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Original Article

Systematic Review of Artificial Intelligence Techniques for Enhancing Financial Reporting and Regulatory Compliance

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Abstract - Artificial intelligence (AI) has transformed and dramatically changed conventional financial practices by automating monotonous processes involving financial reporting as well as that involving regulatory compliance, improved the accuracy of data, and enabled the supervisor to observe their regulatory needs in real-time. This study presents an inclusive literature review of AI in financial reporting and compliance through innovation techniques like neural networks, NLP, and also ML. Among the main conclusions, the significant imposition of AI to enhance fraud detection, automation of journal entries and compliance with sophisticated regulatory frameworks such as AML and KYC through advanced analytics and systems based on NLP are listed. Nevertheless, despite the increasing adoption, explain ability, data privacy, and regulatory acceptance are among the challenges. This review will summarize existing research, establish methodological patterns and areas of gaps to benefit future research and provide information to quality practitioners and policymakers working in the field of AI-based financial governance, rapidly developing in an environment of constant change.

Keywords - Artificial Intelligence, Financial Reporting, Regulatory Compliance, Automated Accounting, Financial Data Analytics.

1. Introduction

The sectors of the financial industry have reached a historically unprecedented development towards digitalization. Data is increasing at an exponential pace, and computing power is evolving rapidly. Given the growth in complexities of financial transaction processing, audit, and regulatory enforcement, traditional financial reporting and compliance approaches have been unable to keep up with the progress [1]. Traditional processes are often slow, lack scalability, and prove to be inaccurate in meeting shifting regulatory obligations. AI is emerging in its own as a powerful actor in the situation, enabling work to be automated, anomaly detection [2], and improving decision-making in traditional financial operations.

ML, natural language processing, as well as robotic process automation are examples of AI approaches being applied to improve the efficiency and regulation of financial reporting These can draw meaning from large raised unstructured data sets to generate reports, track fraud, and automatically monitor compliance obligations in real time [3]. Both financial institutions and regulators are steadily adopting AI tools as a strategy for transparency, decreased human error, and increased efficiency [4]. Therefore, AI is taking a more strategic role in changing the landscape of how organizations think about not only the internal controls related to regulatory compliance, but also the external regulatory mandates themselves.

Although interest in and use of AI in finance are growing, there is still a patchwork of references to how different techniques were applied to the various aspects of financial reporting and compliance. The majority of earlier studies concentrated on particular techniques or case studies rather than offering a thorough synthesis of the procedures, findings, and difficulties [5]. In addition, continued regulatory discomfort with explain ability, accountability, and data privacy will hinder widespread adoption. The time is right for a systematic review to collect existing knowledge, measure the success of AI applications, and identify any trends and gaps that can prompt future research.

The study on AI techniques for financial report production and regulatory compliance applications is thoroughly examined in this article. The review organizes studies by type of AI method used, applications, and industry, and evaluates study findings, challenges to implementation, and potential areas for future research. The review provides an orderly and critical examination of the existing literature to provide direction for researchers, practitioners, and policymakers to assess the potential and limitations of AI in a critical area of financial governance.

1.1. Structure of the paper

This paper is structured as follows: Section II describes AI techniques in finance. Section III describes AI applications in financial reporting. Section IV covers AI and regulatory compliance. Section V provides a literature review, and Section VI concludes the study with future research recommendations.

2. Artificial Intelligence Techniques in Finance

AI has also had a great impact on the financial service industry by providing highly sophisticated methods of automating operations, making decisions, and bridging regulatory gaps. There are a few basic strategies of AI, such as ML, NLP, expert systems, and early neural network models, which were employed in the banking sector before 2019. Financial forecasting, fraud detection, and credit scoring are some of the tasks that have been extensively exploited by ML, in particular, supervised approaches such as support vector machines (SVM), logistic regression (LR), and decision trees (DT). To find out hidden patterns in the transactional data and customer behavior, unsupervised learning methods, such as clustering and dimensionality reduction methods, have been employed.

Thanks to NLP, financial setups could take a look at the unstructured content of reports, news, and social media to understand the mood of the market and draw compliance-related data out of it. Use of expert systems based on a customized and predetermined set of rules and knowledge bases were introduced in areas where logic was more definite with regard giving of advice as in regulatory compliance and risk assessment areas [6]. Also, neural networks, at the early phase of its application to finance, showed promise in analytical sectors such as algorithm trading and pattern recognition in time-series data. Collectively, these AI techniques laid the groundwork for enhancing the accuracy, efficiency, and reliability of financial operations and compliance frameworks before the rise of more complex deep learning models after 2019.

2.1. Machine Learning Algorithms in Finance

ML is still not fully defined in the current literature, but it can be described as a procedure where a system changes its structure through interactions with its environment, as well as the interaction process changes as a result of these structural changes [7]. This is a condensed version of a previously proposed definition for neural networks. Three primary learning paradigms, each with its own set of uses in financial time series prediction, are contained within this general theorem. When a dataset containing inputs and labelled targets is accessible, supervised learning is employed for prediction tasks.

One example would be predicting the direction of a stock price movement the following day, utilizing technical market indicators (binary classification). Regression is another possible use case for supervised learning algorithms; that is, making a continuous value prediction rather than a class label prediction. In the previous example of stock prices, this would mean forecasting the real return or price of the stock rather than picking winners and losers.

2.2. Artificial Neural Network (Anns) Applications in Finance

A relatively new computer modelling technique, ANNs have quickly gained widespread use across several fields for simulating difficult, real-world issues. Over the last few decades, ANNs have served as the basis for a plethora of innovative approaches with a wide range of potential uses, drawing inspiration from biological nervous systems and brain architecture [8]. In a broad sense, highly adaptable, learning, and generalizable information processing systems are known as ANNs.

ANNs are a fantastic answer for subjective information processing, forecasting, decision-making, and related issues because of their high degree of adaptability, as Figure 1 illustrates. These domains have grown in significance over the last few decades in numerous industrial and real-world applications. Recently, NNs have become more and more popular as a tool for financial decision-making because of their many advantageous features. Consequently, the efficacy of NNs in the banking industry has been the subject of conflicting studies.

2.3. Natural Language Processing (NLP)

Financial forecasting using NLP approaches is a new area of study, and the methods being employed are likewise rapidly evolving. There aren't many earlier reviews. The majority of them have just been released. One of the first reviews in the sense of NLFF, as far as we know. Before it, there were some essential conversations on how news affects stock markets. Not precisely what is discussed here, other related ideas that have been studied include either manually processing text or just using numerical data. At the nexus of behavioural economics, ML, as well as linguistics, is text mining for market prediction [9]. This includes the many kinds of input datasets, pre-processing techniques, and ML strategies used.

Despite being somewhat out of date in light of subsequent research developments, many of the ML algorithms that were presented including SVM, Naive Bayes, and decision rules remain widely used in the field. The systematic point of view is the only one that adequately addresses sentiment analysis concerns. By contrast, our poll adds two extra things. Comparing and explaining the various setups used by these systems is the first step; the second is adding the most current focus on sentiment analysis, event extraction, and deep learning.

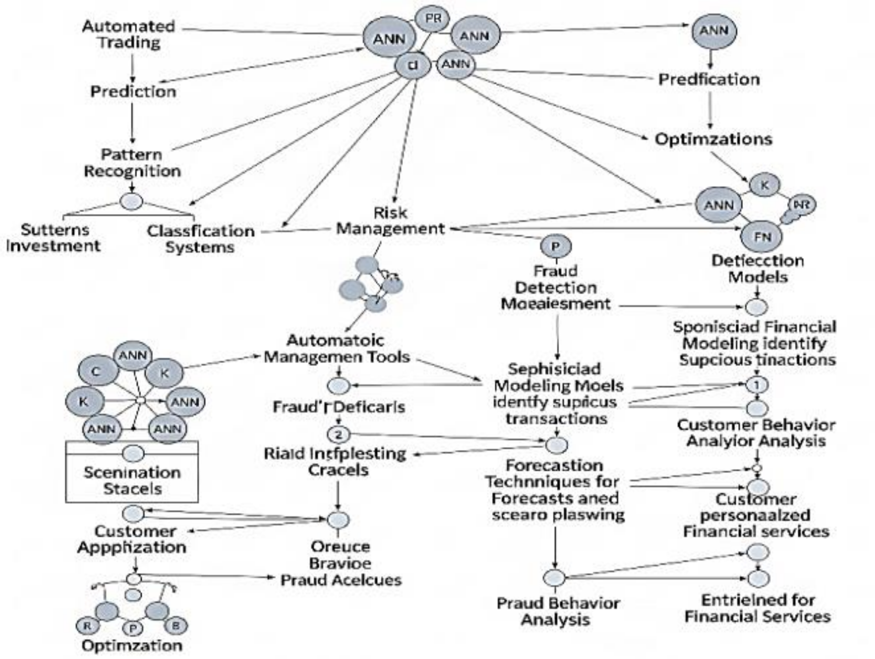

Fig 1: Artificial Neural Network Applications in Finance

3. Applications of Ai in Financial Reporting

AI was increasingly involved in the transformation of financial reporting, primarily through the automation of repetitive tasks, improved accuracy of financial datasets, and increased ability to understand finances. Most of the ML algorithms were used to transform teams' capability to interpret large document sets and process large volumes of financial transactions to generate reports with limited human intervention [10]. These systems were able to learn from historical datasets to identify discrepancies and anomalies and assist in the integrity of financial statements. The use of AI also provided the capability of automating journal entries and similar consolidation applications, improving the productivity of the monthly or quarterly financial-reporting process.

By NLP, AI was able to better complete and standardize financial datasets by extracting pertinent financial data from unstructured documents such as emails, contracts, and bills. Predictive analytics supported by AI increased the capacity of organizations to forecast their financial performance and report on risk as well as making more data-driven decisions. Expert systems could be used to regulate compliance with accounting guidelines by applying a governing ruleset to complex reporting. Collectively, these improvements allowed professionals to work comparatively more quickly, reliably, and transparently during the financial-reporting process when reporting, as the professionals allowed only small deviations from data transaction evidentiary compliance.

3.1. AI and Machine Learning on Financial Institutions

Financial institutions may increase their profitability and efficiency while lowering their expenses and risks in a number of ways with AI and ML. The building of buffers and ultimately system-wide stability would benefit from the higher profitability [11]:

- Increased revenue and decreased costs are possible outcomes of implementing AI and ML into financial institution operations (Figure 2). Financial institutions, for instance, might be able to put more resources into satisfying high-fee or potentially-growth customers if AI and ML help with customer need identification and better targeting or customization of products to profitable customers. It is possible that operational costs may go down if common business processes were automated.
- AI and ML can improve risk management by predicting threats early and more accurately. For example, if AI and ML allow financial institutions to make decisions based on previous correlations between asset values, it is possible that these hazards can be better managed by them. The entire system may benefit greatly from tools that reduce tail risks. Also, fraud, questionable transactions, defaults, and cyber-attack risk may be better anticipated and detected with the use of AI and ML [12], which might lead to improved risk management.
- The amount of data and the open-source nature of AI and ML research may promote cooperation between financial institutions as well as other sectors, including sharing economy and e-commerce enterprises.

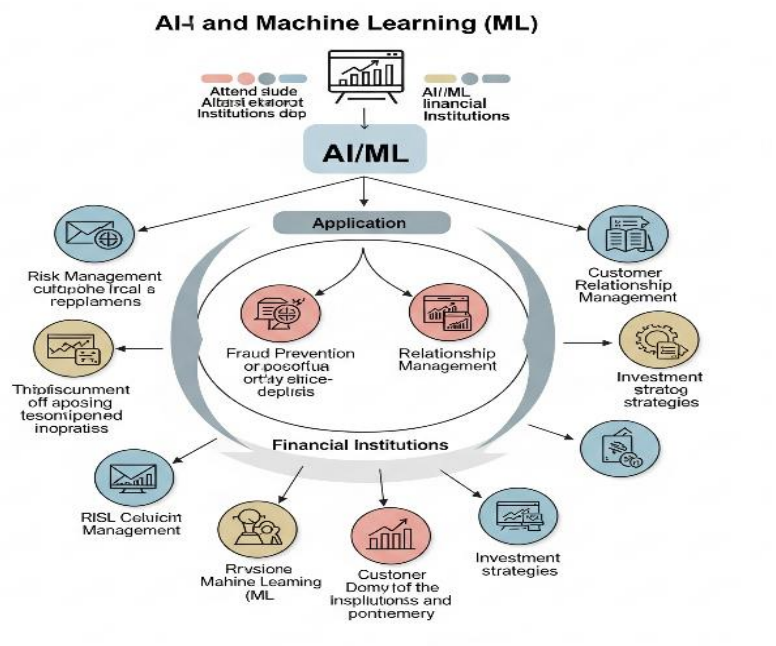

Fig 2: AI and ML in Financial Institution

3.2. Uses of AI in Finance

AI has increasingly become a critical tool in strengthening the financial ecosystem, especially in detecting fraud, enhancing security, and improving decision-making. By leveraging ML, predictive analytics, and intelligent systems, organizations are addressing key challenges in transaction safety, user authentication, and market prediction. The following are notable applications of AI in financial operations:

- **Fraud Detection:** Online fraud has become so prevalent as e-commerce has grown in popularity that it is currently hard to stop [13]. At the moment, the harm from fraudulent transactions in the US alone was thirteen times the real fraud value.
- **Increasing security:** Many organizations are working to improve the security of online transactions and associated services by implementing artificial intelligence. If there is a computer gateway that can precisely forecast unauthorized access, then it is feasible.
- **Spending Pattern Prediction:** Many organizations and financial services utilize AI to identify customer expenditure [14]. Useful for preventing fraud or theft in the event of a stolen card or compromised account.
- **Stock Broker system:** A computer algorithm has been trained to anticipate the best times to buy and sell shares, taking into account the current climate of uncertainty and collapse, to maximize profits and minimize losses.
- **Client-side user authentication:** This can once again verify the user's identity and enable the transaction.

3.3. Fraud Detection and Anomaly Detection

The detection algorithm's classification of fraud detection procedures is the most efficient way to determine which approaches are suitable for the issue area. It is also able to assist us in finding out why specific approaches were taken or were effective. It will also be able to highlight any research gaps by examining algorithms that are not well-experimented with. It was previously mentioned that statistical models and neural networks were studied early in fraud detection research, but it can be added that these remain popular methods [15]. A few investigated LR, the majority employed at least one kind of neural network, and still others employed Bayesian belief networks and other Bayesian techniques. CDA application has been comparatively rare. The LR and neural networks may be selected because of their properly established popularity, which provides them with an opportunity to become a kind of control method in terms of which other methods are checked. Relatively, SVM and genetic programming, which are more advanced, were considered with significantly less attention and that all the methods considered in their study were a type of classification and that they did not conduct any study based on clustering and time-series methods, and the research was mainly on supervised learning rather than unsupervised learning.

4. Applications of Ai in Regulatory Compliance

Regulatory compliance has become a major use case for AI-- particularly given the fast-growing complexity and weight of regulations around the globe. Financial institutions began to implement AI-based technology solutions to help them automate compliance monitoring, maintain compliance and allow their human capital to devote their time to other tasks as opposed to compliance monitoring, as shown in Figure 3. In compliance functions, AI technology application could take on the guise of NLP, which has the power to take large tracts of unstructured regulatory text information and process, parse, and interpret them for updates and changes in rules across many jurisdictions [16]. As a predictive and prescriptive analytic method for identifying and mitigating risk, analytics with ML were helpful to prevent and detect suspicious activity, such as money laundering, market manipulation, and breaches of policies - by looking at patterns associated with transaction history, suspicious user behaviour, and completing reviews of flagged transactions.

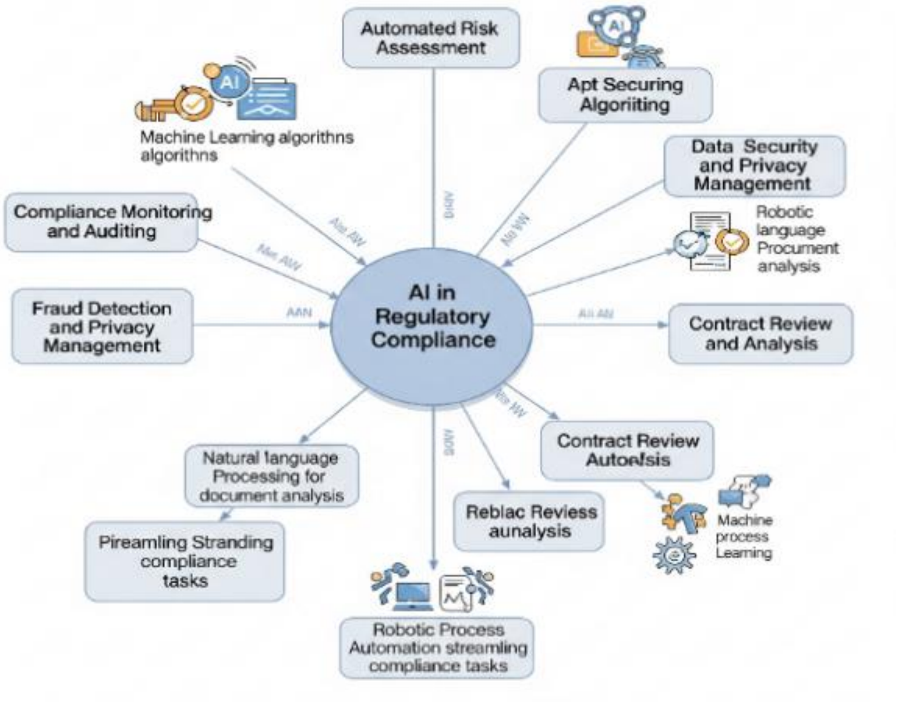

Fig 3: AI in Regulatory Compliance

4.1. Anti-Money Laundering (AML) and Know Your Customer (KYC)

Financial institutions will usually gather, validate, and screen the identities of their customers during the onboarding process to meet the AML and KYC requirements. Blockchain technology can use digital certificates that can be connected to blockchain data and compared to official or government identification to validate and authenticate organizations within a system. After a transaction, data is included and validated on the blockchain; it cannot be removed; this is impossible, only updated. This leaves an auditable trail of transactions that can be tracked to assist in tracing the source and destination of transactions in the system, thus making money laundering harder to achieve.

This prevents double-spending and reversal of transactions as well [17]. Consortium blockchains provide a multitude of uses and opportunities. For example, they would make it possible to create a permissioned, partially decentralized blockchain with many international financial institutions participating, where transactions would require their approval through a consensus vote. Additionally, this would make it possible for several third parties, such as governmental organizations, global regulators, concerned individuals, etc., to directly monitor.

4.2. AI for Regulatory Compliance

The 2008 financial crisis had a major effect on financial firms' reporting to regulatory bodies as well as regulations. As a result, there has been a rise in the number and complexity of regulations. Real-time transaction data monitoring, anomaly detection, and the application of NLP to map regularity criteria to institutional data are examples of AI/ML systems used for regulatory compliance. The technology is also involved in the initiatives initiated by regulatory agencies that aim at ensuring compliance [18].

The financial crisis that happened in 2008 significantly affected how the financial firms reported to the regulatory authorities and regulations. Consequently, this has led to an increase in regulations and their complexity. Monitoring of transaction data in real-time, monitoring of anomalies, and mapping of regularity rules onto institutional data through the use of NLP are typical examples of AI/ML systems being utilized in regulatory compliance. Regulatory authorities also engage in programs that incorporate technologies to assist in compliance assurance programs.

4.3. Compliance Monitoring and Auditing

Initial AI applications in the financial sector began to enhance financial institutions in their regulatory and financial audit process, particularly when it comes to automating the things that are approximated to be in non-compliance and fortifying internal controls. Manual processes of traditional audits based more on samples than on continuous monitoring were increasingly supported by AI-driven systems that allowed continuous monitoring patterns and full-population, rather than sample, analysis. The first versions of the rule-based engines and expert systems were only able to flag any suspicious transaction or policy violation using predefined regulatory frameworks. With the development of AI, ML models were implemented to detect anomalies and any patterns that were a sign of non-compliance, based on the past use of audit logs and transactions. The systems would become optimized with time, becoming more precise with fewer false positives being less.

NLP was also used to do text-based data analysis, like internal communications and policy documents, to find evidence of misconduct or inconsistency with regulatory standards. What is more, AI approaches complement risk-based auditing, as they enable the auditors to better distribute their resources and to focus on the risky areas. In general, the transformation of compliance monitoring and audits by using AI created more transparency, less human error, and increased the timeliness at which suspected compliance violations could be identified and brought to attention, which in later years would lead to the advent of more sophisticated real-time regulation technology (RegTechs).

5. Literature Review

The section reviews research in partnership around big data, transparency in financial reporting, regulatory compliance, and regulation of FinTech, with attention on security-based models of governance, compliance systems, shifting role of the data-driven financial supervision. Sherchan et al. (2019) The present paper describes a pilot activity with one of the regulatory agencies of the Australian Government, where the AI models were generated as a result of the application of the approaches such as natural language processing, machine learning, and deep learning to comprehensively determine the regulatory risk status of texts with personal financial advice. The solution enables adequate cover of documents under review and rapid identification of documents at high risk of failing to comply with the laws of the government by assigning advisory papers with a traffic light rating to various risk factors [19].

Van den Broek and van Veenstra (2018) examine how big data partnerships across organizations plan and manage their operations in light of this conundrum. Building on the literature on IS and Organization Theory, it might develop four archetypal governance arrangements market, hierarchy, bazaar, and network and conceptualize big data as inter-organizational systems. Four use cases involving big data cooperation are then examined to examine these arrangements. This research makes three literary contributions. Initially, they have envisioned IOS governance as the organization that underpins big data partnerships [20]. Bonsall et al.

(2017) This measure will be validated through a series of controlled tests and a regulatory intervention based on archive materials that aim to enhance the readability of prospectus filings. The significance of comprehending the fundamental forces behind quantity-based readability metrics may also be illustrated by it. Researchers should be especially aware that the addition of content such as HTML, XML, and PDFs that is unrelated to the 10-K's underlying language is largely responsible for the fluctuation in Form 10-K file size over time [21].

Agarwal et al. (2017) The complexity of these papers, which need to be read, comprehended, and interpreted by professionals, as well as the sheer rate of legislative change, are making compliance with these rules more and more difficult. For many CFOs, this is their biggest obstacle. The Compliance platform developed by the authors employs a cognitive strategy to accomplish regulatory compliance. They outline important compliance-related duties here and show how compliance aids compliance officers in carrying them out efficiently [22].

Leuz and Wysocki (2016) use international and domestic data sets to review existing research on the monetary impact of rules governing financial reporting and transparency. Emphasizing the difficulties in measuring disclosure and reporting results, calculating regulatory costs and benefits, and extrapolating causal conclusions from regulatory studies, all of which are pertinent to policy. Next, talk about empirical research that connects reporting and disclosure practices to both firm-specific and market-wide financial results. When assessing regulation, it's critical to comprehend these connections [23].

Lang and Stice-Lawrence (2015) Regulatory frameworks and incentives for greater open disclosure are associated with textual features, as are liquidity, institutional ownership, and analyst following, all of which are economic results. Annual report openness increased relative to US and non-US firms with the introduction of IFRS, with less boilerplate and more disclosure generally. When it came to economic effects around IFRS adoption, firms whose financial reporting was the best saw the most gains [24]. Table I illustrates a summary of the available literature that analyzed the utilization of AI techniques to improve financial reporting and regulatory compliance, including the studies' details, methodologies, findings, challenges, and recommendations etc.

Table 1: Comparative Analysis of literature review based on Financial Reporting and Regulatory Compliance

Author	Study On	Approach	Key Findings	Challenges	Future Directions
Sherchan et al. (2019)	Regulatory risk assessment in personal financial advice documents	AI models using NLP, ML, and deep learning techniques	Developed a traffic light rating system for regulatory risk detection, enabling rapid identification of high-risk documents	Limited to a pilot study with an Australian agency	Expand to large-scale, real-time financial document analysis frameworks
van den Broek & van Veenstra (2018)	Big data governance in inter-organizational collaborations	Conceptual framework (Market, Network, Hierarchy, Bazaar)	Developed four archetypal governance models for big data collaborations.	Aligning governance with diverse organizational goals.	Enhancing inter-organizational AI systems governance.
Bonsall et al. (2017)	Readability of regulatory filings (10-K forms)	Controlled experiments and archival data analysis	Identified limitations in quantity-based readability measures; Form 10-K file sizes are influenced by non-textual content.	Difficulty in measuring readability accurately.	Refined tools for measuring textual complexity in regulatory filings.
Agarwal et al. (2017)	AI platform for regulatory compliance	Cognitive computing-based compliance platform	Demonstrated AI's potential in automating complex compliance tasks using natural language understanding.	Manual interpretation of complex, dynamic regulations.	Building scalable AI-based platforms to manage regulatory change.
Leuz & Wysocki (2016)	Economic outcomes of financial disclosure regulation	Empirical literature review	Highlighted the importance of regulation in market transparency and outlined methods to link regulation to firm outcomes.	Quantifying costs/benefits and establishing causal inference in regulatory studies.	Improving measurement of disclosure quality and economic consequences.
Lang & Stice-Lawrence (2015)	Impact of IFRS on financial reporting transparency	Empirical analysis using IFRS as a shock event	Found increased disclosure quantity, reduced boilerplate, and enhanced comparability under IFRS; improved economic outcomes.	Differentiating causal effects of IFRS from other factors.	Broadening analysis across more countries and disclosure metrics.

6. Conclusion and Future Work

The revolutionary potential of AI in enhancing banking sector regulatory compliance is the primary emphasis of this research. The NLP, ML, and block chain-based artificial intelligence have promoted compliance and risk-detection monitoring and auditing processes significantly by automating complex tasks and providing real-time information. With the help of AI, financial organizations will be able to better cope with the increasing complexity of laws and reduce the likelihood of drawing faulty conclusions based on condensed data, and reduce financial fraud and discover faults due to the illegitimacy of transactions. Moreover, AI-based AML and KYC process solutions enhance security through the ability to provide secure records of transactions that cannot be changed later and easier verification of the identity of people.

In the future, it needs to study further to incorporate more AI on regulatory technology (RegTech) to contain more flexible and explainable AI models that are simpler to understand by the auditors and regulators. The possibilities of the combined blockchain and AI technologies regarding the decentralized compliance frameworks and better data security are exciting. What is more, as financial environments become increasingly interconnected, there is need to explore cross-border regulatory issues, and develop standard sets of governance practices regarding big data partnerships. Lastly, data privacy issues and ethics of AI implementation in compliance are a problem that merits an in-depth analysis to ensure sustainable and reputable AI implementation.

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