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Chapter 2: Unpacking artificial intelligence: A catalyst for financial innovation

2.1. Introduction to Artificial Intelligence in Finance

We are experiencing a new era in the global financial industry. Rapid advances in machine intelligence and its application in data analytics, robotics, and virtual assistants have the potential to disrupt traditional financial services with significant benefits to the consumer. Artificial intelligence is becoming an essential tool to transform the industry into a faster, more efficient, more personalized, and more cost-effective space. Financial institutions such as banks are therefore using data-driven insights to connect better with their customers, improve their risk management capabilities, and drive profitable growth, among other overarching strategic objectives. The wider benefits are to society as a whole: a competitive, market-driven, and intelligent financial system is a fundamental contributor to well-being and growth (Dhar, 2016; Brynjolfsson & McAfee, 2017; Bholat et al., 2020).

The use of AI in finance will rely on three critical assumptions. The first is a radical paradigm shift in our preconceptions about how AI applications are developed and applied in the financial field. Although useful predictive models can be developed using existing frameworks, the scale and scope of financial markets require a different type of AI: a mix of techniques to handle unstructured data, advanced pattern recognition, and adaptive machine learning while working with very limited labeled training data. These techniques will also need to be both interpretable, to promote effective human oversight, and explainable, to generate consumer trust. Such AI will also have to manage a complex regulatory and compliance environment currently designed for human interpretation. These technologies will also have to deal with the inherent creativity and complexity of human decision-making, which remains essential for driving human enterprise.

However, there is a knowledge gap between financial institutions and the developers of AI platforms as to what can be achieved and how this can be made possible. What should financial institutions take from existing intelligent applications and how can these applications be concentrated? We provide answers to these questions and propose a set of use case principles. We also recommend a strategic framework for financial institutions that wish to develop their AI intelligence. Second, AI will rely on an environment that is technology-centered and flexible. At present, the financial industry faces major challenges in acquiring and retaining technology talent. AI will also rely on higher access to data and a modern data platform that can handle complex business rules and processes, without being negatively affected by the fact that it reflects customer behavior. In order to be robust, financial institutions will need access to better processes, tools, and leaders who manage change and innovate. Lastly, AI applications will require the cooperation of forces both within and outside the financial industry. Financial institutions cannot truly exploit AI's potential without knowledge-sharing and talent acquisition fostering an open innovation environment. In addition, the decentralization of AI benefits will change the face of financial services, requiring work with different types of expertise as new types of companies emerge. As a result, the long-term success of AI applications will depend on innovation ecosystems (Frost et al., 2019; Ionescu & Sima, 2020).

2.1.1. The Evolution of AI Technologies in Financial Services

The origin of artificial intelligence (AI) dates back centuries, but it has now become both a disruptive and enabling catalyst for a transformative wave that is reshaping many sectors, including financial services. Several branches, including machine learning and natural language processing, have evolved from classical AI, providing new frontiers to simulate intelligent behavior in machines. The common denominator in all of these AI techniques is that models are extracted or trained from data rather than being explicitly programmed. A recurring theme has been the existence of deep learning and convolutional neural networks based on high model accuracy using non-linear data.

Recent advancements in AI technologies have contributed to driving the transformative wave in financial innovations. AI collectively refers to a class of machine learning and neural network methodologies. Increasingly, new AI techniques – natural language programming, deep learning, clustering and market segmentation, processing of complex tasks and high-dimensional data, fast-evolving financial processes, and expediting substantial research and development – are emerging. Each of these techniques can generate certified outputs and aggregate complex tasks that humans typically perform using less computational and human capital. The result of these techniques has established frontiers that can simulate intelligent behavior in machines.

The technologies are contributing to the groundswell of hyper-automation, a technology trend that not only underpins business transformation but also propels a forward-looking investment in the economy.

2.2. Historical Context of Financial Innovation

Technological progress has been a vital catalyst for financial innovation and continues to be a key building block for reform, including the obligatory spin-offs on legitimacy and soundness. A historical look at stock exchanges gives an indication of this technological-organizational relationship. Price quotes have always been crucial for securities markets. The first pre-electric ticker was patented in 1867. However, rapid transcontinental transmission of stock prices was limited because the telegraph was prohibitively expensive. On the New York Stock Exchange, ticker dissemination finally galloped ahead in response to customer demand. In the 1870s, only points between which telegraph connections were made were listed. In 1876, 21 mile-per-hour stock tickers were installed, feeding off a 1.2 million share NYSE. In the 20th century, besides belts and pulleys, pneumatic tubes provided a further increase in ticker capacity. For instance, Bell Telephone launched its first pneumatic tube to Boston in 1904 and to Philadelphia in 1920, and a dozen other cities were added by May 1922.

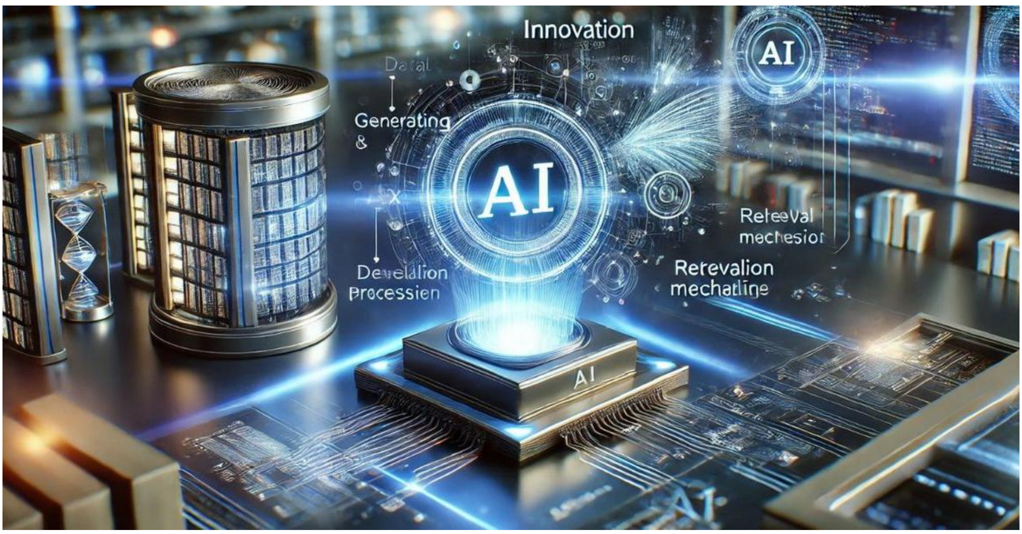

Fig 2 . 1 : Unpacking Artificial Intelligence

Unfortunately for the NYSE, ticker demand was insatiable, and the NYSE deemed it uneconomical to replace its pneumatic tubes with electrical wires. Instead, the NYSE installed telephone lines with a bell system from 1925 onward, around the US telegraph banner; but the radio also began to play a role. It called out the first successful full-span telephone wire account and listing service experiments as late as 1934. Financial innovation has oftentimes not been led by the exchange; for instance, the stock quote 'ribbon' and the ups were substantially earlier inventions. For equity markets, the competition in information provisioning rapidly fell to three basic models, as described by specialists and competitive classes of floor traders, e.g., 'commission men'; brokerages' telephone communication with their clients; and the 'roving correspondent' who would report prices by telephone or telegraph from the trading floor.

2.2.1. The Impact of Historical Financial Innovations on AI Development

Investors expect AI to drive growth in the FinTech sector. We believe that FinTech innovation will, in turn, accelerate progress in AI by giving investment opportunities to private firms and subjecting AI technologies to the most demanding performance tests possible, those of financial markets. We review the impact of historical financial innovations on AI development. We illustrate the process with the case of an AI-driven hedge fund. The proprietary infrastructure of the fund leverages three decades of joint development of financial AI and diversified FinTech. We also illustrate the recent innovation cycle in AI, the deep learning revolution. Contributions combined image processing and neural networks trained on graphics processor units, already in use by the video game industry, obscured that a specific lab, part of a large financial company, had invented both improvements. Ultimately, a company, which had the best graphics processor unit, designed a 'Deep Learning System' optimized for the large datasets and frequent updates in a financial institution. This hardware boost caused all other users of artificial intelligence to benefit from network effects in performance gains.

The development of deep learning is an example of the counterintuitive synergistic effect of financial innovation deteriorating progress in AI and even conventional software. More generally, investing in artificial intelligence often benefits from bad timing. Our paper highlights the currently underappreciated impact of finance on the innovation cycle of artificial intelligence. In the near term, this missing piece of the discourse matters mainly to investors, who underestimate the market's ability to internalize, rapidly and stealthily, knowledge discovered through private finance. We emphasize current trends in FinTech to illustrate interesting opportunities for investments, opportunities created by technological scarcity, determinants of performance that will affect both private firm innovators and those who fund them.

2.3. The Role of AI in Modern Financial Systems

This section provides a high-level synthesis of the rapidly growing technical and theoretical literature underpinning the adoption and use of AI in finance. It starts with an elaboration on common estimation problems in identifying non-linear effects from data. It introduces and summarizes a broad and critical set of topics driven by AI and their practical applications in the financial world. Early on, we study general economic applications of algorithms, and in particular, their optimization algorithms which play a central role in both general applicability and practical usefulness in finance. Modern financial systems are information-rich environments. Central banks deploy an arsenal of big data tools to manage monetary policy and contribute robust decision-making across large-scale complex bureaucratic institutions. Two decades of literature in macro and finance are characterized by an increasing number of structural models, which behave as theoretical foundations of empirical work. After the crisis, public microdata have encouraged a rapid development of various innovative work on banking. Large IT consultants are touting AI technologies as the key to unlocking the potential of established financial institutions. The hype may not be overblown. From an academic standpoint, there is emerging significant empirical evidence that all areas of AI can bring substantial improvements in the financial world, including asset management, risk management, reinforcement learning, and nowcasting economic indicators, to name a few.

2.3.1. Innovations Shaping the Future of AI in Finance

Artificial intelligence in finance is not the "next big thing," but rather an established and ever-expanding universe of technological capabilities across a grand array of cognitive functionalities. From the more "mundane," albeit extremely impactful, foundational roles in algorithmic and high-frequency trading, AI has grown to play direct and assisting roles in personal financial management, chatbots, group and individual banking customer relationship management, recruitment, clearing and settlement, loan origination and credit scoring, insurance and fraud detection, compliance and risk management, and the cutting-edge world of complex financial products such as exquisitely focused ETFs, the science of predictive investing, and the gamification of prediction markets. Spanning a range only second to those of AI in defense, health, and transportation, AI in finance at the same time embodies capabilities unique to the business of financial institutions.

And the future is upon us: the very concept of a bank is changing deeply, allowing the envisaged launch of "bankInABox," i.e., a modular and complete "bank subscription," simply put together from a collection of pre-programmed AI functions. Banks covering all the 4,000-5,000 profiled activities might cease to exist: in a not-so-distant future, there might be only a scant few upper-Matrix banks that will initially keep the few genuinely strategic activities while selling the rest to all the others, who have become AI-enabled banks lacking most of the traditional activities and services. Of course, hyper-scale operations may keep unique capabilities like the willingness to accept risks and large sums of money, while micro-scale local banks incontestably play the roles of dinosaurs' descendants. Small scale does have its advantages, however: they are closer to their customers and are consequently exposed to much less counterparty risk and more direct information.

2.4. Key Technologies Driving AI in Finance

A handful of technologies are driving integrated AI in the finance industry and can be classified into neural network technologies and data technology. The finance industry's considerable innovation adoption means that we are seeing a multitude of finance use cases across the board in just about every AI type. This concept is different from industrial AI maturity; in finance, it's the case of many use cases across the spectrum.

There are a few key technologies driving integrated AI in finance. Typical architectures include technologically advanced integrated full-stack AI banking platforms using big data technologies with advanced NLP, ML, and RPA models and techniques in the cloud. There are also customer-facing AI experiences and infrastructures integrating with AI technologies such as chat support AI, robo-advisors, and credit recommendations. We also see system optimization infrastructures through AI technologies. This includes improved risk models, alternative data sources for stock or commodity trading, and footprint scores. There are also back-office AI combined technologies that include facial recognition or document OCR. Actual examples in business include fraud detection, helpdesk chatbots, and customer credit recommendation engines.

2.4.1. Machine Learning Algorithms

To date, the majority of AI applications in the industry are based on machine learning. Machine learning is a subfield of AI and is sometimes treated as a more general form of representing AI. ML models learn from input data to make predictions or to uncover underlying patterns to determine possible actions. The learning process involves optimizing model parameters iteratively to obtain desired outputs by comparing the ML model output with expected results. ML models are based on various learning techniques, such as supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, models make predictions on labeled data. In unsupervised learning, models extract hidden patterns and methods to distinguish data into organized clusters. Reinforcement learning aims to discover the behaviors of ML models via interactions with environments.

More specifically, for financial service and product decisions, ML and its various models have been widely adopted. Neural networks have been used for high-frequency predictions, forecasting financial risks, and detecting financial crimes. Other supervised learning methods, such as decision trees and ensemble models, have been applied to predicting credit risks and pricing of financial products. Unsupervised learning methods could be used to classify different customer relationships or subsegments. Reinforcement learning has also been proactively asserted in portfolio and risk management. Digital financial platforms and technology-driven financial firms have heavily leveraged ML models to provide financial services and instruments conveniently to consumers. There has been great optimism and impetus regarding ML's potential in enhancing financial innovations. All these applications and practices show that AI, and in particular, its enhancement through ML, brings practical opportunities in the financial domain. However, for ML to truly accomplish its widespread benefits, inherent challenges in ML adoption need to be anticipated and approached, especially within financial institutions.

2.4.2. Natural Language Processing

Natural language processing (NLP) is one of the most transformative subcategories in the AI space that has shown considerable promise in domains like financial news analytics, investment research, customer service, and chatbot interfaces, among others. In simple terms, NLP refers to the utilization of computational techniques that try to learn, discern, or relate natural human language to a useful form. These range from very large data sets to code-switching between languages, essentially simulating a conversational process. The application domains for NLP are exhaustive, and NLP algorithms have been widely applied across diverse business functions from customer service to conducting research and generating customer insights. Activity to date suggests several challenges. First, natural language processing for banking-specific terms is considerably more challenging in comparison to generic terms. Second, linguistic and social ambiguities are the primary purveyors of unsupervised machine translations. Lastly, the majority of natural language processing systems demand large corpuses of specific data, which is difficult to obtain for specific applications. Companies with the capability to innovate, focus on their competitive positioning, and invest widely in deploying NLP should continue to benefit as acceptance and deployment of NLP approaches advance in the coming years.

2.4.3. Robotic Process Automation

Reducing human intervention in the financial services industry has been a journey that began decades ago but continues to evolve today. The industry has systematically applied digital technologies to streamline processes, optimize resources, improve the structure of data inputs, and enhance data quality through real-time validation, thereby facilitating more effective and efficient decision-making. The financial industry started this journey by automating the processes used for transaction processing, including digital payments and post-transaction settlement processes across the various asset classes. Many financial firms today are now looking at their end-to-end process flow, examining non-inventive tasks that demand human bandwidth or are prone to error, and striving to further minimize process execution involving any sort of drag time, trying to reduce latency wherever possible. This has opened up more applications for robotic process automation tools. RPA is a stepping stone, or logical bridge, to the more capable infrastructure artificial intelligence uses when executing cognitive tasks, which goes well beyond the mechanics of rule-based execution. RPA serves in the middle office and back office where there is a predictable pattern of work involved in assembling experiences driven by business rule interaction. The benefit of deploying robotic process automation tools is to increase the level and reliability of automation and consistency in the interaction and workflow for the end users.

2.5. AI Applications in Banking

Casual references to AI often signify the concept rather than the actual idiom of artificial intelligence that is of interest. AI exhibits a broad range of varieties with varying degrees of programmability and complexity. The simplest forms - those that merely substitute for repetitive manual or clerical labor - are usually classified under the broader rubric of business process automation rather than AI. For commercial banks, relative comfort with business process automation is normal. When automation advances under the banner of AI, its technologies can be unsettling.

The promise of AI, however, is not limited to speeding the closure of legacy applications. The software of AI - based upon neural networks and other machine learning principles - offers a foundation from which algorithms grow and flourish in an adaptive and more constructive manner. These algorithms can uncover predictive and prescriptive insights across complex datasets and models in which true interrelationships are not immediately apparent. Such AI capabilities open pathways for generating new revenues, for improving operating efficiencies, and for ameliorating risks. They enhance traditional activities, so as to conceivably recast sections of banking activity itself. With sufficient adoption, it is quite probable that AI will materially transform the experience of banking clients while altering the structure of global banking institutions.

2.5.1. Credit Scoring and Risk Assessment

Credit scoring represents a key "gateway" to credit as well as to various other types of underwritten insurance and the like. Over the past several years, the use of statistically derived credit scores has made a great deal of behind-the-scenes credit and insurance scoring economically feasible for retail and small business customers. But much more can be envisioned. Financial institutions typically use a limited set of credit-related information to make a wide range of pricing and underwriting decisions. Such limitations are based on data collection costs, record maintenance, and other considerations. The detailed use of AI/ML representations should permit firmer and more widespread understanding of various credit-related distributed information patterns. In turn, this should favor more precise recognition and monetization of various customer financial preferences and profiles, which in turn facilitates improved pricing and underwriting discipline. All of these events should help to drive even more user and institutional growth down the road.

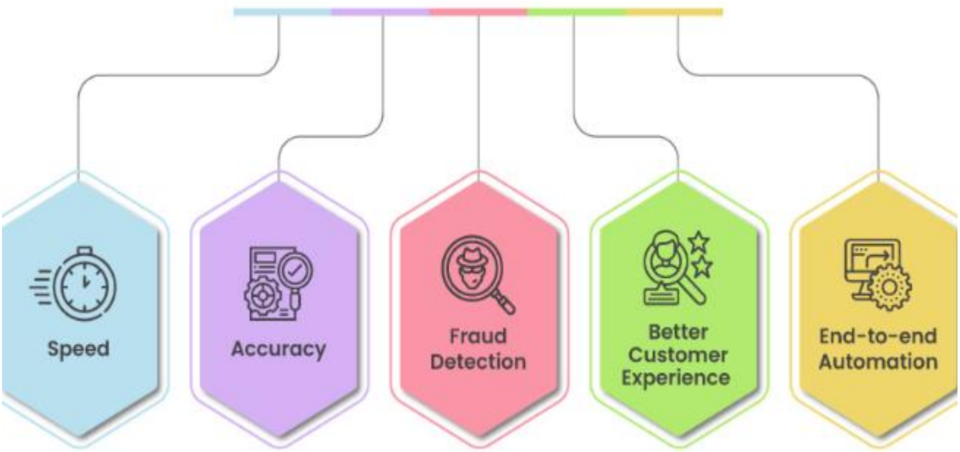

Fig 2 . 2 : Power of AI in Credit Risk Assessment

Quickly emerging new developments in both domain-specific AI applications as well as more general AI technologies will soon offer some traditional financial institutions the opportunity to pursue various proficiency and knowledge benefits of their past skills. This raises widespread questions about the nature and balance of future AI-driven industry competition. Experimenting with various data-driven institutional financing solutions should help to open additional new innovation prospects. Critically, AI technology could help shape the development of new enhancements that might soon help consumers make better, cheaper, faster, and more efficient financial choices.

2.5.2. Fraud Detection and Prevention

The current generation of AI has already been deployed for fraud detection and prevention. Credit card service companies have long used AI to analyze spending habits in real time, while AI techniques can re-expose existing payment authorizations based on the owner's habitual and past behavior. AI also informs fraud models for evaluating transaction patterns and establishing a numerical fraud score. Furthermore, mortgage fraud detection is enhanced by sophisticated networks that can better understand mortgage data. The latest generation of AI has employed convolutional neural networks to identify unusual transactions in user bank accounts and to correlate the user's personal data with social media data. The vocal authentication process is accompanied by deep learning audio verification and validation. These methods assist in the detection of identity and new account fraud. In addition, AI is used to streamline data for regulatory compliance. This has made anti-money laundering practices more precise and less resistant. Crucially, AI networks have also been shown to outperform large financial fraud detection models. However, it is worth noting that the output of these models is determined by the granularity and frequency of the history of the data. The discovery of new, overwhelming models and unusual behavior may be a solution to even more personalized complaints that regulatory technology has to adapt.

2.5.3. Customer Service Automation

Meeting the needs and preferences of consumers by delivering personalized services and a seamless experience has become a key focal point for banks worldwide. By leveraging customer data insights, AI-powered technologies can drive the development of targeted, responsive, and adaptive digital banking and e-commerce solutions that transcend diverse customer segments and demographic cohorts. Fueled by improved analytical precision, functional richness, and a robust suite of e-tools, customer insights and decision-making can support the effective monitoring and evaluation of performance, the optimized delivery of customer service, and the commercial success of fintech, e-commerce, and other digital banking engagement initiatives. In order to provide highly tailored products that meet diverse customer needs and preferences, banks leverage customer data insights to apply various AI-based behavioral economics principles in customer dialogue and engagement designed to elicit the most relevant information and responses from targeted customer segments, such as investigating the reasons for making specific financial decisions or training models to unlock emotional factors. Such insights can derive from storing the results from actual social media channels, websites, e-applications, automated feedback management solutions, loan applications, teller interviews, machine learning, natural language processing, or sentiment analysis.

By integrating a large pool of customer data, potent AI technologies have become crucial to personalize customer service and successfully promote differentiated value propositions. For instance, they can power new capabilities for aggregating, storing, managing, and sharing customer preferences and insights from actual communications and interactions, as well as drive marketing and sales strategies that align with customers' preferences, such as shaping personal loan products or designing profitable, flexible investment strategies. Today, AI can offer digitized answers that represent synchronous customer interactions, offer responsive and proactive professional advice, or point people to the right information and services to get what they need. On an even higher level, banks and fintech can develop interactive and conversational forms of AI-assisted support maintained through bots that can lend a sympathetic ear or provide credible support around weak points in human focus. These new AI-driven models have also played a notable role in automating customer outreach, customer assistance, voice-directed engagement, or customer self-service channel improvements, offering bot-based customer service automation or improved customer service channels such as collaborative virtual assistants available at times of need.

2.6. AI in Investment Management

Aside from serving as a powerful data analysis tool, new applications of AI will also lead to new approaches to investment. Traditional quantitative investment processes usually include the following steps: collecting macro, market, and fundamental data from multiple sources; formulating investment ideas and trading strategies in an ad hoc manner; building and backtesting trading models on small-scale features; cleaning and managing data; validating models; deploying models in real trading; and controlling risks and making investment decisions in real trading. AI can provide effective solutions to improve the performance of each of these individual steps and can also optimize the whole process. To facilitate a thorough understanding of the broad application, in the rest of the section, we provide several examples of applying AI across the different dimensions of the investment process. These examples are called investment strategies here, considering AI's unique role in these strategies.

In this case, we only apply two hidden layers in the model rather than a deep neural network. In addition, we compare our model-based fundamental factor portfolio strategy to well-known factor investing strategies such as value, size, and momentum strategies using the same dataset. We find that a portfolio consisting of the top decile of projections generated by a model is a profitable investment strategy. Specifically, the artificial intelligence-based strategy earns positive risk-adjusted returns in the food sector but also introduces a new industry called artificial intelligence to traditional value, size, and momentum investing and pure utilization of traditional fundamental factors. However, both artificial intelligence techniques obtain excellent performance in stock selection within the alpha model. Subsequently, the significant improvement in stock selection contributes to the good performance of the investment strategy applied as both cross-sectional return prediction and portfolio construction.

The value of this technique used in prediction is capable of capturing some hidden nonlinear relations in financial statements and stock prices. For the empirical results, we mainly focus on the broad stock universe in the markets, but all the methodology used in our fundamental factor investing model is also suitable for multinational companies and global financial markets. With different related commands, the model is especially useful for asset managers to customize the input data and investment universe and to easily obtain the performance parameters without big changes.

2.6.1. Algorithmic Trading

As a matter of first order, algorithmic trading is not one area where AI manifests itself in capital markets. Algorithms in capital markets have been in use since the 1980s, in a bid to address issues such as trade execution, index arbitrage, and retail investor flow. Unquestionably, AI systems classify, comprehend, understand, and make decisions in a way that enables them to engage in trading. It is perhaps the case that such classification and understanding may not be fortuitous as defined in classical probability theory, but that such classification and understanding tend to surface from classification systems that do not model uncertainty. From another perspective, the elementary facts of AI (perception, understanding, communication, reasoning, and decision-making or action) are sufficient to define organizational reasoning in decision-making systems used in capital markets. These decision-making systems have been presented as a critical building block for the functioning of capitalism.

In terms of trading, decisions underlying the asset trading process embody a mix of speculative and portfolio considerations, with AI-enabled cognitive functions being superior in signal classification and comprehension that shape the trading function to cause distress. In contrast with the Fear-Greed model, the object of widespread disapproval is that AI enables successful agents to discern and exploit the mental or psychological weaknesses of less sophisticated agents in AI-powered asset markets. Even in democracies, if exploiting underspecified preferences is key to successful trading in AI, then trading AI is a menace to the proper functioning of both AI stock markets and capitalist democracies.

2.6.2. Portfolio Management

Widely considered one of the foremost uses of AI and machine learning, this technique was famously summarized by the first word of a notable research paper. Stock index investors ignore all information about the market price of unimaginatively selected portfolios of tickers they purchase or sell. Enhanced with advice from experts or models that predict stock prices or the overall index level only, would-be stock selectors face a very one-sided arms race. This technique, the VI coefficient in the Sharpe ratio, was not optional or selective for structural quants. A correlation- or cointegration-based signal is. It did not suffer from drawdowns and could only be wagered. Though hedging was always an option on a modestly negative forward-looking split between expected benefit and realized profit.

To achieve a portfolio efficient at earning that benefit in sharp contrast to suitability or portfolio management techniques that do not skew expected benefit at the time of decision toward the realized profit margin, you seek to populate the portfolio with tickers primed for arrest or reset toward any generalized market price. On the other side of the cointegration structure, a number of dispersion tradable relationships reach back toward the portfolio of infeasible assets. Rather than passive synthetics for individual tickers, combinations of inference commoditized assets for market price bidding. Hedging those general assets that could disintegrate. Unsheath those same cointegration model analysis arrows to efficiently weight an investment in a group of previously identified stocks. As an asset manager, pick individual assets or invest in a collection of stocks primed for market cointegration or market content creation.

2.6.3. Market Prediction Models

Artificial intelligence leads to the type of innovation unbounded by the limits of manual insight. Efficient market operation leverages price to facilitate trade, while market prediction attempts to forecast future price changes. Today, machine learning practitioners integrate financial theory, as well as market microstructure, to fuel a variety of predictive models. A spectrum of contemporaneous economic research illustrates this fact, laying the foundation for our subsequent cursory overview. In the high-frequency market prediction space, algorithms forecast infrequent price changes; these signals contain valuable information that may be utilized across staggered horizons. Machine learning models inform decision-making through various lenses; pair probabilities exploit correlations between traded assets, targeting the arbitrage risk premia of cryptocurrency markets.

Predicting "sigmas," instantaneously quantifying stock volatility, leverages permutation feature importance and variable importance scores to understand exogenous drivers. In the returns prediction space, multifrequencies foster return forecasting in liquid markets. Machine learning best practices parse through the effects of overfitting, while a broader spectrum of asset classes raises the usual questions of data sparsity. Similarly, economic constraints provide a new layer of structure to large-scale risk-factor modeling. Out-of-sample forecasting success winnows the field of competitors. To address the subsample inversion problem, classification algorithms identify opportunity on the back of a broader implementation universe. The classic pairs trade reimagines itself as a machine learning algorithm, coining the concept of "persistently informed pairs trading." Deep reinforcement learning establishes itself within the broader progeny of trading strategies. Drawdowns become informative, as the intuition behind alternative risk management benchmarks inspires the use of scenario analysis and portfolio insurance to create a third generation derivative and hedge European and Asian option assets.

2.7. Regulatory Challenges and Considerations

As technological advances lead to the use of AI in more innovative ways, the regulatory approaches for mitigating the risks associated with these advancements may need to be updated. For instance, the regulation of algorithms and models is not new and already exists for specific purposes, with the use of models being a requirement by multiple regulators for banks and other institutions. These model uses and processes differ, although the underlying goal is generally the same—providing an understanding of the risks associated with the processes in question. The difference lies in the stakeholder and the subsequent outcome. Regulators may be either subject to or users of these models that are driven by AI, and the outcomes range along a wide spectrum. Within financial institutions, the desired outcome is that of an early detection system that is able to understand the financial institution's transactions.

AI can enable the detection of anomalies in transaction patterns that would not have been identified previously, as well as the processes and data behind those transactions. The regulatory uses range from a literal outcome of a model to guidelines for understanding the AI processes and data that are used. The possibilities of AI and their potential risks are vast and can include anything from the potential to identify individual preferences of an AI-using institution to trust and transparency arising from the AI behind a decision. The challenges of the current regulatory regime with respect to AI implementation are likely to be significant given their increasing role in the functioning and distribution of services. These increases flow from both the intrinsic value of AI use by financial services and the increasing scale of data monitoring as well as real-time activities. It is important to emphasize that the financial regulatory approach to algorithmic modeling and AI solutions for financial services is not new, but the pace of innovation and breadth of use cases is.

2.7.1. Compliance with Financial Regulations

Given that regulatory compliance has been established as one of the most promising applications of AI in the financial sector, closer scrutiny of the regulatory frameworks that surround AI is warranted. This is a matter of both substance and date. The gestation of regulation should ideally keep pace with the development of new technologies, not lag behind them. AI should not be held back by concerns about risks that companies may create through non-compliance. These risks will be real if AI is associated with failing to meet existing requirements for managing data security, data privacy, and the safe storage of data backups. It is an issue facing nearly all industries, where regulators suddenly feel that they need to enter the world of AI and machine learning, rather late in the day.

The management of consumer data is increasingly the subject of sector-specific regulation across the globe, particularly in the financial sector where sensitive customer financial data are involved. The most paramount challenge for growth-stage FinTech is usually how to overcome the compliance hurdles imposed by these highly sensitive and complex data protection laws.

2.7.2. Ethical Implications of AI

Opting out of engaging in a discussion about the ethical implications of AI is neither easy nor helpful. The general consensus remains that there are significant untapped societal benefits in AI and related technologies. De-risking AI innovation will be easier when navigating around the rocks of ethical dilemmas embedded within the technology. Different countries are considering different approaches as to how best to shape the wheel of AI and related technologies such that AI innovation drives surplus societal and economic value. A 'no go' recommendation on aggressive regulation is helpful since accepting a less lethal narrative about the unethical misapplication of AI allows the dialogue to focus AI innovation deployment on the achievement of the common goal, while accepting some unevenness when working toward the target. The consensus that the AI value creation narrative is based on the premise that some element of collateral damage may be inevitable. A zero damage threshold simply is not attainable, given that each AI project has an intrinsic level of uncertainty associated with its outcome and impact. The following section details some specific AI applications whereby collateral damage can lead to unintended ethical consequences.

2.8. Future Trends in AI and Finance

As AI gets more sophisticated and overtakes many of the duties currently carried out by scientists, developers, inventors, and entrepreneurs, they can be freed up to do what they do best – create and innovate. Another important aspect of AI in Finance is the use of AI for interpretation of regulatory news and inferences about corporate financial conditions. Consider two key questions: 1) can we use textual analysis to extract leading indicators about regulatory future ?, and 2) can we use AI to predict how a company reacts to investment opportunities, realizing that diving into different growth options will likely result in future creation of value. The answer across the board turned out to be that an aggregator and search engine for news commodities performs as an invaluable substitute for proprietary regulatory databases for tracking corporate compliance, conditional investigatory data published by the regulators and market participants. The AI programs that compiled documents had the ability to propose corporate innovations, profitable investments, and compliance solutions.

The greatest untapped decision-making technologies that AI will enable us to build measures and models of implicit offers, constraints, and preferences of consumers, investors, and governments. Current business intelligence systems rely on surveys and trials, limited by the poor quality of instant survey responses and limited insights into patterns, rhythms, and magic of customers' reactions. However, using insights from both human recruiting and online consumer insights, to develop decision-making systems that ask for the service provider's point of view on decisions of the end-user and learn from agreed-upon domain-specific surveys, can be fruitful in capturing future behaviours and determining guidelines to incorporate into decision-making systems.

2.8.1. Predictive Analytics

Financial sector companies have been massively investing in predictive analytics solutions that leverage AI tools. A major reason that explains this popularity is that the industry has been an early adopter of such solutions to generate value. The lifeblood of banks, insurance companies, or pension funds is data. Their business environment has always been marked by fierce competition where small details can greatly affect the final result in terms of profits. Unlike, for example, companies in the consumer goods industry that can afford to have some trial and error margins, financial industry players are always focused on putting into practice the best decisions at the right moment. No wonder, therefore, the exponential growth trend of investment in predictive analytics solutions by financial industry companies. We believe that what differentiates the most competitive predictive companies is their scope and quality of data, and their innovative use of it.

If the objective of any company in having advanced predictive solutions is to generate more business, support operational decisions that improve the bottom line, provide key information for general business planning, and enable the creation of a competitive advantage, in the case of the financial industry and given its specific characteristics and objectives, business value can be generated supported by this type of AI models, having practically no set-up or limits associated with the creation and use of the best predictive solution. It seems pure magic, and the financial industry has been mostly taking advantage of it to generate added business value.

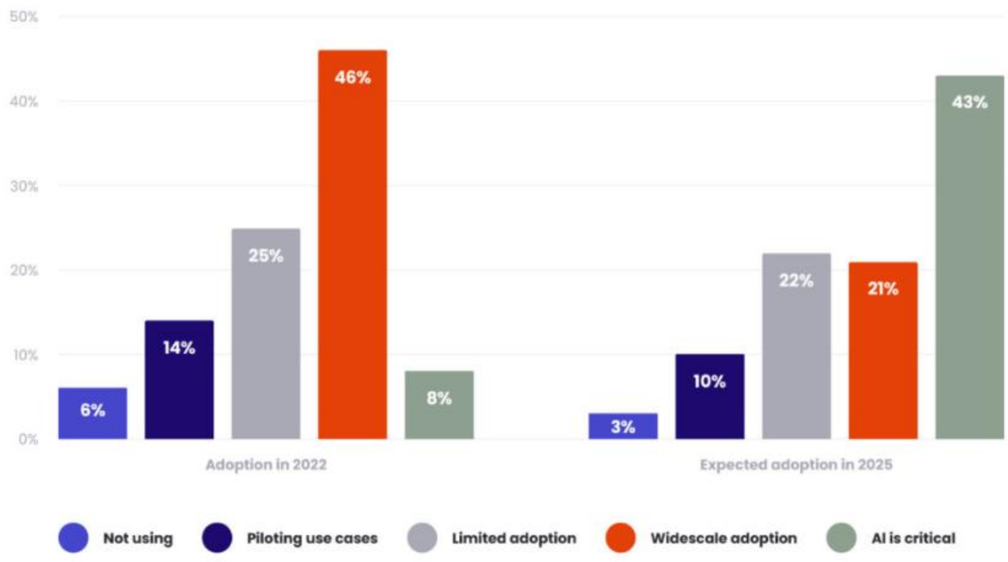

Fig 2 . 3 : AI in finance

2.8.2. Decentralized Finance (DeFi)

AI has the potential to enhance DeFi systems in numerous ways across a broad spectrum of services. It can help to generate more efficient and reliable liquidity and financial crisis prediction and management techniques, among other services.

The creation of stablecoins—cryptocurrencies designed to minimize volatility by being pegged to another asset such as the U.S. dollar—can be enhanced by AI, for example by incorporating statistical AI methods capable of measuring extreme risks, which are common to stablecoins and cause instability in DeFi. Stablecoins are commonly used to allow for such decentralized funds to maintain a stable value relative to real-world assets whose benefits are then handed over to additional financial ecosystems. As stablecoins are often used in DeFi systems, the incorporation of statistical AI methods capable of measuring extreme risks—inherent to stablecoins—is seen as a valuable component in the creation of more reliable DEX.

2.8.3. AI and Blockchain Integration

For AI agents to interact with and transact in blockchains, they need a bridge. Fortunately, several have been built, some of which are based on the principles of both AI and blockchain itself.

With the exception of oracle-based smart contracts, a major expressivity limitation of state-of-the-art smart contracts is stateful storage. The wrapper, object capability, and interoperable smart contracts model for smart contracts addresses the requirement for reproducibly shared state between independent contracts. Using this concept, independent adaptive smart contracts can signal trust and share state, enabling communication and cooperation across different blockchain systems, as well as between blockchains and other digital institutions such as AI agents, which could be part of a network, platform, or any other distributed network, digital business, data, content, or service provider. AI agents in blockchain enable AI to interact with distributed decentralized trusted services, AI platforms, and other resources. AI agents should be part of a business agreement, perhaps governed by a consortium of stakeholders, such as a public permissioned blockchain governance system. AI agents should enable technology missions, business-driven and governed design and development of an AI platform, and incorporate privacy by design and accountability, including representations, attributes, policies, ethics, and model management and operation. The governance of AI agents requires human participation in continuous ethics and governance that should be applied to their authorized behavior.

2.9. Conclusion

The practical promise of general-purpose artificial intelligence has made clear that AI is transformative because it affords the ability to seek the unexpected. The resulting uncertainty can be unsettling. But it is to be embraced rather than feared because approaching the edge of the known and seeking the unknown is where progress hides. Even so, the pursuit of the unexpected does not diminish the web of existing laws and regulations within which innovators must operate. Cooperation among public and private interests to interpret how those requirements may apply to the use of AI to originate, underwrite, and ameliorate credit risk can help accelerate the realization of that promise. The time for these conversations is now. They should be embraced as a positive signal of the potential good that can come from AI. To the extent that it can be pursued and directed in a more transparent fashion, the ability to explore the unknown and seek the unexpected is a critical source of competitive advantage and national strength.

The development of responsible AI – in credit risk and generally – increasingly reflects broad multidisciplinary input. The findings and insights in this text benefit from contributions and support from a wide cross-section of organizations and industries. Yet much work remains to be done, both for the specific question of responsible AI in credit risk modeling and broader questions of deploying AI responsibly in financial services. It is an undertaking that will call for the intellect, domain expertise, and engagement of a broad coalition. However much we collectively try to establish best practices and standards, they are likely to change as understanding of the connected ramifications of and potential in AI evolves. That is the nature of dynamic interaction with the unknown, and it is an essential process to grasp as society continues to examine its approach to AI.

2.9.1. Summary of Key Insights and Future Outlook

Recent advances in machine learning have generated significant interest and tentative excitement about the transformative potential of AI, especially for the financial services industry. This chapter has provided an overview of the unusually rapid progress in AI and machine learning, highlighting both the current state of scientific knowledge and the role of big data and high-performance computing in enabling this evolution. The chapter has also provided an in-depth review of the application of AI to supervised learning problems that mitigate financial transaction costs and other market inefficiencies, and to unsupervised learning problems that provide new insights to analysts. Although the exploitation of these techniques is still in relative infancy compared to consumer applications, there is a wide range of emerging AI-led applications within asset management, equity markets, custom financial index creation, sales and promotions, cash management, credit management, and trading algorithms that minimize instrumental market impact, back office digitization, and regulatory compliance. AI and machine learning provide the financial industry with a powerful new set of tools. They may enhance profits and create new sources of comparative advantage, especially for early adopters. They may drive growth, job creation, and welfare improvements. However, on their own, the technology will not change the distribution of power, income, or financial benefits. On the contrary, abstracting from institutional considerations such as data ownership, privacy, liability, or regulatory aspects, wealth concentration is likely to increase, as new applications will enjoy significant, unique advantages. This risk must be accounted for, a responsibility that AI companies, financial institutions, as well as public actors and regulators cannot and should not fail to meet.

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