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Review

The Artificial Intelligence Revolution in Digital Finance in Saudi Arabia: A Comprehensive Review and Proposed Framework

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Abstract: Artificial Intelligence (AI) has proliferated in the last few years due to the vast data we pro-duce daily and available computing power. AI can be applied in many different sectors, such as transportation, education, healthcare, banking, and finance, among many others. The financial industry is rapidly embracing AI due to its potential for high-cost savings in financial services. AI could transform the financial sector by creating opportunities for tailored, faster, and more cost-effective services. Saudi Arabia is emerging as a fast-growing market in this industry with a strong commitment to technology-driven institutions. While AI is gaining prominence and receiving government support, it has not yet become a critical component for enhancing the efficiency of financial transactions. Limited published research on AI adoption in the Saudi Arabian financial industry calls for a comprehensive literature review to examine the current state of AI implementation in this sector. Therefore, this study explores the benefits, limitations, and challenges of leveraging AI in finance, highlighting the importance of ethical and regulatory considerations for successful AI adoption in the sector. This study's findings reveal that research has been conducted on how AI improves processes in the financial sector by integrating critical components and efficient algorithms tailored to the industry's needs. Based on these findings, this study proposes a sequential framework at the macro and micro levels of management to guide AI's development and integration into the financial sector. Additionally, the framework draws insights from the existing literature to provide a detailed understanding of opportunities, challenges, and areas for improvement to maximize AI's potential in the Saudi Arabian financial sector.

Keywords: Artificial Intelligence; financial industry; Deep Learning; machine learning; finance; AI in finance; fintech; financial regularity; sustainable economic; Saudi Arabia

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1. Introduction

Artificial Intelligence (AI) is the utilization of computer systems and technology to imitate human intelligence. This intricate undertaking combines hardware and software components with the goal of replicating human thought processes. Accurately defining AI can be challenging, as many tasks that require intelligence, such as problem-solving, communicating, planning, programming, and driving, are performed by humans [1–3]. If a machine can perform these activities, it can be considered to possess AI. AI's achievements rely on algorithms, statistical models, and programs that process and analyze extensive data [4–8]. Some common AI applications include expert systems, natural language processing, speech recognition, and machine vision. In recent years, there has been considerable interest in the potential of AI and robotics to revolutionize various sectors, including public and government domains.

Various industries have embraced AI, including the finance sector [3]. AI has been successfully employed in areas such as fraud detection and prevention, customer support, investment management, risk assessment, and regulatory compliance. While challenges exist in eliminating bias, ensuring transparency, and maintaining accountability when using AI in financial services, it has the potential to improve accessibility, affordability, and the overall quality of financial products and services [5–7,9–12].

Integrating AI into the financial industry will revolutionize financial services by enabling the development of new business models, personalized services, and cost savings [13]. AI's analytical capabilities can enhance the quality of goods and services offered to customers, improving efficiency and reducing costs in compliance, fraud detection, and anti-money-laundering measures. Additionally, AI can drive innovation and transform financial service providers into data- and AI-based firms. However, AI's potential impact on financial institutions and the United Nation's Sustainable Development Goals (SDGs) [14] requires careful examination. Leveraging AI in alignment with the SDGs presents significant opportunities, particularly in the societal domain. Using AI responsibly and ethically is crucial to ensuring positive contributions to sustainable development and facilitating transparency and security measures. Integrating AI, AI ethics, and the SDGs is essential to fully harness AI's potential and maximize economic, environmental, and societal benefits while minimizing ethical concerns. This calls for collaborative efforts that are inclusive, harmonious, and interdisciplinary, ensuring that technological advancements support human progress while safeguarding the environment and society as a whole.

The Kingdom of Saudi Arabia (KSA) is renowned for its extensive and advanced financial industry in the Middle East [15]. Key players in this industry include Saudi National Bank (SNB), Al Rajhi Bank, Riyad Bank, and AlBilad Bank, all operating under the regulation of the Saudi Central Bank (SAMA). SAMA [16] has implemented measures, such as Islamic banking, to promote growth. Tadawul [17], the largest stock exchange in the Middle East and North Africa, is home to companies like Saudi Aramco and SABIC. SAMA and Tadawul are committed to incorporating technology-driven sustainability capabilities to enhance customer service. Undoubtedly, the Saudi financial sector is poised for significant growth in the coming years, supported by established standards. AI technologies are increasingly being deployed in finance, enhancing the competitive advantages of financial firms in the country. For instance, financial firms are developing AI predictive models to analyze historical data, mitigate risks, predict cash flow, refine credit scores, and detect fraud. Financial firms have contributed to the country's economic prosperity as outlined in Saudi Vision 2030 [18]. However, Saudi Arabia's IT infrastructure and technological advancements have not received sufficient attention due to its past reliance on oil.

Despite the potential benefits AI can bring to Saudi Arabia's financial sector, the potential risks cannot be denied, such as job displacement, discrimination, and cybersecurity threats that impede its growth and the attainment of the economic progress outlined in Saudi Vision 2030 [18]. Additionally, research on the state of AI and AI adoption in the sector appears limited. Therefore, this study's objective is two-fold: first, to provide a comprehensive review of AI research in finance over the past decade, and second, to provide decision-makers and specialists in the Saudi financial sector with a roadmap of the potential advantages, techniques, and overwhelming challenges of AI applications in finance. The study addresses various research topics, including the current state of AI implementation in the Saudi Arabian financial industry, the advantages, limitations, and challenges of leveraging AI in the sector, the ethical and regulatory considerations for successful AI adoption, and a proposed AI design framework tailored to the industry's needs. Specifically, the following research questions were considered:

- What is the current state of implementation of AI technologies in the financial industry in KSA?
- What are the benefits, limitations, and challenges of leveraging AI in the KSA financial industry?
- What ethical and regulatory considerations must be taken to ensure the successful adoption of AI technologies in the KSA financial industry?
- What design framework could be proposed utilizing significant AI design components and algorithms tailored to the financial industry's needs?

This study's findings will be invaluable to financial industry decision-makers and specialists who need up-to-date information on the capabilities and challenges of AI applications, ultimately allowing them to make informed decisions. We believe this research will provide in-depth insight into the opportunities, pitfalls, and avenues for improvement to maximize AI's potential in the KSA financial industry.

The rest of this paper is organized as follows: Section 2 describes this research's methodology; Section 3 presents the current state of AI deployment in the Saudi financial sector; Section 4 discusses leveraging AI in the Saudi financial sector; Section 5 presents the ethical and regulatory considerations of AI in the financial sector; Section 6 describes significant AI components and their algorithms; Section 7 illustrates the proposed AI framework for the Saudi financial industry; and Section 8 concludes the paper and outlines some of our future work.

2. Methodology

The literature review methodology involves a comprehensive and structured approach to identify, analyze, and synthesize the relevant literature on a specific research topic. This consists of formulating a research question, determining suitable search terms, searching multiple databases, and analyzing the results to locate the pertinent literature. This approach is appropriate for this research topic because it allows for an extensive examination of the current usage of AI in Saudi Arabia's financial sector, including any challenges and potential openings for further research. A comprehensive literature review is the most advantageous method for this topic; quantitative methods are usually preferred in cases where the study question assesses the prevalence of a concept or theme among numerous studies or when it examines statistical trends, patterns, and relationships.

Several published studies on AI from 2018 to the present on its adoption in the financial industry have received positive feedback. However, research on AI adoption in the KSA financial sector is limited despite the increase in financial institutions' adoption of AI. This study utilized the five-phase review design [19] illustrated in Figure 1: set the scope, define the review procedure, identify the relevant literature, assess the quality, and synthesize.

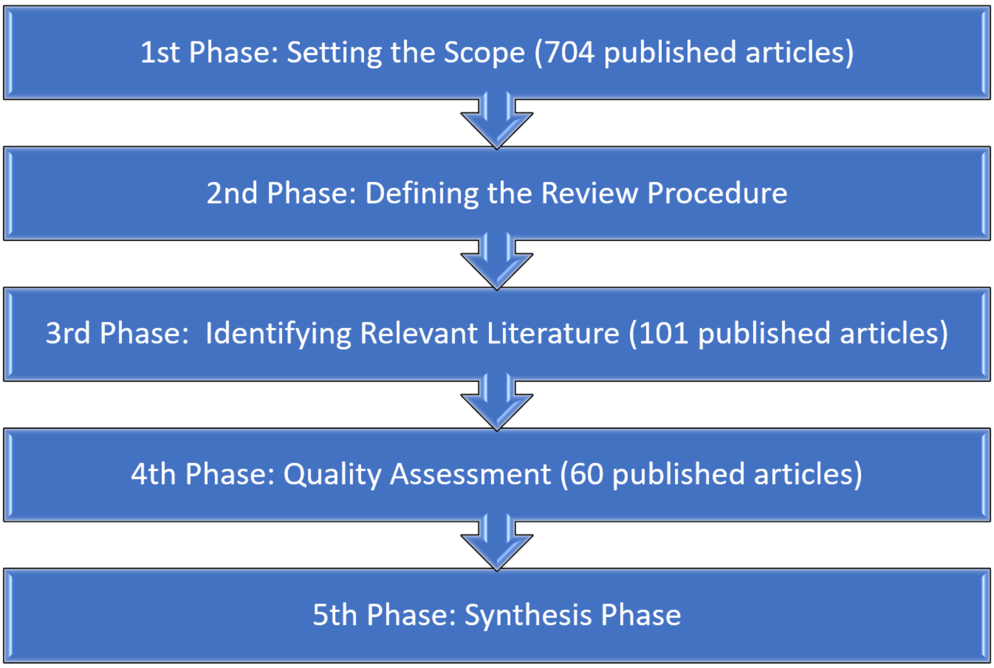

Figure 1. Review design methodology.

To set the scope, search queries were conducted online using keywords such as "AI" and "financial sector", "AI in the financial industry", "AI adoption and implementation", "AI design", "AI algorithms", and "AI in KSA". During this phase, gaps were identified in the field of AI and its adoption in the financial industry. A total of 704 published articles relevant to the subject were found. The second phase, the review process, established criteria to determine which articles should be included or excluded. The inclusion criteria focused on articles that specifically addressed AI in the financial industry and those within KSA. Papers that discussed AI adoption in education or a general context were excluded. After applying these criteria, 101 articles remained.

The third phase identified the relevant literature from these 101 articles. Only peer-reviewed conference papers or journal articles published and indexed either in Scopus, IEEE, Web of Science, or Elsevier and accessible to the public were considered. The time frame for inclusion was 2018 to 2023.

In the fourth phase, 60 articles were selected from the initial 101 based on the relevance of their abstracts, with a focus on findings related to AI's adoption in the financial industry.

Next, a synthesis phase consolidated the articles' titles, publication years, objectives, methodologies, findings, and conclusions to establish a comprehensive understanding of the perspectives on the subject under investigation. This synthesis is presented in Table 1 and encompasses the following areas: the current state of AI in the financial industry, specifically in KSA; AI's benefits, limitations, and challenges in the financial industry; ethical and regulatory considerations related to AI; and AI design components and algorithms suitable for the industry's needs.

Table 1. Literature Themes focusing on Financial Industry.

Themes	Number of Published Articles
State of AI in KSA	9
AI and Financial Industry	17
Ethical and Regulatory Considerations	4
AI Algorithms	30
Total	60

3. The Current State of Deploying AI in the Financial Industry in KSA

AI is revolutionizing the global financial sector by automating regular tasks, optimizing efficiency, and increasing our understanding of customer behavior. KSA has seen an impressive recent upsurge in AI adoption in its financial sector. The industry has been quick to adopt AI technology. Swain and Gochhait's study [20] investigated AI's effects on Middle Eastern financial institutions. To gain insight into this issue, they carried out a literature review that explored topics related to AI integration, blockchain, cloud computing, and data security in Islamic banking. Additionally, they sought potential solutions to tackle any challenges. The study's results indicated that the use of cloud computing flourished during the pandemic in Islamic banking and is still growing. Cloud services provide updates to secure data capture, storage, and interpretation processes. Their research concluded that cloud computing could be hugely beneficial in fortifying the structure and networks within Islamic banking.

SAMA launched a regulatory sandbox initiative in 2018 as an AI implementation, allowing fintech companies to test innovative products and services in a safe environment; this encourages innovation and broadens the use of AI in the financial sector. During COVID-19, it became apparent that AI and IoT were essential in the banking sector. This resulted in urban financial institutions transitioning to using robotics and AI to automate banking processes, along with many fintech companies [16]. The study highlighted that banks are less likely to experience cyberattacks when using AI technologies and improve compliance.

Furthermore, Saudi banks have applied AI technology to improve their services, such as chatbots for customer service inquiries and fraud detection systems. For instance, Saudi National Bank (SNB) implemented chatbots that are accessible 24/7 to provide customers with quick responses and an AI-based fraud detection system to analyze customer behavior and transactions.

AlQudah and Shaalan [21] recorded multiple studies illustrating the increasing use of AI technologies within Saudi Arabia's financial sector, including examples of machine learning (ML) and natural language processing used to improve the customer experience, automate tasks, and analyze data in risk management systems.

Many financial organizations increasingly use AI-powered customer service chatbots to provide personalized assistance. However, Al-Ghamdi and Al-Shehri [22] illustrated a shortage of skilled AI professionals and expertise, hindering its full implementation within the industry. They also noted the need for regulatory frameworks to ensure AI's ethical and responsible use within the finance domain. Vijayakumar Bharathi et al. [23] showed that optimism toward technology positively affects intent when using robots and AI tools for investments, whereas uneasiness and mistrust of technology negatively affect intent. These challenges, the lack of skilled professionals, and the need for ethical regulatory frameworks must be addressed to realize AI's full potential in the KSA market.

4. Leveraging AI in the Saudi Financial Industry

Using AI technologies in the KSA financial sector is becoming increasingly popular. However, the country's financial institutions are facing numerous challenges to implementation. This literature review aims to provide insight into the issues faced by financial institutions when integrating AI technologies into their services.

4.1. Benefits and Limitations

AI technologies can potentially revolutionize the financial sector by enhancing efficiency, cutting costs, and improving the customer experience. However, they also present new risks and drawbacks that must be carefully considered. One of AI's primary advantages in finance is its ability to process massive volumes of data and furnish insights that humans might overlook. These data can train ML algorithms, which can then predict future actions. Another benefit is that AI can automate repetitive or routine tasks and processes. Chatbots and robo-advisors are examples of such tools, which can respond to customer inquiries quickly and accurately [24,25], freeing up human resources for more complex tasks.

Additionally, AI technologies are useful for risk management and fraud detection because they analyze large amounts of data in real-time [24,25]. The earlier malicious activities are detected, the less likely financial institutions will suffer losses or damage to their reputation.

In addition, customers' experience can be improved with AI technologies. For example, chatbots and virtual assistants can give personalized recommendations according to individual needs and preferences [24,25], which could lead to increased customer satisfaction and loyalty.

Nevertheless, some limitations must be considered when deploying AI technologies in financial services. The first is biased decision-making due to inappropriate data used to train algorithms. To avoid this, financing organizations must ensure their data are diverse [24,25]. Data privacy and security breaches must be avoided; measures should be taken to ensure that data are securely stored against cyber threats [20]. Nonetheless, research has suggested that AI offers solutions that would have been impossible without such technology [25].

4.2. Challenges

Despite AI's continuous evolution in the KSA financial sector, certain challenges must be tackled. One of the primary difficulties Saudi financial institutions face is the shortage of qualified AI specialists and experts. As reported by AlBarrak et al. [26] there is an insufficient number of AI professionals in KSA, which impedes the emergence and implementation of AI technologies in the financial sector. This lack of skilled professionals is exacerbated due to the high demand for AI expertise in other industries like healthcare and energy. Ourdani and Chrayah [11] further underscored this challenge in their research, which accentuated the possibility of big data analytics to generate value, rationalize resources, manage risks, increase effectiveness and efficiency, and prevent fraudulence in public finance. They concluded that investing in this technology can be advantageous for authorities. Nevertheless, they mentioned certain obstructions, such as insufficient technical skills and financial resources, that impede big data projects from flourishing in public finance.

Apart from this, the cost is another challenge financial institutions in KSA encounter when implementing AI technologies. AI technologies demand considerable investment in infrastructure, hardware, and software, which can be too costly for certain institutions, especially smaller ones [27]. Additionally, maintaining and upgrading AI systems can also be expensive.

Data quality and availability are also major challenges financial institutions confront when applying AI technologies. Good-quality data are necessary for algorithms to be trained or developed; unfortunately, many financial entities struggle to obtain quality data because of data fragmentation, silos, and the absence of standardization [27,28].

Furthermore, financial institutions may need to establish regulatory frameworks that guarantee the ethical and responsible use of AI technologies within the sector. Insufficient clear directives and regulations create ambiguity and prohibit adoption and usage [28].

5. Ethical and Regulatory Considerations

Incorporating AI technologies into the Saudi financial sector can boost efficiency and improve the customer experience. However, using AI also raises ethical and regulatory issues concerning privacy, security, bias, and accountability. This literature review aims to provide insight into the ethical and legal considerations of using AI technologies in the KSA financial sector.

5.1. Ethical Considerations

Regarding AI applications in finance, several ethical issues must be considered. For instance, an AI algorithm's accuracy is only as unbiased as the data on which it is trained; if the data are biased, the outcome will be biased [29,30]. This can potentially lead to unfair or discriminatory practices in lending, investments, or other monetary activities.

Another ethical dilemma is how AI will affect job prospects. As technology advances, there are concerns that it could replace workers in data analyses and customer service roles. Organizations need to consider how these changes could negatively impact their employees and devise strategies to minimize such impacts as they could cause economic disruptions for displaced employees.

Finally, there are concerns related to protecting customers' personal information. AI models require substantial amounts of confidential financial data to work effectively, and these must be secure and comply with all related data privacy regulations. There is also the risk that an AI model could be hacked, leading to financial fraud or other illegal activities.

Therefore, organizations should approach using AI in finances with ethics at the forefront of their minds. By tackling bias, ensuring employment interests are considered, and following all customer data privacy regulations, organizations can ensure that any use of AI will be positive for all stakeholders involved. Furthermore, financial institutions need to guarantee that their data are varied and representative of all customer groups to reduce the potential for bias in any algorithmic decision-making processes [29,30]. Last but not least, organizations must take steps to ensure customers' personal information remains secure against unapproved access or disclosure [29,30].

5.2. Regulatory Considerations

While utilizing AI technologies, it is essential that financial institutions comply with data protection laws such as the Saudi Arabian Data Protection Law and the General Data Protection Regulation (GDPR) of the European Union [21,22,31]. Moreover, customer consent must be obtained prior to using personal data for AI-related activities. Accountability is a necessary consideration; financial institutions must be accountable for the decisions made by their AI systems, and customers must have access to redress mechanisms if they are adversely affected [21,22,31]

Mishra and Guru Sant's study [24] offers insight into what motivates the adoption of AI in financial investment services and provides guidance on how to promote its use. Therefore, financial institutions must comply with local and international data protection laws and maintain accountability for their AI systems' decisions. This will allow them to maximize the potential of AI technologies to transform the sector and preserve customer privacy and ethical practices.

6. Significant AI Components and Their Algorithms

AI is essential in the financial world because it can automate operations, reduce expenses, and refine decision-making. Yet, one must account for several critical factors to deploy AI that can meet the financial sector's requirements.

6.1. Significant Components

Developing AI systems that meet the financial industry's needs requires careful consideration of several critical components, including data quality, data security, explainability, and human oversight.

Data quality: High-quality data is a critical component of any AI system, and financial institutions must ensure that their data are clean, accurate, and up-to-date [28,29]. Data quality is essential for building accurate machine learning models that can make informed decisions.

Data security: Financial institutions must also consider the security of their data when developing AI systems. Data breaches can have severe consequences for financial institutions, including damage to their reputation, legal liability, and loss of customer trust. Financial institutions must ensure their AI systems are secure and comply with relevant regulations [32–37].

Explainability: It is a critical component of AI systems in the financial industry, where decisions can have significant consequences. Financial institutions must ensure that their AI systems can explain how decisions are made and provide insights into the factors that influence those decisions [32]. This AI component is necessary for building trust with customers and regulators and improving the accuracy of AI systems. Adams and Hagras [38] proposed a risk management framework for implementing AI in banking, emphasizing explainability and outlining the implementation requirements for AI to achieve positive outcomes for financial institutions, customers, markets, and societies. In model-specific explainability, a model is designed and developed to be fully transparent and explainable, eliminating the need for additional explainability techniques. Every customer must be accounted for; any decision driven or informed using AI methods that would impact customers should be clearly explainable by design, with human oversight and risk controls in place to guard against deviations from this principle.

Human oversight: AI systems in the financial industry must have human oversight to ensure they make fair, unbiased, and ethical decisions [29,30]. Financial institutions must ensure that their AI systems are aligned with their organizational values and have mechanisms in place to monitor and correct any biases that may arise.

Financial institutions must invest in infrastructure and talent to ensure their AI systems are secure, reliable, and aligned with organizational values.

6.2. Algorithms

AI algorithms can help financial institutions enhance customer services, manage risks, detect fraud, and improve investment decisions. AI algorithms have become an integral part of the financial industry. Among the algorithms on which AI can be utilized in the finance industry and that are well-known are ML and Deep Learning (DL). Figure 2 below illustrates the relationship of AI with ML and ML with DL:

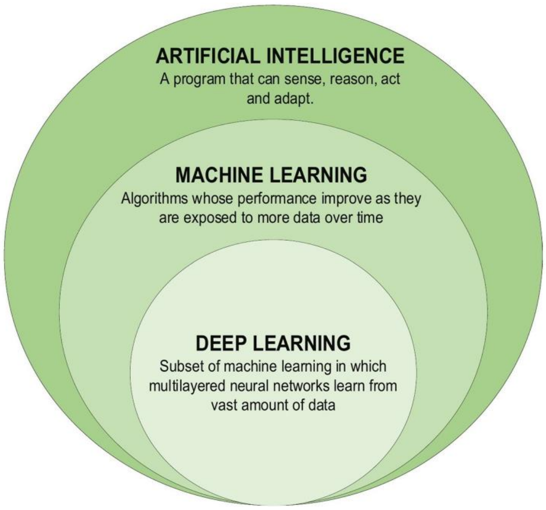

Figure 2. Relationship of AI–machine learning–Deep Learning [39].

6.2.1. ML Approach

The ML algorithms in the studies conducted in [39–44] are among the best AI solutions for the financial industry. Prominent machine learning methods are connected to financial risk and a taxonomy of financial risk management responsibilities, creating a framework for effective risk management strategies. The studies identify major challenges practitioners face and noteworthy papers in the field, and they highlight new trends and research topics for additional exploration. Various ML algorithms and platforms are found and rigorously evaluated based on factors including accuracy, efficiency, speed, and usability. Machine learning offers different trading tactics based on Support Vector Machines (SVMs), neural networks, and quantitative financial factors. Among the well-known ML algorithms used in AI systems in the financial industry are the following:

Artificial Neural Networks (ANNs): ANNs are among the most popular AI algorithms in the financial industry. They are inspired by the structure and function of the human brain, and they can learn from past experiences and use this learning to predict future outcomes. ANNs are used for tasks such as credit scoring, fraud detection, and financial forecasting [34,45].

Random Forest (RF): RF is another popular ML algorithm widely used in the financial industry. RF is a type of decision tree algorithm that uses multiple decision trees to make predictions. It can handle large datasets and provide accurate predictions for complex financial problems. RF is used for tasks such as credit scoring, loan default prediction, and stock price prediction [46].

SVMs: SVMs are supervised learning algorithms that can be used for classification and regression tasks. SVMs are widely used in the financial industry for tasks such as credit scoring, fraud detection, and portfolio management. They can handle large datasets and provide accurate predictions for complex economic problems [45,47].

Several studies reported machine learning's effectiveness in AI systems in the financial sector. Alharbi et al. [15] stated that as a crucial business component, financial risk management aims to reduce losses and increase revenues. With its capacity for information-driven decision making, ML has become a viable source of new techniques and technologies. Yet, comprehending intricate subject matter and the changing literature is difficult. A thorough investigation of machine learning's uses in financial risk management has been performed to fill this gap. These studies offer taxonomies of risk management tasks and link them to applicable ML techniques. Along with highlighting important works, the research identifies key obstacles and new trends. Vats and Samdani [40] claimed that ML has substantially influenced several financial domains, including portfolios, securities, stock market forecasts, risk management, and debt management. Using machine learning approaches in various sectors has enhanced decision-making procedures and results. Algorithms like

SVM and neural networks, along with quantitative factors, have been used to improve trading strategies and provide alphas. Further improving the accuracy and insights offered with ML models are developments in genetic algorithms, back propagations, and wavelet analyses of time series.

The development of ML [8,40] in finance can be traced to the 1970s, with an initial concentration on financial time series forecasting. Improvements in ML approaches have made it possible to apply these models to smaller datasets, leading to successful forecasting across many economic areas. As ML approaches like cross-validation are included in conventional econometric procedures, ML's integration with econometrics has become more widespread. Economic and financial forecasting, stock market simulation, and risk estimates are all examples of ML applications in economics and finance.

Research on the confluence of AI and ML has mostly focused on credit risk assessment. Early research highlighted the effectiveness and durability of neural networks for credit risk prediction, as seen in Duarte and Barboza's study [43]. The best models for predicting credit risk have evolved, including ANNs and decision trees. These models, sometimes referred to as "black box" technologies, have raised questions about how interpretable they are due to their complexity. Duarte and Barboza examined combining methodologies and classifiers to increase prediction accuracy and decrease mistakes. A continual drive in AI research is the desire for additional variables, classifiers, and more forceful techniques. Another study by Sujith et al. [44] confirmed the value of ML approaches for a pattern analysis, insight extraction, and result forecasting across diverse domains in the context of financial decision making inside businesses. Machine learning accelerates the switch from physical to electronic data storage and improves decision making. It helps executives maximize revenues, reduce operational costs, manage risks, enhance productivity, and engage consumers by utilizing massive amounts of data. Management is equipped with clear information for efficient decision making at all levels of the company, thanks to the insights and customized reports provided with ML algorithms.

According to Ali et al. [32], financial fraud is an extensive problem that presents serious difficulties for businesses and organizations. Due to their ineffectiveness and time-consuming nature, conventional fraud detection methods have given way to AI and machine learning techniques. Current machine learning-based fraud detection research has emphasized well-liked methods like SVMs and ANNs. In this context, credit card theft has received substantial study. However, it is also necessary to investigate unsupervised learning techniques, such as clustering, and text-mining methods to convert financial texts into feature vectors. Lakhchini and Hassan [6] used a scoping review in conjunction with an embedded review to assess advancing AI and ML in financial research. Their study outlines important fields where AI and ML are heavily used, such as portfolio management, risk management, financial fraud detection, sentiment analyses, stock market prediction, data protection, and big data analytics. To guarantee ethical and successful deployment, they underline the necessity of addressing ethical issues and their possible effects on the workforce.

Undoubtedly, machine learning has become a viable technology in financial risk management, enabling information-driven decision making to reduce losses and increase revenues for enterprises. Comprehensive surveys have been essential in examining machine learning's uses in this area despite the difficulties of accessing extensive domain knowledge and the evolving literature. The papers mentioned above offer useful taxonomies of risk management activities, link them to pertinent ML techniques, and highlight new trends and challenges. ML has had a substantial influence in several financial sectors, including portfolios, securities, stock market forecasts, risk management, and debt management. The performance and resilience of ML approaches have been demonstrated in various applications, including credit risk assessment and financial fraud detection, although interpretability remains an issue. Machine learning uses large datasets to improve financial decision-making processes by allowing businesses to manage risks, engage consumers, and enhance efficiency. Implementing AI and ML in finance should continue to advance responsibly, and future research should investigate unsupervised learning methodologies and text-mining tools to address fraud detection challenges.

Machine learning improves financial risk management, notably in the banking industry. The banking sector illustrates the advantages and difficulties of using ML in areas including regulatory compliance, market risk management, operational risk management, credit risk management, and operational risk management. Market microstructure, business cycles, recession forecasting, credit scoring, and portfolio optimization are just a few of the numerous themes examined in various research projects. These studies highlight the excellent accuracy and efficiency of AI algorithms with applied ML approaches in the banking sector. They emphasize these algorithms' ability to improve credit risk analyses, fraud detection, and investment decisions. Financial institutions may enhance their decision-making processes, reduce risks, and provide better results across a variety of financial industry areas by harnessing AI's potential.

6.2.2. DL Approach

DL is a subset of ML inspired by the structure and function of the human brain. DL algorithms use multiple layers of artificial neurons to learn from past experiences and make predictions. It is used for tasks such as sentiment analysis, fraud detection, and portfolio management. An exhaustive literature analysis and survey were conducted in a study on DL models in banking and finance [48]. It aimed to systematically examine and evaluate the models and their development and input data. The three critical elements of data quality, model interpretability, and model robustness were also examined because they can significantly impact the outcomes of financial DL models. Several studies thoroughly examined several financial DL model applications, including algorithmic trading, portfolio management, risk assessment, fraud detection, and others [33,35,40,48,49]. These studies compared the efficiency of DL models to more traditional ML and soft computing techniques and provided interesting details on potential future applications of DL research in finance. Among the commonly used DL models are the following:

Recursive neural networks (RvNN) have been a promising technology in the last decade. RvNNs are models for automated learning that analyze data from structured domains [49]. They have the ability to classify outputs using compositional vectors and offer hierarchical predictions. The RvNN architecture is designed to evaluate objects with randomly produced structures, such as graphs or trees. This technique converts a variable-size recursive data structure into a distributed representation with a fixed width.

Recurrent neural networks (RNNs) [50,51] are a popular and well-known DL technique. RNN is frequently used in NLP and speech-processing applications. Unlike conventional networks, RNN uses sequential data in the network. Because the data sequence contains relevant information due to its intrinsic structure, this property is crucial for a broad range of applications.

Convolutional Neural Networks (CNNs) [52–56] are one of the best-known and commonly used DL networks and a special case among DL networks. A CNN constructed for two-dimensional image data consists of one or more fully connected layers after one or more convolutional layers, sometimes with a subsampling layer in between. However, they may be used as one-dimensional data, such as time series and textual sequences. The rise in DL's popularity can be attributed to CNN. Financial institutions may also utilize CNNs to optimize and modify a firm's capital structure, prevent financial crises, and monitor a company's financial situation in real-time [56].

Studies have investigated the use of DL models in the finance and banking (F&B) industry. One study [56] addressed the gap in the available AI literature employing DL models by thoroughly assessing and analyzing 40 publications between 2014 and 2018. Their research demonstrated the connections between the seven fundamental F&B domains and popular DL models. Each paper was assessed as part of a framework that evaluated model preparation, input data, and assessment techniques. This study contributed significant knowledge to financial analysts and academics in F&B deep learning applications, delivering insights into the best DL models for particular domains and providing suggestions based on model viability.

An increasing focus has been placed on early warning systems and risk management in the context of promoting economic growth. According to Sun and Li's study [57], financial regulatory authorities need sensitive and scientifically informed processes to develop an efficient early alert system. In this context, the study examined the process of systemic financial risk and introduced the use of DL technology to reconstruct the index system for assessing financial security and providing early warning. The project used DL approaches to perform empirical research while also giving regulatory agencies a solid platform on which to develop a financial-risk early warning system. In addition, it included a prediction and assessment approach for a DL-based financial-market investment analysis. The empirical findings showed that DL models, such as the deep belief network and RvNN, outperformed reference models like the auto-regressive moving average, improving the assessment and management of exchange-rate risks in the financial investment market.

AI applications have greatly aided financial advances and the creation of intelligent finance systems. Deep learning techniques have drawn a lot of attention due to their effectiveness. Kuiziniene et al. [58] stressed the need to comprehend the variety of DL techniques and how they might be used in the financial industry. The study gave an overview of research publications that examined DL in finance and described the designs of several well-established DL algorithms. It emphasized the widespread use of DL in finance, its focus on predicting problems, the growing use of NLP approaches, and the propensity to mix several models or utilize voting classifiers. The need for balanced datasets and data standardization for training DL networks was also stressed. His paper offers a thorough overview and analysis, making it a useful tool for scholars looking into DL applications in banking.

With DL models gaining popularity due to their superior performance, the topic of computational intelligence in finance has seen increasing interest and investigation. Ozbayoglu, Gudelek, and Sezer [59] proposed a thorough analysis of the most advanced DL models for financial applications. Works were categorized according to targeted subfields of finance, and the specific DL models used were examined. Additionally, they highlighted the research pipeline for existing field investigations and suggested potential future applications. Their survey acts as a road map for anyone curious about the topic by providing insights into the current research environment and spotlighting the durability of DL's effect in finance.

A methodical and thorough literature review was undertaken emphasizing DL approaches in stock market forecasting [60,61]. The study identified four subtasks of stock market prediction and presented a unique taxonomy to classify cutting-edge models based on deep neural networks. The research stressed the need to address time series anomaly detection, continuous learning, and better assessment measures and datasets linked with real-world trading systems. Utilizing self-supervised learning tasks, combining DL methods with online learning strategies, and investigating distributional reinforcement learning and model-based approaches in stock market forecasting were recommended. This study advances the subject of machine learning in stock market prediction by offering a thorough analysis of prior research and suggesting new paths.

Numerous studies and analyses have been conducted using DL models in the F&B industry. For financial analysts and academics, these studies have identified key F&B domains and established connections between these domains and DL models, providing insightful information. Additionally, DL technology has demonstrated success in rebuilding the index system for assessing financial security and early warnings, giving regulatory bodies solid bases for risk management. With an emphasis on predicting tasks and using NLP techniques, DL methodologies have also significantly influenced financial innovations and intelligent finance systems. Furthermore, interest in computational intelligence in finance has increased, with DL models gaining popularity due to their improved performance. Despite that, it is increasingly evident that the research methodology of every study using deep learning models in the future must align with established procedures in the financial sector. While there are several studies on trading strategy, price prediction, and portfolio management, there is a notable lack of research on market simulation, stock selection, hedging strategy, and risk management [62]. By utilizing DL approaches [50–63], several studies showed improvements in financial analyses, risk management, and the creation of intelligent financial systems.

7. The Proposed Frameworks

Drawn from the findings in the previously mentioned literature, two sequential frameworks are introduced in this study. The first framework is on the management level (macro level) and provides a specific financial sector with considerations to address before AI is integrated or adopted into their financial processes in Saudi Arabia, given its unique culture, as shown in Figure 3. The framework is surrounded by dotted lines, indicating that AI design can be influenced by culture, International Organization for Standardization (ISO) standards, and global AI trends.

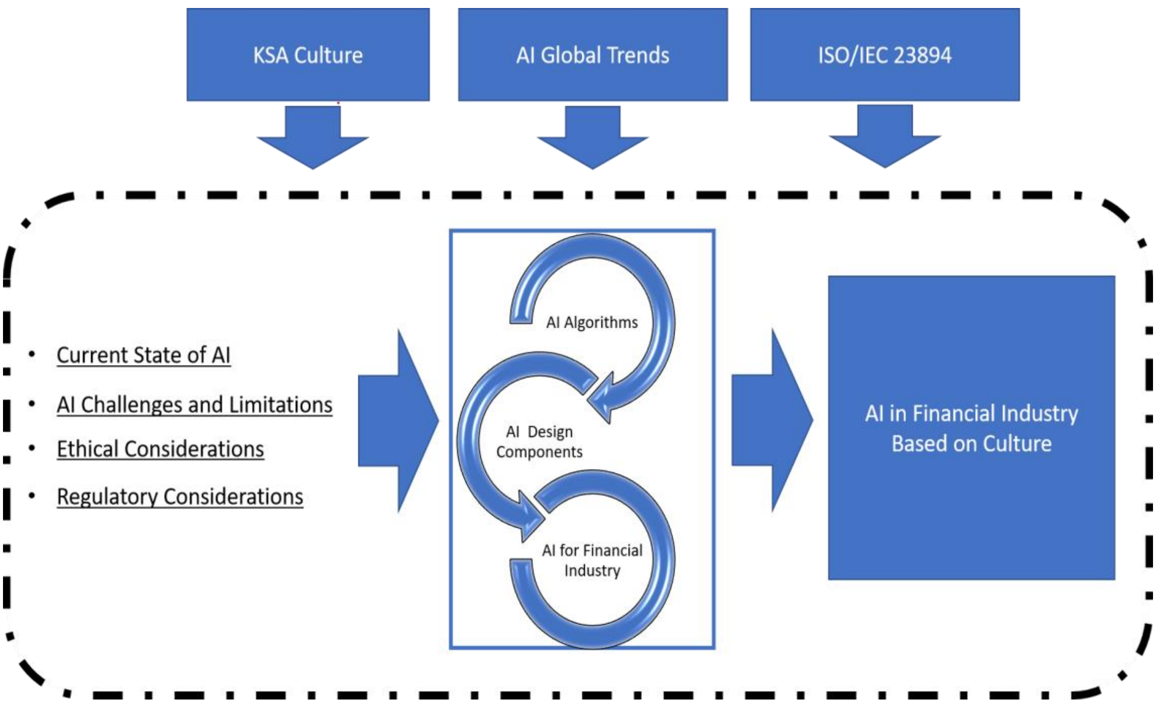

Figure 3. Proposed AI in financial industry framework (macro-level approach).

The framework for AI in the financial industry consists of various inputs, processes, and outputs. It shows the external factors that affect AI adoption in KSA. The inputs include the current state of AI, its challenges and limitations, and ethical and regulatory considerations. These factors are critical in determining AI's design in the financial industry. The process involves the algorithms and AI design components, which must be carefully crafted to ensure efficiency, accuracy, and reliability. The output of this process is AI's implementation in the financial industry, which has revolutionized how financial services are delivered.

Culture plays a significant role in shaping AI design in the financial industry. Considering cultural values and norms is essential to ensure the design aligns with local expectations and regulations. Figure 4 presents the second framework (at the micro level) for developing and integrating AI in a particular financial institution.

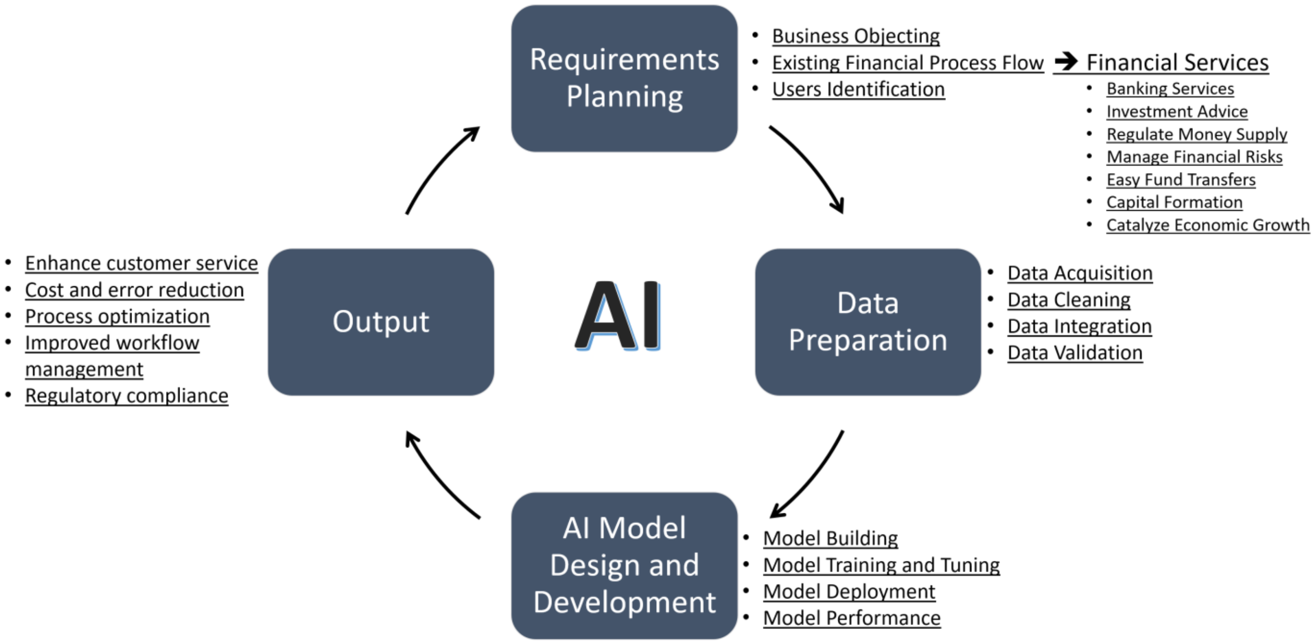

Figure 4. Development of AI in financial industry (micro-level approach).

After integrating the framework, the financial sector is ready to develop AI in its financial processes. Based on the framework proposed in Figure 4, creating and implementing an AI system are the next two phases in the several that make up the AI lifecycle. Understanding the users' present routines and practices is the first step in generating requirements. The goals and challenges that the AI system should confront should be clarified throughout this phase. The next stage is to compile pertinent data and prepare it for analysis. This procedure includes locating the sources of the information, gathering it, and verifying its accuracy and integrity. Data are essential for building AI models since they serve as the basis for pattern recognition and prediction. The process of "model engineering" refers to using tools and methodologies to construct an AI model. First, the data must be cleansed, suitable machine learning methods must be chosen, and finally, the model must be created. The calibration process also involves optimizing and adjusting the model to increase accuracy and performance. The model's inner workings are clarified through interpretation, which also facilitates understanding of how the model produces opinions. In later steps, the AI model is evaluated and confirmed. Verification assures that the model is applied correctly and performs as expected. Validation assesses the model's performance using actual data to ensure it produces reliable and accurate findings. Establishing faith and confidence in the AI system is crucial at this stage. The AI system is employed to complete specified tasks at the output stage, which is the last one. This includes enhancing customer service by offering personalized guidance or support, lowering costs and mistakes by automating laborious tasks, optimizing procedures to boost productivity and efficiency, managing workflows more successfully, and guaranteeing regulatory compliance. These results will show the influence and effectiveness of the AI system in attaining the targeted goals and significantly impacting enterprises.

Thus, the framework for AI in the financial industry is a complex and dynamic process that requires careful consideration of various factors to ensure optimal results.

8. Conclusions

The financial sector has made significant advancements in AI technologies. However, challenges must be addressed, including a shortage of technical expertise and the need to adhere to ethical and regulatory laws to ensure the responsible development and use of AI in the Kingdom of Saudi Arabia. It is crucial for the Saudi Arabian government and financial institutions to collaborate to tackle these challenges and promote the development of the AI ecosystem in the financial sector.

Contrary to common assumptions, the findings further revealed that AI is not a threat that will replace human workers. Instead, it is a powerful tool that enhances human capabilities. By automating mundane tasks and streamlining processes, AI allows financial professionals to focus on more complex and strategic aspects of their work. The application of AI is ushering in a new era of innovation and efficiency in the financial sector. To leverage its full potential, finance professionals can use AI to make faster, more informed decisions, improve customer experiences, and drive overall industry growth and success.

This research introduces two sequential frameworks that can guide financial institutions at the macro and micro levels as they develop and integrate AI into their business processes. The framework serves as a roadmap for these institutions. In future work, the author intends to utilize the proposed framework in a specific business process in a financial institution in Saudi Arabia to evaluate its effectiveness.

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