TRENDY EKONOMIKY A MANAGEMENTU
TRENDS ECONOMICS AND MANAGEMENT
ISSN 1802-8527 (Print) / ISSN 2336-6508 (Online)

2024 42(1): 21–37
DOI: http://dx.doi.org/10.13164/trends.2024.42.21

Transforming Banking with Artificial Intelligence: Applications, Challenges, and Implications

Monika Mucsková

Abstract

Purpose of the article: The purpose of this article is to provide a comprehensive analysis of the role of artificial intelligence (AI) in the banking sector, focusing on its applications, challenges, and implications. By synthesizing existing research and empirical studies, the article aims to inform researchers about the transformative potential and inherent challenges of AI-driven innovation in banking.

Methodology/methods: Using a systematic review approach, the relevant literature on AI integration in banking was identified from electronic databases and leading corporate research departments, ensuring a synthesis of scholarly and industry perspectives.

Scientific aim: With limited academic research on AI in banking, this study aims to shed light on its applications, challenges, and implications.

Findings: The integration of AI in the banking sector has significantly transformed various operational areas, including customer interactions, risk management, compliance, and operational efficiency. AI applications, such as chatbots and smart virtual assistants, have enhanced customer service by offering personalized, 24/7 support, and have demonstrated significant cost and revenue benefits. AI-driven credit scoring and fraud detection have improved risk assessment and mitigation, enabling more precise and informed decision-making. However, AI adoption faces challenges such as high computational costs, data quality issues, the "curse of recursion" where models trained on AI-generated data degrade, and the need to balance trust in AI outputs with their reliability. Additionally, ethical concerns arise regarding the fairness, bias, and transparency of the data used to train these AI systems, which can impact their reliability and trustworthiness. Furthermore, regulatory considerations play a crucial role in AI integration. While the European Union's AI Act aims to ensure the ethical use of AI in finance, it also presents challenges related to compliance and potential over-regulation.

Conclusions: In conclusion, the integration of AI in the banking sector has revolutionized customer service, risk management, compliance, and operational efficiency. However, the adoption of AI also raises concerns about data privacy, security, and the need for regulatory frameworks to ensure ethical use. As AI continues to evolve, it will be crucial for banks to balance technological innovation with responsible practices to maximize benefits and mitigate risks.

Keywords: artificial intelligence (AI), banking sector, fraud detection, anti-money laundering (AML), regulatory compliance

JEL Classification: G21

1. Introduction

In the past decade, the banking sector has undergone a complex transformation driven by technological advancements, marked by the integration of artificial intelligence (AI) into various segments of banking operations. As financial institutions (FIs) strive to enhance their efficiency, mitigate risks, and deliver personalized services, the utilization of AI technologies emerges as a key strategy in reshaping the landscape of modern banking.

The integration of AI in banking represents a shift from traditional banking practices that augments the capabilities of FIs to meet evolving consumer demands in an increasingly digitized environment. Through the fusion of advanced algorithms, machine learning techniques, and data analytics, AI empowers banks to streamline operations, optimize decision-making processes, and offer innovative solutions tailored to individual customer needs. From risk management and fraud detection to customer service and product customization, the transformative potential of AI spreads to every aspect of banking operations, leading to an era of unprecedented efficiency, agility, and competitiveness.

The purpose of this article is to address a gap in the existing academic literature. Given the fact that AI adoption in banking is a recent development, the availability of scholarly research is limited. While several studies have explored specific areas such as chatbots or legislative regulations, there is a lack of comprehensive overviews that encapsulate the multifaceted impact of AI on the banking sector. Furthermore, high-level analyses that do exist struggle to provide an in-depth understanding of the complexities involved. This article offers a more detailed examination of AI applications in banking, providing a more holistic and thorough analysis of the subject.

In the aforementioned context, this literature review synthesizes existing research findings, theoretical frameworks, and empirical studies pertaining to the utilization of AI in banking. By critically analyzing contributions from diverse disciplinary perspectives, this review aims to clarify the opportunities, limitations, and future directions of AI adoption in banking, thereby informing researchers about the transformative potential and inherent challenges associated with AI-driven innovation in the banking sector.

2. Methodology

A systematic review methodology was used to synthesize qualitative data and consolidate insights regarding the utilization of artificial intelligence (AI) in the banking sector. This approach facilitated a structured analysis of existing literature, enabling the identification of key areas of use and implementation challenges pertaining to AI-driven innovation in banking.

To ensure comprehensive coverage of relevant literature, a systematic search was conducted across multiple electronic databases and search engines, including Web of Science, Scopus, Primo, and Google Scholar. The search strategy employed a combination of keywords and Boolean operators to retrieve relevant articles. Keywords included "banking," "generative AI," "artificial intelligence". To maintain rigor and relevance, the search was constrained by predefined inclusion and exclusion criteria. Only articles published in English were considered eligible for inclusion. Moreover, to focus on contemporary developments in the field, academic sources older than 2018 were excluded from the review.

Given the fact that AI adoption in banking is a recent development, resulting in limited availability of scholarly research, additional sources were sought from reputable research departments of prominent corporations such as Citibank and Deloitte in the effort to capture information from a diverse range of sources beyond academic literature. These sources provided valuable insights into industry perspectives, emerging trends, and practical applications of AI in banking, complementing academic scholarship and enriching the review process.

3. Theoretical framework

Existing research on the use of AI in banking spans a variety of focal points, yet often lacks comprehensive depth and breadth. For instance, the study published in the Asian Journal of Management, titled "How Artificial Intelligence is Revolutionizing the Banking Sector: The Applications and Challenges," provides an overview of AI's transformative impact on banking. It discusses improvements in operational efficiency, customer experience, risk assessment, and fraud detection, alongside challenges like data privacy and the need for regulation (Mithra *et al.*, 2023). However, this study remains high-level and somewhat superficial, offering a brief, glossary-like treatment of AI applications without delving deeply into any specific area.

In contrast, the article "Deploying Artificial Intelligence for Anti-Money Laundering and Asset Recovery: The Dawn of a New Era" takes a more focused approach. It critically examines the use of AI in anti-money laundering (AML) and countering the financing of terrorism (CFT), highlighting the need for a balanced regulatory framework to optimize efficiency while safeguarding fundamental rights. While this study provides valuable insights into a specific application of AI in banking, its scope is limited to fraud prevention and AML, neglecting other significant areas of AI application (Pavlidis, 2023).

Lastly, "Banking on AI: Mandating a Proactive Approach to AI Regulation in the Financial Sector" addresses the regulatory landscape, arguing for a proactive approach to AI regulation to avoid over-regulation that could stifle innovation (Truby *et al.*, 2020). This article emphasizes regulatory compliance and the need for rational regulations, yet it primarily centers on the governance aspect rather than providing a comprehensive view of AI's multifaceted applications in banking. Together, these studies highlight the fragmented nature of current research on AI in banking.

Before exploring AI's potential in banking, a solid grasp of key concepts and terminology is essential. This chapter provides a theoretical framework, offering a glossary of crucial terms and concise explanations to clarify foundational concepts necessary for deeper understanding. For consulting the individual terms discussed in the article, see the Appendix 1: Glossary of Key Terms.

4. Use of AI in the banking sector

The integration of AI into banking operations extends across both front and back office, transforming customer interactions, risk management, compliance, and operational efficiency. This chapter explores the various applications of AI in the banking sector, highlighting the key innovations and their impact. In Table 1, areas of AI use in banking can be seen as described by Deutsche Bank Research (Kaya, 2019). However, due to the comprehensiveness of the topic, this chapter will focus only on selected areas that were deemed to have the most potential within the sector.

a) Personalized services and enhanced customer experience

More and more, customers are leaning towards digital interaction with their financial services provider, with COVID-19 only accelerating this transition. According to Deloitte research, more that 35% of customers increased their online banking usage since the start of the pandemic. With this shift, customers' expectations have also evolved.

Table 1. Areas for AI implementation in banking.

Customer-focused & Personalized Services	● credit scoring ● insurance policies ● chatbots ● Know Your Customer
Operations-focused	● capital ● optimization ● model risk management ● stress ● testing ● fraud detection
Regulatory Compliance	● regulatory technology ● macroprudential ● surveillance ● data quality assurance ● supervisory technology
Trading & Portfolio Management	● trade execution ● portfolio management

Adapted from: Kaya, 2019.

Seamless, fast, and personalized experience across various channels is now becoming the standard. To achieve that, FIs are using various strategies (Deloitte, 2021).

Chatbots and smart virtual assistants

In recent years, most of the bigger banks in the world have launched their own chatbot or virtual assistant to help customers with their banking needs, such as account inquiries, bill payments, and budgeting advice. One of the first banks to launch their own assistant was Swedbank, a Nordic bank, who in 2016 launched Nina, a chatbot who was apparently able to resolve 78% of queries during first contact (Nuance Communications, 2016). Since 2018, Bank of America has Erica to assist their customers (Blakey, 2024). The same year, South China Morning Post reported that HSBC launched their AI-powered assistant Amy (Shen, 2018). Two years later, a Belgian bank KBC came on the market with their digital assistant named Kate (Coeckelbergs, 2020). A few years later, in 2022, Wells Fargo followed with a chatbot called Fargo (Wells Fargo, 2022).

An AI development company LeewayHertz define chatbots as software mostly based on NLP and ML that offers effective initial support by managing routine customer inquiries and issues. They can swiftly provide details on account balances, transaction history, and account specifics, allowing human customer service representatives to concentrate on more intricate matters. Leveraging customer data like transaction history and spending habits, chatbots promptly deliver personalized suggestions, minimizing wait times and fostering a favorable customer experience (Takyar, 2024a).

Additionally, these chatbots operate 24/7, guaranteeing customers access to aid and information at any hour (Takyar, 2024a). AI-powered digital assistants surpass the capabilities of chatbots, shifting from reactive to proactive customer support and enabling greater personalization and human-like interactions. Aside from enhanced customer intimacy, digital assistants come with both cost and revenue advantages. Cost savings stem from reduced pressure on customer support and call centers, as well as automated sales and advisory services. Revenue prospects then come from strengthened customer relationships, leading to increased online conversions and greater success in upselling and cross-selling through proactive guidance from digital assistants (Deloitte, 2021).

While chatbots and virtual assistants have significantly improved the efficiency of customer service in banks, they are not without drawbacks, particularly when it comes to handling more complex customer issues. There are growing concerns about customer dissatisfaction, particularly among those whose issues remain unresolved by these automated systems. A significant number of customers express frustration when chatbots fail to address their specific concerns, especially when they are unable to escalate the issue to a live operator. According to a study published in the *Journal of Business Research*, customers often feel neglected when chatbots provide generic responses or misunderstand the complexity of their problems, leading to a perception of poor customer service (Mende *et al.*, 2019)robots with a human-like morphology such as a face, arms, and legs. This dissatisfaction can erode trust and loyalty, potentially driving customers away if their needs are not adequately met. Therefore, banks must consider providing seamless transitions to human agents when necessary to ensure a satisfactory customer experience.

Despite these concerns, an article published in Journal of Internet Commerce suggests, banks should consider adopting chatbot services to meet evolving consumer expectations and stay competitive in the digital banking landscape, as the integration can enhance accessibility, convenience, and efficiency for customers, ultimately strengthening the relationship between consumers and banking brands. Furthermore, they should invest in enhancing system quality to optimize the customer experience, as well as educate consumers about the benefits and safety of using chatbots, leveraging these technologies to reduce customer service costs and improve profitability (Trivedi, 2019).

In summary, AI chatbots revolutionize banking with personalized interactions leading to increased customer satisfaction, improved customer retention, reduced operational costs and improved customer engagement.

Credit scoring

AI-based credit scoring represents a modern approach that employs ML algorithms to analyze extensive data from various sources, offering a detailed and dynamic assessment of credit risk. This method contrasts with traditional models that rely heavily on static historical data. Credit bureaus and lenders use these models to evaluate the likelihood of default, considering factors like payment history, credit utilization, and types of credit accounts (Takyar, 2024b).

AI integration into credit scoring processes can significantly enhance risk assessment methodologies. Unlike traditional scorecard approaches reliant on historical borrowing behavior, AI-driven systems offer a dynamic, real-time evaluation of creditworthiness. By considering current income levels, employment prospects, and earning potential, AI-based models can include individuals lacking extensive historical data but exhibiting high potential. Conversely, they can identify risky behaviors, such as frequent credit card churning, that may not be apparent through traditional assessments. This dynamic approach enables more precise predictions by incorporating a broader range of real-time indicators, facilitating more informed lending decisions (Takyar, 2024b).

Furthermore, AI-based credit scoring systems offer a distinct advantage in their ability to incorporate non-traditional data sources into credit evaluations. These models can analyze social media activity, online behavior, and even geolocation data to provide a more holistic view of an individual's financial reliability. This capability not only expands access to credit for individuals with limited credit histories but also helps lenders identify and mitigate potential risks more effectively. As AI technology evolves, its role in credit scoring will likely become increasingly sophisticated, offering even more precise and inclusive credit assessments (Diatrics, 2024).

b) Fraud detection, risk mitigation and compliance management

In the modern banking landscape, the integration of AI into fraud detection, risk mitigation, and compliance management has become increasingly crucial. The importance of these areas cannot be overstated, as they are fundamental to maintaining trust, stability, and security within the financial system.

A comprehensive study done by KPMG in 2019 states, that the four biggest challenges FIs face when it comes to fraud risks are cyber and data breaches, social engineering, evolving digital channels and faster payments and open banking. In a globalized world, even though a data breach might affect a single company in one country, the compromised data often pertains to individuals worldwide. Cybercriminals can exploit these breaches to acquire large amounts of information, enabling them to commit identity theft, social engineering fraud, and authorized push payment scams by using personal data to gain victims' trust or take over their accounts (Hicks *et al.*, 2019).

Social engineering then refers to the manipulation of individuals to divulge confidential information, such as banking details, passwords, or other sensitive information which can then result in hostile account takeover (customers do not give their permission to access their bank accounts) or so called authorized push payments, where the customer is coerced into transferring the money on the pretext of the fraudster being a legitimate payee (Hicks *et al.*, 2019).

Additionally, faster payment processing can be challenging for banks as it provides less time to scrutinize transactions for fraud. The high speed of these payments also increases the risk of lower fraud loss recovery rates, as funds can be transferred through multiple accounts and moved offshore within seconds. On the other hand, there is an unexpected advantage in this as well, since the increase in digital transactions provides a bigger data set of customer behaviour, it makes it easier for algorithms to spot potentially fraudulent payments (Hicks *et al.*, 2019).

Lastly, open banking refers to transferring the ownership of account information from banks and FIs to their customers. They are then able to share their data with third parties, *e.g.* budgeting applications, FinTechs or investments platforms, through Application Programming Interfaces (APIs). This means that the transaction volumes for banks to review for fraud will likely increase, but also that the banks will have to rely on the security of third parties to protect customer banking information. On the other hand, since regulators seem to be more encouraging or even mandating that the FIs give customers access to these third parties through APIs, higher transparency of customer accounts across banks will likely result in more robust identity verification process, earlier identification of fraudulent accounts, and more efficient tracing of fraudulent funds (Hicks *et al.*, 2019).

A recent article in Journal of Money Laundering Control supports these claims and states that AML and CFT (countering the financing of terrorism) compliance faces challenges due to increasing transaction volumes, sophisticated money laundering techniques, and evolving regulatory environments. Financial institutions face hefty compliance costs and risks, driving them towards technological solutions like RegTech (Regulatory Technology). Thus, investment in RegTech is expected to rise significantly, but success requires both standardization and clarity (Pavlidis, 2023).

A report published by Moody's Analytics was researching the current levels of AI adoption in risk and compliance. They found that approximately one in three organizations, constituting as 21%, are actively employing or experimenting with AI in

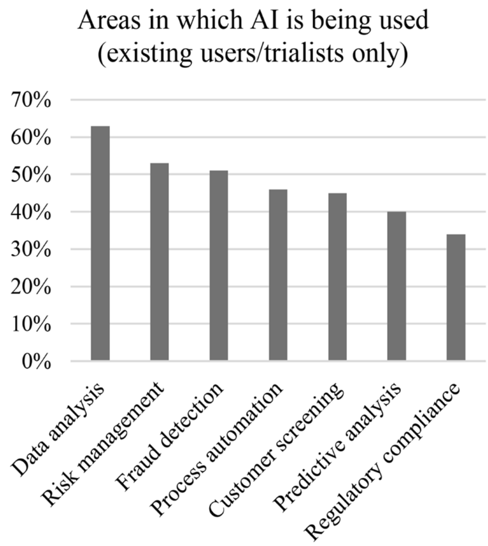

Figure 1. Areas of AI use in risk and compliance. Adapted from: Berry, 2023.

compliance and risk management, with 9% identified as active users and 21% in the trial or pilot phase. In the banking and fintech sectors, 40% and 36% respectively are leading in utilizing or testing AI, while the insurance, asset, and wealth management sectors are trailing behind. Based on their research, 2 out of 3 respondents believe their organization has low data quality, which could offer an explanation on why the majority are yet to start using AI for risk and compliance (Berry, 2023).

Gaining insight into current AI implementations is crucial for anticipating its future effects on risk and compliance. It's no surprise that as teams grapple with escalating data volumes, 63% of companies either actively employing AI or in the trial phase are utilizing it for data analysis and interpretation. Following closely behind are risk management and fraud protection, especially prevalent in the banking sector. Additionally, priorities such as automation, screening, and regulatory compliance are being addressed and are expected to expand as AI technologies become more widespread (Berry, 2023).

Due to its potential to facilitate illicit financial activities and undermine the integrity of the financial system, money laundering remains one of the most significant concerns for FIs. Therefore, effective AML measures are essential for safeguarding banks against regulatory penalties and preserving trust with customers and stakeholders.

Traditionally, banks have attempted to combat money laundering by devising intricate scenarios within rule-based transaction-monitoring systems. These scenarios, formulated with expert input, aim to delineate common behaviors associated with money laundering. However, these scenarios are susceptible to exploitation by money launderers, who employ sophisticated tactics such as smurfing (dividing transactions into smaller amounts), utilizing insurance and securities products, or executing cross-border transfers across various currencies and jurisdictions. As money launderers refine their methods, the challenge of keeping pace with conventional rule-based systems becomes increasingly daunting and costly. That is why FinTech Discai uses AI and ML to eliminate manual sifting through data which significantly improves the average hit rate and claims, that while AI may not offer a panacea for all challenges encountered by financial institutions, it presents a formidable tool in combating financial crimes (De Kok, 2024).

Another area where AI might come in handy in lowering the risk of external fraud is customer education, particularly in regards to scams where customers are facilitating the payments (Hicks *et al.*, 2019). SVAs can push personalized alerts and tips, offering advice on recognizing and avoiding scams and how to best protect their accounts. AI-driven chatbots even analyze transaction patterns and identify potential fraud. The SVA then educates customers through personalized messages and alerts, informing them about suspicious activities and helps them understand how to avoid potential threats (Future Digital Finance, 2024).

When it comes to use of AI in risk mitigation, a use case example could be Deutsche Bank's Alpha-Dig platform that uses AI and ML to quantify geopolitical risk and predict its impact on financial markets. By analyzing global financial news, social media, and Wikipedia, the platform builds a country's political risk profile. It mines news for context, identifies positive and negative indicators using NLP, and adjusts for biases with readership data. Alpha-Dig can detect significant political events by calculating Z-scores and identifying outliers, providing investors with an objective measure of geopolitical risk (Kaya, 2019).

In conclusion, AI has significantly transformed customer interactions in banking through innovations like chatbots and digital assistants. AI-based credit scoring has modernized risk assessment and new algorithms improved fraud prevention and risk mitigation. However, further research is needed to fully exploit AI's potential, especially in areas such as insurance policies, capital optimization, trade execution and portfolio management.

5. Key adoption challenges

As was already mentioned above, the integration of AI technologies in the banking sector heralds a transformative era, promising enhanced efficiency, personalized services, and improved decision-making processes. However, the realization of these benefits is contingent upon navigating and mitigating various adoption challenges inherent in the incorporation of AI systems. This chapter delves into an analysis of the key hurdles encountered in the adoption of AI.

Rise in compute costs

The first issue that arises in the discussions of key adoption challenges is the rise in compute costs. The proliferation of large-scale models, propelled by substantial increases in both parameter counts and input dataset sizes, has led to a dramatic surge in computing requirements. While the average performance of GPUs (Graphics Processing Units) has seen incremental improvements, the doubling times for computational capacity appear insufficient to match the exponential growth in model complexity (Baum *et al.*, 2023).

Based on data from existing models, researchers were able to predict the total cost of the future models and they indicate an alarming trajectory, suggesting that sustaining these escalating computational requirements will soon become unfeasible, with estimates suggesting that by 2030, the cost of training large-scale models could surpass the entire U.S. GDP. Discrepancies in cost forecasts among studies underscore the complexities of extrapolating trends, highlighting the need for cautious interpretation (Lohn, Musser, 2022).

As researchers grapple with the challenge of sustaining the computational resources required for AI innovation, these findings underscore the imperative to explore alternative avenues for enhancing model performance, such as algorithmic refinements and data quality improvements and approach future developments with circumspection and strategic foresight.

Data quality and bias

When discussing data quality, it is crucial to first define data. In this context, data encompasses virtually all digitized information, particularly focusing on human-generated content available online, including text, annotated images, and curated resources such as Wikipedia articles, IMDb images, videos, news articles, coding materials, and online discussion forums. Leveraging these diverse data sources, both businesses and researchers can refine and enhance their models to generate more precise outcomes as their algorithms and computational inputs evolve (Baum *et al.*, 2023).

Nonetheless, this process is subject to

constraints. One significant limitation arises from the challenge of data quality, which becomes increasingly pronounced as models advance in complexity. Recent research (Gunasekar *et al.*, 2023) highlights that employing a smaller corpus comprising "textbook quality data" can yield substantial performance enhancements for AI models compared to those trained on similar or larger datasets sourced from online coding forums. This underscores the critical influence of input quality parameters, which can mitigate issues related to scalability and costs that often confront large-scale models.

When delving into the discourse on data quality, it becomes imperative to scrutinize the foundations of generative AI systems, which rely on vast troves of training data. As of now, the content used for training is still mostly human written, which means it is inherently flawed when it comes to its susceptibility to bias or inaccuracies, particularly if it reflects the prevailing gender, racial, and various other biases prevalent in both online platforms and society at large (Baum *et al.*, 2023).

It is imperative to acknowledge that the data quality discourse extends beyond the mere volume of data to encompass considerations of its origin, composition, and representational accuracy, all of which significantly influence the efficacy and reliability of AI systems. Considering these complexities, addressing the challenge of data quality assumes heightened importance, as it not only impacts the performance and accuracy of AI models but also underpins ethical considerations and societal implications associated with their deployment.

The Curse of Recursion

The advancement of large-scale models utilized for language processing and text-to-image synthesis has sparked conjecture regarding the future landscape of online content. Projections suggest that within the forthcoming decade, a substantial portion, possibly 50% or more, of online content will either be directly generated by artificial intelligence (AI) systems or substantially influenced by them (Baum *et al.*, 2023). However, the optimism underpinning these forecasts often overlooks the pivotal role of human-generated content essential for the refinement and enhancement of such AI models.

In a study conducted in 2023 by researchers affiliated with Oxford and Cambridge universities, a critical issue was discovered concerning the utilization of large AI models when trained on their own outputs. This study sought to address the implications of employing outputs from language-based models (LLMs) as training datasets for models such as GPT-n. A phenomenon termed "the curse of recursion" was discovered, wherein the self-feeding process led to a degradation in model performance, characterized by irreversible deficiencies gradually manifesting as a curtail of predictive outcomes compared to models trained on original human-generated content. This phenomenon, they argued, results in a loss of diversity in predictions, akin to inbreeding, ultimately hindering the attainment of the variety of outcomes characteristic of human-level intelligence (Shumailov *et al.*, 2023).

The findings presented underscore the critical importance of preserving a balance between AI-generated content and human-generated content in shaping the future landscape of online information. While the progress of large-scale AI models holds promise for revolutionizing content generation, relying solely on AI-generated content risks compromising the diversity and richness of online information.

Trust in output vs its reliability

The rapid advancement of language models, exemplified by the widespread adoption of platforms like ChatGPT, underscores the enthusiastic embrace of Generative AI technologies by consumers. However, this surge in popularity is accompanied by growing concerns regarding the propensity of such models to generate factually incorrect statements and disseminate misinformation. While recent research indicates a correlation between the size of language models and their authenticity levels, with larger models exhibiting improved coherence, the persistence of inaccuracies necessitates a re-evaluation of current approaches. Given the high levels of consumer trust in Generative AI interactions, as evidenced by studies such as Capgemini's comprehensive survey, which reported a substantial majority (73%) of respondents expressing trust in content generated by AI, the necessity to uphold accuracy becomes even more paramount. This is especially pertinent in sectors such as financial services, where the implications of misinformation can have profound ramifications (Baum *et al.*, 2023).

The phenomenon of "hallucinations" in language models, where AI generates plausible sounding but factually incorrect information, is another significant concern. These hallucinations often stem from poorly framed or ambiguous prompts, which can lead the AI to produce confident yet misleading or outright false responses. A recent study by researchers from Cornell, Washington, and Waterloo, found that while the quality of prompts does influence the accuracy of AI outputs, even well-crafted prompts cannot entirely eliminate the problem. Language models can still produce errors, especially when addressing questions outside their training data or inferring information not present in the prompt. This issue underscores the importance of continued refinement in prompt engineering and the need for users to approach AI-generated content with a critical eye, particularly in high-stakes fields like finance and healthcare, where inaccuracies can lead to significant consequences (Zhao *et al.*, 2024).

This argument helps further prove that there exists a pressing need to enhance the robustness and reliability of language models, not only to bolster consumer confidence but also to ensure accuracy and integrity in AI-driven interactions. Forthcoming efforts in GenAI research and development should thus prioritize curbing the spread of falsehoods, promoting transparency, and improving accountability mechanisms to counteract the harmful impact of misinformation.

AI regulation in the financial sector

Over the past decade, numerous propositions for regulating AI have emerged from both regulatory bodies and private entities. One of the studies to underscore the significance placed by AI experts and leaders in risk and compliance on regulation within this domain was published by Moody's Analytics. There is a strong consensus of 79% indicating that new legislation concerning the use of AI is crucial for the profession (Berry, 2023). In 2023, scholars and industry leaders even advocated for a temporary halt on AI advancements, citing existential risks posed to humanity (*Pause Giant AI Experiments: An Open Letter*, 2023). However, the feasibility and enforceability of such proposals regarding AI applications remain ambiguous.

Recent challenges have also arisen concerning copyright issues related to the data utilized in training large language models and text-to-image applications. In June 2023, OpenAI and Microsoft faced a $3 billion class-action lawsuit for alleged privacy infringements by their chatbot, highlighting the complexities of copyright legislation and data privacy concerns. This lawsuit echoes previous legal battles faced by these companies, such as the 2022 case where GitHub programmers sued over unauthorized use of their code (Xiang, 2023).

Despite emerging international consensus on principles governing artificial intelligence, regulatory translation of these principles (transparency, data protection, privacy and accountability) into tangible frameworks within the financial sector remains elusive.

In an effort to maintain competitiveness in the global pursuit of AI advancement, financial regulators, traditionally characterized by caution, are exhibiting an unprecedented openness to the introduction of experimental technologies into their environment. This leniency and minimal regulatory oversight, however, puts consumers and financial stability at risk. Thus, the potential aftermath of unregulated AI software looms large, threatening to provoke a public and regulatory backlash resulting in excessive regulation that could stifle future innovation (Truby *et al.*, 2020).

In the past, several global economies and jurisdictions have expressed their opinion on how they plan to tackle this rising topic. One of the first countries to do so was China in 2017, when it unveiled their plans to become a global power in AI by 2030. Following China was of course the U.S., when American President Donald Trump issued an Executive Order to maintain US technological superiority in the domain of AI. Meanwhile, India stated that they will try to develop AI to assist in human development, calling the initiative "AI for All". Additionally, both OECD and the European Commission has released their own positions papers, outlining the main principles and guidelines designed to inform legal reforms in the EU concerning the use of AI. From those, a set of foundation principles has arisen, such as transparency, privacy and data governance, importance of user consent, human agency and oversight, explainability, diversity and fairness and accountability (Truby *et al.*, 2020).

Fairly recently, in February 2024, in a significant development, Members of the European Parliament have reached a political agreement with the Council on the Artificial Intelligence Act, aimed at ensuring the safety and ethical use of AI in Europe while fostering innovation and positioning Europe as a global leader in the field. The Act introduces stringent regulations concerning AI applications deemed high-risk, prohibiting certain practices such as biometric categorization systems using sensitive characteristics and emotion recognition in workplaces and educational institutions. Law enforcement exemptions for biometric identification systems are subject to strict safeguards, including prior judicial authorization and limited use for specific purposes. Obligations for high-risk AI systems entail fundamental rights impact assessments and mechanisms for citizen complaints and explanations regarding AI-driven decisions. Guardrails for general AI systems will require transparency measures, technical documentation, and compliance with copyright laws, with more stringent obligations for high-impact models with systemic risk. Measures to support innovation and SMEs include regulatory sandboxes and real-world testing to facilitate AI development. Non-compliance with the regulations could result in significant fines based on the severity of the infringement and the size of the company (Yakimova, Ojamo, 2023).

The impact of the AI Act on the financial sector is multifaceted. It introduces heightened requirements for high-risk AI use cases in finance, such as creditworthiness assessments and insurance risk assessments, with further development expected by European standardization bodies. National competent authorities will play a crucial role in ensuring compliance with these new AI governance and risk management requirements while potentially offering sector-specific guidance for these use cases. Moreover, the AI Act introduces requirements for general-purpose AI systems, including large language models and generative AI applications, which are increasingly being explored by financial institutions. The newly established AI Office by the European Commission will oversee the enforcement of rules for these AI systems, ensuring compliance and assisting users in their implementation. Financial institutions will retain ultimate responsibility for the tools and services they utilize, as outlined in sectorial legislation. While the adoption of the Artificial Intelligence (AI) Act represents a significant milestone, the implementation of the AI Act will be even more essential to promote responsible AI use in the financial sector and enable European citizens to leverage the benefits of AI (Parente, 2024).

In addition to the AI Act, the European data strategy, comprising legislation such as the Data Act and the Data Governance Act, shapes the landscape for AI use in the financial sector. These initiatives aim to facilitate data re-use and access, fostering innovation and competition among financial institutions. The proposed Financial Data Access (FiDA) regulation further aims to open consumer data held by financial institutions to third parties, potentially enhancing competition and consumer choice. However, questions remain regarding data access, usage, and consumer protection, which will be addressed during the legislative process (Parente, 2024).

Moving forward, NCAs must integrate these new regulatory frameworks into their supervisory activities. Initiatives such as the Digital Finance Supervisory Academy can support up-skilling and adoption of new technologies for supervisory purposes (Suptech). Additionally, promoting convergence at the international level, as envisioned by bodies like the International Association of Insurance Supervisors (IAIS), will be crucial for aligning regulatory approaches and fostering global cooperation in AI governance (Parente, 2024).

All in all, the adoption of the AI Act is a good step forward in creating a regulated approach, to ensure that the financial sector is not exposed to risk and uncertainty. However, it will remain crucial that lawmakers avoid over-regulation that may stifle innovation (Truby *et al.*, 2020) and when drafting consistent and uniformly applicable regulatory frameworks that ensure all participants are subject to equitable rules, they consider the interests of all stakeholders, thus fostering a level playing field in AI adoption.

Existential concerns

The emergence of Generative AI has sparked widespread discussions regarding the potential existential threat posed by artificial intelligence, eliciting diverse perspectives from experts amidst varying regulatory landscapes. While some experts advocate for the transformative capabilities of GenAI, others express apprehension regarding its potential negative ramifications. These contrasting viewpoints underscore the complexity of the debate surrounding AI regulation and its implications for society. Given the multifaceted nature of AI's impact, it is evident that the discourse surrounding this issue is unlikely to dissipate in the foreseeable future, reflecting ongoing concerns and uncertainties within the broader societal framework.

Another point of view that is important to consider in this discourse is from the businesses and their workforce. The gradual pace of change is a characteristic feature as companies navigate the adoption of emerging technologies, such as AI, through iterative processes of experimentation and learning. This approach allows companies to develop requisite processes and equip their workforce with the necessary skills to capitalize on emerging opportunities. However, the integration of AI technologies presents unique challenges, as apprehensions regarding trust, understanding, and potential job displacement may hinder the adoption efforts. As such, the fear of implementing unfamiliar technologies, coupled with concerns about job displacement, may result in reluctance among stakeholders to embrace AI-driven innovations (Baum *et al.*, 2023).

As discussions surrounding AI regulation persist, it becomes increasingly evident that a comprehensive and inclusive approach is necessary to address the multifaceted challenges posed by AI technology. Rather than advocating for a specific viewpoint, it is essential for stakeholders to engage in constructive dialogue and collaborative efforts aimed at fostering responsible AI development and deployment. By recognizing the complexity of the debate and embracing diverse perspectives, policymakers and industry stakeholders can work towards developing regulatory frameworks that promote innovation, safeguard societal values, and ensure ethical AI practices in the evolving technological landscape.

6. Conclusion

In conclusion, the integration of AI into the banking sector represents a transformative leap forward, reshaping customer interactions, risk management, compliance, and operational efficiency. From personalized services driven by chatbots and virtual assistants to advanced credit scoring mechanisms leveraging machine learning algorithms, AI is revolutionizing how banks operate and interact with their customers. Furthermore, AI's role in fraud detection, risk mitigation, and compliance management has become increasingly vital, offering proactive solutions to combat evolving threats and navigate complex regulatory landscapes.

However, the adoption of AI in banking is not without challenges, including rising compute costs, data quality and bias concerns, regulatory ambiguity, and existential considerations regarding AI's long-term impact. Despite these challenges, the regulatory landscape is gradually evolving to address AI's ethical and societal implications, as evidenced by initiatives like the Artificial Intelligence Act in Europe. Moving forward, collaborative efforts between policymakers, industry stakeholders, and regulators will be essential to foster responsible AI development, promote innovation, and ensure ethical AI practices in the financial sector's ever-evolving technological landscape.

References

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, pp. 82–115. DOI:10.1016/j.inffus.2019.12.012.

Baum, A., Danely, C., Feng, T., Hales, S., Kaplowitz, A., Lin, A., Malik, A., Naito, T., Radke, T., Shirvaikar, A., Wilkie, M., Zaccone, S., Boolani, F., Donnelly, P., Goyal, S., Joseph, N., Lee, P., Liu, C., Merchant, A., … Harchandani, A. B. (2023). *Unleashing AI: The AI Arms Race* (p. 57). Citi GPS: Global Perspectives & Solutions.

Berry, K. (2023). *Navigating the AI landscape: Insights from Compliance and Risk Management Leaders* (p. 24). Moody's Analytics. Retrieved from: https://events.moodys.com/2023-11-emea-mau21682-ma-kyc-ai-in-compliance-web#about-tab.

Blakey, D. (2024, August 4). BofA's Erica surpasses 2 billion interactions, helping 42m customers since 2018 launch. *Retail Banker International*. Retrieved from: https://www.retailbankerinternational.com/news/bank-of-america-virtual-assistant-erica-passes-2-billion-interactions/.

Coeckelbergs, R. (2020, November 24). Meet Digital Assistant Kate – When Digital Transformation Gets Personal. *The Banking Scene*. Retrieved from: https://thebankingscene.com/opinions/meet-digital-assistant-kate-when-digital-transformation-gets-personal.

Contri, B., Baumann, N., Celner, A., Galaski, R., Sier, C. (2018). *The new physics of financial services: How artificial intelligence is transforming the financial ecosystem*. Deloitte. Retrieved from: https://www2.deloitte.com/content/dam/Deloitte/br/Documents/finance/new-physics-financial-services.pdf.

Cussins Newman, J. (2019). *Towards AI Security: Global Aspirations for a More Resilient Future*

(White Paper Series). Center for Long-Term Cybersecurity. Retrieved from: https://cltc.berkeley.edu/wp-content/uploads/2019/02/Toward_AI_Security.pdf.

De Kok, R. (2024, October 1). Is AI the answer? Six key factors for financial institutions to consider. *Discai*. Retrieved from: https://discai.com/blog/six-key-factors-before-using-ai-financial-service/.

Deloitte. (2021, August 24). How digital assistants differentiate financial institutions. *Deloitte Research*. Retrieved from: https://www.deloitte.com/be/en/Industries/financial-services/research/how-digital-assistants-differentiate-financial-institutions.html.

Diatrics. (2024). How Credit Scoring Engines Work: A Data Science and Machine Learning Perspective. *Diatrics*. Retrieved from: https://www.datrics.ai/articles/credit-scoring-using-machine-learning.

Future Digital Finance. (2024). *Bank of America's Erica AI Surpassed 1.5 Billion Client Interactions: Here's What That Means for the Future of AI in Banking*. Retrieved from: https://futuredigitalfinance.wbresearch.com/blog/bank-of-americas-erica-ai-surpassed-15-billion-client-interactions-heres-what-that-means-for-the-future-of-ai-in-banking.

Gunasekar, S., Zhang, Y., Aneja, J. (2023). Textbooks Are All You Need. *Microsoft Research*, 26. DOI:10.48550/arXiv.2306.11644.

Hicks, D., Caplain, J., Faulkner, N., Olcina, E., Stanton, T., Chin Kok, L. (2019). *Global Banking Fraud Survey*. KPMG International Cooperative.

Kaya, O. (2019). *Artifical intelligence in banking: A lever for profitability with limited implementation to date*. Deutsche Bank Research. Retrieved from: https://www.dbresearch.com/PROD/RPS_EN-PROD/Artificial_intelligence_in_banking%3A_A_lever_for_pr/RPS_EN_DOC_VIEW. calias?rwnode=PROD0000000000435631&ProdCollection=PROD0000000000495172.

Lohn, A. J., Musser, M. (2022). *AI and Compute: How Much Longer Can Computing Power Drive Artificial Intelligence Progress?* Center for Security and Emerging Technology. DOI:10.51593/2021CA009.

Marr, B. (2023, July 24). The Difference Between Generative AI And Traditional AI: An Easy Explanation For Anyone. *Forbes*. Retrieved from: https://www.forbes.com/sites/bernardmarr/2023/07/24/the-difference-between-generative-ai-and-traditional-ai-an-easy-explanation-for-anyone/.

Mende, M., Scott, M. L., Doorn, J. van, Grewal, D., Shanks, I. (2019). Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses. *Journal of Marketing Research*, 56(4), pp. 535–556. DOI:10.1177/0022243718822827.

Mithra, A., Duddukuru, V. C., Ks, M. (2023). Asian Journal of Management How Artificial Intelligence is Revolutionizing the Banking Sector: The Applications and Challenges. *Asian Journal of Management*, 14, pp. 2321–5763. DOI:10.52711/2321-5763.2023.00028.

Nuance Communications (2016, April 25). Nina Virtual Assistant from Nuance Brings Human Touch to Swedbank Customer Service. *Nuance Communications Inc.* Retrieved from: https://news.nuance.com/2016-04-25-Nina-Virtual-Assistant-from-Nuance-Brings-Human-Touch-to-Swedbank-Customer-Service.

Parente, F. (2024, February 21). AI Act and its impacts on the European financial sector. *Eurofi Magazine*. Retrieved from: https://www.eiopa.europa.eu/document/download/5dc730b7-29b6-44dd-819b-3a04476416ed_en?filename=ai-act-fausto-eurofi-magazine_ghent_february-2024%20128.pdf.

Pause Giant AI Experiments: An Open Letter. (2023, December 4). Future of Life Institute. Retrieved from: https://futureoflife.org/open-letter/pause-giant-ai-experiments/.

Pavlidis, G. (2023). Deploying artificial intelligence for anti-money laundering and asset recovery: The dawn of a new era. *Journal of Money Laundering Control*, 26(7), pp. 155–166. DOI:10.1108/JMLC-03-2023-0050.

Shen, A. (2018, January 14). HSBC's Amy and other soon-to-be released AI chatbots are about to change the way we bank. *South China Morning Post*. Retrieved from: https://www.scmp.com/business/companies/article/2128179/hsbcs-amy-and-other-soon-be-released-ai-chatbots-are-about-change?campaign=2128179&module=perpetual_scroll_0&pgtype=article.

Shumailov, I., Shumaylov, Z., Zhao, Y., Gal, Y., Papernot, N., Anderson, R. (2023). The Curse of Recursion: Training on Generated Data Makes Models Forget. *ArXiv.Org*. DOI:10.48550/arXiv.2305.17493.

Takyar, A. (2024a). AI in banking and finance: Use cases, applications, AI agents, solutions and implementation. *LeewayHertz*. Retrieved from: https://www.leewayhertz.com/ai-use-cases-in-banking-and-finance/.

Takyar, A. (2024b). AI-based credit scoring: Use cases and benefits. *LeewayHertz*. Retrieved from: https://www.leewayhertz.com/ai-based-credit-scoring/.

Trivedi, J. (2019). Examining the Customer Experience of Using Banking Chatbots and Its Impact on Brand Love: The Moderating Role of Perceived Risk. *Journal of Internet Commerce*, 18(1), pp. 91–111. DOI:10.1080/15332861.2019.1567188.

Truby, J., Brown, R., Dahdal, A. (2020). Banking on AI: mandating a proactive approach to AI regulation in the financial sector. *Law and Financial Markets Review*, 14(2), pp. 110–120. DOI:10.1080/17521440.2020.1760454.

Wells Fargo. (2022, October 24). Wells Fargo's New Virtual Assistant, Fargo, to Be Powered by Google Cloud AI. *Wells Fargo Newsroom*. Retrieved from: https://newsroom.wf.com/English/news-releases/news-release-details/2022/Wells-Fargos-New-Virtual-Assistant-Fargo-to-Be-Powered-by-Google-Cloud-AI/default.aspx.

Xiang, C. (2023, June 29). OpenAI and Microsoft Sued for $3 Billion Over Alleged ChatGPT 'Privacy Violations. *Vice Magazine*. Retrieved from: https://www.vice.com/en/article/wxjxgx/openai-and-microsoft-sued-for-dollar3-billion-over-alleged-chatgpt-privacy-violations.

Yakimova, Y., Ojamo, J. (2023). *Artificial Intelligence Act: Deal on comprehensive rules for trustworthy AI*. European Parliament. Retrieved from: https://www.europarl.europa.eu/news/en/press-room/20231206IPR15699/artificial-intelligence-act-deal-on-comprehensive-rules-for-trustworthy-ai.

Zhao, W., Goyal, T., Chiu, Y. Y., Jiang, L., Newman, B., Ravichander, A., Chandu, K., Bras, R. L., Cardie, C., Deng, Y., Choi, Y. (2024). *WildHallucinations: Evaluating Long-form Factuality in LLMs with Real-World Entity Queries*. Retrieved from: https://arxiv.org/abs/2407.17468.

Appendix 1: Glossary of Key Terms

Artificial Intelligence (AI): Range of technologies characterized by their adaptive predictive capabilities and varying levels of autonomous learning. The aim of these technologies is to significantly enhance our capacity to identify patterns, anticipate future events, formulate effective rules, make sound decisions and engage in effective communication with others (Contri *et al.*, 2018).

Chatbot: An AI-powered software engineered to simulate human-like interactions through textual or auditory interfaces. Utilizing natural language processing (NLP) and ML learning methodologies, chatbots engage in conversations, responding to user inquiries and prompts in a manner akin to human communication (Baum *et al.*, 2023).

Data bias: Report from a research collective from Citibank defines outcomes that demonstrate partiality or inaccuracy stemming from the training dataset, particularly when influenced by the gender, racial, and various other biases prevalent in online platforms and society (Baum *et al.*, 2023).

Deep learning: Center for Long-Term Cybersecurity at UC Berkeley defines it as a promising area of machine learning representing an architectural model that uses neural networks inspired by human brain, enabling the interpretation of data through numerous layers of processing. Through this iterative process, deep learning identifies various features within the data, until it achieves the desired outcome. Deep learning methodologies are also responsible for recent progress in fields such as computer vision and language processing (Cussins Newman, 2019).

Explainable AI (XAI): Refers to a branch of artificial intelligence (AI) focused on developing systems and algorithms that provide understandable explanations for their decisions and actions. XAI aims to enhance transparency and interpretability in AI models, allowing users to comprehend and trust the reasoning behind AI-driven outcomes (Barredo Arrieta *et al.*, 2020).

Fraud prevention & anti-money laundering (AML): Strategies and protocols employed by FIs and regulatory bodies to detect, deter, and mitigate fraudulent activities and the illicit flow of funds. These measures utilize advanced technologies, data analytics, and regulatory compliance frameworks to identify suspicious transactions, verify customer identities, and ensure adherence to anti-money laundering regulations (Hicks *et al.*, 2019).

Generative AI (GenAI): In contrast to so called traditional AI, GenAI distinguishes itself by producing outputs of greater complexity. While traditional AI systems predominantly engage in data analysis and predictive tasks, GenAI extends beyond by synthesizing novel data akin to its training dataset (Marr, 2023). Rather than a number or a label, it generates entire high-resolution images or complete pages of text generated word by word. This introduces a novel dimension to AI where multiple correct answers are possible, leading to a significant degree of creative freedom and variability. GenAI models are typically extensive and resource-intensive, demanding terabytes of high-quality data processed over prolonged periods on large-scale, GPU-enabled, high-performance computing clusters (Cussins Newman, 2019).

Machine learning (ML): Systems capable of self-teaching, enabling them to draw inferences and make predictions based on data, rather than being programmed for specific tasks. Within ML, it is important to distinguish between "supervised" and "unsupervised" learning. With supervised learning, a set of correct answers accompanies the data input (Cussins Newman, 2019), while with unsupervised learning, the model is trained without corresponding target outputs with the intention of discovering patterns, relationships or structures within the data on its own, without any prior knowledge or guidance (Baum *et al.*, 2023).

Natural Language Processing (NLP): A subfield of AI and linguistics aimed at facilitating computers' comprehension, interpretation, and generation of human languages. Its applications include transcribing spoken words into text and providing responses in conversational interfaces such as chatbots (Baum *et al.*, 2023).

Traditional AI: Often termed Narrow or Weak AI specializes in executing specific tasks intelligently within predefined parameters. These systems, such as voice assistants and recommendation algorithms, excel at making informed decisions based on data but do not generate new content. For instance, in computer chess, the AI adheres to programmed strategies rather than innovating new approaches. While effective within their designated scope, traditional AI systems lack the ability to create novel solutions or outputs (Marr, 2023).

For better understanding of how some of these concepts relate to each other, see Figure 1.

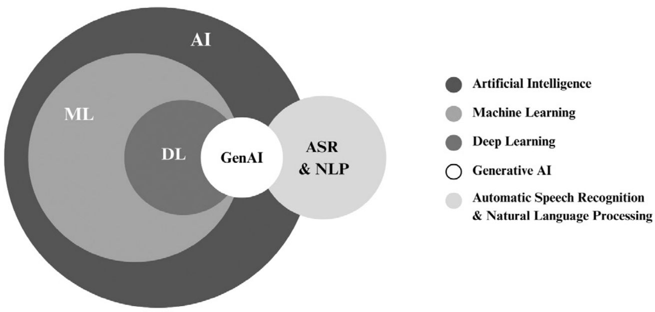

Figure 2. Generative AI. Source: Baum et al., 2023.

Received: 18. 6. 2024
Reviewed: 23. 8. 2024
Accepted: 31. 8. 2024

Ing. Monika Mucsková
Brno University of Technology
Faculty of Business and Management
Department of Economics
Antonínská 548/1, 601 90 Brno
Czechia
Phone: +420 733 121 758
E-mail: 222676@vutbr.cz