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Artificial Intelligence Impact Evaluation: Transforming Paradigms in Financial Institutions

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Abstract

Artificial Intelligence (AI) is a term shaped by socio-behavioural rationales of human capabilities. AI is broadly characterized by a suite of technologies and capabilities, which are largely autonomous and predictive. Expectations of AI are derived and often benchmarked against human intelligence. The corollary is understanding that AI may be approached by attempting to understand human intelligence itself. The pace of AI application in industry is clearly accelerating as companies begin to leverage AI to increase profitability and achieve scale. This review is centred around how AI is currently being applied in Financial Institutions providing services by covering key implementation aspects, underpinning new products and services, playing a strategic role in digital transformation. This also covers how financial service providers across the globe are meeting the challenges of AI adoption with its emerging risks and regulatory implications, as well as the impact of AI on the competitive landscape and employment levels. In the findings, it reveals how AI is expected to galvanize a paradigm shift within the Financial Services industry, driven by data and innovative algorithms to transform business model transformations. Financial Institutions are beginning to leverage AI to increase profitability and achieve scale, but their success will be highly dependent on the evolving investment into use cases, adoption pattern, and regulatory environment.

Keywords

machine learning, robotics process automation, artificial intelligence, financial services, technology innovations, FinTech

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Оценка воздействия искусственного интеллекта: трансформация парадигм в финансовых учреждениях

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Аннотация

Искусственный интеллект (AI) – это термин, сформированный социально-поведенческими обоснованиями человеческих возможностей. AI в целом характеризуется набором технологий и возможностей, которые в значительной степени автономны и предсказуемы. Ожидания от AI часто сравниваются с человеческим интеллектом. Следствием этого является понимание того, что к AI можно приблизиться, пытаясь понять сам человеческий интеллект. Темпы применения AI в промышленности явно ускоряются, поскольку компании начинают использовать AI для повышения прибыльности и достижения масштаба. Этот обзор сосредоточен на том, как AI в настоящее время применяется в финансовых учреждениях, предоставляющих услуги, включая ключевые аспекты внедрения, поддержку новых продуктов и услуг, играя стратегическую роль в цифровой трансформации. Это также касается того, как поставщики финансовых услуг по всему миру решают проблемы внедрения AI с его новыми рисками и регуляторными последствиями, а также влияние AI на конкурентную среду и уровни занятости. В выводах показано, как ожидается, что AI вызовет смену парадигмы в отрасли финансовых услуг, управляемую данными и инновационными алгоритмами для преобразования бизнес-моделей. Финансовые учреждения начинают использовать AI для повышения прибыльности и достижения масштаба, но их успех будет в значительной степени зависеть от развивающихся инвестиций в варианты использования, модели внедрения и нормативно-правовой среды. В выводах показано, как ожидается, что AI вызовет смену парадигмы в отрасли финансовых услуг, управляемую данными и инновационными алгоритмами для преобразования бизнес-моделей. Финансовые учреждения начинают использовать AI для повышения прибыльности и достижения масштаба, но их успех будет в значительной степени зависеть от развивающихся инвестиций в варианты использования, модели внедрения и нормативно-правовой среды. В выводах показано, что AI, как ожидается, вызовет смену парадигмы в отрасли финансовых услуг, управляемую данными и инновационными алгоритмами для преобразования бизнес-моделей. Финансовые учреждения начинают использовать AI для повышения прибыльности и достижения масштаба, но их успех будет в значительной степени зависеть от развивающихся инвестиций в варианты использования, модели внедрения и нормативно-правовой среды.

Ключевые слова

машинное обучение, автоматизация робототехнических процессов, искусственный интеллект, финансовые услуги, технологические инновации, финтех

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1. Introduction

In modern world, fought with multidimensional and complex ecosystems, organizations need to enhance digital operations to achieve a disruptive and agile advantage more than ever. A blueprint to provide common understanding of the future goals to align strategic objectives and tactical demand is one of the key elements to achieve that. They need to take a customer led approach to support dynamic and rapidly evolving needs. A scalable and open technology, which is easy to use, always available, engaging experiences, products, and services to attract and retain customers, is the new pivot. Artificial intelligence (AI) comes to the forefront with the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The spectrum of AI harbours a plethora of technologies that solve real problems now – including computer vision, natural language processing, speech recognition, and machine learning. These technologies can be combined to create new capabilities for specific needs to achieve continuous improvement, phenomenal speed and more effective utilization of resources. AI is a vital part of an increasingly converging field of digital disciplines, which sees an unprecedented overlap of technical developments with various structured, unstructured, and predictive technologies to lift organizational synergies. The boundaries of AI have always been somewhat subjective. Having said that, 2 broad categories of AI are prevalent and are used to classify most of the developments. They are Weak and Strong AI. While Weak AI defines "Simulated" thinking without any kind of consciousness about what it's going, strong AI does "Actual" thinking with a conscious, subjective mind. Machine Learning (ML) at the core of AI, uses algorithms to learn from data sets & perform tasks without being explicitly programmed and hence forms the basis of most of the AI use cases. According to a definition which was originally coined [1] and refined by [2], machine learning describes the change of a system resulting from an interaction with its environment. Most spectacular recent discoveries in AI have been achieved in Machine Learning and Deep Learning, which have been hugely benefited from increased data availability and computing power.

Notwithstanding the type of AI, the objective of AI is to be able to adapt to an uncertain and changing complex environment, interact naturally with humans, deal with complex and heterogeneous data and combine several tasks in the most integrated way possible. Currently machine learning is leading the way for today's AI major business applications, which is enabled by actionable insights from data to drive business and user decisions, leading to build and operate increasingly autonomous systems. To bridge the multitudes of gap between "Weak" and "Strong" AI, an unprecedented number of investments has been made, but at the same time organizations are confronted with questions around Ethical and unbiased use of AI.

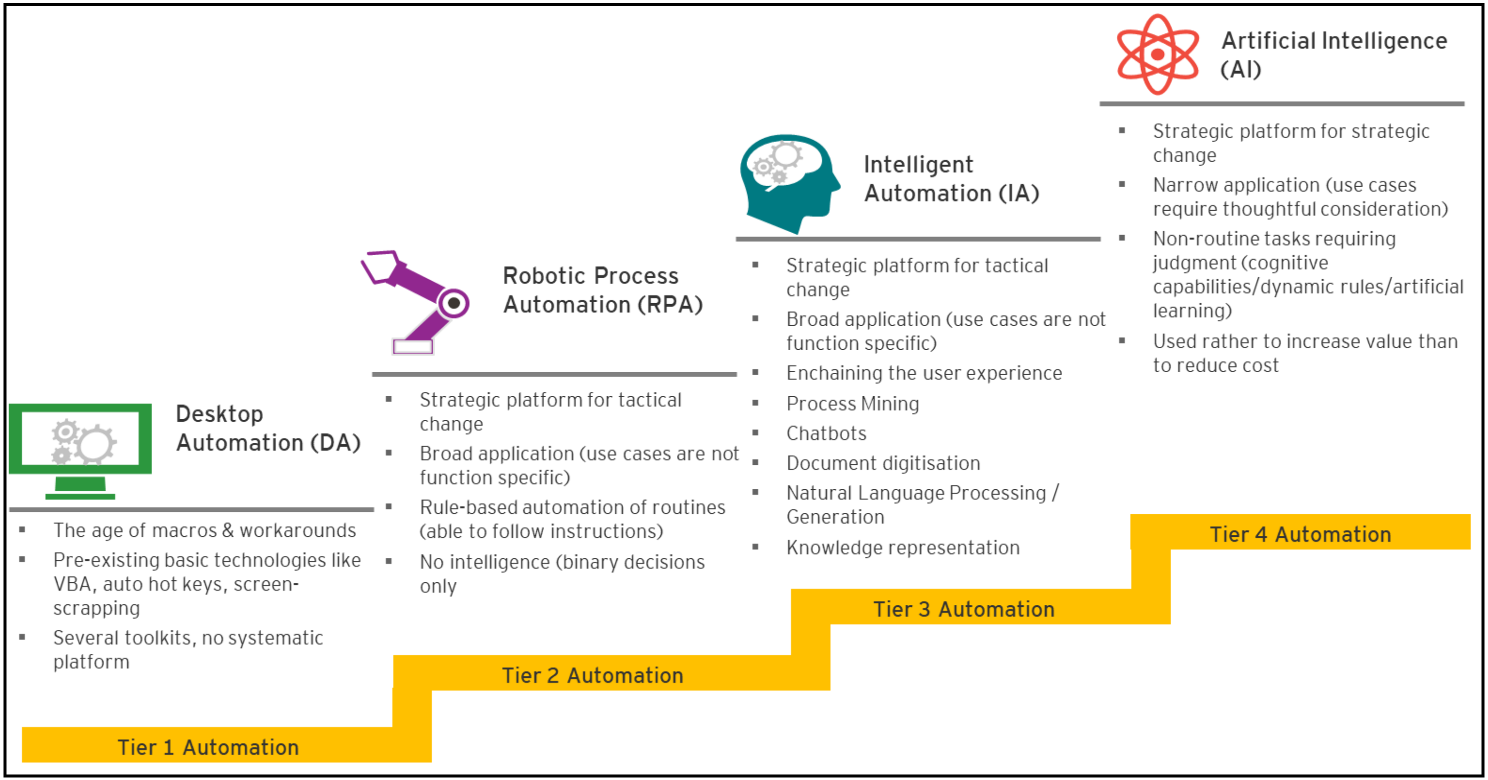
The aim for the review is to highlight the stakes of AI within the financial sector and their implications. However, beyond the news headlines and opinion pieces, there is still very limited empirical evidence available on the current state of AI adoption in finance and its implications. This review will provide some empirical data and shed light on the evolving landscape of AI-enabled Financial Services analyse and look the potential applications, and risks that might propagate with it. This will serve as an important reference for leaders in all sectors to better understand current areas of focus, attitudes toward AI and future considerations that need to be addressed, in order to deploy AI technology to transform their businesses, in both traditional Financial Services and Fintech.

2. Theoretical background

Through history we have seen three significant industrial revolutions so far. The first revolution started in 1784 when we saw the first steam engine. The second revolution was in 1870 when we saw the start of electricity. Third revolution was the IT revolution in 1969, and we are now witnessing the fourth revolution, AI [3]. The fourth revolution is about big data, intense automation, and a world where everything is connected based on AI technology. In 1950, five years before the term ‘Artificial Intelligence’ (AI) was coined by John McCarthy, Alan Turing already posed the question “Can machines think?” and devised the Turing Test described in his paper, “Computing Machinery and Intelligence”, to be used as a guideline to measure the machine`s capability to think as a human. 70 years on, the world’s computational capability has grown by leaps and bounds, and so has the application of AI across a wide array of industries, including Financial Services. This revival of AI was also attributed to heavy investments from Japan, the UK, and the US, which further propelled AI solutions to various industrial domains.

For last 2 decades, the US has been the main player within AI technology. Having 3033 start-ups or 37.41 % of all AI start-ups worldwide [4]. This accounts for a significant 71.78 % of the world’s total funding. They were also the first country investing heavily into AI. In the time period from 2012 to 2016, the US invested $18.2 billion towards this technology compared to $2.6 billion in China and $850 million in the UK. However, from 2017, the US has lost their leading position to China who has started investing heavily in this technology and surpassed the US in total funding [5]. In the Asian market China leads along with a proportion 68.67 % of Asian AI start-ups the last five years. There are two main reasons for the explosive growth in AI the last few years. First and foremost, the amount of data available has increased tremendously. Today we create 2.5 quintillion bytes of data every day, and 90 % of all data generated has been generated over the last two years alone. Secondly, the increase in computing power and data storage combined, have given us more possibilities in developing new AI solutions. Worldwide we have established 5154 AI start-ups over the last five years, 175 % growth relative to the previous twelve years [6]. Europe on the other hand has fallen a bit behind in the AI race, and based on data from McKinsey’s digital survey in 2017, the same gap between Europe and China / USA remains [7]. Despite having the similar size of GDP as of US and China, the spending on AI in Europe is significantly lesser than that of China and US. On the other hand, the AI intellectual capital that Europe has, has a formidable advantage over US and China. European Commission has also taken the AI situation seriously and are putting up a fund of public and private investments to invest €20 billion each year from over the next decade [8].

According to current market trends, AI model development and management is a priority focus area, however data management challenges persist, as data scope or quality is among the top three challenges to AI / ML adoption [10]. There are still very organizations with AI systems having complete access to all relevant data. Data sourcing, synthesis and ingestion have been touted as key capabilities to have in order



Leading firms are on a journey, moving from traditional process automation to intelligent automation.
Source: Artificial intelligence (AI) in Financial Service, EY Analysis, 2021

to reap full benefits of the AI systems in the long-run (see figure). Key market players believe that the cloud stack is very important in relation to ML and they plan to use public cloud to train AI models in the future. In juxtaposition to that, 5G, IoT and Edge computing are emerging as a hotbed for AI application.

3. Current state and issues of artificial intelligence usage in financial services

According to the OECD [9] "AI has pervasive, far-reaching and global implications that are transforming societies, economic sectors and the world of work, and are likely to increasingly do so in the future." With the potential of AI in mind, many public and private institutions have investigated the application of AI on Financial Services. The key aspects of AI applications relevant to Financial Institutions are Market Adoption, Application, Business model creation and transformation, Workforce transformation, and Regulation.

a. Market Adoption: The market adoption of AI allows for differentiated product and service offerings and there has been a significant uptick in adoption, where major industry players are seeing AI as a priority and have AI projects at business unit(s) level. However, Enterprise-wide AI strategy is still on a lower side. Financial institutions are seeking to differentiate themselves by using AI to build new products and data ecosystems [11].

Financial institutions are grappling with the dilemma of whether to go for enterprise-wide digital transformation or continue to adopt on a need basis to achieve growth. Though, the rise of new technologies is increasing user expectations and attracting competitors to the market [12], but while implementing AI, organisations face many practical challenges to its implementation including leadership, expertise and data quality and the top three reasons of such failures are AI technology not performing as expected, Lack of skilled staff and Unrealistic expectations. However, to mitigate this and effectively implement machine learning and AI at scale, organisations will likely need to make considerable investments in data capabilities to ensure the organisation has widespread access to high-quality and relevant data, both internally and externally [11]. Alongside investments in data, organisations have invested heavily in AI implementation itself. In a 2017 survey, 52 % of respondents in the Financial Services industry indicated they were making 'substantial investments' in AI. 66 % said they expected to be making 'substantial investments' in AI over the next three years, and 72 % of business decision-makers believed that AI would significantly advantage their business in the future [13]. To remain competitive, incumbent institutions are leveraging data and analytics to predict client needs and improve profitability. They may eventually implement AI to unlock insights and reallocate staff to higher-value work [12]. Therefore, deriving maximum impact from AI, and the wider embracing of digitalisation, will require organisations to have the necessary infrastructure and talent. Financial disruptors, FinTechs, who do not need to transform their core business offerings, may therefore be at an advantage in the race to the adoption of AI.

b. Application: Organisations are applying AI in a variety of ways to streamline back-office processes, to enhance the digital customer experience and to improve revenue models. Technology providers have launched multiple platforms and solutions, with a strong focus on growth through launching platforms / solutions organically and in partnership with customers / other tech firms. For example, with the goal of 'Watson Anywhere', IBM extended the reach of Watson platform so that it could be deployed on any private, public, hybrid, or multi-cloud environment. Among the suite of AI applications, research to date has found that the capabilities of AI are strongest when leveraged in tandem with other technologies and that many applications of AI use a combination of automation and enhancement of existing processes.

The World Economic Forum publication, The New Physics of Financial Services, affirmed that cloud computing provides the data storage and the processing power necessary to train new AI models, making cloud infrastructure critical in implementing AI solutions [11]. Similarly, the 2019 Refinitiv Machine Learning Survey found financial organisations increasingly rely on data and analytics to drive business decisions, gleaning insights through the application of Artificial Intelligence [14]. Moreover, in addition to cloud technology and big data, Application Programming Interfaces (APIs), open-source algorithms and the Internet of Things (IoT) are often applied in tandem with AI [15].

The application of AI is predicted to become increasingly sophisticated not only by automating simple tasks, but also through helping humans make decisions and learning from the interactions between humans and the technologies [12]. The marketplace is becoming busier with start-ups, funding in AI rapidly to grow, and at the same time acquisition spree is not slowing down.

c. Business Model Creation and Transformation: The use of AI in Financial Services has wide-ranging implications for competitive positioning and dominant business models within the industry. The most notable of these shifts is the tendency for AI algorithms to exhibit a 'flywheel' effect that rewards early movers with the potential to establish barriers to entry. This 'AI flywheel' is the tendency of AI models to exhibit self-reinforcing economies of scale wherein an accurate model attracts new users and additional data that increases the model's accuracy. This flywheel effect will redefine how organisations establish successful business models in the Financial Services sector, increasing the importance of granular data flows and the likelihood of 'winner-takes-all' dynamics [11]. Hence, with these competitive dynamics in mind, organisations are making bets on new capabilities and business models enabled by AI.

Many new AI-enabled business models place emphasis on creating a reimagined customer experience, allowing customers' finances to run themselves and acting as a trusted adviser in moments of need. As financial institutions continue to apply AI to customer advice and interactions, they lay the groundwork for 'self-driving finance' which will upend existing competitive dynamics, and ultimately push returns to the owner of the customer experience [11]. This needs to rapidly acquire new capabilities may have played a role in the increased interest of incumbent financial institutions in forming partnerships with FinTechs that they once viewed as potential competitors. When these partnerships work, both institutions stand to benefit. Incumbent Financial Services firms are able to leverage the technological expertise of FinTechs and the FinTech is able to rely on the pre-existing reputation and customer reach of the incumbent firms [16]. Therefore, this literature suggests that the impact on competitive dynamics will be a key determinant of the overall impact of AI. As such, this research seeks to further understand these dynamics.

d. Workforce Transformation: As AI evolves, financial service providers will race to be the quickest to adopt the technology, to acquire the most valuable AI talent, and to create the most value [17]. The innovations driven by this small cadre of workers has transformed the talent needs within financial institutions. With the streamlining of back-office processes, organisations may become leaner. According to [18], the jobs with the highest probability of becoming automated are those which do not require specific skills or training. In their study of OECD countries, researchers found higher levels of education translated into a lower risk of job automation [18].

The increased use of AI will largely impact routine and mundane roles where tasks performed are repetitive. However, because these roles account for a considerable number of jobs in the Financial Services industry, net job losses are likely. Having said that, other studies assert that AI will not be significantly impactful on the number of employees at financial organisations over the next couple of years instead of, even that the number of roles will increase among the most technologically advanced companies [19]. Hence, financial institutions are working rigorously to retrain their workforce to shift their expertise to more strategic and outcome-driven tasks.

e. Regulation: AI is also changing how organisations interact with regulators. As the sophistication of algorithms and the volume of data rises, the uses of AI in finance are expanding, and so are pertaining risks [20]. The Financial Stability Board (FSB) and the Bank of England, amongst other regulators and supervisors, have highlighted this concern, citing the potential additional and unknown challenges associated with new technologies [21]. With these additional and unknown challenges, there are also implications for user trust. As the industry continues to transform, regulation will be integral to managing the risks, appropriately regulating the use of AI and instilling trust in consumers.

While regulation may increase costs and delay product development, it also provides a pathway to user trust. In particular for new entrants, regulation provides reassurance for users and investors as they do not have an established brand name. The role of generalised trust in promoting FinTech adoption has been highlighted as significant in previous studies [22]. There is an ongoing debate regarding whether there are appropriate frameworks in place for the gathering, storing, sharing and usage of data. Moreover, policy is generally lagging the development and deployment of AI [23]. The current regulatory environment is also fragmented, with regulation which affects AI being initiated by state, national and global regulatory authorities, both financial and non-financial. Regulatory themes relevant to AI include everything from non-bank supervision to financial stability, operational resiliency and cybersecurity to consumer protection [23]. Both regulators and the industry are still searching for the optimal regulatory approach to AI [23], for instance the Monetary Authority of Singapore (MAS) has worked with a range of public and private sector organisations to develop principles for the use of AI and data analytics as they relate to decision-making in Financial Services. The principles aim to provide financial firms with a set of foundational principles to consider when using AI in decision-making, assist firms in contextualising and operationalising governance of AI use in business models and structures, and promoting public confidence and trust in the use of AI and data analytics [24]. Recent published EU Commission proposal for a Regulation on Artificial Intelligence (draft AI Regulation), took three years of intense policymaking on Artificial Intelligence (AI) on European level and represents a joint commitment of the EU Member States to foster the development and use of AI. Similar to the General Data Protection Regulation (GDPR), the draft AI Regulation comes with an extraterritorial effect, covering not only EU but also organizations outside of the EU. The draft AI Regulation takes a risk-based approach when it comes to categorization of AI systems, resulting in corresponding legal requirements. Since it complements the GDPR, using or deploying an AI system will need to comply with both regulations. Additionally, Swiss organizations under the scope of the revised Swiss Federal Act on Data Protection (revFADP) must confirm to the Swiss data privacy requirements as well. In addition to the GDPR and revFADP requirements, the draft AI Regulation further covers risk management, data and data governance practices, technical documentation, record-keeping, transparency and provision of information to users, human oversight, accuracy and robustness, and cybersecurity. From an accountability perspective, the AI system provider must be able to demonstrate compliance with these requirements.

The World Economic Forum's latest report on AI, Navigating Uncharted Waters, calls for further public-private cooperation. The report maintains that unlocking the potential of AI will require an understanding of its risks to the financial system. Financial institutions, regulators and policymakers should seek to deploy AI systems in the current financial ecosystem and harness the potential of a financial ecosystem built on responsible AI [25].

4. Methodology and limitations

Research involves characterizing and redefining problems, formulating hypothesis or recommended solutions; gathering, organizing and evaluating information; making rationalizations and reaching conclusions; and finally testing the conclusions to make a decision if they fit the presumption [26]. A qualitative research approach was taken due to the novelty and uncertainty linked with AI. The aim of this approach is to study about AI in finance in a broader and detailed way. The advantage of this method is that it is flexible and easy to adapt to changes in the research environment and variables. While quantitative data defines, the qualitative data is described. McNamara and Bono [27] suggest that the methodology is thoughtfully chosen to ensure that the results do not depend on the method used, but instead reflect the nature of the reality as precisely as possible.

As mentioned earlier that AI applications in the highly regulated financial domain are still in early stages, therefore, apart from reviewing academic literature, industry reports were used to a large extent to validate various hypothesis and provide required context. Hence, a systemic content analysis approach was used to analyze relevant literature publications, with focus on the subject area and its various nuances as it provides the chance to evaluate the data collected by professional groups, academic institutions, online publications and independent researchers which can almost never be obtained by any other research method, and these records are also very accessible. For example, reports by various international institutions and financial organizations are based on long-term studies that one researcher cannot perform. These kinds of documents have therefore been very helpful for this study and most are accessible through the official web pages of particular organizations. Like in any analytical methods in qualitative research, document analysis needs data to be checked and analyzed in order to interpret meaning, gain understanding, and develop knowledge [28]. This review focuses on the broad journal's database, as well as reports of major institutions such as MAS, KPMG, WEF, etc. for covering content. This review as a whole has certain limitations and its methodology in particular. AI is a broad, diverse, and complex area with myriad applications and underlying technologies. Thus, a comprehensive coverage of all of them wouldn't have been feasible. Instead, it has been focused on pulling together a practical approach to realistically explore the AI applications in financial institutions of today with an outlook to future. It has been aimed to cater to a broader audience in order to understand the fundamentals of AI in Financial Institutions rather than focusing on application of a particular AI technology in a use case.

5. Discussion: current state and future aspects of AI in financial institutions

5.1 Current State: Case Studies

AI Enabled Credit Analysis: Utilising AI to make credit decisions provides a range of obvious benefits for lenders – it makes for a faster, more accurate, and more automated decision-making solution. A large number of players in the Deposits and Lending sector use AI-enabled credit analytics. By harnessing existing datasets of loan applications, AI-enabled credit decision-making systems can be trained to predict default probabilities, determine risk-based interest rates or directly make lending decisions. Alternatively, AI may be used to calculate alternative credit scores which serve as an aid to conventional human decision-making. A 2019 paper conducted by researchers at UC Berkeley found significant racial discrimination in the American consumer lending market, with Latin / African-American borrowers being charged nearly 8 basis points more for mortgage products. Algorithms used by FinTechs were found to reduce pricing discrimination by approximately one third, with no discrimination occurring in binary lending decisions (accept / reject). The research also found that discrimination was declining throughout the examined timeframe (2009–2015) which may suggest a positive outlook through making the lending market more accessible for previously disadvantaged groups [29]. Conversely, the results of this study show that almost half of all participant organisations state that bias in credit analytics does currently exist and that AI will exacerbate that bias, with a further 15 % stating that AI will, in fact, introduce bias. While it might seem intuitive that replacing the human component in credit analytics could reduce bias, the use of AI for lending decisions does possess potential shortcomings, some of which relate to the wider risks of AI.

The first major issue – especially for organisations with little to no existing control over and/or awareness of bias in datasets – is bias propagation. Using existing, biased datasets to train new AI systems will carry this bias forward into subsequent decision-making. More specifically, there is a fundamental question around whether previous credit rejections should be factored into the training process of AI. The alternative, solely using data on actual defaults, leads to sparse datasets, relating to the technical issue around class imbalance, which may complicate training machine learning algorithms to detect defaults. Bias propagation may be further exacerbated through the 'black box' characteristic of many systems which underlie AI – the notion that certain learning processes and decision-making in most machine learning algorithms are difficult to explain, especially regarding contributions of individual inputs.

Besides the obvious issue of depriving lending decisions of insight into the influence of input factors, the lack of an explainable decision-making framework might also make it difficult to handle appeals and customer complaints. Users of non-traditional data (such as social media, browsing preferences, or psychometric testing) in AI-enabled credit analytics are more inclined to state that AI will exacerbate or create bias. Intuitively, one would expect more granular datasets which encompass more individualised behavioural patterns to reduce ethnic or other biases. However, the lack of structure and the multitude of information contained in these sources might lead to the loss of overview over the correlation between the data on hand and biased features, meaning that input features may effectively serve as proxies for biased factors if not monitored and controlled appropriately. Where the technical and/or organisational hurdles towards implementing these controls become too high, third-party solutions may become an alternative. Notably, there are organisations which actively address this issue in a B2B context, such as the FinTech ZestFinance, which is applying contemporary research on algorithmic explainability to construct credit models with associated indications of fairness for input signals [30].

AI Driven Investment Management: AI is widely adopted in the Investment Management sector, where it is becoming a fundamental driver for revenue generation. The value proposition of AI for asset managers, is dependent on the direct contribution of AI towards investment returns in the short, medium, and long term. The current market trends indicate that only a handful of players perceive AI to contribute 'highly' or 'very highly' to their investment returns, in the long-term outlook. Taking into account the different strategies which will be highly supported by AI for generating investments returns, a few observations can be made. Majority of investment managers are currently using AI in their investment process. Portfolio risk management is currently the most active area of AI implementation at an adoption rate of 61 %, followed by portfolio structuring (58 %) and asset price forecasting (55%). Often, these use cases are combined, leveraging the economies of scale of AI.

The current contribution of AI to investment returns, primarily focuses on AI-enabled impact assessment and sustainable investment. Approximately 27 % of firms using AI in that area perceive AI to possess a 'high' or 'very high' current impact on investment returns. This points towards a direct effect of the convergence between digitalisation and sustainability [31], allowing financial organisations to extract value by the combination of these two trends. Examples of companies applying AI-enabled impact assessment and sustainable investing strategies are Arabesque Asset Management, Clarity AI and Motif: On the other hand, it is notable that users of AI for asset price forecasting do not widely perceive AI to significantly increase actual investment returns, despite its relatively high implementation rate. In the long-term, other AI-enabled use cases than sustainable investing is expected to contribute more significantly towards increasing investment returns. Majority of AI adopters currently using asset volatility forecasting and asset price forecasting, respectively, anticipate AI to contribute 'highly' or 'very highly' to investment returns in the long term. This points to a future where organisations could attain technological maturity to forecast financial market time series accurately. This prediction is in part supported by research confirming that machine learning algorithms, such as neural networks, systematically outperform simpler (linear) models in certain financial forecasting tasks [32]. As indicated in previous sections, however, real-world adoption may still be thwarted by data-related issues and a lack of algorithmic explainability.

The State of AI-Enabling Technologies: The long-established, simple machine learning algorithms are currently more widely used than complex solutions. Consequently, many firms are not yet using highly sophisticated AI applications – even those that are already commoditised to a certain extent. This is due to the primary hurdles which prevent the construction of AI systems in the first place. Autonomous decision-making – one of the defining technological facets of AI – remains difficult to implement in organisations. Underlying technologies, such as reinforcement learning, do not seem to have reached a state of maturity comparable to other established algorithm classes used in natural language processing or computer vision. Furthermore, the implementation of autonomous decision-making in organisations is shown to be hindered by trust and adoption issues. AI Leaders use a larger portfolio of more demanding AI techniques which are, in turn, enabled by a range of more complex underlying algorithm classes. These findings complement earlier conclusions and demonstrate the commitment that AI Leaders have made to shaping their business through AI. FinTechs' training and deployment of AI systems are widely centred around cloud-based solutions, whereas many Incumbents still rely on legacy computational infrastructure. However, evidence from AI Leaders shows that firms with heavy organisation-wide computational workloads might also consider on-premises GPU solutions.

5.2 Future Aspects

For harnessing the potential of AI inevitably demands understanding the state of underlying technologies. Tying together high-level techniques in AI as well as enabling low-level machine learning algorithm classes and algorithms, various AI applications can be stacked in terms of technology adoption, usage, and deployment to determine their relevance to organisations and evaluate the potential impact on future trends surrounding AI.

Based on the type and applicability of Al would be further described into the following sub-sections as follow:

A. Autonomous AI – the Future of Financial Services

The fact that autonomous decision-making remains the least-implemented application field of AI with a very low overall implementation rate, and that even AI Leaders do not show significantly higher adoption rates, illustrates how far the Financial Services industry remains from harnessing AI systems which make independent decisions free from human input. There are three reasons namely Regulation, Trust, and Technological Limitations are specifically impeding companies from implementing autonomous AI:

Regulation – While the regulation of AI is an ongoing consideration for regulators, autonomous decision-making poses specific challenges which policymakers are just beginning to address. For instance, a 2019 bill proposed in the US state of Washington (State of Washington, 2019), intends to investigate different notions concerning the human influence on algorithmic decisions (including whether decisions are final, contestable or reversible), bias against groups or individuals, ability for explaining decisions, as well as data management, storage, and security. This area of regulation might also become a priority for organisations to navigate, with one respondent specifically expressing the need for a better understanding of the regulatory framework around autonomous decision-making. Similarly, as seen in recent European Commission data strategy consultation, authorities are exploring benefits of data-driven AI and ML (including public policy benefits), so the regulatory and legislative focus is likely to promote combination of increased AI adoption and efforts to mitigate the risks it may bring.

Trust – Trust issues may be caused by the lack of explainability inherent in many prevalent AI solutions. Thus, this aspect remains especially relevant for investment managers – where the ability to substantiate AI decisions may be prioritised over accuracy. Building trust requires transparency and communication, which is drawing a lot of attention from regulators and governments in many countries. Transparency and communication with customers have long been key to build trust but AI in financial services will require a paradigm shift in approaches and techniques, to achieve that. Effective explanations will also require a degree of subtlety; given the huge potential range of use cases, close attention to the context of each will be key. Organizations are exploiting potential for alignment of scope of 'data ethics' and AI guidance across different authorities, depending on sector, service, and wider context.

Technological limitations – Whereas technological advances such as deep reinforcement learning have attained impressive levels of algorithmic decision-making capabilities in closed environments, real-world applications (in open environments) are more challenging. Furthermore, meta-learning – applying learned rules and patterns to completely different environments – remains a major challenge [33]. Indeed, survey findings illustrate that trust and user adoption are perceived to be the most significant hurdle to AI implementation for those stating that use AI for fully autonomous decision- making, followed by access to talent, as well as access and quality of data Incumbents and FinTechs still overwhelmingly utilise AI as a tool which merely complements human decision-making, as very few FinTech companies see their AI solutions characterised as 'fully autonomous', while majority believe that the AI solutions that they employ do not make any business-relevant decisions. This raises an obvious question as to whether the increased autonomy of AI in FinTechs can be explained by more advanced technology or higher trust and willingness to adopt coming from the user side.

B. Implementation of Underlying Machine Learning Paradigms

Machine learning is a scientific domain at the core of AI, which uses algorithms to learn from data sets & perform tasks without being explicitly programmed. It forms the basis of most AI use cases. Machine learning directly benefits from increased data availability and computing power, therefore it has become instrumental in advancing most of the other AI fields. Current investments are largely focused in machine learning. Deep learning is a subset of machine learning where neural networks-algorithms inspired by the human brain-learn from large amounts of data. Similarly, to how we learn from experience, the deep learning algorithm would perform a task repeatedly, each time tweaking it a little to improve the outcome. Three types of deep learning namely supervised, unsupervised and reinforced.

- Supervised learning relies on a system that is fed/shown multiple iterations of labelled training samples to train itself. Throughout the training, the system learns to correctly classify inputs according to desired output labels defined by the user. Supervised learning is the most frequently implemented domain. Many mainstream applications of AI, especially in the areas of classification and forecasting, are based on supervised learning algorithms.
- Unsupervised learning algorithms discover the underlying (latent) structures in chaotic datasets which are not labelled. For example, it clusters random images according to the aggregate similarity of their pixels, that can be used for supervised classification after being labelled.
- Reinforcement learning is radically different from the two aforementioned paradigms in that it is based on an action-response model, where certain action policies maximise expected rewards in environments that are governed by a set of rules (or laws). In theory, a trained reinforcement learning algorithm is capable of making autonomous decisions in dynamic environments.

Through high-level machine learning libraries such as Keras' sophisticated deep learning algorithms may be constructed with very little technical knowledge. Furthermore, pre-trained machine learning algorithms represent a significant value proposition as they eliminate the need for curating massive datasets and/or building complex neural architectures from scratch. These high-level machine learning libraries directly integrate ready-to-use datasets as well as pre-trained algorithms, to implement deep learning solutions serving various industry and consumer use cases.

C. The Ease to Interface with Clients

With increased platform interoperability, it is easier to simplify interfaces by offering users the option to build programs using natural language instead of written code. Most Financial Institutions seeking to differentiate themselves through technological advances may explore different directions. Some of which might combine modular technologies to create powerful multi-purpose platforms and Services, creating tailored solutions for specific purposes, by potentially exploiting niche datasets. There are challenges revolving around algorithmic explainability, interpretation of results, and other issues in the field of machine-human interaction such as data collection and processing, feature engineering and visualisation,

D. The Use of Computational Resources

New age FinTechs utilise cloud computing more compared to local GPU- and CPU-based solutions, respectively, whereas Incumbents appear to be using a diverse mix of computational solutions. This might be attributable to the fact that Incumbents still use legacy infrastructure to train and run AI systems whereas the cloud offers the (financial) flexibility and agility needed for FinTech's use cases. Cloud offerings have increasingly grown more tailored towards AI use cases, with most products including the possibility of scaling GPU configurations. Cloud computing also offers considerably easy set-up and seamless integration with machine learning libraries and back-ends as well as maintenance, and easy upgrading to newer hardware, which is pivotal given the speed of advances in processing power. However, heavy, consistent users of GPUs may be better off utilising an on-premise computational solution. Aside from obvious benefits in data protection and security, on-premise computational facilities may also end up being less costly at full utilisation compared to mainstream cloud solutions [34].

6. Conclusion

The aim of this review has been to discuss impact of AI in financial services and understand the trends across the financial institutions proving services, look at developing AI capabilities with the help of a few case studies, and outline the future of AI technologies. A qualitative research approach was taken to gain great insights on how financial institutions can leverage AI to position themselves to better manage future risks, get required skill sets and operate efficiently to remain viable in the time to come.

It is clear that for many organizations, the potential of artificial intelligence (AI) is easier to envision than the reality, and for them the transformation has only begun. The transformative power of the AI applications remains on the horizon. AI success in financial institutions will depend on their operating models that can embrace AI and drive improved decision-making. The overriding need for a data-rich interface between buyers and suppliers for a set of services are crucial to the development of AI models. Concurrently companies must build trust with AI and embed the frameworks necessary to ensure AI solutions operate within acceptable limits and provide appropriate transparency into the outcomes to achieve widespread adoption. Company sizes, company maturity, existing organisation structures, and the market-specific use cases will reshape the structure and competitive dynamics of the Financial Institutions.

AI technologies are being used to create new products and service lines that are increasingly in demand as Financial Institutions are to create long-term value for their customer. But there is a learning curve, and they risk getting left behind if they do not understand what AI can do and have the people with the expertise to use it effectively. As a result, Financial Institutions will be incentivised to be on the distributing end of AI-enabled products and services rather than the receiving one. Frontrunners in the development of AI will be better positioned to increase the scale of internal data flows, maintain talent pool, instil trust and overcome regulatory issues, which allow them to improve the quality of their AI systems. For the lower tier players, AI as a service will be better suited at supporting certain commodifiable use cases across their organizational hierarchy.

There is still a significant amount of uncertainty around how AI will affect the competitive environments existing within Financial Services in near future. Incumbents, FinTechs, and ‘Big Tech’ all bring complementary capabilities to the table. On one hand, Agile FinTechs have the privilege of being nimble and adaptive in building new IT systems with a significantly lower cost base, but they lack existing customer scale, which is proving expensive and time-consuming to acquire in both B2C and B2B domains. On the other hand, Incumbents have the scale of customers, recognised brands and, for the most part, the trust of customers and regulators. However, most Incumbents are burdened by costly legacy systems with heavily siloed data structures, which makes AI projects implementations patchy around the core business of the organisation. Moreover, big financial institutions are subject to intense political / regulatory pressure in their core areas of operation driven by both industry watchdogs and governments. The evolving AI Regulatory framework, once adopted, will have significant impact on use of AI by organizations in different areas of activities. Financial services organization need to focus mainly on considering AI regulatory requirements in the early stage of deployment of their AI systems / tools, compliance of decision-making algorithms and reporting with the new AI rules, and applying a risk-based approach to implementation.

In a world shaped by constant change, AI is viewed by the financial institutions as a technology that has the potential to shift key focus from primarily providing internal transparency and transactional services to that of a business partner providing added value to its clients. Largely basing their decisions, forecasts and communication on better data-driven AI applications will be decisive toward achieving these objectives and compete in the evolving landscape.

Reference

1. **Mendel J. M., McLaren R. W.** 8 Reinforcement-Learning Control and Pattern Recognition Systems. *Mathematics in Science and Engineering*, 1970, vol. 66, pp. 287–318. DOI 10.1016/S0076-5392(08)60497-X
2. **Haykin S.** Neural networks: A Comprehensive Foundation. Prentice Hall PTR, Upper Saddle River, NJ, United States, 1998. ISBN:978-0-13-273350-2
3. **Skilton M., Hovsepian F.** The 4th industrial revolution: Responding to the impact of artificial intelligence on business. 2018. 315 p. DOI 10.1007/978-3-319-62479-2
4. **Buchanan G. B., Cao X. C.** Quo Vadis? A Comparison of the Fintech Revolution in China and the West. 2018. Working Paper, 02. URL: https://swift institute.org/wp-content/uploads/2018/10/SIWP-2017-002-_Fntech_China_West_ BuchCao_FINAL.pdf
5. CBINSIGHTS. The 2018 Global CVC Report. 2018. URL: https://www. cbinsights.com/research/report/corporate-venture-capital-trends-2018/
6. **Marr B.** How Much Data Do We Create Every Day? The Mind-Blowing Stats Everyone Should Read. Forbes. 2018. URL: https://www.forbes.com/sites/ bernardmarr/2018/05/21/how-much-data-do-we-create-every-day-the-mind-blowing-stats-everyone-should-read/#61c686d260
7. **Bughin J., Seong J., Manyika J., Hamalainen L., Windhagen E., Hazan E.** Tackling Europe's gap in digital and AI. McKinsey Global Institute. 2019. https://www.mckinsey.com/featured-insights/artificial-intelligence/tackling-europes%20gap-in-digital-and-ai
8. European Commission. Digital Single Market: Artificial Intelligence. 2019. URL: https://ec.europa.eu/digital-single-market/en/artificial-intelligenc
9. OECD. Recommendation of the Council on Artificial Intelligence. 2019. URL: https://legalinstruments.oecd.org/fr/instruments/OECD-LEGAL-0449
10. **Miller M.** The Present and Future of Artificial Intelligence, Gartner Report. 2019.

11. **McWaters R., Blake M., Galaski R., Chubb C., Uykur D., Blickling A., Muench T.** The New Physics of Financial Services. *World Economic Forum*, 2018, pp. 1–165. URL: http://www3.weforum.org/docs/WEF_New_Physics_of_Financial_Services.pdf
12. **Dhar N., Holly T., Ryan D., Galeaz G.** Top financial services issues of 2018. *PWC*, 2017, pp. 1–33. Top financial services issues of 2018: December 2017 (pwc.com)
13. **Curran C., Garrett D., Puthiyamadam T.** A decade of digital: Keeping pace with transformation. In: 2017 Global Digital IQ Survey: 10th anniversary edition. PWC, 2017, pp. 1–29. URL: https://www.pwc.com/sk/en/publikacie/assets/2017/pwc-digital-iq-report.pdf
14. **Rao A. S., Verweij G.** Sizing the Prize. In: Publications. PWC, 2016. URL: www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html.
15. **Duin S., Bakhshi N.** Artificial Intelligence. *Deloitte*, 2018, pp. 4–32. https://www2.deloitte.com/content/dam/Deloitte/nl/Documents/deloitte-analytics/deloitte-nl-data-analytics-artificial-intelligence-whitepaper-eng.pdf
16. FinTech Innovation Lab. In: Mind the Gap: Addressing Challenges to FinTech Adoption, Accenture, 2018, pp. 2–9. URL: https://www.accenture.com/_acn media/pdf-74/accenture-FinTech-challenges-adoption.pdf
17. MMC Ventures. The State of AI: Divergence. 2019. URL: https://www. stateofai2019.com/summary
18. **Nedelkoska L., Quintini G.** Automation, skills use and training. *OECD Social, Employment and Migration Working Papers*, 2018, no. 202, pp. 1–124. DOI 10.1787/2e2f4eea-en
19. **Chui M., Malhotra S.** AI adoption advances, but foundational barriers remain. 2018. Adoption of AI advances, but foundational barriers remain | McKinsey
20. **Proudman J.** Cyborg supervision – the application of advanced analytics in prudential supervision Workshop on research on bank supervision. Bank of England, 2018, pp. 1–9. URL: https://www.bankofengland.co.uk/-/media/boe/files/speech/2018/cyborg-supervision-speech-by-james-proudman.pdf
21. Artificial intelligence and machine learning in financial services. Market developments and financial stability implications. *Financial Stability Board*, 2017, pp. 1–40. URL: https://www.fsb.org/wp-content/uploads/P011117.pdf
22. **Sarkar S., Chauhan S., Khare A.** A meta-analysis of antecedents and consequences of trust in mobile commerce. *International Journal of Information Management*. 2020, vol. 50, pp. 286–301. DOI 10.1016/j.ijinfomgt.2019.08.008
23. KPMG. AI Compliance in Control. Financial Services Regulatory Challenges. 2018, pp. 1–15. URL: https://advisory.kpmg.us/content/dam/advisory/en/pdfs/2019/ai-compliance-in-control.pdf
24. Monetary Authority of Singapore.: Principles to Promote Fairness, Ethics, Accountability and Transparency in the Use of Artificial Intelligence and Data Analytics in Singapore's Financial Sector. 2019, pp. 3–14. URL: https://www.mas.gov.sg/~/media/MAS/News%20and%20Publications/Monographs%20and%20Information%20Papers/FEAT%20Principles%20Final.pdf

25. **McWaters R., Blake M., Galaski R., Majumdar I., Soni H.** Navigating Uncharted Waters: A Roadmap to Responsible Innovation with AI in Financial Services. *World Economic Forum*, 2019, pp. 1–133.
26. **Kothari C. R.** Research Methodology: Methods and Techniques. Second Revised Edition. New age publishers. New Delhi, 2004. ISBN (13): 978-81-224-2488-1
27. **Bono J. E., McNamara G.** From the editors: Publishing in AMJ – Part 2: Research design. *Academy of Management Journal*, 2011, vol. 54, iss. 4, pp. 657–660. DOI 10.5465/amj.2011.64869103
28. **Bowen A. G.** Document Analysis as a Qualitative Research Method. *Qualitative Research Journal*, 2009, vol. 9, iss. 2, pp. 27–40. DOI 10.3316/QRJ0902027
29. **Bartlett R., Morse A., Stanton R., Wallace N.** Consumer-lending discrimination in the FinTech era. National bureau of economic research. NBER Working Paper 25943, 2019, pp. 1–42. URL: http://www.nber.org/papers/w25943
30. **Fuscaldo D.** Zest-Finance Using AI To Bring Fairness to Mortgage Lending. 2019. URL: https://www.forbes.com/sites/donnafuscaldo/2019/03/19/ zestfinance-using-ai-to-bring-fairness-to-mortgage-lending/?sh=71d75f0c7f2d
31. **Kiron D., Unruh G.** The Convergence of Digitalization and Sustainability. In: MIT Sloan Management Review, 2018. URL: https://sloanreview.mit.edu/article/the-convergence-of-digitalization-and-sustainability/
32. **Ryll L., Seidens S.** Evaluating the Performance of Machine Learning Algorithms in Financial Market Forecasting: A Comprehensive Survey. 2019. URL: https://arxiv.org/pdf/1906.07786.pdf
33. **Schizas E., McKain G., Zhang B., Ganbold A., Kumar P., Hussain H., Garvery K., Huang E., Wang S., Yerolemous N.** The Global RegTech Industry Benchmark Report. Cambridge Centre for Alternative Finance, 2019, pp. 4–71. DOI 10.2139/ssrn.3560811
34. **Villa J.** Choosing your deep learning infrastructure: the cloud vs on-prem debate. 2018. URL: https://www.determined.ai/blog/cloud-v-onprem

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