate, AI is already reshaping how financial institutions operate, compete, and create value, making it a central topic for the study of modern financial markets.

¹⁰ n.d., *Indagine Fintech nel Sistema Finanziario Italiano*, Banca d'Italia Eurosystem, 2025, dicembre.
<https://www.bancaditalia.it/pubblicazioni/indagine-fintech/2025-intermediari/index.html>

Chapter 2 – How Financial Institutions Apply AI in Financial Markets

In this paragraph, we will analyze how AI is being applied in major financial institutions, highlighting its advantages and main applications. The financial institutions that the thesis will focus on will be divided into 3 main categories, including: Banking Sector, Asset and Investment Management, and Market Intermediaries.

2.1 AI in Banking

The banking sector is one of the most advanced and comprehensive contexts for deploying artificial intelligence. Banks operate at the intersection of massive data flows, complex risk management requirements, and highly competitive customer-facing services, a combination that makes them natural early adopters of AI technologies. The main actors of this analysis are: Investment banks, whose focus is on capital markets, securities trading, mergers and acquisitions advisory, and underwriting; commercial banks, which provide credit intermediation, deposit-taking, and transaction services to retail and corporate clients; and digital banks and neobanks operate as technology-native platforms offering financial services without physical branch networks. Despite these structural differences, all three bank dimensions have embraced AI as a central tool for operational transformation. Over the last few years, there has been an increase in the speed at which AI Technologies are being adopted by Banks. According to the EY-Parthenon Generative AI in Banking Survey 2025, it was found that approximately 77% of banks have completed the launch or soft-launch of GenAI applications before mid 2025, compared to 61% in 2023. Furthermore, it was reported that 47% of participants indicated they were utilizing full GenAI applications in 2025, while

only 10% utilized GenAI in 2023. It appears that the banking industry transitioned rapidly from testing to the productive use of AI.¹¹

2.1.1 Trading, Risk Management, and M&A Advisory

AI has made its most profound impact on how investment banks execute trades, manage risks and provide advice to their clients. In the bank trading area, AI-powered trading systems have been used to automatically make trades based on algorithms, to monitor markets in real-time for unusual activity, and to identify when prices may be out of sync. By applying Natural language processing (NLP) models to earnings call transcripts, company announcements, government filing requirements, and economic reports, and then utilizing this sentiment data to inform quantitative trading models, the ability to accurately forecast future trends and prices of assets is enhanced. From a technical standpoint, the literature documents an evolution in the models employed. Early approaches relied on traditional classifiers such as SVM¹², achieving approximately 78% accuracy in categorizing news as positive, negative, or neutral, with measurable price effects observed up to 30 days after publication. More recent studies adopt advanced neural architectures (RNN-LSTM¹³ and CNN¹⁴) that integrate, at the same time, textual data and historical price series, increasing stock movement prediction accuracies of up to 76–80%.¹⁵

¹¹ Kher P., Gupta S., Trull Z., *How AI in banking can result in major transformative benefits*, EY-Parthenon, 2025, 19 September. https://www.ey.com/en_us/insights/banking-capital-markets/ai-in-banking-ey-parthenon-genai-survey-insights

¹² SVM is a machine learning method used to separate observations into classes, so SVM tries to find the best dividing boundary between categories. There may be many possible lines or planes that separate two groups. SVM chooses the one that leaves the largest possible distance between the boundary and the nearest points of each class. This distance is called the margin. So, the optimal hyperplane is the one that maximizes the margin.

¹³ RNN-LSTM (Recurrent Neural Network – Long Short-Term Memory) is a type of neural network architecture designed to process sequential data by retaining information over long time intervals, particularly suited for time series and natural language tasks.

¹⁴ A CNN (Convolutional Neural Network) is a type of deep learning model designed to automatically detect patterns in data that has some spatial or structured organization, especially images.

¹⁵ Ferreira F.G.D.C., Gandomi A.H., Cardoso R.T.N., *Artificial Intelligence Applied to Stock Market Trading: A Review*, IEEE, 2021. <https://ieeexplore.ieee.org/document/9350582>

The use of AI also assists investment banking firms with the merger and acquisition due diligence process. Due diligence involves extracting information from numerous large volumes of financial documents. According to Deloitte's 2025 M&A Trends Survey, 97% of corporations were using AI for due diligence by 2025, compared to 69% in 2022. AI tools allow deal teams to process approximately 70% of documents within minutes. For example, one AI tool created by JPMorgan was able to complete a task that formerly took lawyers 360,000 hours each year in just a matter of seconds. Overall, AI will allow investment banks to improve the efficiency and effectiveness of advisory mandates provided to clients while reducing costs and enhancing the overall quality of analysis provided.¹⁶

2.1.2 Credit Assessment and Lending

Credit assessment represents one of the areas where AI has produced the most empirically documented impact, particularly in commercial and digital banking. Machine learning models evaluate borrower creditworthiness by incorporating a significantly broader range of data inputs than traditional scoring methods allow, including utility payment records, transaction histories, VAT invoice data, and other alternative sources. This approach reduces the informational asymmetries that have historically disadvantaged small and medium-sized enterprises (SMEs) and borrowers without a formal credit history.

Empirical evidence from a large-scale study conducted on a dataset of over 4.5 million loans issued by a major Chinese commercial bank documented the concrete impact of integrated AI and big data systems: the adoption of these technologies led to a 40.1% reduction in unclassified credit ratings and a 29.6% decrease in loan default rates. Critically, the study demonstrates that while AI alone yielded moderate improvements, the subsequent integration of big data analytics more than doubled the gains, underscoring the synergistic relationship between algorithmic capability and data infrastructure.¹⁷ Digital banks have further extended

¹⁶ Elmahy N.S., *Is AI the New Junior Associate? The Rise of AI in M&A Due Diligence*, SSRN, 2025. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5665131

¹⁷ Chen B., Guo D., Xia J., Zhang Z., *The Transformative Role of Artificial Intelligence and Big Data in Banking*, FDIC Center for Financial Research Working Paper, 2025, July. <https://www.fdic.gov/center-financial-research/transformative-role-artificial-intelligence-and-big-data-banking.pdf>

this logic by deploying AI-based underwriting models natively within their platforms, enabling near-instant loan approvals for standardized products.

2.1.3 Fraud Detection and AML

Fraud detection and anti-money laundering represent high-priority applications across all three banking models, though the specific implementation and data sources differ by institution type. Unlike traditional statistical models that often fail to keep pace with market volatility, AI-based systems use machine learning (ML) algorithms to process massive amounts of data. These models identify subtle patterns and irregularities by analyzing variables such as transaction amount, geographic location, time of day, and user purchasing habits in real time. AI systems are trained to identify specific Anti-Money Laundering (AML) schemes, such as "structuring" (breaking large sums into small transactions to avoid scrutiny) and concealment through shell companies. The new AI-based systems do not have fixed parameters like older systems. Therefore, they will evolve and improve their ability to detect new fraud patterns and emerging tactics, as well as develop an evolving method for detecting money laundering¹⁸. According to the Banca d'Italia's 2025 Fintech Survey, fraud detection and AML represent one of the primary drivers of AI investment among Italian financial intermediaries.¹⁹

An example of how agential AI may be used in fraud detection is the multi-agent-based approach to AML investigations described by Deloitte. This multi-agent-based AML investigation includes three agents that work together to investigate potential violations. The first agent examines the alerts produced by the Transaction Monitoring System (TMS) and identifies which compliance rule has been violated. The second agent uses its knowledge about past and present transaction behavior to determine whether there appears to be a problem. The third agent combines all the information from the previous two agents and provides recommendations regarding what steps should be taken next. Finally, once a human

¹⁸ Patil D., *Artificial Intelligence in Financial Risk Assessment and Fraud Detection: Opportunities and Ethical Concerns*, SSRN, 2024, 30 November. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5057434

¹⁹ N.d., *Indagine Fintech nel Sistema Finanziario Italiano*, Banca d'Italia Eurosystem, 2025, dicembre. <https://www.bancaditalia.it/pubblicazioni/indagine-fintech/2025-intermediari/index.html>

compliance officer validates the results of the review process, he or she may instruct another autonomous agent to electronically submit a Suspicious Activity Report to the relevant government authorities.²⁰

2.1.4 Customer Experience and Personalization

Customer-facing AI applications are most prevalent in commercial and digital banking, where the competitive pressure to deliver personalized, frictionless services at scale is most intense. In this segment, services like chatbots and virtual assistants powered by large language models can enhance customer support, helping customers solve small problems on their own, improving customer satisfaction while reducing the average cost per interaction.

Digital banks have pushed personalization furthest, using machine learning algorithms to deliver real-time spending categorization, automated budget management, dynamic pricing, and personalized savings recommendations. These capabilities, which would be prohibitively expensive to deliver at scale through human advisors, can be offered to mass-market customers at near-zero marginal cost.

2.1.5 Operations, Back Office Automation, and Agentic AI

Across each of these banking model types, artificial intelligence has significantly improved efficiency in back-office operations by automating a number of routine tasks that include document preparation, regulatory reporting, reconciliations, and Know Your Customer ("KYC") reviews²¹. GenAI software supports the creation of regulatory compliance documents, summarizes regulatory information, and creates client-facing documentation. The use of these applications enables banks to realize quantifiable decreases in their costs as well as redirect human capital to focus on high-value analytic and advisory-type functions.

²⁰ Sharma P., Srinivas V., Chauhan A., *How Banks Can Supercharge Intelligent Automation with Agentic AI*, Deloitte Insights, 2025. <https://www.deloitte.com/us/en/insights/industry/financial-services/agentic-ai-banking.html>

²¹ KYC (Know Your Customer) refers to the regulatory process by which financial institutions verify the identity of their clients and assess their suitability and risk profile before establishing a business relationship.

2.2 AI in Asset and Investment Management

The asset and investment management industry encompasses a heterogeneous set of institutions, such as traditional asset managers running mutual funds and ETFs, quantitative hedge funds deploying systematic trading strategies, and wealth managers providing personalized advisory services to private clients. Despite their structural differences, all three models have embraced artificial intelligence as a central tool for operational and strategic transformation. This is because the asset management industry operates at the intersection of data abundance and decision complexity, making it a perfect but also more ambitious frontier for AI. Investment management requires the system to generate forward-looking judgments in environments of genuine uncertainty, non-stationarity, and adversarial competition.

2.2.1 Portfolio Construction and Asset Allocation

Portfolio creation involves determining the amount of money a fund manager allocates to each asset; this choice affects the performance of a portfolio as well as its inherent risk. The most utilized theoretical framework to guide this decision-making process was developed by Harry Markowitz. He stated that investors make their selections based upon two variables: either maximizing the potential return on a portfolio for a specific amount of risk, or minimizing the risk associated with a portfolio while attempting to realize a particular level of return. Other typical traditional approaches include Factor Models. These models describe the behavior of asset returns based on the degree to which assets are exposed to various systematic risks. Traditional models will typically create portfolios that appear "optimal" from a theoretical perspective; however, these same portfolios tend to be extremely fragile when placed into actual application. Traditional models rely heavily on several assumptions that have proven to be inaccurate under conditions of high-stress markets. Machine learning offers flexibility in modeling complex relationships such as non-linear effects between predictors, asymmetry in return distributions, and regime-dependent correlation structure, among other things. As such, machine-learning-based systems can capture aspects of financial data that traditionally modeled systems cannot.

The empirical case for machine learning in asset pricing has been documented by Gu, Kelly, and Xiu (2020), who analyzed nearly 30,000 individual stocks over 60 years and identified several key findings regarding predictive accuracy and economic gains. Their results demonstrate clearly that ML systems provide substantially more accurate predictions of future returns for individual stocks than traditional ordinary least squares (OLS)-based regression systems. A portfolio strategy timing the S&P 500 using neural network forecasts achieved an annualized out-of-sample Sharpe ratio²² of 0.77, compared to 0.51 for a buy-and-hold investor. Additionally, long-short portfolios created using ML-based return signal forecasts exhibited annualized Sharpe Ratios that were roughly twice those of similar factor-based strategies²³.

For mutual funds, AI adoption in portfolio construction has followed a more gradual trajectory. Currently, the primary uses of AI in mutual fund portfolio construction are related to quantitative screening and involve training machine-learning models to score individual securities according to some combination of fundamental and alternative data signals. Generative AI tools are increasingly used to synthesize research and process earnings call transcripts, augmenting analyst productivity without replacing the human judgment required for final investment decisions. No statistically significant differences were found in raw returns or alpha²⁴ between AI and non-AI funds. However, in equity funds, the use of AI is associated with slightly lower costs (about 15 basis points, or 10% lower than the average),

²² Sharpe ratio measures how much return a strategy generates for each unit of risk. A higher Sharpe ratio means better risk-adjusted performance. R_p is portfolio return, R_f is risk-free rate and σ_p is volatility of the portfolio returns

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p}$$

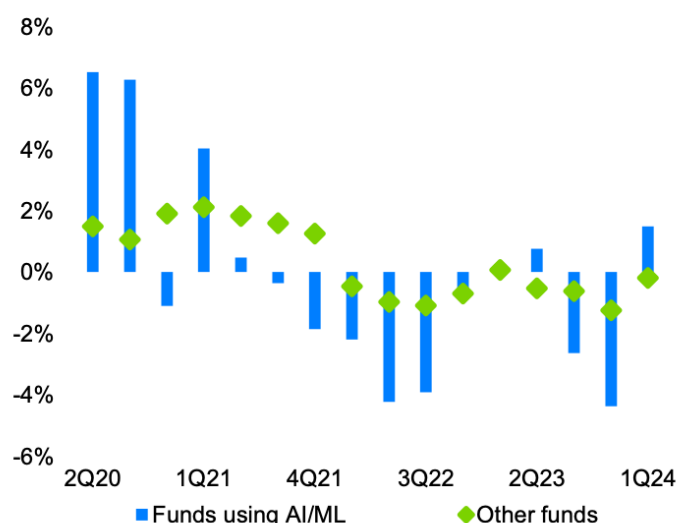
²³ Gu S., Kelly B., Xiu D., *Empirical Asset Pricing via Machine Learning*, *The Review of Financial Studies*, Vol. 33, No. 5, 2020. <https://academic.oup.com/rfs/article/33/5/2223/5758276>

²⁴ Alpha the risk-adjusted return relative to the fund's technical benchmark. R_m is market or benchmark return and β_p is β_p portfolio sensitivity to the market

$$\alpha = R_p - [R_f + \beta_p(R_m - R_f)]$$

a finding statistically significant at the 5% level. These findings indicate that at least one component of operational efficiency resulting from the use of AI is passed through to investors²⁵.

Uneven inflows into funds with AI use. Source: Morningstar, ESMA



Note: Bars represent investor flows (in % of AuM) for 133 EU open-end investment funds that state using AI or ML in the investment process. Squares represent investor flows (in % of AuM) for 34,000 EU open-end investment funds investing in equity, fixed income, mixed assets and alternative assets.

2.2.2 Alpha Generation and Systematic Trading

Hedge funds create their competitive advantage on the ability to identify statistical regularities in financial data at speeds and scales unavailable to discretionary managers, and machine learning has significantly expanded the range of signals they can process and the complexity of the strategies they can execute. Leading the pack was computer-driven hedge fund heavyweight, Renaissance Technologies, which was launched by the late billionaire Jim Simons. The two primary investment funds for investors at Renaissance (Renaissance Institutional Equities Fund and Renaissance Institutional Diversified Alpha Fund) both generated returns of 22.7% and 15.6%, respectively, according to a person knowledgeable

²⁵ N.d., *Artificial Intelligence in EU Investment Funds: Adoption, Strategies and Portfolio Exposures*, ESMA TRV Risk Analysis, 2025, 25 February. https://www.esma.europa.eu/sites/default/files/2025-02/ESMA50-43599798-9923_TRV_Article_Artificial_intelligence_in_EU_investment_funds.pdf

about the company. Artificial intelligence advancements have also spurred an effort to improve systems and processes. An AI-focused fund being developed by Leopold Aschenbrenner, who is an alumnus of OpenAI, has received backing from the co-founders of Stripe, as well as the former CEO of GitHub, Nat Friedman; the goal of this fund will be to build AI that can match or exceed human performance²⁶.

The methodologies employed are very diverse. Statistical arbitrage uses Machine Learning (ML) algorithms to recognize temporary mispricing in similar stocks using high-frequency historical stock price and trade volume data. Trend Following strategies (Man AHL, etc.) employ Machine Learning to adjust both their signal generation and position sizing based upon asset class. Sentiment from Earnings Call Transcripts, SEC Filings, and News Feeds generated using Natural Language Processing provides an Informational Advantage for several hours and/or days after Corporate Disclosures. According to Lopez De Prado (2018), the greatest Methodological Challenges are not the level of complexity of the Models; however, it is avoiding Over-Fitting: Financial Data has low Signal-To-Noise Ratios, Non-Stationary and Overlapping Observations; therefore, Standard Machine Learning Validation Techniques will be Unreliable unless adapted specifically for the Domain²⁷.

2.2.3 Robo-Advisory and Wealth Management

Wealth management combines investment management with financial planning, tax advisory, and goals-based asset allocation, and thanks to AI the potential of human advisory has increased through robo-advisory automation. The wealth management consulting is divided into five steps: Identifying the investor profile, asset Allocation (portfolio construction to meet expectations), monitoring and rebalancing by continuous management of risk and portfolio weightings, and performance review by analyzing results compared to client expectations. With Robo-advisors, these phases become much easier to manage; this

²⁶ N.d., *Renaissance Tech and Two Sigma lead 2024 quant gains*, Hedgeweek, 2025, January 14. <https://www.hedgeweek.com/renaissance-tech-and-two-sigma-lead-2024-quant-gains/>

²⁷ de Prado L., *Advances in Financial Machine Learning*, Wiley, 2018. <https://www.wiley.com/en-us/Advances+in+Financial+Machine+Learning-p-9781119482086>

is why it is among the major wealth management tools employed by financial institutions for allocating and managing investments, based on customers' risk profiles and investments. Traditionally, phases 2 (profiling) and 5 (reporting) were managed by dedicated customer teams and had low scalability, because they required a proportional increase in staff. Now financial organizations can save a significant amount on fixed costs, such as the monthly wages of hiring human advisors. This is why the global robo-advisor market has grown from \$297 billion in 2017 to \$1.802 billion in 2024, with a projection of exceeding \$2.334 billion by 2028²⁸.

There are different types of robo-advisors: there is a scale from 1.0 to 4.0. The 1.0 models are limited to passive asset allocation, while the 4.0 level uses artificial intelligence algorithms for fully automated investments and active asset shifts. Modern Portfolio Theory (MPT)²⁹ provides the main mathematical logic behind many robo-advisors, especially those that build diversified portfolios automatically. In the initial levels of automation (robo-advisor 1.0), the software assists investors in portfolio construction. Algorithms use MPT principles for risk management (robo-advisor 2.0) and to propose or execute automatic portfolio rebalancing (robo-advisor 3.0), seeking to maintain the optimal asset allocation initially defined. The validity of MPT-based algorithms is often measured by comparing their risk-adjusted performance to market benchmarks. Studies indicate that by following these strategies, robo-advisors tend to have "neutral" performance, in line with market indices, without necessarily outperforming them³⁰.

²⁸ Arenas-Parra M., Rico-Pérez H., Quiroga-Garcia R., *The Emerging Field of Robo Advisor: A Relational Analysis*, Heliyon, Vol. 10, 2024. <https://www.cell.com/heliyon>

²⁹ MPT goal is to find portfolios that offer the highest expected return for a given level of risk, or the lowest risk for a given expected return. A standard MPT optimization is represented by w which is vector of portfolio weights, μ vector of expected returns and μ^* target return.

$$\min_w w^T \Sigma w \quad \text{subject to} \quad w^T \mu = \mu^* \quad \text{and} \quad \sum_{i=1}^n w_i = 1$$

³⁰ Cardillo G., Chiappini H., *Robo-advisors: A Systematic Literature Review*, Finance Research Letters, Vol. 62, 2024, April. <https://www.elsevier.com/locate/frl>

2.3 AI in Market Intermediation and Infrastructure

Market Intermediaries and Financial Infrastructure serve as the Operational Frameworks of Modern Capital Markets. To gain access to a trading venue (either through an exchange or ECN), Retail and Institutional Clients must use the services of brokers. Dealers and Market Makers create liquidity in markets through continuous bidding/asking price quotes. Stock Exchanges match and execute orders submitted to them. Post-Trade Infrastructures (such as Central Counterparties and Clearing Houses) ensure that trades are settled. Although structurally different from one another, each of these entities has one thing in common - they all exist at the nexus of massive Data Flows, extreme Speed Requirements, and extremely stringent Regulatory Oversight. Due to these factors, each is naturally positioned for AI adoption. The scale of the underlying market is substantial. Globally, algorithmic trading activities in public equities are led by the United States, with increasing adoption in other regions, driven by local market development initiatives aimed at improving efficiency, such as the implementation of smart order routing, direct market access, and colocation facilities. The algorithmic trading market was valued at USD 14.27 billion in 2024 and is projected to grow by 16.7% through 2030³¹.

2.3.1 AI in Brokerage: Smart Order Routing and Trade Execution

Brokers occupy a pivotal position in the trade lifecycle, acting as intermediaries between investors and trading venues. AI has transformed brokerage operations along two main dimensions: trade execution optimization and regulatory compliance.

³¹ N.d, *Algorithmic Trading Market Growth Analysis - Size and Forecast 2026-2030*, Technavio Research Report, 2026, March. <https://www.technavio.com/report/algorithmic-trading-market-industry-analysis>

Artificial intelligence has already overcome the limitations of classical analytical solutions (such as the Almgren-Chriss framework³²) and static heuristics (TWAP³³ and VWAP³⁴), thanks to the implementation of Reinforcement Learning (RL). An RL-based agent learns to time orders based on real-time market conditions, avoiding "selling on weakness" and waiting for mean-reversion moments to get better prices. The system acts as a Smart Order Router, learning to split orders between different trading venues (e.g. Market A and Market B) based on liquidity and bid/ask prices available at any given time. It was demonstrated that the RL agent achieved significantly better results (with an advantage of about 0.65 bps over TWAP) for the following reasons: The TWAP strategy is static, divides the order into equal parts over time, continuing to sell even when the price drops. The Safe RL agent has learned to time its trades by observing the market state. For example, it slows execution when the price drops and waits for a mean reversion to obtain a better price. The graph below the comparison of RL (Reinforcement Learning) approach against the benchmark TWAP and VWAP strategies³⁵.

³² The Almgren–Chriss framework is an optimal execution model used to determine how a large order should be split over time to minimize total execution costs. It balances two main components: market impact execution risk

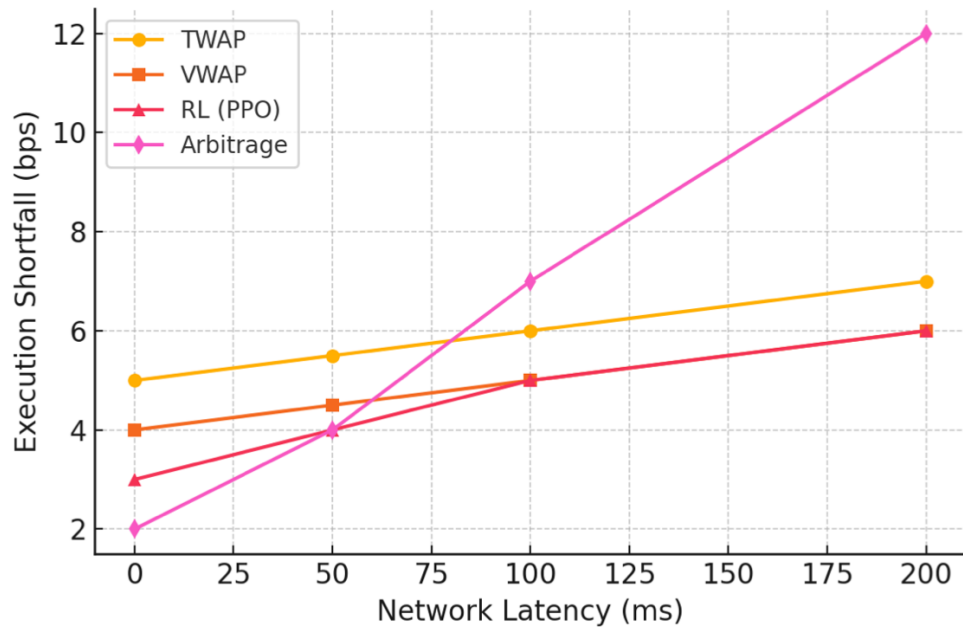
³³ TWAP is a static execution strategy that divides a large order into equal quantities over time, executing them at regular intervals. Where P_t is the price observed at each interval and N interval.

$$TWAP = 1/N \sum_{t=1}^N P_t$$

³⁴ VWAP is an execution strategy that distributes the order according to market trading volume, allocating more of the order to periods of higher liquidity.

$$VWAP = \frac{\sum_{t=1}^N P_t V_t}{\sum_{t=1}^N V_t}$$

³⁵ Borjigin A., He C., *Safe and Compliant Cross-Market Trade Execution via Constrained RL and Zero-Knowledge Audits*, Probe Group Pte. Ltd. Singapore, 2025, October 7. <https://arxiv.org/html/2510.04952>



2.3.2 Dealer Operations with Algorithm Trading and Market Making

Empirical evidence from the academic literature documents the positive impact of algorithmic trading on market quality. Trading in accordance with algorithms is also linked to lower bid-ask (spread) prices than those of other types of traders; thus, trading according to an algorithm can result in lower transaction costs and better execution for the investor. Algorithmic systems have a positive impact on both the liquidity and the quality of the order book. In comparison to traditional traders who widen spreads through their aggressive or reactive behavior during times of high market volatility, algorithmic systems will generally continue to increase the number of orders in the order book but maintain more adaptable and selective order management strategies as well. This is demonstrated through higher cancellation rates and/or the ability to dynamically respond to changing market conditions.

In a Reinforcement Learning (RL) system applied to trading, the action space represents the set of all possible decisions that an agent can make when interacting with the market to maximize profit. In this paradigm, the agent is restricted to a predefined set of actions, usually three: "buy" (Long), "sell" (Short), or "hold." This approach forces the dealer to trade a fixed

number of shares for each trade, drastically limiting strategic flexibility. The introduction of algorithms such as Twin-Delayed DDPG (TD3) allows for operating in a continuous action space, usually defined in the interval $[-1,1]$. Unlike discrete models, TD3 not only chooses the market direction (Long or Short) but simultaneously calculates the dynamic number of shares to trade. Adopting a continuous space offers critical advantages for a dealer's operations, as Risk Optimization and Capital Protection. The ability to leave some money outside the market is a fundamental risk mitigation strategy. Sources show that, especially in markets like the stock market (e.g., Amazon), the TD3 agent uses this flexibility to protect the dealer from total losses and manage highly uncertain situations³⁶.

Algorithmic trading has also several other important issues: it may create sudden volatility when a trader excessively relies on automated orders and causes the market to experience an unpredictable flash crash of automated orders simultaneously creating an increased withdrawal of automated orders, in addition, as machine learning models become increasingly complex (overfitting) using historical data more extensively than is necessary, there will be no certainty that future market scenarios are going to mirror these past market scenarios.

2.3.3 AI in Stock Exchanges and Post-Trade Infrastructures

Stock exchanges and post-trade infrastructures represent the most systemic layer of financial market organization. At this level, AI is deployed primarily for two purposes: ensuring market integrity through surveillance and improving the efficiency of clearing and settlement operations. The stock exchanges have progressively moved from static rule-based detection systems toward adaptive, machine learning-based frameworks. Nasdaq began applying AI to its U.S. equity market surveillance to detect irregular and potentially malicious trading activity. Presently, Nasdaq's U.S. market surveillance team reviews more than 750,000 alerts annually, identifying unusual price movements, trading errors, and potential manipulation,

³⁶ Majidi N., Shamsi M., Marvasti F., Algorithmic trading using continuous action space deep reinforcement learning, ScienceDirect, 2024, January. <https://www.sciencedirect.com/science/article/pii/S0957417423017475>

combining anomaly detection algorithms with explainability mechanisms designed to satisfy regulatory accountability standards.³⁷

The Depository Trust & Clearing Corporation (DTCC)³⁸ reported its DTCC Subsidiaries' processed securities were valued at \$3.7 trillion in 2024; thus, it recognizes AI as an area of opportunity that can improve the efficiency of markets, manage risk, and improve liquidity, utilizing its predictive analysis capabilities to enable better processing of past data and recognize patterns. In addition to this recognition, DTCC has taken several tangible steps in order to promote AI across its organization, such as the establishment of a cross-functional AI council and an AI enablement team charged with facilitating the integration of AI across all areas of DTCC's business³⁹. As AI becomes an integral part of market structure, the line between what constitutes technology infrastructure and what constitutes regulatory/governing mechanisms for the markets continues to blur, with significant ramifications for government regulators/policymakers that are explored in detail within the subsequent chapters.

³⁷ MarketInsite, For the First Time, Nasdaq Is Using Artificial Intelligence to Surveil U.S. Stock Market, Nasdaq, 2019, 7 November. <https://www.nasdaq.com/articles/for-the-first-time-nasdaq-is-using-artificial-intelligence-to-surveil-u.s.-stock-market>

³⁸ DTCC (Depository Trust & Clearing Corporation) is a key financial market infrastructure that provides clearing, settlement, and transaction processing services. It helps ensure that securities trades are completed safely and efficiently, reducing operational and counterparty risk.

³⁹ DTCC, Annual Report 2024 - Year of Execution, DTCC, 2024. <https://www.dtcc.com/annuals/2024/files/DTCC-Annual-Report-2024-Print.pdf>

Chapter 3 - Systemic Implications and Regulation of AI

The previous chapters identified the nature of Artificial Intelligence, why it has become increasingly important in Financial Services, and how specific types of financial organizations are deploying AI throughout their value chains. In this chapter, the focus will shift from an institutional perspective to an evaluation of the overall financial system regarding AI. The intent is to determine the consequences of AI adoption in financial markets and to assess the regulatory frameworks that have emerged in response.

3.1 The dual nature of AI Adoption

AI systems allow financial institutions to process volumes of data that would be impossible to handle manually, to automate repetitive operational tasks, and to reduce the marginal cost of providing services such as customer support, credit assessment, and portfolio rebalancing. The aggregate effect is a structural reduction in operating costs across the industry up to 80%, allowing claims professionals to focus on more complex cases⁴⁰. At the same time, the same technological capabilities that improve risk assessment, fraud detection, and operational efficiency in individual institutions also have the potential to increase concentration, herd behavior, and amplify systemic risks overall. Therefore, AI is defined as having inherently dual effects on financial stability. These dual effects relate to how the ability of an individual institution to reduce risk is amplified through increased market exposure and/or reliance upon other firms within the economy (and ultimately increases its vulnerability to system-wide shocks). This duality is not a problem to be solved but a feature of the technology itself.

The FSB understands the potential for large increases in productivity through AI adoption, in addition to enhanced ability for financial institutions to identify cyber-attacks. However, it has identified several growing vulnerabilities that are particularly relevant when adoption is expanding rapidly, such as the use of third parties, the dependence on models, and the

⁴⁰ Purwar P., *The Transformational Impact of AI Across Financial Services*, Northwestern University, USA, 2025, 6 April. <https://al-kindipublisher.com/index.php/jcsts/article/view/9388>

decisions made by AI systems during times of stress⁴¹. In particular, the high cost of development and the huge computational resources required favor a strong concentration of supply in a few large technology suppliers, creating potential systemic dependencies.

Moreover, AI remains limited in its ability to replicate human judgment and emotional intelligence. Clients rely on the judgment of an advisor when making financial decisions, particularly when seeking a trusted relationship that is built upon empathy; additionally, they also want advisors to be able to consider both qualitative and behavioral elements. The limitation of robo-advisors to identify the client's needs will produce an impression of limited flexibility and, therefore, a reduced possibility of customization with the model. There has been a noticeable move toward this direction due to growing concerns regarding bias embedded in AI. Bias potentially produces inaccurate results or discrimination against certain individuals. Also, it has created serious regulatory problems, as a lack of transparency and explainability undermines accountability and makes it difficult to achieve compliance⁴².

A more recent contribution extended the duality argument by connecting it to the relationship between financial crises and technology. It observes that during times of stability, these technologies improved the micro-level efficiencies, but they could become a vector of crisis transmission in periods of stress, particularly when many institutions rely on similar models trained on similar data and react in correlated ways to common shocks⁴³. Overall, AI is not simply a tool for efficiency, but a technology that simultaneously expands the decision-making capabilities of financial institutions and introduces new vulnerabilities, making its profoundly ambivalent.

⁴¹ N.d., *The Financial Stability Implications of Artificial Intelligence*. Financial Stability Board, 2024, November 14. <https://www.fsb.org/2024/11/the-financial-stability-implications-of-artificial-intelligence/>.

⁴² Singh R.K., Mishra R., Kumar S., Bag S., *Applications of Artificial Intelligence for Optimizing Banking and Financial Operations: A Systematic Literature Review and Future Research Agenda*, Journal of Economic Surveys, Wiley, 2025. https://onlinelibrary.wiley.com/doi/epdf/10.1111/joes.12693?saml_referrer

⁴³ Ozili P.K., *Artificial Intelligence (AI), Financial Stability and Financial Crisis*, in *International Encyclopedia of Business Management*, Elsevier, 2026. <https://doi.org/10.1016/B978-0-443-13701-3.00487-4>

3.2 Risks and Vulnerabilities of AI at the Institutional Level

3.2.1 Model Risk and the Black-Box Problem

At the level of the individual institution, the deployment of AI introduces a set of risks that are qualitatively different from those associated with traditional ones. Model Risk is one of the most common ones, but it must be differentiated from the traditional quantitative risk. The common feature of contemporary AI models is their large number of variables as well as their numerous interactions at various levels within the overall model. As a result of these two features of AI models, both the input into a particular layer or stage of the AI process and the subsequent output produced by those same inputs do not necessarily have a direct relationship to one another. Additionally, while the institutional user may understand generally how a specific AI model produces certain outputs based upon certain inputs, they often do not know specifically which particular combinations of input were necessary to produce the final output⁴⁴. This is the so-called black-box problem, which has direct implications for risk management and regulatory accountability, and it is one of the main reasons why senior investment professionals continue to treat AI outputs as analytical inputs to be validated rather than as autonomous decision-making engines.

3.2.2 From Data-Related Risk to Systematic Risk

Data-related risks constitute a second major category. While some of the problems caused by data scarcity and privacy have been addressed through the use of synthetic data⁴⁵, this type of data brings their own set of potential challenges; synthetic data is highly dependent on the quality of the generation algorithm, it assumes knowledge of the underlying process which generated the real data, and the continuous use of synthetic data will lead to an erosion over time of all the information contained in the tail end of the distributions. In addition to having data-driven risks related to individual firms or organizations, there are also systemic aspects of data-driven risk. As previously mentioned, the market for aggregating financial data has

⁴⁴ N.d., *Regulatory Approaches to Artificial Intelligence in Finance*, OECD Artificial Intelligence Papers No., 2024, September 24. <https://doi.org/10.1787/f1498c02-en>

⁴⁵ Synthetic data are artificially generated data that imitate the statistical properties of real-world data, but are not collected from actual events, people. They are produced by algorithms that learn the patterns of a real dataset and then generate new, fictional observations that resemble the original.

become very concentrated, and when large numbers of firms rely on relatively few providers of aggregated financial data to train their models, their predictions and risk assessments will tend to be correlated.

This similarity tends to heighten market stress during economic downturns. When many institutions deploy similar algorithms trained on similar data, their reactions to a market shock may be correlated, producing the kind of synchronized selling pressure that historically has been associated with flash crashes⁴⁶. The deployment of these models in relatively comparable market environments contributes to a phenomenon known as "convergence" where many of the trading decisions made by those institutions' respective models will be very similar. The loss of diversity among the many different possible approaches to make investment or trading decisions reduces the potential for an investor or trader to profit from a shock. The implications of competitive AI systems producing homogeneous portfolio selections or homogeneous trading decisions reduce the potential for responses to shocks. Under certain reasonable assumptions regarding how AI systems make decisions, it can be demonstrated that AI systems will produce responses to shocks that are both amplified and synchronized⁴⁷.

Finally, artificial intelligence introduces additional attack surfaces for malicious actors to exploit, as well as new types of attacks against data. Two examples include data poisoning and prompt injection. Data poisoning involves manipulating training data to produce incorrect behavior from a trained model. Prompt injection involves crafting specific input prompts to obtain private/confidential information from Large Language Models (LLMs). These sources of vulnerability illustrate that data-driven vulnerabilities are not limited solely

⁴⁶ Majidi N., Shamsi M., Marvasti F., *Algorithmic trading using continuous action space deep reinforcement learning*, ScienceDirect, 2024, January. <https://www.sciencedirect.com/science/article/pii/S0957417423017475>

⁴⁷ N.d., *Monitoring Adoption of Artificial Intelligence and Related Vulnerabilities in the Financial Sector*, FSB, 2025, October. <https://www.fsb.org/2025/10/monitoring-adoption-of-artificial-intelligence-and-related-vulnerabilities-in-the-financial-sector/>

to issues with data quality in a static context but are present throughout the life cycle of data in an AI system, connected to the model risks⁴⁸.

3.2.3 Operational and Concentration Risk

Another problem related to the use of AI is connected to operational vulnerabilities and a growing dependency upon third-party suppliers. Since many financial institutions lack both technical capabilities and computing capacity to create their own foundational AI models, they rely upon third parties to provide them with the foundational architecture for those models. As a result, this creates additional third-party risk as well as privacy concerns regarding customer data, especially when an external provider's foundational models are modified using internal data or confidential information⁴⁹.

There are operational indicators that supervisory authorities can use to monitor systemic risks related to financial institutions' reliance on external AI service providers. The metrics that have been presented include the proportion of third-party providers that financial institutions use for their AI-based systems to indicate the degree to which they depend upon third-party vendors in general. The second is the total number of significant cyber and operational events that occur with third-party vendors who provide an institution's AI-based services, and these are reported to regulatory bodies. This metric indicates how frequently institutional vulnerabilities result in the loss of operational capacity. A third metric is the number of critical AI-based services provided by a single or highly interdependent group of third-party service providers. It represents the potential impact if one or more key AI-based services were to become unavailable due to the failure of a common vendor. Finally, there is also a fourth metric. This fourth metric is based on the number of banks designated as Systemically

⁴⁸ N.d., *The Financial Stability Implications of Artificial Intelligence*. Financial Stability Board, 2024, November 14. <https://www.fsb.org/2024/11/the-financial-stability-implications-of-artificial-intelligence/>

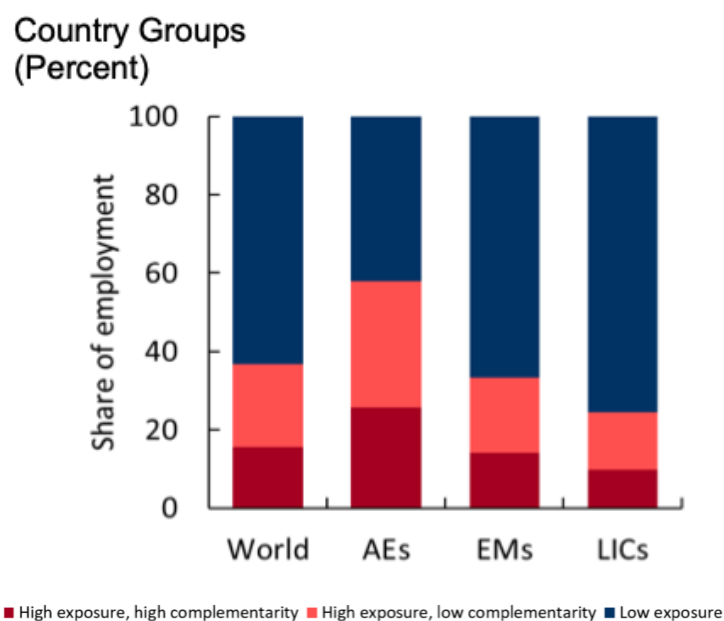
⁴⁹ Leitner G., Singh J., van der Kraaij A., Zsámboki B., *The rise of artificial intelligence: benefits and risks for financial stability*, European Central Bank, 2024, May. https://www.ecb.europa.eu/press/financial-stability-publications/fsr/special/html/ecb.fsrart202405_02~58c3ce5246.en.html

Important Financial Institutions (SIFIs) that use third-party vendors for their critical business functions⁵⁰.

3.2.4 Future Human Capital at Risk

A fourth dimension that has recently gained relevance concerns the impact of AI on human capital and the workforce of financial institutions. The International Monetary Fund estimates that 40% of global employment is exposed to AI, with a share rising to 60% in advanced economies, where cognitive-intensive occupations are more heavily represented.

Employment Shares by AI Exposure/Complementarity. Source: IMF



Note: Country labels use International Organization for Standardization (ISO) country codes. AEs = advanced economies; EMs = emerging Market economies; LICs = low-income countries; World = all countries in the sample.

⁵⁰ N.d., *Monitoring Adoption of Artificial Intelligence and Related Vulnerabilities in the Financial Sector*, FSB, 2025, October. <https://www.fsb.org/2025/10/monitoring-adoption-of-artificial-intelligence-and-related-vulnerabilities-in-the-financial-sector/>

The IMF has said there is a wide range of income levels that will be exposed to the risk of being displaced. However, it's the higher-income individuals who have an opportunity for increased wages because of the added ability to take advantage of complementary technologies such as AI, whereas lower-income employees in jobs that are repetitive or involve job tasks that can be done with less skill could potentially lose those jobs due to automation. It is possible that if financial institutions do not prepare for these changes through investments in training programs and career development opportunities, the long-term consequences could result in losing young professional talent on which to build their future leaders⁵¹.

3.3 The Regulatory Response: European approach

The implementation of this regulatory architecture relies on the coordinated action of European supervisory authorities. The combined effect of these supervisory provide the factual basis for translating the obligations of the AI Act and the sector-specific directives into concrete expectations. The regulatory architecture pictured here follows the structure of the risk factors described above, at the micro-economic level, there exist various risks that need to be adapted by current risk management structures; at the macro-economic level, as well as other new systems of fragility through the concentration of AI infrastructure, the homogeneity of strategies used by algorithms and the speed of algorithmic interaction, which may not yet fully be captured by traditional tools of financial stability.

3.3.1 The AI Act and Regulatory Coordination

Since we have now discussed the risks associated with the usage of AI by financial Institutions, it is time to understand how these risks are managed from a regulatory point of view, and how authorities deal with AI and regulatory applications. As previously mentioned

⁵¹ Cazzaniga M., Jaumotte F., Li L., Melina G., Panton A.J., Pizzinelli C., Rockall E., Tavares M.M., *Gen-AI: Artificial Intelligence and the Future of Work*, IMF Staff Discussion Note SDN/2024/001, 2024, January. <https://www.imf.org/en/Publications/Staff-Discussion-Notes/Issues/2024/01/14/Gen-AI-Artificial-Intelligence-and-the-Future-of-Work-542379>

in Chapter 1, we begin this analysis by analyzing the European Regulation. The European Union has positioned itself as the most advanced jurisdiction in the regulation of artificial intelligence, with a layered framework that combines AI-specific regulation with sectoral financial legislation. Regulation (EU) 2024/1689, known as the AI Act, entered into force on 1 August 2024 and constitutes the first comprehensive legal framework on artificial intelligence in any major jurisdiction⁵².

For financial institutions, the most relevant category is high-risk, which is defined in Article 6 and detailed in Annex III. The important part of this article is under Article 6(2), where it states that: an AI system is considered 'high-risk' if it intends to be used for purposes contained within any of the high-risk areas listed in Annex III. In this Annex, AI systems used to evaluate the creditworthiness of natural persons or to establish their credit score are classified as high-risk AI systems. The financial industry is especially affected by this rule. This particular rule demonstrates the worry that there will be unintended discriminatory results from the use of A.I. in making decisions and/or that current prejudices will continue and/or be hidden in ways that consumers can neither see nor contest⁵³. In particular, Recital 58 of the EU AI Act emphasized that not all automated financial AIs fall into the category of high risk. It explicitly excludes from this classification those that use AI for fraud detection when offering a service of financial services, or those used by regulated entities for the calculation of regulatory capital requirements⁵⁴.

The obligations imposed on providers and deployers of high-risk AI systems are substantial. They include requirements regarding data quality and data governance (Article 10), risk management systems (Article 9), technical documentation (Article 11), record-keeping and traceability (Article 12), transparency and information to deployers (Article 13), human oversight (Article 14), and accuracy, robustness, and cybersecurity (Article 15). Article 10

⁵² *Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*, Official Journal of the European Union, 2024, July 12. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L_202401689

⁵³ Annex III of the EU AI Act: High-Risk AI Systems Referred to in Article 6(2). <https://artificialintelligenceact.eu/annex/3/>

⁵⁴ Recital 58 of the EU AI Act. <https://artificialintelligenceact.eu/recital/58/>

outlines the criteria for a system's use of data in terms of risk. The article states that all high-risk AI systems will need to have been validated and tested using training, validation, and test datasets that are relevant and sufficiently representative, and, to the greatest extent feasible, free from errors. High-Risk AI Systems must also implement an appropriate policy for managing their data, which includes collecting, labeling, cleaning, updating data, and identifying areas where there may be data gaps. The major goal of Article 10 is the recognition and reduction of bias. For example, in financial markets, this is especially important since AI systems can create new inequities based on historical financial data or can make it difficult for certain social classes to compete with others.

Financial institutions already comply with sector-specific frameworks concerning governance, operational resilience, consumer protection, and risk management. The AI Act adds an additional horizontal layer of obligations specifically focused on AI-related risks. For example, banks and insurance companies can expect to be required to comply with both their current financial supervision obligations and the specific AI obligations that they may find under the AI Act, which may create an overlap of regulations. Moreover, there could be an issue regarding some of the most used AI systems in financial markets, which would likely not automatically fall within one of the "high risk" categories identified in Annex III. Therefore, some examples of commonly used AI tools by financial institutions, such as investment services, trading, portfolio allocation, market forecasts, internal risk management, etc., are unlikely to require regulation at the EU level. The key point here is that the focus of the AI Act appears to be much stronger in relation to consumer-facing financial decision-making than it is in relation to how those decisions are made using AI. This led to a regulatory coordination problem. Regulated Financial Institutions are likely already subject to regulations under various frameworks, including but not limited to MiFID II and DORA. As such, the primary future challenge will be how to ensure that the implementation of the AI Act is done to avoid duplicative regulatory obligations or legal ambiguity for regulated financial institutions⁵⁵. These tensions do not undermine the

⁵⁵ Passador M.L., *AI in the Vault: AI Act's Impact on Financial Regulation*, Bocconi Legal Studies Research Paper, SSRN, 2024, 17 December. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4898828

legitimacy of the European framework, but the regulatory architecture must be understood as an evolving project rather than as a static body of rules, which must evolve in parallel to the ongoing evolution of the financial market.

3.3.2 MiFID II (Markets in Financial Instruments Directive II)

The risks associated with algorithmic trading, discussed in Section 3.2, were already addressed by Directive 2014/65/EU (MiFID II), which entered into force in January 2018 and constitutes the principal regulatory framework for trading activity in the European Union. Article 17 of MiFID II requires all trading houses that use automated trading systems (algorithmic trading) to have systems and processes in place to control risk, including trading volume limits, price limits, and other controls to prevent the entry of large numbers of trades at similar prices, and thus to prevent excessive volatility or significant disruption to financial markets. Firms must also test those systems thoroughly before using them and continuously monitor for technical issues. The most important aspect of article 17 from the perspective of the finance industry is its focus on ensuring that there is no market abuse; whereas many of the provisions of the EU AI Act are focused on protecting consumer rights when artificial intelligence is used to provide services, article 17 of MiFID is focused solely on maintaining market integrity; it does so by ensuring that financial markets operate fairly and with appropriate levels of liquidity⁵⁶. Because MiFID II was drafted before the most recent wave of AI adoption, the challenge for supervisors is to ensure that the validation and testing requirements designed for rule-based algorithms remain meaningful when applied to machine-learning systems.

3.3.3 DORA (Digital Operational Resilience)

Regulation (EU) 2022/2554, the Digital Operational Resilience Act (DORA), addresses the third category of systemic risk discussed in Section 3.3, the operational and third-party concentration risks. While the AI Act concentrates on the risk-generating capacity of the decision-making of AI systems, DORA focuses on the operational resiliency of the

⁵⁶ Directive 2014/65/EU (MiFID II), Article 17 (Algorithmic trading).
<https://www.esma.europa.eu/publications-and-data/interactive-single-rulebook/mifid-ii/article-17-algorithmic-trading>

technological infrastructure in which these systems operate⁵⁷. As most AI service providers deliver services through cloud technology and dependency on a small number of significant suppliers, DORA covers especially systemic and operational risk and provides an additional regulatory control mechanism for ICT⁵⁸ third-party providers who were previously classified as critical, enabling European supervisors to supervise entities that were previously excluded from the scope of EU financial regulations.

The AI Act, MiFID II, and DORA are best described as an example of a "layering" model. In this model, the AI Act is the governing authority over all things related to the operation of AI systems; MiFID II is the law governing the use of those AI systems in relation to trading activities; and DORA addresses issues regarding third-party and operational aspects of technology infrastructure that support AI systems. A Layered Model clearly demonstrates a deliberate regulatory choice to add AI-specific regulatory provisions into an already established financial regulatory framework rather than establishing a standalone regulatory requirement specifically for AI. However, due to the fragmentation of the institutional regulatory framework, it is plausible that this leaves a partial regulatory gap in addressing systemic interactions between AI-driven models or labour market transformation.

⁵⁷ Digital Operational Resilience Act (DORA) https://www.eiopa.europa.eu/digital-operational-resilience-act-dora_en

⁵⁸ Third-party ICT providers are external companies that provide information and communications technology (ICT) services to financial institutions.

Chapter 4 – Case Studies

How leading companies react to AI

4.1 Purpose of the Case Units

In this chapter, we examine how artificial intelligence is implemented in two different segments of the financial services industry, and assess whether the expected benefits, risks, and governance challenges identified in the previous chapters emerge in practice. These case studies are included not merely as descriptive examples, but as an empirical tool to investigate how AI is concretely integrated into financial services organizations with different business models that we had previously analyzed in chapter 2. The comparison allows the thesis to move from theory to practice and to evaluate whether the opportunities and risks associated with AI emerge differently depending on the institutional setting. The objective is not statistical generalization, but analytical insight into how AI is operationalized across different segments of the financial services industry.

The Case Units we are going to discuss refer to two top leading financial institutions, which operate in different fields with different business models, client bases, and strategic priorities. These institutions were selected because they represent two distinct, highly relevant applications of AI in finance:

- **BlackRock Inc.:** BlackRock, Inc. is a U.S.-based global financial services firm. The Company was founded in 1988. Initially, BlackRock provided corporate and government issuers with fixed-income institutional portfolio management and risk management services. As of 2025, BlackRock is the world's largest asset manager, managing over \$12.5 Trillion in assets. Headquartered in NYC, BlackRock has 70 offices globally across 30 countries and provides services to clients in 100 countries. Upon completion of its merger with Barclays Global Investors in 2009, BlackRock acquired numerous shareholdings of several major Italian companies that were previously owned by Barclays. Those shareholdings totaled approximately €8.9

Billion. BlackRock's investment portfolio within Italy expanded to nearly €58 Billion by mid-April 2014.

- **Isybank S.p.A.:** Isybank S.p.A. Is a digital banking service provider in Italy. The bank was originally named "Banca ITB" when it was founded in July 2008. (The Bank would be renamed "Banca 5 S.p.A." from 2016 to 2022.) Isybank became a subsidiary of Intesa SanPaolo in December 2016. By January 1st, 2023, it had changed its name to Isybank, anticipating the launch of Isybank as the banking group's digital bank. On June 15th, 2023, Isybank went live and generated approximately €38 million in revenue; €36 million, or approximately 95%, was based on transaction processing fees. The bank also assisted with processing approximately €9 billion.

4.2 Methodological framework

4.2.1 Qualitative Comparison Framework

This analysis is not focused on the organization itself, but on the organizational use of AI within each firm, with a focus on objectives, applications, governance, perceived benefits, and operations. This chapter adopts a qualitative comparative case study methodology based on sources and structured interviews with relevant professionals. The objective is not statistical generalization, but analytical generalization.

To ensure comparability, both cases are analyzed through a common framework based on six dimensions: strategic rationale, AI applications, value creation mechanisms, governance and control, risks and limitations, and human-AI interaction. This allows for a comparison at the end of the chapter to understand the different approaches.

4.2.2 Case Selection and Interviews Methodology

The two cases were selected purposively according to three criteria: relevance, sectoral contrast, and analytical comparability. They are relevant because both provide meaningful examples of AI adoption in financial services; they are contrasting because they belong to

different segments of the industry, namely global asset management and digital retail banking; and they are comparable because in both cases, AI is embedded in broader strategies of technological and organizational transformation.

Interviews are used as complementary qualitative evidence. Their purpose is to enrich the case studies with practitioner perspectives and to triangulate, where possible, the information derived from sources. A semi-structured interview format is adopted in order to maintain consistency across the two case studies while preserving enough flexibility to explore firm-specific issues emerging during the conversation. The views expressed by the professionals interviewed are strictly personal and do not necessarily represent the views, positions, or policies of their respective firms.

4.3 Case Unit 1 - Blackrock Inc. (Asset and Investment Management Perspective)

4.3.1 Strategic rationale: from AI lab to AI operating system

BlackRock's strategic posture towards artificial intelligence has been exposed by Chairman and CEO Larry Fink, whose 2026 Annual Chairman's Letter to Investors places AI as one of the most powerful forces reshaping global finance, alongside the modernization of portfolios and the expansion of private markets⁵⁹. The direction is not recent. BlackRock established a dedicated AI Lab in 2018 and has been developing predictive analytics, pattern recognition and machine learning models for years, before the broader generative AI wave began to attract public attention⁶⁰.

This long-term perspective is consistent with the view expressed in a personal interview by Davide Baldini, Senior Advisor on projects for leading financial institutions at BlackRock. According to Baldini, the strategy is deliberately broad rather than narrowly defined:

⁵⁹ Fink L., *BlackRock 2026 Annual Chairman's Letter to Investors*, BlackRock, 2026, March. <https://www.blackrock.com/corporate/investor-relations/larry-fink-annual-chairmans-letter>

⁶⁰ N.d, *How BlackRock is finding new alpha as AI Transformation becomes a critical business driver*, Microsoft Cloud Blog, 11 December 2024. <https://www.microsoft.com/en-us/microsoft-cloud/blog/2024/12/11/how-blackrock-is-finding-new-alpha-as-ai-transformation-becomes-a-critical-business-driver/>

"The strategy is fairly wide in scope. The firm recognizes the potential of AI and tries to extract the maximum from these tools, which means pursuing multiple directions at once — process efficiency, expansion of analytical capabilities, and identification of new use cases."

(Baldini, personal interview, 16 April 2026)

In his view, AI belongs to the same class of general-purpose technologies that will reshape productivity across every department rather than being deployed as a specialized module. Part of this strategy is represented by Aladdin, BlackRock's proprietary technology platform. Aladdin is described as the "central nervous system" of BlackRock because it integrates portfolio management, risk analysis, trading, compliance, and operations into one platform, recording years of investment decisions. This creates a massive structured dataset that can be used as an AI training data factory operating at a global scale. At the same BlackRock raised around \$30 billion in initial capital, potentially mobilizing up to \$100 billion, including debt financing. This money is intended to support investment in data centers, energy infrastructure, and computing capacity. This is important because AI does not depend only on algorithms. It also requires huge amounts of electricity, chips, servers, cloud infrastructure, and data centers, which means that BlackRock is not only investing in AI applications; it is investing in the infrastructure that makes AI possible.⁶¹

A further dimension of the strategic rationale concerns the cultural dissemination of AI within the organization. Baldini emphasized that, alongside centralized teams dedicated to studying AI applications (such as BlackRock AI Labs, the firm's internal AI research and development hub), BlackRock also pursues a deliberate policy of informing and educating each employee about the possibilities of these tools, so that individual employees themselves identify the areas in which AI can support their own work.

⁶¹ Kitishian D., *BlackRock's AI Strategy: Analysis of Dominance in Asset Management*, Klover, 2025, 20 July. <https://www.klover.ai/blackrock-ai-strategy-analysis-of-dominance-in-asset-management/>

4.3.2 AI applications: Aladdin ecosystem and beyond

The practical deployment of AI at BlackRock is best understood through Aladdin. As Baldini described it, initially designed to operate as an investment management and portfolio risk management/analytical engine, Aladdin has now grown into a complete operating system for the institutional investor.

But Aladdin is not only used as a dataset to train AI systems; in fact, the most visible AI-driven evolution of the platform is Aladdin Copilot, a generative AI tool launched in 2023 and subsequently rolled out to Aladdin clients in 2024. According to BlackRock's description, Aladdin Copilot is designed to strengthen the connectivity across the platform, surfacing answers instantly to support key business decisions. A parallel initiative, eFront Copilot, extends the same generative-AI architecture to private markets data and analytics. The tool is built on a secure connection through which all personal information is filtered out and analyzed to provide personalized information about the client's portfolio⁶².

Baldini offered a concrete example of how generative AI is being integrated into the investment process itself. He discussed using large language models to analyze earnings calls; before the use of AI, analysts were tasked with manually reviewing many hundreds of these calls, looking for specific signals. Teams now create prompts that direct the LLM as to what to look for and where to find it. His examples included prompting the LLM to identify those parts of an earnings call transcript when a CEO responded evasively to a question asked by an analyst. By doing so, firms can perform analyses they have never had the resources to complete previously. At the same time, the responsibility for making interpretations based upon these analyses remains solely in the hands of human investment professionals.

In conclusion, Baldini added an important qualification to this picture. When discussing the technical evolution of LLM, he pointed out that not every analytical task benefits from being

⁶²N.d., *Instant resolution for stronger resolve*, Aladdin BlackRock, 2024.
<https://www.blackrock.com/aladdin/solutions/aladdin-copilot>

moved to a generative-AI engine. A simple regression can be performed by a deterministic function in Excel or Python in a few milliseconds at essentially zero cost; asking a large language model to perform the same computation would take several seconds and consume far more resources, while introducing a risk of non-deterministic output. The conclusion, in his words, is that:

"If you tried to do everything with AI, it would take several seconds but would cost much more. Not everything is worth improving with AI."

(Baldini, personal interview, 16 April 2026)

This is a significant methodological point. It suggests that, within BlackRock, the adoption of generative AI is not driven by technological enthusiasm, but by a cost-benefit calculation.

4.3.3 Governance, risks, and the evolving role of investment professionals

The governance of AI at BlackRock has both a product-design dimension and an organizational dimension. At the product level, we had already analyzed Aladdin Copilot and eFront Copilot, even if these systems are not designed to give investment advice or to answer questions outside the platform's functional boundaries. At the organizational level, the emphasis in the interview was on supervision: human oversight is presented as a non-negotiable principle rather than a temporary precaution.

"I don't think we are yet in a position where we can fully delegate activities to AI. AI in this phase is a very useful tool, but it must be targeted to a specific analysis [...]. We are not yet in a situation where we can tell the AI to choose which companies to invest in — that is still science fiction."

(Baldini, personal interview, 16 April 2026)

According to the interviewee, the current equilibrium within BlackRock is that AI produces analytical outputs from well-organized inputs, and those outputs are then reviewed by human investment professionals before they are inserted into actual portfolio decisions.

When the interviewee was asked about the risk that AI could push the industry towards a homogenization of investment strategies, he rejected this as the likely equilibrium. His argument was explicitly market-based:

"If every investor asks the same language model to construct the same portfolio, the resulting uniformity would itself create an incentive for someone to deviate and build a differentiated strategy. In his view, the market self-regulates from the standpoint of strategy diversity. [...] a degree of homogenization already exists through passive investing, so this phenomenon is already partly present; it is not a risk that emerges only with AI, and AI is not necessary to construct passive investment strategies."

(Baldini, personal interview, 16 April 2026)

His view is that competitive pressure pushes competitors to use those tools differently and maintain distinct portfolios.

Baldini stated that on the human-AI interaction dimension, there has been little to no evidence of organizational changes (as a result of the introduction of AI) at BlackRock, other than the formation of a team for AI research (BlackRock AI Lab). However, he also said internal discussions have made clear that it is expected that some of those jobs (typically filled by entry-level employees), such as conducting research, creating summaries, and running detailed analyses that would take a lot of time but do not involve senior-level judgment, will be partially substituted by AI. He immediately qualified this observation with what he described as a standing concern in corporate discussions:

"If we don't hire juniors today, we won't have seniors tomorrow. But this is a well-known fact. We must tread carefully because we must understand the implications of the decisions we make, so we can't make a decision that has too much impact and might have an immediate impact but create problems in the long run."

(Baldini, personal interview, 16 April 2026)

The last analytical point for this study refers to the scope or boundaries of application of Artificial Intelligence (AI) technologies. Baldini stated that there exists a specific area where he believes it is difficult to substitute technology for people: the relational aspect of the business. He describes the relationship and trust developed with customers, as well as the interpersonal aspects of working with other employees, as "intangibles" that are hard to replicate through machines. This perspective suggests that over the near-term future, senior professional positions at BlackRock will likely continue to focus on the relational and strategic dimensions of their work, while increasingly relying upon AI support for the more technical aspects of their work.

4.4.1 Case Study 2 - Isybank S.p.A. (Digital bank Perspective)

4.4.1 Strategic rationale: AI as native infrastructure

Within this strategic setting, AI is not presented as an optional technological overlay but as a constitutive element of the business model. In the interview conducted, Angelo Lapenta, Head of Business Development & Products, responsible for the marketing and customer-relationship area at Isybank, framed the role of AI in digital banking through three complementary lenses: as an engine of operational efficiency, as a driver of customer acquisition at scale, and, above all, as an enabler of personalized customer experience in a market increasingly exposed to commoditization, meaning that services become increasingly similar across, as this effect increase more customers will struggle to tell differences from one bank to another.

"In a digital bank like Isybank, same as Revolut, the market dynamic is that every day we acquire between one and two thousand new clients, the size of a small Italian town. AI is what makes this kind of acquisition scalable: there are processes and technologies that only AI allows you to operate efficiently at these volumes."

(Lapenta, personal interview, 10 April 2026)

The efficiency logic described by the interviewee is reinforced by Isybank's cost-income ratio, which is reported at approximately 29%, compared to other competitors (a significant level for a sector in which the cost-to-income ratio is one of the most closely observed indicators of operational efficiency), and a total inventory exceed €2,6 billion, with an average balance per account of €3.000, well above the fintech industry average⁶³.

The interviewee was very clear that the structural architectural advantages of being able to adopt AI as a digital bank are vastly different from those available for banks using an architecture that is only tactical. Isybank has been designed and built natively on the Cloud. Therefore, by design, native integration of AI tools into all data and service layers of the platform is possible. In comparison, in a traditional banking environment with many years of legacy information systems, AI solutions are usually added to a process after it has already existed, "at the back" of the workflow, versus as part of the workflow itself, resulting in significant decreases in overall effectiveness. Indeed, a modern digital bank, he argued, has the advantage of real-time, already-structured data flows. In a traditional bank, by contrast, the report arrives a day or two later, and any AI applied to that data inherits the delay. This real-time, structured data environment is what ultimately enables AI to operate on the customer experience rather than on the back office alone. This demonstrates that the real bottleneck of AI adoption in banking is not just the sophistication of the models but the quality and accessibility of the data on which those models are trained and deployed.

4.4.2 AI applications: customer personalization and fraud prevention

Customer onboarding is the first point at which AI becomes operationally indispensable. Isybank's account-opening flow is entirely digital: a new customer downloads the app, uploads an identity document, records a short video of their face, and the account is activated in real time. Behind this user-facing simplicity sits a technological stack that integrates

⁶³ Nubola V., *Isybank, Intesa Sanpaolo's digital bank, is growing: its second year of profitability and over one million customers*, First Online, 2025, 9 August. <https://www.firstonline.info/en/isybank-la-banca-digitale-di-intesa-sanpaolo-cresce-secondo-anno-in-utile-e-oltre-un-milione-di-clienti/>

document recognition with multiple private and public databases to verify the identity of the applicant and, critically, to detect AI-generated deepfakes used in fraud attempts.

"Creating a non-real image with AI today is very easy. So you need software that catches those attempts immediately. From onboarding onwards, in fraud prevention, AI is not just useful — it is fundamental. Otherwise, you are fighting with unequal weapons, because your fraudster already has the most advanced tools."

(Lapenta, personal interview, 10 April 2026)

Fraud and risk management represents the second, and in many ways the most critical, area of AI deployment. Banca d'Italia's 2025 Fintech Survey confirms that fraud detection and anti-money-laundering are among the primary drivers of AI investment in the Italian financial system⁶⁴. Lapenta observed that a transfer today settles in two seconds on the recipient's account, and the recipient can immediately forward the funds, with the result that the window in which a fraudulent transaction can be stopped has collapsed from days to seconds. This technological logic connects directly to a systemic-risk dimension that Lapenta raised explicitly during the interview. Because Intesa Sanpaolo is a systemically important bank, and because Isybank sits within the Group, the bank must be prepared not only for isolated fraud attempts but also for structured attacks aimed at institutions that represent the country.

Another important point raised by Lapenta is that personalization will become “the key differentiator” for digital banks, especially in light of the risks posed by commoditization. He noted that, essentially, all apps provide the same basic service, such as money transferring, so unless customers can receive a bank experience that is truly personalized to their specific needs at the time they require it, there is no reason why they cannot use another bank. With its ability to personalize experiences for tens of millions of customers, AI is the tool that allows banks to move beyond commodity status.

⁶⁴ n.d., *Indagine Fintech nel Sistema Finanziario Italiano, Banca d'Italia Eurosystem*, 2025, dicembre. <https://www.bancaditalia.it/pubblicazioni/indagine-fintech/2025-intermediari/index.html>

"AI can personalize, or almost hyper-personalize, the customer experience in near real time. This is a fundamental element for transforming your services from a commodity into something more important."

(Lapenta, personal interview, 10 April 2026)

The interview also surfaced a use case that does not typically appear in publicly available material about digital banks: the use of synthetic customer profiles "digital twins" for market research. By using AI to construct thousands of synthetic client profiles drawn from web and social signals, the marketing team tests product hypotheses and communication strategies in a simulated environment before engaging real customers.

This approach represents a qualitatively new form of AI-enabled market research. It was found that LLM-powered digital twins achieved 88% accuracy in predicting individual responses to behavioral tasks including purchase decisions and economic preference experiments. This suggested that synthetic profiles can simulate not just stated opinions, but actual decision-making patterns. It is likely that it will be difficult to simulate this type of environment using conventional banking environments and above all a great use of resources. Overall, replication of behavioral tasks are typically successful; however, additional research will likely be necessary to confirm whether or not the digital twin simulations also capture atypical behaviors or accurately represent the range of political and domain specific beliefs among all members of a population⁶⁵.

4.4.3 Governance, risks, and the human–AI relationship

The governance of AI at Isybank must be understood within the regulatory perimeter of the Intesa Sanpaolo Group. The operational translation of this was summarized by Lapenta in two interconnected principles: data anonymization and a governance structure dedicated to AI risks.

⁶⁵ Kalda J., Levy O., Toubia O., *Twin-2K-500: A Data Set for Building Digital Twins of over 2,000 People Based on Their Answers to over 500 Questions*, Marketing Science, 2025. <https://pubsonline.informs.org/doi/10.1287/mksc.2025.0262>

"The European financial sector is heavily regulated, so it is hard to imagine that I simply take a customer's data and feed it to AI. The way it actually works is that data is anonymized, so the AI works on an individual level, and when the output comes back to your personal app, it was produced without a direct link to the individual."

(Lapenta, personal interview, 10 April 2026)

The governance structures related to Artificial Intelligence for both Intesa Sanpaolo and, therefore also for Isybank, operate on several cross-linked Risk Dimensions that are Data Quality, to ensure that models do not learn from "dirty" data; Bias to avoid discriminatory processes for Credit, Pricing, Offers.; Model Risk to avoid loss of accuracy.

On the human-AI interaction dimension, the interview converges with the BlackRock case in identifying augmentation rather than substitution as the dominant pattern, but the argument is framed in the specific terms of a digital banking context. Lapenta's position is explicit:

"AI without human touch is stupidity. [...] At Intesa Sanpaolo, no one has lost their job because of AI; on the contrary, 3,200 young people have been hired on these technologies. We can do more, do it better, and people have been progressively freed from low-value-added activities to focus on higher-value-added work."

(Lapenta, personal interview, 10 April 2026)

For example, Lapenta referred to the continuous transformation of the consultative relationship in traditional banking. Historically, advisors have had weeks to develop portfolios for high-net-worth clients. However, with the use of AI, they are able to provide a basic structured outline of proposals in about thirty minutes, with the advisor and client working together to refine the proposal. The use of AI does not eliminate the advisory role, since clients still appreciate the interpersonal relationships involved with private banking. However, the role of the advisor is transforming from focusing on retrieving and assembling documents to using judgment, building a relationship, and creating customized products. Lapenta's observation mirrors what was noted by Baldini at BlackRock, where AI focuses

on the labor-intensive analytical work and the human professional retains responsibility for interpretation and the relational aspects of the work.

Finally, looking ahead to future developments related to digital banking and AI, Lapenta indicated that he believes that over time, customers will be interacting with their banks through AI agents, that enable routine financial activities such as paying bills or transferring funds via an algorithmic intermediary. In this model, the customer delegates these tasks to an algorithmic intermediary that acts on their behalf, meaning that the bank's primary interlocutor is no longer the customer themselves, but a third-party AI agent optimizing for their interests. The AI agent acts as an intermediary. It communicates with the bank, executes transactions, and makes micro decisions, all on behalf of the customer. However, this vision remains largely speculative nowadays. It is true that AI-driven intermediation are gradually taking shape, but they still face significant practical and regulatory barriers. Furthermore, according to Lapenta, if customers begin to rely heavily on these AI agents to perform their banking functions, then the relational depth established by Isybank today could potentially be disintermediated by layers of conversations between the bank and its customers' agents. Therefore, while Lapenta was attempting to prevent the commodification of banking by developing personalized experiences for his customers, AI could make the customer experience itself feel standardized. If customers interact mainly through similar AI agents, the bank may lose part of its distinctive identity. For this reason, banks will need to combine AI-driven personalization with emotional, experiential, and relational elements so that customers continue to perceive the bank as a trusted partner rather than just a provider of digital services.

4.5 Cross-case Synthesis

The BlackRock and Isybank cases, read together, reveal that the adoption of artificial intelligence in financial services follows institutionally specific logics that reflect the nature of the business, the structure of the customer base, and the architecture of the underlying technology used. On the one hand, there is Isybank, whose nature is built on technological and cloud-based infrastructure. Within this system, AI is not simply an additional tool, but a

foundational component of the business model. A digital-native, cloud-based bank cannot operate at the intended scale and cost-to-income ratio without AI embedded across its business lines. On the other hand, there is BlackRock, a far more complex and historically established financial institution. In this case, AI is framed less as the core foundation of the business model and more as a general-purpose productivity technology layered on top of a pre-existing data environment. The difference in use of artificial intelligence by the two companies reflects their differences in B2B versus B2C business models; however, this also illustrates a larger trend: The primary role of artificial intelligence in asset management is to support human experts, whereas the primary function of AI in banking is to provide scale for services that were too expensive for humans to deliver.

Both interviewees stressed that AI has to be viewed mainly as an augmentative technology to assist humans in performing their jobs rather than as a replacement for them. They both believed that the role of AI would be to take over many of the routine analytical and operational tasks currently being performed by humans. While they see potential for some areas of the business to be significantly impacted by automation, they were unanimous in identifying the relational component of the business, such as building trust, establishing relationships with clients, and being accountable, where the human element is most resistant to substitution.

When taken together, these two case studies confirm a clear vision: The opportunity, risk, and regulatory challenge created by the adoption of AI technology differ significantly based upon the institutional setting within which the technology is implemented. As shown through these comparisons, organizations implementing AI into their operations cannot treat AI in the same way; it should be understood as a flexible technology whose effects are shaped by the adopting institution's structure.

Chapter 5 – Conclusions

The main point of this thesis was the recognition that artificial intelligence is no longer an experimental technology in finance, and it has already become a strategic infrastructure that financial institutions use. The objective was to understand what AI inside financial institutions does, why it has emerged as a key tool in this sector, and what risks it introduces at institutional and systemic levels.

In the beginning, we indicated that current AI is not a single technology but instead a collection of various computational methods, including Machine Learning and Large Language Models, whose principal characteristic is their ability to "learn" from data rather than execute pre-coded rules. It's the peculiar nature of AI that explains why it's so significant in finance. Financial Institutions function in an environment that includes large amounts of data, decisions made in real-time, and the continuous identification of minor trends in uncertain conditions. As a result, the transition from Expert Systems to Data Driven Learning represents much more than simply an evolutionary step in computer science. Rather, it is the fundamental cause of how AI went from being an intellectual curiosity of academia to a valuable resource for the financial industry. The magnitude of this shift can be seen in the numbers provided in the same section, showing that 85% of firms operating in the financial services area are currently using AI, and estimates project that the global AI in Finance Market will increase from \$18.9B in 2024 to \$78.6B by 2030.

After providing the context, we illustrated that this strategic relevance is reflected in significantly different uses among the three primary areas examined. Within the banking segment, AI is used throughout the entire operational stack: from Algorithmic Trading, Mergers & Acquisition, Due Diligence to Credit Scoring, Fraud Detection, Customer Personalization & Back Office Automation. An example of empirical evidence supporting these findings includes a commercial bank having reduced unclassified credit rating classifications by 40.1% and default rate classifications by 29.6%. Within Asset/Investment Management, AI is applied in support of Portfolio Construction and Alpha Generation. Robo-Advisory has dramatically expanded Wealth Management Services to mass market clientele at low-cost margins that were unimaginable ten years prior. Within Market Intermediaries

and Infrastructure, AI has been implemented into Smart Order Routing, Market Making, Surveillance, and Post Trade Processes. AI is now integrated into the flow of financial markets themselves. AI cannot be viewed uniformly. Its purpose, application, and value creation principles differ greatly depending upon where within the financial structure it is employed.

All these advantages carry a necessary counterweight. The same abilities that technology will provide for each institution to enhance decision-making and efficiency will create risks at the systemic level. This dual nature of using AI is not an unintended consequence that needs mitigation but is structural to the technology itself. These exposures include model risk and black box problems in auditing outputs; data-related risks (quality issues and correlated behavior) as multiple institutions develop similar models based on similar data sets; operational and concentration risks due to reliance on a few cloud and AI infrastructure providers; and human capital impacts represent long-term implications with respect to future development of investment professionals. Regulatory responses from Europe through the AI Act, MiFID II, and DORA have tried to address some of these exposures by taking a layered approach, but analysis identified that the regulatory framework continues to evolve and gaps remain with respect to capturing the systematic interactions between AI-driven models, which no single regulation was originally intended to oversee.

The two case studies presented in Chapter 4 were designed to test whether this theoretical picture holds when one looks inside financial institutions. The comparison of BlackRock and Isybank provided results that confirm the research. The application of artificial intelligence provides similar opportunities, risks, and governance issues across the financial services sector, but they are all impacted by the institutional context in which they are implemented. In Isybank, a digital native bank, AI is integrated as part of the business model utilizing cloud architecture. Conversely, in Blackrock, AI is being used in addition to an existing data environment and is viewed as a productivity tool as opposed to the basis of the business model, consistent with a company managing trillions of dollars in assets, treating AI as one of many productivity layers. Although both institutions view human oversight as a required aspect of their respective businesses, rather than as a temporary safeguard, there is

convergent thinking from both institutions regarding human oversight. From a theoretical standpoint, the similarity of both organizations' views toward human oversight illustrates that, regardless of their business model differences, the current state of AI does not allow for complete delegation of decision-making to algorithms. The fact that two professionals operating in opposite segments of the financial industry arrive independently at the same conclusion is a strong indication that the augmentation logic, rather than the substitution logic, is the dominant pattern of AI adoption in finance today.

This thesis has, of course, several limitations that should be explicitly acknowledged. The analytical focus was narrowed to concentrate on the European regulatory environment. The conclusions derived from the research should be interpreted as analytical generalizations versus statistical generalizations. Furthermore, AI is a developing technology, and some of the technologies discussed in this thesis may become obsolete within a relatively short period of time. Beyond those specific areas, this thesis contributes broadly by combining an institutional approach with a systemic one, and by integrating theory with empirics approach to understand how financial institutions implement this technology. It appears clear that artificial intelligence represents a powerful technology and will have significant strategic implications depending on how it is incorporated into work, depending on the choices that financial institutions, regulators, and professionals make. Therefore, understanding these decisions and the rationale underlying them will continue to represent an essential task in studying financial markets in the years ahead.

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