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THE IMPACT OF ARTIFICIAL INTELLIGENCE IN THE FINANCIAL SECTOR: OPPORTUNITIES AND CHALLENGES

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Abstract

This article explores the transformative impact of Artificial Intelligence (AI) in the financial sector, highlighting its various applications and associated challenges. Through a detailed analysis, key technologies such as machine learning, computer vision, and natural language processing are examined, which have revolutionized critical areas such as customer service, risk management, and financial advising. Although AI has significantly improved operational efficiency and service personalization, it also presents important risks and limitations, such as data privacy, lack of model interpretability, and cybersecurity. Additionally, the article addresses future forecasts for AI adoption in finance, suggesting that its integration will continue to expand, driven by technological advances and regulatory improvements. However, this expansion must be balanced with adequate oversight to mitigate potential risks and maximize benefits. Overall, this study offers a balanced view of the opportunities and challenges that AI presents for the future of global finance.

Keywords

Artificial Intelligence in Finance, Automated Customer Support, Data Privacy in Financial Services, Ethical Implications of AI in Finance, Innovation in Financial Services

1. Introduction

Artificial Intelligence (AI), as a computational technique that simulates human intelligence through machine learning, is also present in the field of economics, particularly in the area of financial services (Jung et al., 2019). The development of this technique in finance has evolved progressively as it became known and developed by financial entities, such that today its applications are numerous and are used by all financial subsectors, yielding very beneficial results for both financial institutions and their clients (Lynn et al., 2019; Eccles et al., 2021).

AI's ability to process large volumes of data and perform complex analyses has enabled financial institutions to significantly improve operational efficiency, personalize customer services, and optimize risk management. From customer service automation through chatbots to the use of robo-advisors for investment management, AI applications are transforming the way financial institutions operate and interact with their customers.

This study aims to explore in depth the current applications of AI in the financial sector, highlighting both its opportunities and challenges. Additionally, the inherent limitations of these technologies will be analyzed, including risks associated with data privacy, algorithm transparency, and cybersecurity. To contextualize this study within the framework of contemporary research, references to recent works that address the impact of AI in different areas of the financial sector are included. The work also seeks to provide a perspective on the future of AI adoption in finance, emphasizing areas where this technology is expected to continue evolving and expanding its influence.

The work is organized as follows: first, an analysis of the main AI applications in the financial sector is presented. Next, the limitations and risks associated with these technologies are discussed, highlighting challenges in terms of privacy, cybersecurity, and algorithm transparency, as the use of this computational technique is not without risks, in addition to having certain limitations. The final part of the document addresses these issues, along with general conclusions summarizing the main findings and proposing future directions for research and practice at the intersection of AI and finance.

2. Applications in the Financial Sector

2.1. Chatbots and Virtual Assistants: Automated Customer Support

Traditionally, the financial sector has accumulated a vast amount of information about its customers. This information was used to improve their internal management processes and offer a wider variety of products to their customers. The advent of AI-powered chatbots and virtual assistants has enabled these immense volumes of information, combined with machine learning, natural language processing, and historical interaction, to be useful in offering new services to customers and thus achieving a strategic differentiation for financial entities (Riikkinen et al., 2018).

As Adamopoulou et al. (2020) point out, chatbots have become very common tools because they reduce service costs and can handle many customers simultaneously. As Raval (2020) explains, they are used in customer service in the financial industry similarly to other sectors for general purposes, such as providing quick 24/7/365 responses to simple questions, i.e., answering frequently asked questions with "standard" responses or by tracking sources. They can also suggest actions based on a customer's browsing activities or recent common queries on the entire website. Therefore, this technology has significantly reduced management costs in financial entities and facilitated the progressive improvement in the quality of the information they provide, which is usually highly valued by customers (Quah & Chua, 2019).

Specifically, the main uses and applications of AI-powered chatbots in the financial sector are:

- From the customer's perspective:
  - Uninterrupted customer service at any time.
  - Notification of possible fraudulent use of their credit card.
  - Personalized simulation of the contracting of new financial products or services.

- From the financial entity's perspective:
  - Personnel cost savings.
  - Obtaining feedback on the customer-entity relationship.
  - Access to bots provides information to workers to improve the financial marketing process.

2.2. Robo-Advisors: Financial Advisory Services

Digital platforms known as robo-advisors use AI to provide automated financial advice to clients. They replace the traditional process of financial advising (Maedche et al., 2016; Sironi, 2016), being capable of assessing the client and advising them on the management of their investment portfolio. Therefore, they transform the "person-to-person" process into a "person-to-computer" interaction.

Robo-advisors evaluate the client's investment goals, risk aversion, and return expectations. Additionally, the evaluation may include ethical preferences or sectors in which the client wants to invest (Jung et al., 2018).
Increasingly, there is a pursuit of humanizing robo-advisors; however, studies like that of Back et al. (2023) highlight greater psychological barriers to seeking advice from human-like robotic advisors, pointing out the potential risks of imbuing them with social design elements. They emphasize that robo-advisors can mitigate the discomfort that arises after learning that an investment decision generated losses.

In this regard, authors like Moussawi et al. (2022) state that there is evidence of a decreasing impact of social design elements on the continued use after adoption in the context of speech-based digital agents (e.g., Apple's Siri or Amazon's Alexa).

Sometimes, human interaction is necessary with robo-advisors, such as in situations like fraud management. Nevertheless, the cost savings for financial entities are very significant, especially in the case of retail clients.

The products that are usually contracted through a robo-advisor include Investment Fund Portfolios, Exchange-Traded Fund (ETF) Portfolios, Socially Responsible Investing (SRI) Funds, and Pension Plans.

One of the advantages of robo-advisors is the low fees borne by the user. Being a digitized service with minimal human intervention, the client pays service fees that typically range around 1%, although this percentage may fluctuate depending on the entity or the financial product in which it is invested.

2.3. Cash Deposit Machine and ATM Machine Helpline

Automated Teller Machines (ATMs) are self-service terminals that allow cash deposits at any time, eliminating the need to stand in long lines at banks to deposit cash. After each successful transaction, the customer receives a receipt as proof. Additionally, these ATMs also allow payments to different accounts. On the other hand, ATM Machine Helplines provide assistance to customers in contacting their respective banks in case of an emergency.

AI has also been implemented in ATMs, incorporating various technological segments such as machine learning for ATM cybersecurity, computer vision cameras to enhance security and customer experience, facial recognition, predictive maintenance of ATMs, and forecasting cash demand in these devices (Kaur et al., 2020).

2.4. Managing Finance

The use of AI has simplified financial management in the field of finance. Personal Financial Management (PFM) has become a competitive advantage for financial entities and represents one of the latest advancements in AI-based financial management. PFM offers clients personalized and actionable information based on their banking transactions, priorities, and savings goals, along with real-time intelligent suggestions to help them better manage their finances. These recommendations enable clients to take appropriate actions at the right time and make optimal financial decisions (Bhatnagar, 2022).

PFM is similar to a wallet developed by Walletstarted, a San Francisco-based startup that uses AI to build algorithms that help consumers make intelligent decisions about their money while spending it. In this case, the application collects data from the user's online activity and generates spending graphs. Although this process may raise concerns about Internet privacy and could be considered a crime, it might be the future that awaits us.

From micro-level investments to large-scale investments, AI and its associated technologies are set to become a regulatory element in fund management (Maruti techlabs, 2019).

In recent years, financial entities have developed applications for the financial management of their clients. Notable examples include the "Money Plan Apps" application by Banco Santander, which acts as a financial product aggregator by bringing together all cards and accounts in a single platform. The intelligent application "NOMI" by the Royal Bank of Canada (RBC) sends alerts, reminders, and personalized information based on the client's banking habits to help them make more informed financial decisions (Bhatnagar, 2022). Machine learning algorithms have enabled the development of tools that offer semi-personalized portfolio management services through automated online platforms. These robo-advisors create and manage investment portfolios based on the client's investment preferences.

2.5. Customization of End Products and Services

Based on the information obtained from customers, AI in financial services allows entities to offer a personalized user experience and even extend it beyond traditional banking services. For example, they can send alerts about account status while customers are shopping using geolocation (Fernández, 2019). AI can recommend personalized products based on each customer's internal and external data, as well as create a dynamic opportunity meter to help financial entities and insurance companies monitor and capitalize on sales opportunities more effectively (He et al., 2018).

Customer service is key to retaining clients and keeping business and financial sectors operating globally. The Millennial Disruption Index reports that "73% of millennials would be more excited about a new financial services offering from Google, Amazon, Apple, PayPal, or Square than from their own national bank." Many of them say, "I don't see the difference between my bank and others." This is why many fintech startups have gained customers by using AI technologies such as natural language programming (NLP) to offer better and more immediate service (Jain, 2021).

AI has provided a competitive advantage to financial services companies by enabling them to offer personalized and accurate advice to their wealthy clients. BlackRock, the world's largest investment group with more than $6 trillion in assets under management, has a specialized AI lab that assists in its operations. Other global organizations are adopting AI to add value to their customers by improving their forecasts. Swiss bank UBS recently revamped its platform by introducing two new AI systems. One of them identifies trading patterns by analyzing large volumes of market data and then formulates and advises trading strategies to the bank's clients for greater returns. The other deals with allocation preferences after negotiations with their clients (Mehrotra, 2019).

2.6. Mobile Banking

A large number of people have easily adopted mobile banking as part of their daily lives as mobile devices become increasingly smart. AI-powered mobile banking applications have thus generated strong interest among consumers. Having a personal virtual assistant, whether it's Apple's Siri or Amazon's Alexa, is highly attractive and has been widely accepted and embraced by users worldwide. Mobile applications can easily meet customers' needs. There are intelligent apps that can track user behavior and offer personalized advice and information on savings and spending. Today, all banks offer mobile banking and messaging services. Thanks to mobile banking, everyday transactions like money transfers and payments are more convenient. With the incorporation of AI into mobile banking, consumers can better plan their finances, receive intelligent financial advice, and conduct faster and more efficient transactions (Kaur et al., 2020).

2.7. Claims Management

AI-based technologies intelligently collect and evaluate data to ensure the quality of results. They learn the behavior patterns of users or customers to detect unusual activities and send alerts about atypical transactions or incidents. In the area of claims management, these technologies play a crucial role, especially machine learning (ML) techniques that help streamline various stages of the claims settlement process. AI-powered technologies efficiently facilitate data management. Through an automated settlement process, the overall processing time has been reduced, ultimately lowering the costs associated with claims settlement and improving the customer experience in this process (Malali & Gopalakrishnan, 2020).

Scanning and recognition technology allows insurers and banks to manage customer claims more effectively. For example, they can automatically process large amounts of documents by scanning and analyzing software, which reduces labor costs. Additionally, by applying natural language processing (NLP) technology, insurers can convert real-time conversations between customers and customer service representatives during phone calls into text, analyze and extract relevant information, and take appropriate actions. These actions may include categorizing calls into specific groups and assessing their priority to quickly identify customer issues, reduce call duration, and improve customer satisfaction. Insurance companies can also use AI technology to conduct remote assessments. For example, in the case of car insurance claims, AI can analyze images to assess the extent and severity of damage, then assign the claim to the appropriate workflow, thereby reducing costs. Furthermore, AI can automatically predict the severity of customer claims by modeling data and analyzing large volumes of internal, external, and social media data using neural networks, which improves the accuracy of claim predictions (He et al., 2018).

2.8. Insurance Management

Insurance companies, like banking services, can accelerate many of their processes through automation. AI has various applications in the data-driven insurance sector. Whether in underwriting policies or settling claims, insurance companies need to gather as much information as possible about customers, such as their education, health, lifestyle, personality, and the circumstances of the claimed event, which can be achieved more effectively using AI algorithms (Mehrotra, 2019). These algorithms enable better modeling and the creation of formulas to improve customer service and product development. For example, the American startup Lemonade used a bot called "Jim" that resolved an insurance claim in less than 3 seconds by simultaneously executing multiple internal processes. Another startup, MetroMile, uses AI to develop an innovative business model where the insurance premium is calculated based on actual vehicle usage through an IoT device that collects user data (Jain, 2021). The IBM Watson AI platform calculates claims payments by analyzing data such as medical certificates, medical history, and risk factors, helping insurers reduce costs and improve fraud detection (He et al., 2018).

Additionally, AI can help insurers prevent customer churn through data modeling. By integrating internal and external data sources and applying multiple data analysis algorithms to compare their performance and find the optimal algorithm, insurers can use AI to more accurately predict customer churn. Finally, AI can perform property status assessments and risk assessments during the underwriting and pricing stages using big data. For example, dynamic car insurance pricing is possible by detecting and monitoring data on drivers' behavior. Geographic image data and image recognition technology can be used to underwrite home and agricultural insurance (He et al., 2018).

2.9. Accurate Decision-Making

In the era of data-driven management, businesses such as banks, financial companies, and insurers seek to make management decisions at a lower cost. These institutions pose questions to systems rather than experts. By analyzing vast volumes of data, systems and machines reach the desired results, helping managers and their subordinates make appropriate decisions (Malali & Gopalakrishnan, 2020).

AI is particularly efficient at searching massive databases and making decisions based on patterns, leading to AI classifications focused on tasks where humans are not proficient, such as making decisions from large amounts of data. However, humans are still better at evaluative judgments and exercising wisdom, areas where AI does not excel. To address specific problems, AI can use one or several technologies, such as natural language processing, computer vision, neural networks, and robotic process automation, among others. These AI technologies can provide descriptive, predictive, exploratory, prescriptive, or automated decision-making (Väyrynen et al., 2023).

2.10. Predictive Analysis in Financial Services

Predictive analysis plays a crucial role in the financial services sector, impacting areas such as business strategy development, increasing sales and turnover, generating revenue, and optimizing resources. Thanks to AI, predictive analysis becomes faster, smarter, and more actionable than ever before (Akerkar, 2019). By leveraging large amounts of data, AI has the ability to identify patterns and forecast relevant information easily and accurately. These results and insights reveal what will happen in the future, such as consumer purchases, the amount they will buy, the time an employee will remain with the company, among other aspects. Consequently, predictive analysis provides authentic conclusions through sophisticated data mining (Malali & Gopalakrishnan, 2020).

Recently, there has been notable integration between AI and predictive analysis, allowing algorithmic models to play a crucial role in portfolio optimization and anomaly detection in the insurance, banking, and investment sectors (Paul et al., 2021). A prominent example of predictive analysis is credit scoring. This score is based on a person's credit history and is used to predict the likelihood of fulfilling their debts. Although predictive analysis has been used for decades in financial services, it has recently become a fundamental tool in other industries. Advances in data collection and processing technologies have enabled predictive analysis to be applied to nearly every aspect of a business, from logistics to sales and human resources (Akerkar, 2019).

There are millions of people and small and medium-sized enterprises financially excluded without access to bank credit due to their limited or non-existent credit history. Banks find it challenging to grant loans to these customers due to the lack of adequate credit history. In response to this situation, numerous fintech companies use AI-based algorithms to transform the lending sector, providing AI solutions targeted at the unbanked population in emerging markets. New fintech companies employ AI to collect and process alternative data, such as location, employment history, age, spending habits, educational background, criminal records, social media, and other digital signals, to make lending decisions in these cases. Therefore, predictive analysis as a derivative of AI can help calculate credit scores, prevent failed loans, and provide insights into future credit needs and customer purchase preferences (Mehrotra, 2019).

2.11. Blockchain Technology and Banking

Blockchain is a decentralized, secure, distributed digital ledger. It consists of digital information (blocks) stored in a public database (chain). AI acts as the brain or engine that enables decision-making and helps analyze the collected data. It is often mistakenly believed that blockchain technology is only beneficial for the cryptocurrency sector, but this is not true. Blockchain technology aims to solve various problems related to digital transactions, such as data security and fraud prevention. Blockchain represents the future of interbank transactions, cross-border remittances, crypto banking, record storage, loan syndication, increasing transparency, and compliance with the "Know Your Customer" (KYC) procedure, which is a verification process that companies carry out to know their users before initiating business relationships with them (Kaur et al., 2020).

2.12. Control of Anti-Money Laundering (AML) - Fraud Detection and Management

Concern about money laundering cases and fraud detection management has increased significantly with the rise of online banking. Recent cases in the financial sector have highlighted this concern (Jaeger, 2018; Edwards et al., 2018).

The banking industry's ability to detect cybercrimes or identify anomalies must adapt to changing technology. For this purpose, artificial intelligence is proving to be an effective tool in detecting inconsistencies or anomalies in known data, such as differences between the registered geographical location of an account holder and the location of a transaction, or in detecting irregular purchasing patterns. Thus, anomaly detection-based anti-fraud solutions are more common than those using predictive and prescriptive data analysis. For example, artificial intelligence helps perform adequate analysis of digital footprints to detect if the person is who they claim to be.

This also includes users attempting to open bank accounts with stolen IDs, those trying to launder money, those abusing bonuses, and potential fraudsters attempting to access other people's accounts.

2.13. Credit Scoring

The occurrence of continuous "black swans" in the economy has severely impacted the global financial sector. The past financial crisis exposed credit granting models, and the coronavirus crisis brought to light other risks that are not adequately managed in business models. The reality is that all credit granting rests on a proper risk assessment. Credit scoring is a central element for financial institutions, as it pivots on decision-making in credit granting, the main activity of any financial institution, to avoid granting loans with a high probability of non-repayment.

A good credit scoring model can effectively group customers into specific groups according to default risk. The more efficient it is, the more costs it can save a financial institution (Goh & Lee, 2020). The scores these ratings yield are a measure of customer solvency. Starting in the mid-20th century, statistical and computational models began to be used to classify debtors. Durand, Altman, or Ohlson, among others, were pioneers in these studies. Many techniques have been employed, from discriminant analysis to differentiate between good and bad debtors to developing insolvency prediction models with logistic regressions or other more robust and significant methods (Logit or MDA). Currently, AI and the recent enthusiasm driven by financial technology (FinTech) are capturing all the attention of credit scoring models.

However, as Demajo et al. (2021) indicate, the biggest obstacle in most AI systems is their lack of interpretability. This lack of transparency limits their application in different domains, including credit scoring, as these models must ensure that algorithmic decisions are understandable and consistent. For example, a recently introduced concept is eXplainable AI (XAI), which focuses on making "black box" models more interpretable.

But AI applied to credit scoring is not only used by financial institutions for credit allocation; small businesses can also use AI tools to easily and quickly decide whether to proceed with a business or if it poses a risk of non-payment that requires halting the operation with a customer. This fact also provides significant cost savings, as smaller companies with fewer resources do not need to have departments dedicated to gathering and processing information.

2.14. Regulatory Compliance

The greater analytical capacity provided by AI tools facilitates compliance with certain regulatory requirements (e.g., risk management, reporting obligations, etc.), as well as tracking changes in regulation (Fernández, 2019).

Over time, it can be observed that certain AI-based methodologies are increasingly used by financial institutions to address systemic risks, market manipulation on trading platforms, and other uses related to the proper advising of financial services users (Lee, 2020). However, as highlighted by FUNCAS in its document 64/21 (FUNCAS, 2021), AI is often discussed too generally in the financial sector without identifying the specific segments where its application is most efficient.

At the level of internal regulatory compliance, the use of AI is also seen in banking models for credit impairment. The change in criterion reflected in IFRS 19 (IASB, 2024), shifting from an incurred loss criterion to an expected loss criterion, has involved the use of greater methodological and computational sophistication to estimate the probability of default and comply with regulatory requirements for credit impairment, aiming to anticipate the best possible estimate of future default.

On the other hand, it is essential to know the Regulators' position on the use and applications of AI concerning regulatory compliance in the financial sector. The reality is that this issue is beginning to concern supervisors who want to monitor that the use of AI does not pose new financial stability risks. The Basel-based Bank for International Settlements (BIS, 2021) has produced a report addressing the appropriate use of AI in the financial world. Among some of its conclusions, the BIS indicates that there are currently no concrete practical guidelines from regulators on the use of artificial intelligence. Therefore, it advocates that respective national regulators and supervisors be proactive in identifying best practices.

2.15. Lending Using AI

Granting a loan involves considering all kinds of parameters. The more thorough the study of all conditions, characteristics, and aspects affecting the borrower, the higher the final repayment amount and, therefore, the lower the risk of the operation.

Thus, factors such as employment status, current income, expected income during the loan's life, owned assets, savings, fixed expenses, and already assumed commitments (such as previous loans or mortgages), among others, are some parameters that AI processes through its complex algorithms to confirm or deny the granting of financing, credit cards, or pre-approved loans.

Today, the algorithms hidden within AI replace humans when selecting the type of financing and its amount, as they can make more precise estimates. Empirical studies, such as those by Costello et al. 2019 or Hughes et al. 2022, demonstrate this.

2.16. Making Payment Networks Safer / Processing Payments and Managing the Business Infrastructure Using AI

Mobile network payment gateways are growing explosively (Wang et al., 2021) and are also gaining significant weight in commercial efficiency, precisely due to the application of AI. Specialized entities predict more than half a trillion transactions on digital payment platforms soon. A revolution induced by new market entrants that compete with traditional payment methods provided by financial entities with new payment solutions (Carsten, 2020).

The use of these new technologies allows users to select the most interesting payment method at any given time with a high level of security. This represents a more personalized management and approach to the end customer. A good case is card transaction routing (intelligent routing), i.e., accepting a card based on the issuing bank, amount, and timing, among other variables. Additionally, these processes also allow for streamlining and improving security through real-time fraud risk analysis or generating a proprietary risk scoring.

In this regard, AI is causing both entities and users to enjoy greater security in their transactions. For some time now, security improvements in payment platforms, such as blocking or alerting according to the number of purchase attempts (false positive detection) or even according to the terminal used by the buyer to browse an e-commerce site, have been implemented.

Generating greater security on payment platforms also leads to greater user confidence in accepting new business models in the financial sector, such as the emergence of installment payments and other alternatives, which improves the sector's profitability ratios and creates new financing opportunities for the end customer.

2.17. Risk Assessment

The application of AI to risk assessment is of great importance, as it replaces human analysts in identifying and evaluating financial risks. Risk management with AI allows for a better understanding of risks and more effective mitigation, revealing information that traditional analysis does not reach.

Fraudulent transaction detection is an essential component of risk control in e-commerce markets. As Thennakoon et al. (2019) point out, there is a continuous shift in fraud patterns, so financial entities seek to counteract risks as quickly as possible. Real-time credit card fraud detection is a topic that causes significant losses to banks and requires rapid responses to prevent them. For this reason, banks seek real-time risk management offered by artificial intelligence to decide whether a specific transaction is genuine or fraudulent and notify the end-user at the moment the transaction occurs. Machine learning models are based on fraud patterns, such as unknown web addresses, transactions exceeding a certain amount, or the location of the operation, among others.

2.18. Pricing of Financial Products

In the options market, we find, among others, simple European options whose payoffs depend on the current market price of the underlying asset at the expiration date, and Asian options, also known as average options, whose payoff depends on the average price of the underlying asset over a specified period. Therefore, they are not sensitive to price variations of the underlying asset within the expiration date, presenting lower risk than European options. Within Asian options, there are two types: geometric and arithmetic. The former, as Vecer (2001) explains, are valued by numerically solving a partial differential equation (PDE) or through a Monte Carlo simulation, while the latter present a challenge in their valuation with traditional numerical methods due to costly repetitive calculations and simplified models with unrealistic assumptions, as noted by Gan et al. (2020).

The valuation difficulty has been solved by various authors who have developed machine learning-based models, such as the one developed by Gan et al. (2020), focused primarily on arithmetic Asian options with use also in geometric ones, or the model by Halperin (2017) that employs a Q-Learning reinforcement method to dynamically learn the optimization of risk-adjusted returns for a portfolio that replicates European options.

2.19. Financial Trading

Financial trading is the buying and selling of financial instruments: stocks, indices, forex, or commodities. This trading is based on a basic principle: predicting whether something will rise or fall in price, as this determines whether one makes a good profit or loses a lot of money. The importance for an investment company to determine as accurately as possible the future market position makes the use of AI extremely important, as it examines past data and predicts how it will repeat in the future, analyzing anomalies that occur and providing a plan to avoid those anomalies in the prospective forecast (Dhanabalan & Satish, 2018).

As Malali et al. (2020) point out, AI could offer solutions tailored to different demands depending on the investor's risk profile. For a risky profile, it could provide information on when to buy, hold, or sell stocks. On the other hand, for less risky profiles, AI can focus on issuing alerts about when the market will rise or fall, helping the company decide whether to invest more, stay with the current investment, or exit the market.

2.20. Wealth Management for Masses

As Django Stars (2019) notes, automation in the banking and financial sector is increasing daily, inserting AI and machine learning (ML) techniques into everyday business operations. The so-called AI-based Smart Wallets observe users' behavior and purchasing actions, generating analytical and predictive patterns to help manage clients' daily finances, who receive information that helps them make decisions about their finances. For example, by analyzing a client's payment data, AI can anticipate movements and remind them through notifications of an upcoming payment to avoid overdrawing their account.

Computerized advice has made wealth management services accessible to markets of clients with small assets, helping them manage their daily finances.

3. Limitations and Risks in the Use of AI in the Financial Sector

The use of AI in the financial sector is subject to a series of limitations that, in some cases, involve risks.

These limitations lead to the existence of undesirable risks related to confidentiality, the incorporation of inaccurate information, or excessive dependence on the algorithms used, which may hinder the proper interpretation of results. This dependence often results in this tool being used as a complement rather than a substitute.

The privacy of the information provided by clients to financial entities is a limitation in the use of this technology (Martens et al., 2016). AI use can also be limited by the risk that the decision-making process may be influenced by the spread of fake news (Parne, 2021). For example, the false report of an attack on the White House in 2013 (Karppi & Crawford, 2015) that caused widespread and atypical movements in financial markets. These limitations justify that this technology sometimes needs human oversight to avoid such risks.

Another limitation of AI that involves risks is using machine learning without sufficient training or proper feedback. For example, using an AI model in a stress test without a sufficiently long and diversified time series (FSB, 2017). This limitation in the quantity and quality of information significantly increases the possibility of not detecting systemic or specific risks of the financial entity.

The massive use of clients' personal information requires a high level of cybersecurity. Financial entities must make substantial investments to ensure that this confidential information will not be compromised by cyberattacks or misuse by its users.

Another limitation of AI in finance is the possibility of creating "black boxes" (Knight, 2017) that pose interpretation problems for human users, as they may not understand how the results were obtained. This situation could, for example, prevent explaining to a client why their financing was denied.

4. Conclusions

The comprehensive analysis of Artificial Intelligence applications in the financial sector has demonstrated its capacity to profoundly transform this field, offering innovative solutions ranging from customer service automation to the optimization of financial advising and risk management. AI technologies, such as machine learning, natural language processing, and computer vision, have enabled financial entities to significantly improve operational efficiency, reduce costs, and provide personalized services to clients.

However, it is essential to recognize the limitations and risks inherent in implementing AI in finance. Among the most prominent challenges are data privacy, the need for robust cybersecurity, and the lack of interpretability in some AI models, which can generate mistrust among users and regulators. Excessive dependence on algorithms and the possibility of biased or erroneous decisions due to insufficient data quality or poorly trained AI models are also crucial concerns that must be addressed to ensure the reliability and transparency of these technologies (Martens et al., 2016; Demajo et al., 2021).

Despite these risks, the potential of AI in the financial sector is undeniable. As technology continues to evolve, it is foreseeable that AI adoption will expand further, becoming more deeply integrated into critical processes such as investment management, fraud prevention, and the optimization of personalized financial services. The increasing sophistication of AI models, coupled with improvements in interpretability and regulatory oversight, could mitigate some of the current risks, enabling a safer and more efficient use of these technologies (BIS, 2021; Goh & Lee, 2020).

In the future, AI is expected not only to continue revolutionizing the financial industry but also to play a key role in developing new business models and creating more inclusive and accessible financial markets. The advance towards greater automation and the development of hybrid systems that combine AI with human oversight could mark a new era in which AI not only complements but radically transforms global finance (Jung et al., 2019; Back et al., 2023).

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