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Hybrid artificial intelligence: Application in the banking sector

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Abstract

The integration of smart technologies, from data mining to Artificial Intelligence, has revolutionized the way financial institutions manage and use information. This progress has driven the development of hybrid artificial intelligence solutions, which fuse neural networks, fuzzy logic, genetic algorithms and intelligent agents, improving efficiency and accuracy in finance. Key application areas include implementing machine learning for personalized financial services, using artificial intelligence to improve credit risk assessments, and automating operations for greater efficiency. This study aims to analyze the implementation of hybrid artificial intelligence in the banking sector. The findings suggest that machine learning significantly personalizes services, increasing customer satisfaction and retention. Artificial intelligence has refined credit risk assessment, reducing errors and improving accuracy, while AI-enabled automation has streamlined operations. In addition, artificial intelligence helps analyze trends and innovate products. The combination of traditional and data-driven artificial intelligence techniques was identified as offering significant competitive advantages for financial institutions.

Keywords: Artificial intelligence; banking sector; automation; efficiency; financial operations.

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Inteligencia artificial híbrida: Aplicación en el sector bancario

Resumen

La integración de tecnologías inteligentes, desde la minería de datos hasta la Inteligencia Artificial, ha revolucionado la forma en que las instituciones financieras gestionan y utilizan la información. Este progreso ha impulsado el desarrollo de soluciones de inteligencia artificial híbridas, que fusionan redes neuronales, lógica difusa, algoritmos genéticos y agentes inteligentes, mejorando la eficiencia y la precisión en las finanzas. Las áreas clave de aplicación incluyen la implementación del aprendizaje automático para servicios financieros personalizados, el uso de la inteligencia artificial para mejorar las evaluaciones de riesgo crediticio y la automatización de las operaciones para una mayor eficiencia. Este estudio tiene como objetivo analizar la implementación de la inteligencia artificial híbrida en el sector bancario. Los hallazgos sugieren que el aprendizaje automático personaliza significativamente los servicios, lo que aumenta la satisfacción y la retención de los clientes. La inteligencia artificial ha refinado la evaluación del riesgo crediticio, reduciendo los errores y mejorando la precisión, mientras que la automatización habilitada por ella ha agilizado las operaciones. Además, la inteligencia artificial ayuda a analizar tendencias y a innovar productos. Se identificó que la combinación de técnicas de inteligencia artificial tradicional y basada en datos ofrece ventajas competitivas importantes para las instituciones financieras.

Palabras clave: Inteligencia artificial; sector bancario; automatización; eficiencia; operaciones financieras.

Introduction

The evolution of Information and Communication Technologies (ICT) has been transforming the banking sector over the decades. From the rise of databases in the 1980s and 1990s to the rise of Big Data, Artificial Intelligence (AI) and the Internet of Things in the 2010s, the banking sector has been part of a substantial transformation in the way it manages information and makes critical decisions (Fernández, 2019).

Artificial Intelligence (AI) has emerged as a transformative technology in the banking sector, driving digitalization and innovation in a competitive environment marked by the growing presence of fintechs and digital banks. Its application ranges from improving customer service through chatbots and virtual assistants to optimizing fraud detection and credit risk assessment (Moposita & Jordán, 2022; Rodríguez, 2023). In addition, AI enables the automation of operational processes, increasing efficiency and reducing human errors (Arbeláez-Campillo, Villasmil & Rojas-Bahamón, 2021; Maita-Cruz et al., 2022). However, its adoption presents significant challenges, including the need for large investments and ethical considerations regarding data privacy. Despite these challenges, AI promises to transform financial services, offering more personalized and secure experiences to customers.

In this context, ICT and intelligent techniques, such as data mining, neural networks, expert systems, fuzzy logic, genetic algorithms, and intelligent agents, have been integrated to form hybrid AI systems in the banking sector, combining multiple artificial intelligence approaches to optimize efficiency and accuracy in decision making and process automation.

This research paper aims to analyze the implementation of hybrid artificial intelligence in the banking sector. This paper uses a theoretical-bibliographic research method, focused on the review and analysis of existing literature on the implementation of hybrid artificial intelligence in the banking sector. Relevant academic and technical sources were selected and analyzed to explore the applications of machine learning for personalized financial services, improving credit risk assessments using AI, and automating operations for greater efficiency. This approach allows us to synthesize previous knowledge and critically assess the advances and challenges in the adoption of hybrid AI systems in banking.

This paper aims to analyze the implementation of hybrid artificial intelligence in the banking sector, addressing three key areas: Machine learning for personalized financial services, improving credit risk assessments through AI, and automating operations for greater efficiency. Through a theoretical-bibliographic review, the advances, benefits, and challenges associated with these applications will be explored, providing a comprehensive view of the impact and potential of hybrid AI systems in modern banking.

1. Methodology

This study is based on a theoretical-bibliographic research method, focused on the exhaustive review and critical analysis of the existing literature on the implementation of hybrid artificial intelligence in the banking sector. To this end, relevant academic and technical sources have been identified and examined that address various applications of AI, such as machine learning to personalize financial services, improving credit risk assessments, and automating operations to increase efficiency. This approach allows us to synthesize the accumulated knowledge in these areas and critically assess both the progress made and the challenges that still persist in the adoption of hybrid AI systems in the banking industry.

Three leading academic databases are incorporated: Web of Science, Scopus, and Google Scholar. This integrated strategy was designed to leverage the distinctive advantages offered by each database, ensuring a comprehensive and nuanced understanding of our research topic.

Web of Science and Scopus were chosen due to their rigorous selection of peer-reviewed journals and inclusion of high-impact research. These databases offer advanced bibliometric tools, facilitating detailed citation analysis and trend identification, allowing for a nuanced review of the literature. Their rich metadata and analytical functions allow for tracking the evolution of research topics, identifying seminal works, and assessing the scholarly influence of various publications.

Complementarily, Google Scholar, with its broad reach into scholarly materials such as theses, books, conference papers, and grey literature, enabled a broader review of the literature. Its open access and algorithmic retrieval of relevant content ensured that no important research was overlooked, especially that outside traditional scholarly publishing channels. This approach ensured a comprehensive survey of existing research and also allowed for critically evaluating and synthesizing findings from a wide range of sources.

2. Artificial Intelligence: Evolution, components and characteristics

Information and Communication Technologies (ICT) encompass a broad spectrum of digital technologies, tools and systems that enable the manipulation, transmission and presentation of information in multiple formats. This field ranges from traditional networks to digital media and mobile technologies, with its evolution marked by different historical stages. In the 1980s and 1990s, relational databases and systems such as SQL were consolidated, laying the foundations for the management of large volumes of data. In the 2000s, the explosion of digital data drove digitalization, e-commerce and social networks, facilitating the processing of Big Data through tools such as Hadoop (Bialecki et al., 2005). The decrease in data storage costs was significant, allowing companies to handle massive volumes of information.

In the 2010s, the rise of Big Data was reflected in greater investment in technologies for its use, highlighting the use of tools such as Apache Spark for real-time analysis (Zaharia et al., 2016). The proliferation of connected devices in the Internet of Things (IoT) and the development of Artificial Intelligence (AI) and Machine Learning (ML) increased data generation and the demand for advanced analytical solutions.

Finally, in the 2020s, Edge Computing emerged as a key strategy, bringing data processing closer to its source of origin, especially relevant for IoT and mobile devices. The integration of AI and ML into Big Data and real-time analytics solutions, together with the development of edge artificial intelligence, has been instrumental in meeting the growing demand for computing services and improving efficiency in data management (Zhou et al., 2019).

Database- and AI-based technology offers techniques to capture both individual and collective knowledge, thereby expanding the knowledge base of organizations. Data mining helps to develop knowledge from large databases, providing new insights to improve performance and operational strategies. AI techniques such as expert systems, fuzzy logic, genetic algorithms, and intelligent agents automate routine tasks and capture tacit knowledge, generating solutions to complex problems and improving business decision-making.

Data mining is a technique for identifying patterns and extracting hidden information from large data repositories such as databases and data warehouses Bramer (2016). It involves using mathematics, statistics, computer science, and other methods to process a large amount of information in order to derive useful conclusions and provide valuable decisions for people (Zhang et al., 2022). Data mining plays a crucial role in discovering hidden patterns and relationships within large data sets, thereby providing valuable insights across various domains and supporting informed decision-making processes (Bellazzi & Zupan, 2008).

The application of data mining extends to diverse areas such as e-learning systems, customer behavior analysis in the banking sector, and customer churn prediction in telecommunications, demonstrating the wide scope of its applications (Han et al., 2007; Shaheen et al., 2010; Thongsatapornwatana, 2016; *Doğuç,* 2022).

On the other hand, neural networks are computational models inspired by the structure and function of the human brain, consisting of interconnected nodes that work together to process complex information and learn patterns (Prieto et al., 2016). The development of deep learning algorithms and architectures has significantly accelerated progress in neural network research (LeCun, Bengio & Hinton, 2015). These networks have found applications in various fields including mechanics, hydroelectricity, structural engineering, and computer science. The solutions provided by neural networks appear to be cutting-edge from the versatility in mechanical data for physics (Koeppe et al., 2022), in the prediction of water inflows to hydroelectric reservoirs (Berdnikov, 2021), or the diagnosis of faults in high-speed train bogies (Zhao, Guo & Yan, 2017).

The architecture of neural networks typically includes different types of layers, such as convolutional, pooling, and dense layers, which contribute to their ability to effectively process and analyze data. Moreover, the development of new neural network algorithms, such as the optimized backpropagation algorithm based on genetic algorithms, has addressed challenges related to local minima and convergence rates (Ding, Su & Yu, 2011). Furthermore, artificial neural networks led to the development of wavelet neural networks, which offer alternative approaches to traditional nonlinear activation functions (Zhang et al., 2022), a transformation in network design.

Artificial Intelligence (AI) involves the simulation of human intelligence in computer systems and machines, with the aim of addressing complex problems and improving the efficiency of knowledge management. AI relies on processes such as machine learning, reasoning ability, and self-correction, allowing machines to acquire information, apply rules to draw conclusions, and continuously adapt. This is essential for AI to perform tasks that normally require human intelligence, such as problem solving and decision making Haenlein & Kaplan (2019). AI enables the automation of repetitive tasks, increasing efficiency and freeing up time for strategic activities.

Furthermore, the application of AI in knowledge management is evident in its ability to process and analyze large amounts of data quickly and accurately. AI techniques can unravel complex patterns in massive data sets, further expanding the scope of AI in knowledge management (Nabi, Bansal & Xu, 2021).

Machine learning (ML) is a subset of Artificial Intelligence (AI) that focuses on the development of algorithms and models that enable computer systems to learn and make predictions or decisions based on data (Tyagi & Chahal, 2022). It involves building systems that can automatically learn and improve from experience without being explicitly programmed. ML techniques enable computers to identify patterns, extract meaningful insights, and make decisions, thereby improving their ability to perform specific tasks more accurately over time (Rahmani et al., 2021).

ML has found applications in several domains, including medicine, networking, and materials science. In medicine, ML has been used for tasks such as predicting mortality risk and analyzing medical images for diagnostic purposes (Rahmani et al., 2021). In networking, ML has been leveraged to optimize network performance and security (Wang et al., 2018).

ML techniques encompass a wide range of approaches, including supervised learning, unsupervised learning, and reinforcement learning, each suited to different types of problems and data. These techniques have the potential to transform industries and drive innovation by enabling systems to autonomously learn and adapt to complex challenges.

An expert system is a computer system that emulates the decision-making capability of a human expert. It is designed to solve complex problems by reasoning through bodies of knowledge, represented primarily as "if-then" rules, rather than through conventional code. Expert systems are built from knowledge obtained from human experts, traditionally (Alonso et al., 2012). These systems have been developed and applied in diverse domains, including law, medicine, agriculture, engineering, and business, to provide intelligent decision support and problem-solving capabilities (Susskind, 1988; Mansingh, Reichgelt & Osei, 2007).

The development of expert systems involves the acquisition and representation of expert knowledge, usually in the form of rules, and the use of inference engines to reason and make decisions based on this knowledge. Expert systems have been used for tasks such as fault diagnosis in power generation, voltage and VAR control in large-scale power systems, and pest and disease management in agriculture (Le, Negnevitsky & Piekutowski, 1997; Mansingh et al., 2007). They have also been applied in international marketing, image processing and electronic surveillance in medical oncology, showing their versatility in different domains (Çavuşgil & Evirgen, 1997).

The use of expert systems has been driven by the need to capture and leverage expert knowledge to solve complex problems, especially in situations where human experts may not be readily available. These systems have demonstrated the potential to improve decision-making processes, automate tasks, and provide valuable insights in a number of fields, making them a valuable tool for augmenting human expertise and addressing complex challenges.

Fuzzy logic is a system that can handle both numerical data and linguistic knowledge simultaneously (Klement & Slany, 1993). It has been widely adopted in criticality assessment models for failure modes and effects analysis, where it efficiently helps formulate effective criticality assessments of potential causes of failure (Mendel, 1995). Furthermore, fuzzy logic has been used in various fields such as medical sciences to diagnose disease risk (Braglia, Frosolini & Montanari, 2003), artificial intelligence to create music (Ivančan & Lisjak, 2021), and, thanks to its ability to handle approximate reasoning modes, it has been used in the analysis of corporate social responsibility.

The concept of fuzzy logic is based on the use of intuitionistic fuzzy logic to interpret perceptions and solve vague problems. It also has its roots in the concept of fuzzy sets and the amalgamation of multi-valued continuous logic systems (Zadeh, 1996). Fuzzy logic is a subtype of multi-valued logic and can be used in combination with other types of controllers such as PI, PID, neural networks, and genetic algorithms (Tamir, Rishe & Kandel, 2015). Genetic algorithms (GAs) are optimization methods based on biological evolution and genetics, widely used in diverse fields such as computer science, artificial intelligence, and mathematics (Sivanandam & Deepa, 2008).

GAs are known for their ability to perform global searches in complex and large search spaces, making them effective in scenarios where conventional optimization methods fail to produce the desired results Gen & Cheng (1999). They are stochastic search algorithms that use genetically inspired operators to transform potential solutions into offspring populations, allowing the identification of optimal or near-optimal solutions (Koshka & Novotny, 2020).

Furthermore, GAs have been recognized for their robustness and simplicity, making them suitable for solving optimization problems, particularly in cases where the search space is large and complicated, and conventional optimization methods are not effective. They have also been integrated with other optimization techniques such as fuzzy C-means clustering to address specific problems such as vehicle routing for autonomous driving (Zhu, 2022). Furthermore, GAs have been combined with other artificial intelligence methods, including neural networks and fuzzy logic controllers, to create unified software platforms for solving complex problems.

Intelligent agents, within the context of artificial intelligence, refer to autonomous entities that interact with their environment through observations and actions, aiming to achieve specific goals with the help of rewards. These agents have been widely used in various domains, including sales training with the use of artificial intelligence (AI) coaches to improve the skills of sales agents (Luo et al., 2021). Furthermore, intelligent agents have been employed in the product design, process design, and production stages, demonstrating their applicability in solving complex problems (Wang et al., 2020).

Furthermore, intelligent agents have been associated with the concept of rogue agents, which are capable of opposing assigned goals or plans, as well as the attitudes or behaviors of other agents (Coman & Aha, 2018). Collaboration of intelligent agents through intelligent interfaces has been proposed, highlighting the potential of combining intelligent agents at the software level through standard interfaces for communication (Bryndin, 2019). Furthermore, progress in technology and processing power has enabled the development of sophisticated AI agents, further emphasizing their importance in AI systems (De Vreede, Raghavan & De Vreede, 2021).

In the field of Predictive Analytics and Decision Making, banking institutions have adopted technologies such as Machine Learning (ML) and Big Data to improve credit assessment and decision making (Angelini, Di Tollo & Roli, 2008; Mhlanga, 2021). Credit risk assessment, which refers to the likelihood of a borrower defaulting on financial obligations such as repaying a loan, has evolved with the advent of AI. Previously, credit risk management was based on statistical models and human judgment. However, with AI, financial institutions have more powerful tools to assess and manage risks more accurately:

a. Predictive analytics: AI uses advanced models such as support vector machines and neural networks to predict a borrower's behavior. These models are trained on large data sets that include borrower financial information, payment history, transactions, among others, allowing them to accurately predict the likelihood of default.

b. Unstructured data processing: Unlike traditional models that primarily use structured data (such as income, credit history), AI can analyze unstructured data, such as social media texts, phone records, or online behaviors, to gain additional insights into a borrower's financial strength and trustworthiness.

c. Decision automation: Once set up, AI models make decisions in real time. For example, when applying for a credit card online, AI can assess the application and approve or reject it in a matter of seconds.

d. Adaptability: AI models have the ability to learn continuously. As more data is fed in, the models adjust and improve, allowing them to adapt to new market conditions or emerging patterns in borrower behavior.

e. Advanced segmentation: AI makes it possible to segment borrowers into more specific groups based on similar characteristics. This makes it easier to tailor specific credit products to niche markets and define more precise risk management strategies.

f. Bias reduction: While AI models can perpetuate biases present in the data they are trained on, with proper design and oversight, AI has the potential to reduce human biases in credit decision-making, leading to more objective decisions.

g. Improved portfolio management: Financial institutions can use AI to monitor the health of their loan portfolios in real-time, identify emerging trends, and proactively adjust strategies.

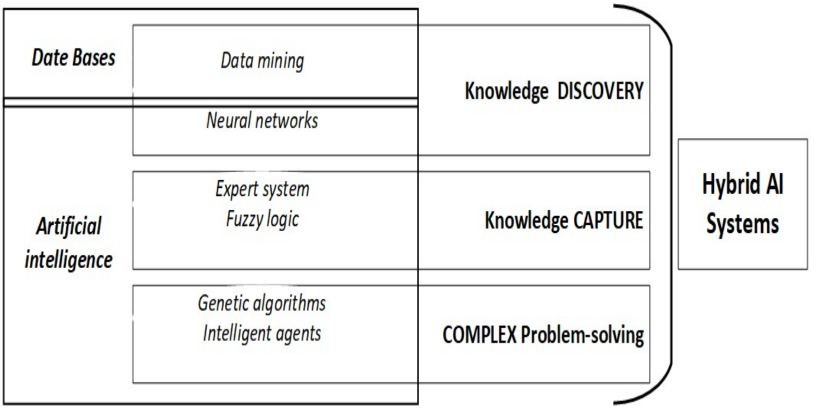
h. Integration of diverse data sources: AI enables the integration of diverse data sources, such as credit bureaus, banks, non-bank financial institutions, social media, among others, to obtain a more complete view of an individual's credit profile.

In the area of fraud detection, AI and ML-based systems identify anomalous patterns in financial transactions, enabling real-time fraud detection and prevention (Aslam et al., 2022). Financial fraud is a persistent and ever-evolving problem that represents significant losses for institutions and their customers. With the integration of AI and ML, the ability to detect and prevent fraud has taken a qualitative leap, allowing institutions to anticipate and act with unprecedented speed (Ryman-Tubb, Krause & Garn, 2018).

As for considerations, it is important to take into account data privacy, since the efficiency of fraud detection by AI depends on the analysis of large amounts of data, always in compliance with privacy regulations. Likewise, given the increasing technological dependence, it is essential to have contingency plans in case of system failures or cyberattacks. Despite the efficiency of these systems, human intervention and review remain crucial, especially in complex or ambiguous cases.

3. Hybrid systems: Practical examples

Having gone through the above, it is important to emphasize the concept of hybrid artificial intelligence systems (see Figure I). These systems combine various AI techniques and approaches, such as neural networks, expert systems, fuzzy logic, genetic algorithms, and intelligent agents, to create more powerful and versatile solutions than systems based on a single AI technology (Medsker, 2012). These hybrid systems offer a number of advantages over individual AI solutions, such as a greater ability to handle ambiguous information, adapt to changing situations, and provide more accurate and effective solutions in a variety of contexts (Khosla & Dillon, 2012).



Source: Own elaboration, 2024.

***Figure I:* Hybrid AI systems**

Within the panorama of leading companies in the development of hybrid Artificial Intelligence (AI) systems, which cover a wide range of services and technologies, companies such as IBM, Google DeepMind, OpenAI, Microsoft, NVIDIA, Palantir Technologies and SAS stand out.

IBM, through its Watson platform, provides solutions that combine neural networks, expert systems and other AI techniques for various applications in industries such as health, finance and commerce (Ventura-Fernández, Vidalón-Soldevilla & Ventura-Fernández, 2021). For its part, Google DeepMind, a subsidiary of Alphabet, has created systems capable of learning autonomously and applying that knowledge to complex problems (Powles & Hodson, 2017). OpenAI, recognized for its advances in language models such as GPT-3, is also dedicated to the research and development of hybrid AI systems, covering everything from deep learning to planning (Julianto et al., 2023).

Microsoft, through its Azure AI platform, offers a wide range of tools and services that integrate multiple AI techniques, from neural networks for natural language processing to expert systems for business decision-making (Tiutiunnyk & Rybachok, 2021). NVIDIA, famous for its graphics cards, is also involved in AI development with its AI and Deep Learning platform used by researchers and companies for the creation and implementation of hybrid AI models (Gilman & Walls, 2021). Finally, Palantir Technologies, for its part, focuses on the development of software that integrates AI elements for the analysis of large volumes of data, using everything from fuzzy logic to machine learning, especially geared towards intelligence and analytics applications for government and corporate clients (Lanzing, 2023).

Recently, two companies have created specific applications for the banking and financial services sector that deserve recognition. EPAM Systems is a global software engineering, information technology and digital design consulting company, established in 1993 and has grown to become a leading provider of technology services to companies in the banking and financial sector. It counts among its clients five of the main investment banks, as well as retail and commercial banks, payment providers, wealth management institutions, among others.

One of its notable solutions is Pling, a voice-activated tool built on Microsoft's

Azure platform. Pling allows users to carry out banking operations using voice commands, making the process easier and eliminating the need to access specific banking applications.

On the other hand, Softtek offers various artificial intelligence solutions and advanced technologies aimed especially at banks and financial institutions. These solutions cover IT infrastructure and support technologies, automation and digitization of banking processes, banking customer experiences, digital banking and payments platforms, remote workforce enablement, Ellenton (Data Masking) solutions, Fintech solutions, cost optimization IT and operational intelligence. Softtek focuses on improving the digital consumer experience, optimizing business processes and providing innovative solutions for the financial industry.

4. Hybrid artificial intelligence in the banking sector

The practical applications of hybrid Artificial Intelligence (AI) systems in the banking industry are discussed below, focusing on six fields of action observed in developed markets. Regarding Personalization and Customer Experience Improvement, the use of Machine Learning (ML) by financial institutions focuses on several key areas. First, financial recommendations are used to analyze customer behavior and transactions, offering personalized products or services such as loans, investments or credit cards. The abundance of data available on customer behavior and transactions provides the opportunity to offer tailored experiences for each customer.

In addition, fast and efficient analysis is carried out on large amounts of data generated by customers, including transactional data such as purchase histories, purchase amounts, locations and frequency of spending, as well as behavioral data such as frequency of access to banking applications, interaction with online services, responses to previous offers or communication preferences. This allows for offering personalized products and services, such as loans that identify interested or needy customers, investment opportunities tailored to the customer's risk profile and financial goals, and credit cards with specific benefits that align with the customer's spending habits.

These practices not only benefit financial institutions by increasing customer satisfaction and retention, but also improve marketing efficiency by specifically targeting customer needs and preferences, and improve decision-making by better understanding what the customer needs in terms of product development and market strategies.

Optimizing operations and efficiency through process automation is a key focus in the field of AI (Artificial Intelligence). This automation refers to the use of advanced systems to carry out tasks that previously required human intervention, especially those that are repetitive, predictable and high-volume. The main objective is to increase efficiency, reduce errors and free up employees to focus on higher value-added activities, mainly of a commercial nature.

In the realm of financial operations, AI has proven to be particularly effective in areas such as account reconciliation and transaction categorization. For example, in the account reconciliation process, which involves reconciling an organization's internal and external records, AI can quickly process large data sets and reconcile accounts in real-time or at specific intervals, identifying discrepancies and alerting the relevant teams. Furthermore, AI systems can learn from past transactions and, using ML (Machine Learning) techniques, automatically categorize incoming transactions into appropriate categories, such as "travel expenses," "office supplies," or "salaries."

Another area where AI is transforming operations is in investment management, through so-called robo-advisors, digital platforms that offer automated investment management services. These systems use algorithms and ML techniques to advise users on where to invest their money based on their risk profile, financial goals, and other personal factors (Belanche, Casaló & Flavián, 2019). Robo-advisors have democratized access to investment management, offering affordable solutions to a wide range of clients (Shanmuganathan, 2020), and allowing financial services firms to operate more efficiently and scale their operations without needing to proportionally increase their staff.

Before making any investment recommendations, robo-advisors typically ask users to complete a questionnaire to determine their risk tolerance, expected time horizon for investment, financial goals, and also whether all of this is in line with their current financial situation. Using this information, the algorithm defines an investment profile for the client and automatically selects a diversified investment portfolio based on this profile, which can include stocks, bonds, funds, and other financial instruments.

Additionally, some robot-advisors offer tax optimization strategies, where loss-making investments are intentionally sold to offset gains, thereby reducing the investor's tax bill. In addition to offering investment management services, many robo-advisors provide educational resources, such as articles, tutorials, and simulators, to help clients better understand the world of investing.

The term Big Data is derived from the enormous volumes of data that, due to their size, velocity or variety, cannot be efficiently processed with traditional applications. This data, when properly analyzed, offers valuable insights that can be used to make strategic decisions across multiple industries, including the financial industry.

Trend analysis involves observing and analyzing historical and current data to identify patterns, changes and possible future directions in various areas, such as markets, consumer behaviors and macroeconomic factors. In the financial sector, some specific applications include identifying market opportunities, managing risks by anticipating possible crises or recessions, evaluating products and services to tailor offerings, and anticipating market movements such as interest rates, stock prices, commodities and other financial instruments.

Customer segmentation involves dividing a company's customer base into smaller, homogeneous groups based on similar characteristics, such as age, income, purchasing behaviors or financial needs. This allows for offering personalized and effective products and services, as well as more precise and relevant marketing communications. In the financial sector, this translates into product customization, effective marketing and advertising strategies, improved customer service, and segmentation-based price optimization.

The financial industry is constantly evolving, regularly facing new needs and challenges for individual customers, businesses, and financial institutions themselves. To stay competitive and relevant, these institutions must continually innovate their product and service offerings. Big data analytics provides valuable insights that guide and accelerate the innovation process.

New product development involves researching, creating, and launching new offerings to meet identified needs in the market. Some of the areas where this process is applied in financial market research include identifying underlying needs through the analysis of large volumes of customer data, pilot testing to fine-tune and refine products, personalizing offerings based on big data insights, demand forecasting, and continuous improvement based on monitoring and tracking product performance in real time.

Financial institutions use big data to innovate their products and services. Examples include flexible savings accounts based on customer transaction analysis, and thematic investment platforms that respond to trends and needs observed in investor activity and interests.

The financial sector globally is heavily regulated to maintain economic stability, safeguard consumers, and deter illicit activities. These regulations are intricate and subject to frequent changes, posing compliance challenges for financial entities. The emergence of advanced technologies like Artificial Intelligence (AI) and Big Data has spurred innovation in Regulatory

Technology (RegTech), facilitating more efficient and cost-effective compliance solutions. RegTech, a burgeoning field within fintech, utilizes technology to streamline regulatory compliance processes, as outlined by Anagnostopoulos (2018); and Bayramoğlu (2021). This includes real-time monitoring of operations, leveraging AI to detect anomalies or violations and prompt necessary actions.

Furthermore, RegTech solutions leverage Big Data analytics to process vast transactional data, identify patterns, and facilitate automated reporting in adherence to regulations. These technologies also aid in risk identification, employing AI and predictive analytics to assess and address potential risks like money laundering or fraud. RegTech systems also support staff training by utilizing AI for ongoing education and content updating to align with evolving regulations.

Examining specific cases, RegTech tools are instrumental in Anti-Money Laundering (AML) efforts by tracking suspicious transactions based on patterns or unusual behavior. For Know Your Customer (KYC) processes, AI automates customer verification, document validation, and security checks, minimizing biases. Additionally, with data privacy regulations such as GDPR, RegTech tools ensure institutions comply with laws regarding the handling and storage of customers' personal data, enhancing overall data privacy compliance efforts.

Conclusions

The combination of traditional and data-driven artificial intelligence techniques was identified as offering significant competitive advantages for financial institutions. This translates into greater operational efficiency, improved decision-making, and a greater ability to anticipate and respond to customer needs.

A comprehensive strategy is suggested that includes staff training in new technologies, the establishment of strategic collaborations with specialized technology companies, and the development of flexible regulatory frameworks that encourage innovation without compromising data security and privacy.

On the other hand, the need to further explore the impact of hybrid AI on financial risk management, the customization of banking products and services, as well as its potential to boost financial inclusion and reduce the digital divide in certain populations is highlighted. These areas represent promising fields for the development of new research that contributes to expanding knowledge and optimizing the application of artificial intelligence in the banking sector.

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