Deep Science Publishing
https://doi.org/10.70593/978-93-49910-40-9_11

Chapter 11: Case studies in smart finance: Real-world applications of artificial intelligence across industries and enterprises

11.1. Introduction

AI dramatically transforms finance through effective modelling of diverse financial data, scenarios and systems. With increasing complexity in business and finance, data sources and applications, financial modelling has broadened in scope from single-market modelling to multi-market modelling, from classical dependence modelling to deep modelling, and from local modelling to distributed modelling to combat challenges imposed by big finance and big data. A clear separation of macro/micro modelling in some recent literature is misleading. The relationship among different types of modelling is a grand challenge for both AI and finance.

Big finance follows big data in touching new frontiers of opportunities not well utilized. Various types of financial modelling help to capitalize on big opportunities in finance, economy and society via innovative practices across disciplines. Irrespective of data locality, a better understanding of AI-based modelling of deep/deep distributed finance on captured data offers clear insights into financial, economic and social phenomena. With explicit semantics, advanced analytics can help quantify and capture embedded properties. The power of robust AI-enhanced modelling also lies in social implications. Causal inferences can be made from deeper traces of finance, economy and society. Continuous surprises across finance, economy and society can be expected with style, exceptions, and proximity. AI-enhanced modelling of finance/economics/society can help economists govern the economy. Differences in asset pricing and market behaviours can be captured across markets, businesses, channels, sectors, or nations. By jointly modelling different data types of a financial entity, hidden pattern differences and multicentric behaviours can be captured (Chang et al., 2017; Bandi et al., 2023; Deloitte et al., 2024).

Thinking of commonly used exploratory data analysis should be re-evaluated given the emergence of big finance, big data, and new opportunities. AI methods have not benefited from the big data revolution in finance. Emerging opportunities provided by new management, behaviour, data can be explored, and corresponding advanced techniques can be developed. Conducting modelling research also requires consideration of business opportunities. Historical challenges may appear as new opportunities. Domain knowledge and data-driven analytics should be enhanced to capture business opportunities. Integrating advanced new and classical AI techniques can generate new horizons .

Fig 11.1: Artificial intelligence (AI) use cases in banking and financial sector

11.1.1. Background and significance

The swift expansion of artificial intelligence (AI) and machine learning (ML) technologies across various industries has prompted an increased interest in the application of these techniques within the financial sector. Industry estimates suggest an expanding role for AI and ML in such domains as risk management, asset allocation, automated trading, and market analysis. By 2025, the AI services market for companies with revenues greater than $100 million is expected to rise to $45 billion, up from $13.5 billion in 2020. The investment banking sector was projected to grow by 30% over the same period. With finance increasingly digitized and new opportunities arising from the continuous expansion of digital data in finance, the possible implications of AI and ML are vast. This thesis deals with empirical applications of AI and ML in finance with a focus on hedge funds and an investigation of AI-assisted stock-picking strategies. A rational asset-pricing model reveals a portfolio of misestimated securities. High-quality financial news is likely to enhance information efficiency and market stability in a complex financial environment. Anticipating the growing volume of new knowledge in financial data that is rapid and likely to be free from statistical arbitrage, ML-based methods are proposed to capture high-dimensional and irregular time series patterns. The results reveal a dramatic increase in the number of hedge funds, while their subsequent performance is mixed and unfamiliar to markets. AI and ML have produced a diverse range of implications for the fintech revolution with opportunities and challenges for financial institutions. The current digital finance ecosystem is data-driven, and the rise of alternative data has spurred interest in fintech innovation. Alternative data in general can be any nontraditional datasets. In finance, a large amount of alternative data has started to be used to inform investor decisions, including open web data, social media data, mobile location data, news data, environmental data, and web traffic data. Currently, investment managers scout data from trading venues, other market participants, and the Internet in an effort to add informational value to their investment procedures. But with the flood of new data from diverse sources, myriad possibilities arise. This uncertain situation is neither purely an opportunity nor purely a risk: it is a double-edged sword with potential implications for the future landscape of active asset management, which has not been widely examined.

11.2. Overview of Smart Finance

The increasing popularity of the Internet of Things (IoT), blockchain, artificial intelligence, and big data analytics brings digital transformation to every industry and enterprise every day. AI and big data provide a delightful opportunity for enhancing smart devices and the management of data analytics as well as the understanding of the properties and intricacies of data and machine learning. Intelligent transportation systems (ITS), smart marketing and finance, and intelligent cities are some of the many applications of smart devices, data, and machine learning across multiple domains. Finance has always been a smart and interesting sector to study, analyze, and understand. Finance–economics (EcoFin) problems are complex. A combination of EcoFin theories and tools, and AI and big data techniques enables a better understanding of their working mechanisms and properties as well as their modeling, learning, and management using appropriate mathematical and statistical tools.

The development and prosperity of the Internet, information, and communication technology bring knowledge and data for every enterprise and every individual every minute and every second. AI and big data offer further opportunities to understand the insights and wisdom from data. Digital consumer–customer–market systems have formed across multiple industries and sectors. Understanding the properties and intricacies of data and their anomalies has received significant attention in network, marketing, and finance research. AI, machine learning, and statistics are often employed for modeling, analyzing, and optimizing socially complex network and EcoFin problems, systems, behaviors, and events. However, EcoFin theories, cognitive and intelligent methods, and tools are still outdated. AI–machine learning models are still black boxes, and knowledge is needed for a better understanding of EcoFin systems and their intelligent models.By including the case with such different fields and setups, it is trained that the findings of the case studies regard practical implications of the development of AI that operate in completely different environments, making it broader applicable. In order to counter being biased by the already technical AI implementation, a financially competitively employee specialist is interviewed regarding their experiences on the AI implementation process.

11.2.1. Research design

The focus of this paper is to study two different case studies about the implementation of AI in business practice. The first case study describes a project in which AI techniques were used to analyze transaction data in order to measure the equality of the processing of transactions and thus a control to monitor irregularities in transactions. The second case study describes a project in which AI was implemented in order to automate the trading process in financial instruments in an unstructured market environment.

The practical cases include implementations that vary greatly in focus and field of application. The first project will be referred to as Case Study number 1, while the second will be referred to as Case Study number 2. By including different business fields, it is trained to gain a broader understanding of the implementation process of AI in practice. With AI research being a hot topic, the expected existing computer science knowledge on the technical functioning of the described AI technologies will also result in non-technical answers. Hereby an effort is made to include applications that emphasize different computer science capacities of AI, respectively focus on its predictive capabilities and focus on its classification capabilities. This greatly extends the applicability of the findings of the research protocols.

11.3. Artificial Intelligence in Finance

Artificial intelligence (AI) is trusted to be a kind of smart and new finance enabling technology to transform and improve traditional finance, financial research, and applications. It is fundamentally challenged by the unique characteristics and principles of finance. Relevant advanced algorithms, modelling and approaches face security, safety, fairness, explainability, reliability, effectiveness and risk considerations, which

Fig 11.2: AI in Finance Industry Use Cases

also challenge the existing knowledge, theories and tools in finance. The generic AI/ML/DM/SDA theories and approaches are also typically bespoke and designed for the applications and data domains. Finance is essentially different from other scientific, engineering or business domains, and its problems, data and processes are generally complex and fine-grained, challenging existing data-oriented AI methodologies. The AI models and processes in finance are typically multi-dimensioned, cross-source, mixed and evolving data streams and series, and are usually complex and discipline-informed and causation-based, challenging generic and off-the-shelf techniques. There are also generic challenges, such as the nature of models and processes, uncertainties, fuzziness, complexity and consideration concerns of timing, expert opinions, delays and other factors.

11.3.1. Definition and Scope

Intelligent Financial Technologies (FinTech) is a multi-disciplinary and cross-domain area that integrates theories, technologies and tools from finance and economics and Artificial Intelligence (AI) and data science. It aims to deeply understand, characterize, formulate, model, analyze, optimize, control and manage complex socio-economic systems and their events and problems based on cross-disciplinary synthesis of EcoFin and AI knowledge, theories, techniques and tools. It also aims to develop AI, machine learning (ML) and deep learning (DL) theories and tools with EcoFin aspects and applications to address, optimize and manage complex socio-economic problems. The theories, technologies and cross-disciplinary tools developed can help to protect and better serve the well-being and sustainability of economic behavior, finance, data-driven modelling and decision making. The systematic, comprehensive and aforementioned understanding, modelling, analysis, optimization and forecasting theories and tools require the synthesis of certain EcoFin knowledge, theories, solutions and tools into AI theories and tools. Classic mathematical modeling and statistical modelling, theories and tools at different levels of agent: firm, household, market, network, industry, stock market, volatility and economy; and working mechanism at micro, meso and macro levels will enrich the foundations of AI theories and tools. The theories and tools also include model-driven cross-validation of AI-based decisions and decisions impact estimation on EcoFin systems, processes and problems.

The theories can target the design of robust algorithmic EcoFin implementations and infrastructures with tolerance to endogenous factors. Agents or entities with intentions need to purposefully emit information or decisions and media. When events or problems such as news items, regulations or forecasts occur, the systems and technologies to acquire their respective siloed information need to be identified. Such information acquisition usually relies on a feedforward mechanism from agents or entities. The success that led the 2008 global financial crisis was thought to be due to widely undisclosed information about mortgaged-backed ETFs. Presumably, human agents exchanged and traded behaviours or actions rather than information. Artificial agents that detect or discover information might generate a cascading failure.

11.3.2. Historical Context

The integration of AI in finance has a history that dates back to the latter half of the 20th century. Initially, financial institutions deployed rule-based systems for various functions, such as automated trading and risk analysis. However, these systems suffered from several shortcomings. They were often unable to handle complex scenarios or vague inputs, resulting in unreliable outputs, especially in times of market turmoil. As a result, financial institutions turned to statistical techniques that rely on well-defined rules and theorems, resulting in the adoption of statistical analysis packages and programming languages.

With the rapid development of neural networks in the 1990s, the potential of non-linear techniques began to be explored. This prompted a new wave of statistics and AI-based applications across financial institutions. However, neural networks and their offspring have a fundamental flaw. Their black-box nature, although allowing flexibility in model formulation and appealing in terms of computational efficiency, drastically reduces insight levels discarded in data pre-processing steps. This is especially problematic given the upcoming European Union Guidelines on the Use of Artificial Intelligence in Financial Services, which call for enhanced clarity in AI and ML model outputs, driving financial institutions to reassess their strategy around AI and latent technologies.

AI has become quite popular in recent years, especially due to Machine Learning. ML algorithms are an alternative to traditional econometric techniques often referred to as statistical methods in finance. They are based on statistical learning theory, which assumes that the underlying relationships between financial variables can be learned by observing historical time series data. The application of AI in financial settings dates back before popular ML algorithms, with the first implementations actually utilized as rule-based systems after the invention of computers. Initially, they were used for executing trades or assessing risk to some extent; however, their inability to robustly derive outputs in many scenarios soon led to the adoption of statistical techniques.

11.4. Sectoral Applications of AI in Finance

The finance industry is a vast sector, bound by the same economic principles, and connected via regulatory frameworks and cross-organizational issues. Finance is itself complex and requires data from multiple sources. Events such as bankruptcies, mergers, insider trading, scandals, and natural and economic disasters generate a large quantity of digital and textual data, all of whom are likely to help a deep understanding of the collective finance ecosystem and its micro and macro behaviors, and supported to intelligently discover hidden knowledge that can be used for insight, alert, and strategic and tactical actions.

The investment banking sector has to do with quantitative models backed by empirical data and devising analysis and other decision support tools to help the analysts select stocks from a list covered by investment research houses, develop earnings forecasts with historic data, and predict earnings surprises based on market and news feeds. It includes Quantitative Research, a combination of several scientific disciplines and techniques covering public equities, quantitative research, natural language processing, databases, programming, statistical modeling, and securities. The commercial bank sector in the finance industry has public, private, and commercial banks. Actions include credit approval, consumer relationship management, cross-selling, marketing, and so on.

There are company mergers, IPO issuances, funds raising, analyst ratings, rating downgrades and upgrades, syndication deals, buy-outs, stock splits, and so on in all investment banks. In commercial banks, there are credit requests and approvals, loan collections, credit card approvals, deposit marketing, cross-selling, and so on. In the stock market, behaviors include dividend issues, stock buy-backs, right issues, block trades, share repurchases, and many other public activities. House deals require data from public records, news, and social networks, covering events and people. There are partners, associates, experts, clients, and peer firms within the firm.

AI is booming in financial services. Companies are investing significantly (and in some cases, extravagantly). Bigger institutions project AI paths into the future. Smaller firms seek partners for financial surveillance, product generation, marketing, or client contact. Interest has surged in hiring analytics firms or fintech start-ups that claim to offer an AI advantage. Central banks, regulators, and auditors are paying attention. In front offices, Harmony Mutual deploy AI and big data to monitor markets. The acquisition and update of Quant House exemplifies the move to data provision by a market information provider and conduits dealing and more traditional methodology at the core of finance.

11.4.1. Banking

The deployment of AI in banking, insurance, asset management, and real-estate is becoming more prevalent. Self-service agents, robo-advisory, and autonomous vehicles (AV)— all use artificial intelligence (AI). The banking sector is on a cusp of massive technology-driven change and AI is at the forefront of transformation. Examples of the application of AI in banking revolve around product generation, marketing, risk assessment, fraud detection, and on-boarding (particularly of wealth management clients). The case studies in this Sector describe restructuring through attention to data quality and capture, deployment of ML, change management, redeployment of staff, and taming management expectations.

Robots, Chatbots, and AI systems are now able to process natural language documents across various modes (for example credit, risk, and mortgage valuation) and streamline these functions. Research has demonstrated that these functions, often, but not always, internally focused processes, can be done quicker, more reliable and in a less biased manner than by people. Current AI methods are able to not just process "what did" questions given data, but also to apply models or expert systems to the output. This enables a more powerful form of "what if" questions to be posed to AI as it can model consequence. Data processing, document workflow, Gini models, credit modeling and other similar functions could and should be done using AI forthwith.

11.4.2. Insurance

Insurers want to estimate the risk they take by accepting a consumer and the expected claims costs. The higher the risk of the consumer, the higher the expected costs for the insurer, and the higher the premium that should be charged. If consumer H is applying for insurance, the insurer gathers information about the consumer that is expected to relate to the cost of claims. For example, if the insurer is a car insurer, it may gather data about the consumer's age, sex, address, driving experience, and car type. For previous data as well about the number of traffic claims, the consumer has filed, the type of consumer car, day-time speeding, and the consumer make use of hands-free equipment.

The insurer determines the premium that it should charge for H. For low-risk consumers, the insurer decides that the consumer has a low expected claims cost. The insurer charges such consumers a low premium. For consumers that are expected to have a high claims cost, a bet that is more than 1 is made and high premiums apply. For medium-risk consumers, the insurer decides that the consumer has a medium expected claims cost. The insurer charges such consumers a medium premium.

An AI system can be described as ‘a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that influence physical or virtual environments. Traditionally, insurers mostly determined the risk associated with the premium manually. Aiming to predict insurance claims, the insurer defines a model. Due to the model, the insurer can estimate the risk of a consumer by gathering information about that consumer and feeding it into the model. If the output of the model is lower than a threshold, the insurer decides that the consumer may be acceptable, and if feed extra premium sets. Since a few years, insurers increasingly use AI. AI systems can perform tasks that normally require human intelligence. For example, word processing, facial recognition, stock trading, and all kinds of decision systems. AI techniques that insurers apply at the moment are fuzzy logic, evolutionary algorithms, multi-agent systems, and Bayesian networks.

11.5. Case Study: AI in Banking

Currently, in banking, there are several applications of artificial intelligence (AI). Regarding customer support, banks have already invested in chatbots to provide customer support services. Chatbots can help customers in critical situations, such as when they lose their cards, and banks have put effort into training chatbots in the last few years. Over time, chatbots become smarter because they learn from past interactions the things that customers are looking for and how they are asking for them. Such a service can help avoid some serious problems for customers and make them feel safer. Chatbots can also help avoid mistakes by having information in one place, enabling customers to easily access functionalities. This means that customers will achieve what they want more easily, making both customers and banks happier. Additionally, banks could offer specific products tailored to the client by analyzing how they managed to interact with the service.

Additionally, regarding the analysis of loan applications, applying for a loan is among the first banks' services where AI will substitute humans, as AI is better at analyzing enormous amounts of data comparably quickly than the human mind. A recent development in discussible automated decision-making is that AI eliminates cognitive bias on behalf of the expert, as it will treat all laws equally. The pathology of AI makes sense, but since AI will still need to be programmed, it is likely bias will still occur as the programmers forget one of the laws or are simply not aware of it. AI will also be helpful in assessing credit histories, detecting fraudulent transactions, and ensuring compliance with regulations.

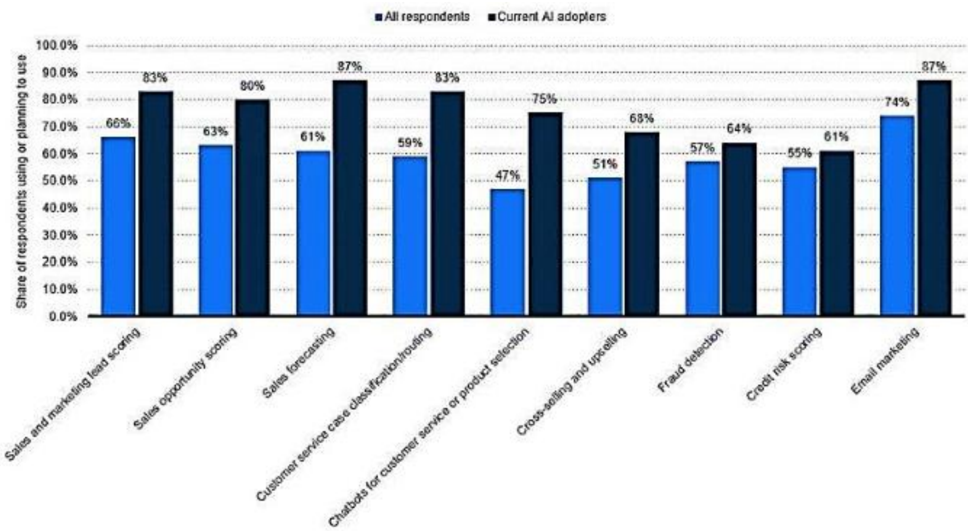

Fig : AI Use Case Adoption Worldwide

11.5.1. Fraud Detection Systems

Perpetrators of fraudulent behavior are motivated by the fraud triangle, or opportunity, incentive or pressure, and rationalization. A genuine incentive or pressure motivates an individual to commit fraud, such as financial difficulties, peer pressure, or a need to preserve a reputation. Opportunities for fraud arise through loopholes, vulnerabilities, or lack of oversight of internal controls. A fraud perpetrator must reconcile, rationalize, or justify the crime to be at ease with their conscience. Understanding the nature and underpinnings of fraudulent behavior has been a subject of significant scholarly attention for ages.

Machine learning is a field of computer science and artificial intelligence that enables systems to learn from training data and make intelligent predictions. Generally, machine learning systems comprise four key components: a data source, a learning algorithm (the model), a trainer, and a testing mechanism. A data source is information on which predictions are based, such as historical sets of transactions. A learning algorithm is a set of steps for computer algorithms to learn from data, such as artificial neural networks or decision trees. A trainer includes a committee of experts specialized in a given area to tune and enhance the model. The testing mechanism evaluates the predictive capacity of the resulting model on a sufficiently different dataset.

Fraud is a disturbing menace, made worse by the advancement of new technology. Traditional frauds, such as credit card and travel reimbursement frauds, persist, but there are also new types of fraud, such as mobile telecommunications scams, benefit frauds, computer breaches, and insider trading. The Monetary Policy Committee of the Bank of England sanctioned a fraudulent Bond Portfolio Model. The technological advancement driving the global economy is simultaneously enabling new avenues for fraud.

11.5.2. Customer Service Automation

As AI technology matures, it is increasingly finding applications outside of Hollywood's imagination. Generative AI has arrived at a time when the forces of a potential economic downturn have begun to intensify, which could reconsider the priorities of every industry and firm. The focus will likely shift away from extraordinary measures such as hiring freezes, layoffs, and divestitures toward better leveraging existing resources. This analysis takes a look at the various ways organizations can utilize generative AI. With rapid advancements, organizations are scrambling to identify potential use cases and how to apply this technology immediately. Generative AI makes it easier to unlock the latent capacity of knowledge workers through the prior time-consuming, cognitively expensive tasks that it can now automate, such as writing, brainstorming, and programming.

Generative AI takes naturally occurring data, such as text and images, and, using machine learning, mimics what it has observed to create new data. The capabilities go well beyond chatbots and text generation, however. In particular, two technologies have gained traction: large language models trained on vast amounts of text data and diffusion models trained on images with associated text prompts. Generative AI models can be fine-tuned to specific industries and tasks. Businesses would be well advised to examine how these technologies could be applied to leverage their human expertise and captivate and engage their customers. Generative AI can also cut costs: fewer customer service agents are necessary to handle the same volume. On the flip side, there could be reputational costs if the generative text is poor quality or incorrect.

One company has adopted this pilot study to test a generative AI chatbot to provide answers to customer questions about technical issues. Rather than seeking to adopt new technology quickly across the business, firms would be best advised to keep an eye on key questions that the profits workings could tackle. One possible initial approach would be to collaborate closely with attendance firms to develop partnered pilots and tests that address important broader peer- and firm-wide questions. If the pilots offer promising results, co-development efforts could then be used to devise approaches.

11.6. Conclusion

It is evident that AI is well established in some sectors and much sought after in many others. A timeline of AI-related developments between 1956 and today includes the first conference on AI, the introduction of the first computer vision algorithm to identify pigeons on a university campus, and the first fuzzy expert system for analysis of complex data adopted by a supermarket, etc. There is skepticism concerning the effectiveness of AI applications in an investment decision-making process. Research findings have been criticized and shown not to hold in practice. The skepticism can be attributed to two factors. Firstly, an AI company with a novel and effective approach to finding investment opportunities generally does not share key details and hence cannot be scrutinized by market participants. Secondly, well-established hedge funds that want to enter this sphere spend a considerable amount for consulting and training offered by leading research institutions and invest hundreds of millions in talent and supercomputer hardware. Thus, there are no established benchmarks on which new technologies/results could be compared to believe them.

The investment management community is characterized by its current state and competition to attract talent. Many companies, startups, and investment funds want AI to be successfully incorporated in the investment decision-making process. It has been over-stylized as alpha hunting, quant hunting, etc. Digital footprints on news channels concerning some catastrophes related to AI-driven decision-making are numerous. There are public companies engaged in research and development in this field. Similar companies did not exist a decade ago, but even five years ago, AI-driven funds were exotic. The biggest players hold a dominant position and their advantage grows as they reinvest colossal profits in research and new technologies.

11.6.1. Future Trends

The future trends of AI in finance are as varied as the domains of AI. A number of advancements that can be anticipated and speculated on based on current trends are described in the following. AI-augmented finance services are poised to grow exponentially. The exponential growth in crowd-sourcing data, social media, and IoT data streams will spool up the issues discussed in 8.1 as multi-party data insurance, privacy protection, and distributed AI. A nation-state policy that demands financial action will prompt modelling capacity considerations on a global scale, as in 8.2. The explosion of 5G or better mobile access will see financial services on mobile phones for the current offline population. This will be accompanied by massive modelling capability growth in places not considered today as centres of big finance, such as central Africa. Massive modelling capabilities will prompt political and ethical considerations, as in 9.2. Financial service chains will be instantly adaptable, as in 6.1. Building on multi-grained behind-the-market simulation models, a 3D centrifuge for black-market big-finance action will be a decade-long game-playing consideration. On a softer side, it would be an integrated city-wide urban sense-making which "hacks" the human terminations of finance and economy and the co-evolution of economics-nature-society-finance complex systems on planetary scales and long time spans, as in 9.3. These are epic progressions for hubristic modelling, although the literature of social-hubristic modelling is still thin. The rise of AI ways of running AI systems will prompt finance ways of doing similar. In this case, a nation-state actor could build a GP AI finance within a month. This go-along could be seen as a leap into the cyber-sphere level of finance breakdown at the discretion of multi-layered go-at AI macro-agent devices. Along these penetrating avenues of modelling complexity, AI and finance would breed swathes of long-tailed applications with societal risks and philosophical dealings. Ethics, regulation, and operational safety are perplexities of AI in finance. More seriously, finance's understanding of the AI complications inherent in its realm still lags the pace of technology applications. In keeping with the new means of modelling complexity, a new science of knowledge in AI-finance should be ushered in. The latter implies an interconnected semantics of cross-realm, -scale, -time models of AI and finance, the understanding of which can bridge the gap for a more normal civic AI and finance.

References

Brynjolfsson, E., & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. W. W. Norton & Company.

Cockfield, A. J., & Pridmore, J. (2020). Artificial intelligence and tax law: Predictive analytics as a challenge to the rule of law. World Tax Journal, 12(1), 1–30.

Accenture. (2022). Finance reimagined: The future of finance with AI. Retrieved from https://www.accenture.com

Deloitte. (2021). AI in tax: A new era for compliance and strategy. Retrieved from https://www2.deloitte.com

KPMG. (2020). The future of finance: AI, automation and the rise of cognitive accounting. Retrieved from https://home.kpmg