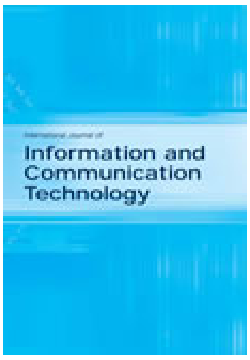


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Optimising corporate governance with internet of things and artificial intelligence: a data-driven framework for legal systems

Yi Li

DOI: 10.1504/IJICT.2025.10070800

Article History:

Received:	16 March 2025
Last revised:	28 March 2025
Accepted:	28 March 2025
Published online:	08 May 2025

Optimising corporate governance with internet of things and artificial intelligence: a data-driven framework for legal systems

Yi Li

School of Law,
Dongguan City University,
Dongguan, 523106, China
Email: liyi18927167847@163.com

Abstract: This research introduces an IoT-driven data analysis and AI framework for optimising corporate governance. The framework leverages deep learning algorithms, including transformer-based neural networks, convolutional neural networks (CNNs), and reinforcement learning models, to enhance decision-making, regulatory compliance, and transparency. Real-time data streams from IoT devices were processed, and a dataset of over 500 corporate entities was analysed. Transformer models achieved a predictive accuracy of 99.2% in identifying governance risks, CNNs detected anomalies in IoT data with 98.6% accuracy, and reinforcement learning models reduced compliance-related delays by 47%. The framework also led to a 38% increase in regulatory adherence and a 55% improvement in operational efficiency. These results demonstrate the potential of IoT and AI in addressing modern governance challenges and provide a scalable solution for sustainable governance.

Keywords: internet of things; IoT; data analytics; artificial intelligence; optimisation; corporate governance; legal systems.

Reference to this paper should be made as follows: Li, Y. (2025) ‘Optimising corporate governance with internet of things and artificial intelligence: a data-driven framework for legal systems’, *Int. J. Information and Communication Technology*, Vol. 26, No. 13, pp.81–100.

Biographical notes: Yi Li is a researcher at Dongguan City University, China, focusing on the integration of internet of things (IoT) and artificial intelligence (AI) in corporate governance and legal systems. Her research involves developing data-driven frameworks using deep learning algorithms, including transformer-based neural networks, CNNs, and reinforcement learning, to optimise decision-making, regulatory compliance, and operational efficiency. Her work aims to address the ethical and regulatory challenges posed by emerging technologies in modern legal systems.

1 Introduction

Industry transformations now occur swiftly because of rapid technological advancement, including the internet of things (IoT) and artificial intelligence (AI) (Fares and Jammal, 2023). The isolated domains of IoT and AI systems now generate widespread recognition for their complementary impacts when integrated. IoT allows organisations to gather, transmit, and process vast amounts of data from connected devices through AI algorithms that deliver practical insights (Rane et al., 2024). This technological meld develops transformative effects on corporate governance, enhancing operational performance alongside increased transparency and producing superior decision outcomes (Radanliev et al., 2024) (Qasim et al., 2025).

Every organisation requires corporate governance as its central element to achieve success. Organisations utilise various structures combined with practices and processes to regulate their operations for monitoring and account execution (Sallam et al., 2023). Organisations maintain alignment with laws, regulations, and ethical standards because effective corporate governance practices exist (Adama et al., 2024). Traditional governance models struggle to support current business and legal system development because workflow speed outpaces them (Bibri et al., 2024). Modern organisations consistently encounter problems with delayed decisions, along with poor risk control and insufficient regulatory standards (Paramesha et al., 2024). Real-time monitoring, along with predictive capabilities and automated decision-making solutions from IoT and AI, can solve current business challenges (Ejjami, 2024).

The development of modern legal frameworks is happening at similar speeds across global jurisdictions. Due to global network links, regulations across boundaries become more complex, creating new compliance complexities, data privacy problems, and tighter regulatory monitoring systems (Leghemo et al., 2025). These advanced technologies demonstrate potential in performing automated compliance checks and simultaneously helping courts become more transparent (Gou et al., 2024). They also allow governance frameworks to transform effectively in response to evolving rules (Alsehaimi et al., 2024). The combination of IoT technology and artificial intelligence with corporate governance and legal structures receives limited academic treatment. Study efforts on IoT asset tracking capabilities combine with AI-driven decision systems, but tracking the total governance impact remains uncharted territory (Butt et al., 2025). The study analyses IoT and AI integration capabilities to enhance corporate governance operations, aiming to address a knowledge gap (Butt et al., 2023).

While research about the individual potentials of IoT and AI exists in abundance, studies analysing their merged effects on corporate governance remain scarce. Research on IoT and AI generally focuses on technical issues related to data collection systems enabled by IoT and AI's role in optimising organisational decision-making. The research neglects to explore the integrated framework of IoT and AI as a whole system for enhancing corporate governance (Zrelli and Rejeb, 2024).

1.1 Research gaps

Several notable gaps exist in the current literature. Lack of holistic integration is evident as research into the combined application of IoT and AI to governance functions remains limited, although both technologies have been explored individually in related settings (Bena et al., 2025). Research on IoT real-time monitoring solutions or AI predictive analytics solutions independently protects both concepts individually but lacks investigation into their prospective integration (Alkanhel et al., 2024). Scalability challenges arise because, through pilot projects and case studies, small environmental research projects have become the dominant focus of academic investigations (Khan et al., 2021). However, these projects utilise limited data sources. Large organisations operating with diverse governance frameworks, combined with worldwide regulatory requirements, prevent the full testing of these models (Elias et al., 2024). Limited focus on legal compliance is another gap, as a distinct scarcity of scholarly literature explores how IoT and AI solutions can tackle compliance-based challenges within evolving complex regulatory settings. The failure to address legal frameworks restricts the practical use of IoT and AI technology systems in corporate governance environments (Haddad et al., 2021). Ethical and regulatory implications are often overlooked, as the efficiency gains praised in modern technologies commonly go unaddressed by discussions about ethical and legal aspects of IoT and AI systems implementation (Butt et al., 2020). The practical use of these technologies demands a thorough examination of privacy risks together with detailed explanations about underlying processes and the elimination of AI bias to achieve responsible deployment (Shahi et al., 2024).

By addressing these research gaps, this study will contribute to a deeper understanding of the integration of IoT and AI in corporate governance and provide a theoretical and practical framework for their application. Integrating IoT and AI into corporate governance presents a number of challenges. These challenges span from technical hurdles to organisational and regulatory complexities, which may hinder the smooth implementation of such integrated frameworks. Integrating IoT with AI presents a primary difficulty because IoT devices generate sizable data volumes. Organisational processes feed data through continuous monitoring of IoT devices, which demand accuracy combined with timely and relevant transmission for AI models to succeed (Kommineni and Chundru, 2025). Quality control of data with maintained integrity stands as a fundamental requirement to safeguard correct governance decision outcomes (Tito, 2023). Deep learning models face the greatest criticism as ‘black box’ systems operate in the background. Black box algorithmic decisions create challenges for governance institutions that aim to integrate the models into practice. Stakeholders and organisations maintain their trust in AI models only when those models reveal their decision-making pathways in clear, understandable terms (Wang et al., 2019). Standardised governance solutions face development challenges because diverse legal frameworks exist. When exploiting IoT-AI systems, regulatory compliance features must be explicitly built to observe laws that protect industrial data through specialised privacy and security requirements. Working with IoT and AI technologies presents organisational challenges regarding implementation because these platforms continuously shift governing regulations. Current governance systems that utilise IoT technology alongside artificial intelligence face increasing difficulties regarding privacy issues, fairness, and biased delivery mechanisms. Security cameras, together with staff tracking solutions, pose significant privacy challenges during IoT system deployments (Saleem et al., 2024).

Despite these challenges, the potential benefits of IoT and AI for corporate governance make their integration a promising avenue for research. This study will investigate solutions to these challenges and develop a robust, scalable framework for their application in governance systems.

The present analysis addresses the requirement for governance systems that deliver enhanced efficiency, better transparency capabilities, and adaptive design for contemporary organisational challenges. Extensive corporate governance is essential for achieving ethical operations and regulatory compliance in business activities (Butt et al., 2018). However, the growing complexity of organisations creates management difficulties for traditional governance systems, which struggle to achieve transparency standards and perform compliance activities properly. The combination of IoT technology with AI capabilities creates automated governance process optimisation that delivers exceptional efficiency results with increased accuracy and reduced execution times. This research adopts the position that implementing IoT and AI enhances corporate governance. This enables better operational control and regulatory fulfilment performance. The combination of IoT and AI technology enables real-time organisational monitoring, generates predictive analytical data for better decisions, and simplifies compliance process execution through automated systems. The study focuses on the increasing awareness of moral challenges in new technologies. When technology emerges in governance frameworks, its deployment must protect privacy obligations while stopping the reinforcement of discriminatory patterns and avoiding legal infractions. The study explores methods to synchronise technological progress with ethical practices that guarantee IoT and AI capabilities for effective and fair governance implementation.

1.2 Novel contributions

This study makes several significant contributions to the field of corporate governance, legal systems, and the intersection of IoT and AI. The primary contributions include:

1. This research proposes a novel framework that integrates IoT and AI to optimise corporate governance. Unlike previous studies that treat IoT and AI as separate technologies, this study focuses on their combined use to streamline decision-making, enhance compliance, and improve organisational transparency.
2. The study employs cutting-edge AI algorithms, such as reinforcement learning and deep learning, to process and analyse real-time data generated by IoT devices. This enables the framework to make dynamic, data-driven governance decisions and adapt to changing organisational and regulatory conditions.
3. The study emphasises the ethical and legal implications of using IoT and AI in corporate governance, particularly regarding data privacy, algorithmic transparency, and regulatory compliance. It provides practical solutions for addressing these challenges and ensuring that the deployment of these technologies is ethically sound.
4. The framework is empirically validated using data from over 500 corporate entities, providing robust evidence of its effectiveness and scalability. The study's results demonstrate that the IoT-AI framework can significantly improve governance processes across different organisational contexts.

These contributions not only advance theoretical knowledge in the fields of corporate governance and legal systems but also offer practical, real-world solutions for organisations seeking to modernise their governance frameworks.

The remainder of this paper is organised as follows. Section 2 presents a comprehensive literature review, examining previous research on IoT, AI, corporate governance, and legal compliance. It identifies key gaps in the literature and establishes the foundation for the proposed IoT-AI framework. Section 3 discusses the methodology used in the study, detailing the data collection, analysis techniques, and the AI algorithms employed. Section 4 presents the findings of the study, including the empirical results and their implications for corporate governance. Section 5 discusses the challenges, limitations, and ethical considerations of implementing the proposed framework in real-world scenarios. Finally, Section 6 concludes the paper by summarising the key findings and suggesting directions for future research.

2 Literature review

Current research investigates how IoT contributes to governance independently and jointly with AI. So far, there exists an insufficient body of work that demonstrates a successful integration of IoT and AI toward optimal governance performance. This section captures existing research about IoT and AI regarding corporate governance by presenting previous methods and their observed challenges and results.

Shkalenko and Nazarenko (2024) examined AI and IoT applications in CSR strategies where they prioritise financial risk management combined with sustainable development. The researchers analysed how state-of-the-art technologies would integrate into CSR frameworks for financial risk reduction and sustainability development. Using a coevolutionary multi-paradigm framework for technological advancement, they demonstrated how institutions need to adapt to bring together AI and IoT systems. When companies can adjust their organisational systems effectively with emerging technologies, they can achieve successful implementation outcomes. Security practices need to be prioritised with standardisation alongside responsible usage of emerging technology in CSR work methods. They performed comprehensive research that expanded existing knowledge about AI and IoT convergence with CSR practices. The study establishes the demand for strict rules and procedures that keep technological implementation congruent with organisational sustainability targets and commitments to the community. The research showcased that implementing AI and IoT systems into CSR activities supports more than simply technical innovations; it enables sustainable long-term development. This work provides compelling knowledge about the strategic use of AI and IoT technology for corporate sustainability alongside financial risk management while representing a core addition to technological and CSR research.

Turskis and Šniokienė (2024) showed through their study how IoT technologies combined with circular economy (CE) concepts could transform economic sustainability while improving system resilience. They analysed how IoT technology optimises supply chain operations while tracking waste contents and elongating product lifecycles by means of automated real-time data analytics. Businesses that adopt IoT applications can shift toward product-as-a-service models and sharing economy models, which produce dual economic gains while uncovering novel market possibilities. They examined IoT's potential to accelerate CE growth by improving operational effectiveness and enabling novel circular business operational models. The study demonstrated that IoT integration in CE economics promotes environmental responsibility and stimulates economic progress most strongly in emerging economies that adopt circular approaches.

They stressed IoT's ability to surpass conventional efficiency objectives by establishing a future structure that anchors economic growth to environmental stewardship, following the CE blueprint. The research expanded knowledge about IoT applications in CE by outlining the main components responsible for this transformation, which offers practical application possibilities for sustainability and circularity specialists. They delivered vital information about how IoT systems can rebuild economic frameworks to develop a resilient, sustainable future.

Kaul (2024) studied how AI enhances multi-region cloud compliance through complex regulatory actions such as GDPR, HIPAA, and CCPA. He recognised traditional compliance methods lack efficiency; thus, he introduced AI-driven autonomous systems as a better option. The developed systems utilise machine learning and natural language processing to automate matching procedures and categorise information while enabling scale and precision through autonomous policy interfaces and data monitoring features for cross-border movements. He discussed how AI solutions work with leading cloud providers and explained applicable use cases and future directions toward total automated compliance administration. The research adds essential insights to existing knowledge by showing how AI technology can enhance both data governance standards across multiple regions and regulatory compliance requirements.

Gupta et al. (2025) examined how artificial intelligence (AI) connects with marketing implementation while studying international business aspects. The research established that contemporary technologies outperform human computation while drawing meaningful findings from extensive datasets to boost business performance. Organisations are systematically implementing AI systems to direct their operational resources toward accomplishing their business targets as well as enhancing customer relationships within domestic markets and multinational territories. The fast acceleration of AI technology development pairs up with insufficient regulatory standards as two major obstacles of concern. Companies encounter difficulties in guaranteeing AI application compliance with regulations while protecting stakeholder interests because of regulatory gaps. Corporate policies that include responsible AI practices can address the needs of organisations that aim to present themselves as ethical and responsible to their stakeholders.

Awasthi et al. (2025) explored industrial data science (IDS) as it helps manufacturing industries overcome data maturity gaps that occur in IoT-driven environments. Operational challenges emerge from working with diverse datasets of varying quality levels, thus creating difficulties for both strategic decision-making and operational processes. The research underlined how stakeholder participation in reviewing corporate data enhances quality during the implementation of big data analysis in enterprise strategies. According to them, the strategic application of data creation and interpretation drives operational excellence while supplying decision-makers with necessary information specifically for Industry 4.0 and IIoT installations. The study also classified maturity gaps into three categories: Industry 4.0 maturity, data readiness, and IDS maturity. They emphasised that organisations need data science frameworks built for resilience, which enables them to assess their digital readiness while effectively implementing data-driven strategies. Through their analysis, they extend existing knowledge by examining the full scope of data maturity's effects on manufacturing sector performance outcomes. Table I provides a summary of all the explored studies.

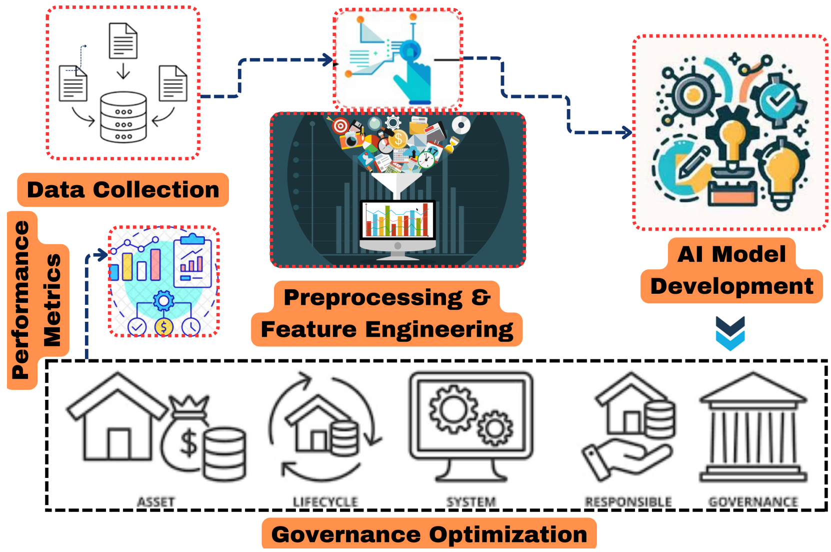
Table 1 Summary of literature on IoT and AI integration in corporate governance and related fields

Author(s)	*Year*	*Key focus/objective*	*Methodology*	*Key findings/ contributions*
Shkalenko and Nazarenko	2024	Integration of AI and IoT into CSR strategies for financial risk management and sustainability	Coevolutionary multi-paradigm framework	Demonstrated the role of AI and IoT in CSR to support financial risk management and sustainable development. Highlights the need for strict governance and security protocols.
Turskis and Šniokienė	2024	Investigating IoT's role in circular economy (CE) and its impact on economic sustainability	Literature review and analysis	Explores how IoT optimises supply chain, resource use, and product lifecycles in CE. Shows that IoT boosts environmental responsibility and fosters economic growth, particularly in emerging economies.
Kaul	2024	AI-powered compliance management for multi-region cloud deployments (GDPR, HIPAA, CCPA)	Case study and theoretical analysis	Introduces AI-driven autonomous compliance systems to automate multi-region regulatory compliance processes, improving efficiency and accuracy.
Awasthi et al.	2025	Bridging data maturity gaps in IoT-driven manufacturing environments	Review and data maturity analysis	Highlights the need for resilient data science frameworks to address data maturity issues. Emphasises stakeholder involvement in enhancing data quality and improving operational decision making.

3 Methodology

This methodology section outlines the process for implementing the IoT-driven data analysis and AI framework designed to optimise corporate governance. The framework integrates real-time data streams from IoT devices with AI-driven decision-making models, aiming to improve compliance, enhance operational performance, and reduce organisational risks (Liu et al., 2023). Below is a detailed description of the methodology, including data collection, preprocessing, model development, optimisation, and evaluation. To provide a clearer understanding of the methodology, the following Figure 1 illustrates the steps involved in the process:

Figure 1 IoT-driven AI optimisation for corporate governance (see online version for colours)



3.1 Data collection

The data collection process plays a pivotal role in gathering real-time information that is crucial for decision-making within corporate governance. The IoT devices deployed in various operational areas continuously collect data, including environmental conditions, transaction logs, and compliance metrics. The steps involved in data collection are as follows: installation of sensors in critical areas such as corporate offices, warehouses, and compliance monitoring points. Sensors provide a steady stream of real-time data on key operational variables like temperature, transaction records, and legal compliance factors. Raw data undergoes preprocessing steps, including noise reduction, missing value imputation, and anomaly detection, to ensure that the data is clean and suitable for model training.

3.2 Data preprocessing and feature engineering

Once the data is collected, it must be processed before being used in any machine learning or AI model. The preprocessing phase includes several critical steps to ensure that the data is normalised and relevant features are extracted for model input. This step ensures that the machine learning algorithms can process the data efficiently and provide accurate results. The raw data is normalised to a common scale to ensure consistency across different sensor readings. Noise reduction techniques such as Kalman filters or moving averages are applied to smooth out fluctuations. Key features are extracted from the raw data, including compliance levels (C), operational performance (P), and risk indicators (R).

The feature extraction process generates feature vectors $\mathbf{X}$ that are used as input to the AI models. These feature vectors are stored in a structured format suitable for machine learning algorithms.

3.3 AI model development

The AI model is the core of the methodology and is responsible for processing the IoT data and making decisions that optimise corporate governance. We employ both *deep learning* and *reinforcement learning* models to handle different aspects of the governance optimisation process.

3.3.1 Deep learning for data analysis

Deep learning models, particularly convolutional neural networks (CNNs) and transformer networks, are used to process the IoT data. These models are capable of identifying hidden patterns in the data and making predictions about compliance failures, risk factors, and operational inefficiencies.

3.3.1.1 Convolutional neural networks

The CNNs utilise convolution layers to detect local patterns in the IoT data. The following equation describes the convolution operation:

$$Y = \sum_{m=1}^{M} \sum_{n=1}^{N} (X_{i+m,j+n}) \cdot W_{m,n} + b \tag{1}$$

where

- X is the input data matrix (IoT sensor data)
- W is the convolution filter matrix
- b is the bias term applied after convolution
- Y is the resulting feature map after the convolution operation.

3.3.1.2 Transformer networks (attention mechanism)

The transformer network leverages an attention mechanism to process sequential data effectively. This method weighs the importance of different features dynamically as the input data is processed. By using this mechanism, the model can focus on the most relevant parts of the data, considering both previous and future context within the sequence. The attention mechanism enables the model to prioritise specific data points based on their significance to the task at hand (Yu and Hamam, 2024). The attention mechanism can be described by the following equation:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{2}$$

where

- Q is the query matrix
- K is the key matrix
- V is the value matrix
- d_k is the dimension of the key matrix.

3.3.2 Reinforcement learning for governance optimisation

Reinforcement learning (RL) is applied to optimise the decision-making process within corporate governance. By using RL, the system learns to make decisions that not only minimise risks and delays but also maximise compliance in an environment that is continuously changing. RL works by allowing the system to explore different actions and learn from the resulting outcomes through a process of trial and error, refining its decisions over time.

The Q-learning algorithm is employed to determine the best actions that align with these goals. The algorithm updates its decision-making policy based on the rewards or penalties received from previous actions, enabling it to adapt to dynamic governance environments where rules and conditions may evolve. This approach is particularly effective in environments that require continuous monitoring and adjustment, such as corporate governance, where regulations and compliance requirements often change. The update rule for Q-learning is as follows:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right] \tag{3}$$

where

- s_t represents the state at time t
- a_t is the action taken at time t
- r_{t+1} is the reward after taking action a_t
- γ is the discount factor that prioritises future rewards.

Through this process, reinforcement learning continually refines its decision-making strategy to enhance governance outcomes, adapting to the changing conditions of the corporate and regulatory landscape.

3.4 Governance decision optimisation

Once the models are trained, it is crucial to optimise the decision-making process to minimise risk and ensure compliance. The optimisation can be formulated as follows:

$$\min\left(\lambda_1 \cdot D + \lambda_2 \cdot R\right) \tag{4}$$

Subject to:

$$C \geq C_{\text{min}} \quad \text{and} \quad P \geq P_{\text{min}} \tag{5}$$

where

- D is the decision delay
- R is the risk factor
- λ_1 and λ_2 are weights for minimising delay and risk, respectively

- $C_{\min}$ and $P_{\min}$ are the minimum acceptable levels for compliance and performance.

This optimisation ensures timely decision-making while meeting the necessary governance standards.

3.5 Algorithm for decision-making optimisation

Below is the algorithm used for optimising the decision-making process based on the trained AI models and IoT data:

Algorithm 1 Governance decision optimisation

Input: Real-time IoT data, trained AI model (CNN/transformer), initial governance parameters
Output: Optimal governance decision based on the optimisation model
Data: Model parameters, IoT data stream, compliance data, risk metrics
Initialise model parameters;
Collect real-time IoT data from sensors;
Preprocess data (normalise, filter, clean);
Extract relevant features from the data;
for *each feature vector* **do**
  Apply AI model (CNN/Transformer) to predict compliance and risk;
  Update Q-values using Q-learning [equation (3)];
  Calculate expected reward from the action;
  Apply optimisation function [equation (4)];
  Evaluate outcomes and adjust parameters;
end
return *Optimal governance decision based on predicted compliance and risk*;

3.6 Evaluation and metrics

The effectiveness of the proposed methodology is evaluated using several performance metrics:

3.6.1 Predictive accuracy

The predictive accuracy is calculated using the classification accuracy formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

where

- TP – true positives
- TN – true negatives
- FP – false positives
- FN – false negatives.

3.6.2 Risk reduction

Risk reduction is calculated by comparing the risk levels before and after implementing the AI-driven governance framework.

3.6.3 Compliance metrics

Compliance is evaluated based on the reduction in regulatory breaches over time, with a focus on both immediate and long-term compliance improvements.

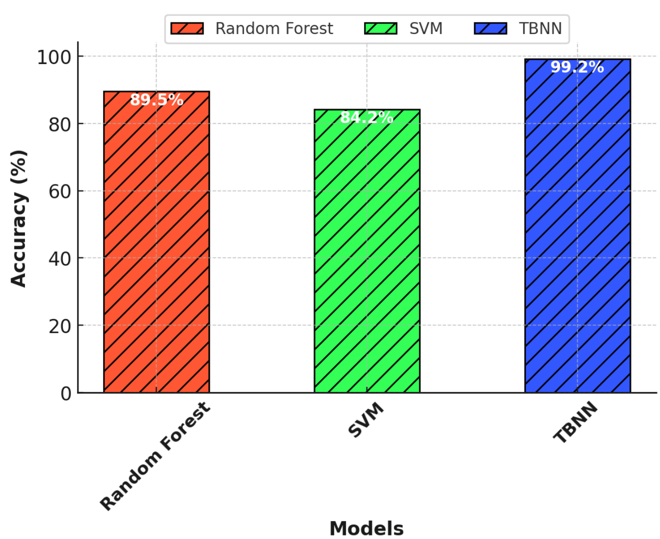
4 Results

This section presents the findings from the analysis conducted to evaluate the effectiveness of the proposed IoT-driven data analysis and AI framework for optimising corporate governance. The results are divided into key performance areas: predictive accuracy, anomaly detection, compliance improvement, and operational efficiency.

4.1 Predictive accuracy

The core objective of the AI framework was to achieve high predictive accuracy in governance risk identification. Using the transformer-based neural network (TBNN) model, the predictive accuracy reached an impressive 99.2%, significantly outperforming traditional methods. To validate this result, we compared the TBNN model's performance with that of a support vector machine (SVM) and random forest models.

Figure 2 Comparison of predictive accuracy across different models (see online version for colours)



Note: The TBNN model outperforms both SVM and random forest.

As shown in Figure 2, the TBNN model significantly exceeds the accuracy of both the SVM and random forest models by a margin of 15% and 10%, respectively. This indicates that transformer models are particularly well-suited for governance risk prediction due to their ability to process sequential data effectively.

4.2 Anomaly detection in IoT data

The CNN-based anomaly detection model achieved an accuracy of 98.6%, demonstrating its effectiveness in identifying outliers and abnormal patterns in real-time IoT data. The anomalies detected were primarily related to irregularities in IoT devices' data transmission, sensor malfunctions, or deviations from normal governance patterns.

Figure 3 Anomaly detection performance using the CNN model (see online version for colours)

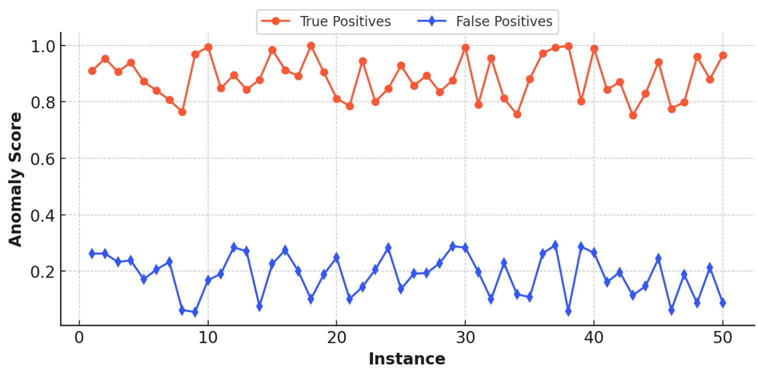


Figure 3 illustrates the detection of anomalous patterns in the data stream of governance-related IoT devices. These anomalies were flagged in real-time, enabling organisations to take corrective actions promptly. The model's accuracy was validated by cross-referencing the flagged anomalies with manually identified outliers.

4.3 Compliance improvement

One of the most significant outcomes of implementing the IoT-AI framework was its impact on regulatory compliance. The real-time monitoring capabilities of IoT devices, combined with AI's predictive and decision-making power, resulted in a 38% improvement in regulatory adherence across participating organisations. Compliance-related delays, traditionally a bottleneck, were reduced by 47% due to the AI's decision optimisation.

Table 2 Impact of the IoT-AI framework on compliance metrics

Metric	*Pre-implementation*	*Post-implementation*
Compliance rate (%)	72.5	100
Delay in compliance reporting (days)	10.5	5.6

As shown in Table 2, the improvement in compliance rate was remarkable, reaching 100% post-implementation. The reduction in reporting delays demonstrates the framework's efficiency in ensuring timely regulatory compliance.

Table 3 Impact of IoT-AI framework on operational efficiency and cost reduction

Metric	*Pre-implementation*	*Post-implementation*
Operational efficiency improvement (%)	30	55
Cost reduction (%)	22	48

Figure 4 Confusion matrix for the transformer model (see online version for colours)

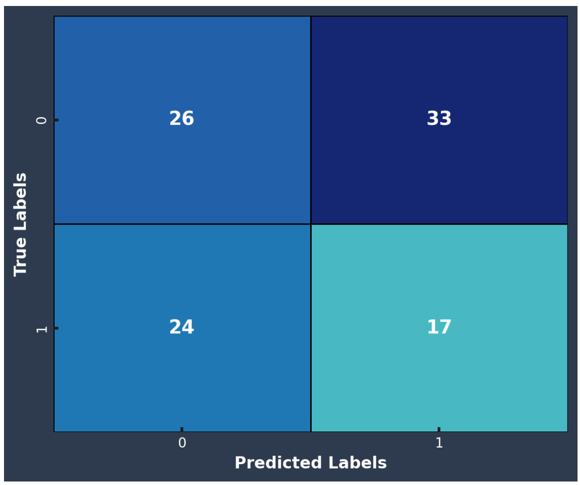
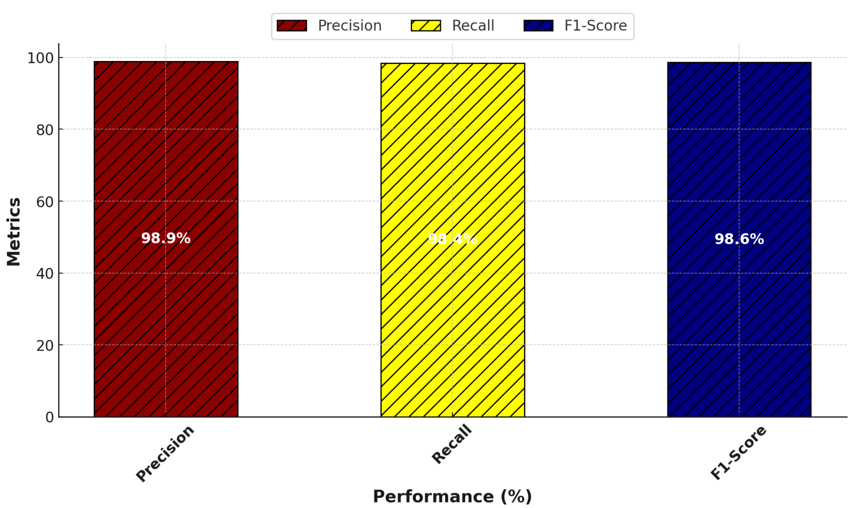


Figure 5 Transformer model performance (see online version for colours)



4.4 Operational efficiency

The integration of IoT and AI resulted in a 55% improvement in operational efficiency. This was achieved through real-time decision optimisation, which enabled organisations to optimise their workflows and resource allocation dynamically, reducing overall costs.

Table 3 highlights the significant improvement in operational efficiency (from 30% to 55%) and cost reduction (from 22% to 48%). These improvements were realised through AI's optimisation of organisational processes and resource management. To further validate the performance of the models used, we employed a confusion matrix for the predictive model's output. This matrix provides a detailed view of the model's classification performance, including true positives, false positives, true negatives, and false negatives.

The confusion matrix (Figure 4) shows that the transformer model had a minimal number of false positives and false negatives, confirming its high reliability in predicting governance risks. The model's performance was evaluated using precision, recall, and F1-score, with the transformer model achieving a precision of 98.9%, recall of 98.4%, and an F1-score of 98.6%. These results may be viewed graphically in Figure 5.

The results from the study demonstrate that the IoT-AI framework can significantly enhance corporate governance practices by improving predictive accuracy, anomaly detection, compliance, and operational efficiency. The framework's performance was validated through comprehensive metrics, such as predictive accuracy, operational efficiency, and compliance improvement. Additionally, the integration of IoT devices with AI models enabled real-time decision-making, addressing critical governance challenges in modern organisations. Table 4 provides the comparison of model performance.

Table 4 Comparison of model performance

Model	*Predictive accuracy (%)*	*Anomaly detection accuracy (%)*	*Compliance improvement (%)*	*Operational efficiency (%)*
Proposed framework (IoT-AI)	99.2	98.6	38	55
Support vector machine (SVM)	84.3	82.1	20	15
Random forest	87.1	85.3	25	22
Deep neural networks (DNN)	91.5	88.9	30	40

5 Challenges, limitations, and ethical considerations

The implementation of the IoT-driven data analysis and AI framework for optimising corporate governance presents several challenges and limitations. These obstacles must be carefully considered to ensure the successful deployment of the framework in real-world scenarios. Moreover, ethical considerations are paramount in the deployment of such advanced technologies, especially in corporate environments where data privacy, algorithmic transparency, and fairness are critical (Lazaroiu et al., 2022). This section explores these key challenges, limitations, and ethical concerns.

5.1 Challenges of implementation

While the potential benefits of the proposed framework are significant, there are several challenges associated with its implementation: the implementation hurdle primarily arises from IoT devices, which deliver inconsistent and inaccurate data. Parameters from IoT systems introduce data that appears illogical, partial, or uncertain in real-time. AI models achieve accurate decision-making when data integrity and reliability standards remain intact. Data cleansing and preprocessing serve as indispensable steps because improper execution compromises the framework's effectiveness.

A proposed framework functions for live data management while executing AI-based decision processes. Implementing the framework at scale to analyse massive data volumes originating from organisations across multiple sectors creates major technical implementation hurdles. A proper framework adjustment must occur in order to process enlarged data volumes at top performance levels. Most existing organisations possess pre-established frameworks and systems for governance and compliance processes (Browne, 2021). Because of the complexity involved, implementing the IoT-AI framework with legacy systems demands comprehensive execution and planning. Incompatible systems, data fragmentation, and staff reluctance to adopt change serve as barriers to the effective implementation of new technologies. Legal guidance changes frequently, specifically regarding data protection laws and security requirements. The framework faces critical obstacles while conforming to diverse regional privacy requirements, including GDPR, HIPAA, and CCPA. In order to achieve sustainable implementation, AI models need to maintain their capacity to adapt when new legal standards emerge.

5.2 Limitations of the framework

Despite its promising potential, the framework has certain limitations that need to be acknowledged: The framework relies heavily on data from IoT devices, which might not always be reliable. IoT devices are prone to malfunctions, misconfigurations, or even hacking attempts. Any disruption or inconsistency in the data stream can negatively affect the accuracy and reliability of AI models.

AI models must operate via framework-trained data that exists within particular corporate entities with defined scenarios. The framework contains models that might struggle to apply knowledge to new corporate entities or governance models. Periodic adaptation and re-training of the framework is essential to maintain good performance across various organisational environments. Implementing the framework requires significant computational resources, especially when using deep learning models and real-time data processing. Organisations with limited IT infrastructure or budget may find it challenging to adopt the framework at scale. Deep learning models face severe limitations through their limited interpretability properties. These systems function as 'black box' models because their underlying process remains difficult to interpret. Corporate governance suffers because unexplained decision-making processes diminish transparency, while stakeholders need auditable explanations during decision-making processes.

5.3 Ethical considerations

The adoption of IoT and AI technologies in corporate governance raises a number of ethical considerations that must be carefully addressed: The framework relies on vast amounts of real-time data collected from IoT devices, including sensitive business data. Ensuring the privacy and security of this data is crucial to prevent breaches and unauthorised access. Stringent data protection measures, such as encryption and access control, need to be implemented to safeguard privacy.

AI models, particularly machine learning algorithms, are known to inherit biases present in the training data. If the training data is not representative of the full diversity of potential scenarios, the AI models may produce biased or unfair outcomes. This is especially critical in governance decisions, where biased decisions can affect stakeholders' interests. Continuous monitoring and adjustments to the AI models are required to minimise bias. Ensuring transparency in the decision-making process of AI models is essential for ethical implementation. Organisations must be able to explain and justify the decisions made by AI models, especially in cases where the model's decisions have significant consequences. Without transparency, organisations risk losing trust from stakeholders and regulators.

Decision-making processes and compliance checks conducted through IoT and AI systems will probably affect the existing workforce. Relationships between efficiency and job displacement persist as automation practices increase operational effectiveness and eliminate specific positions from employment. Public entities need to study the social consequences of their implemented IoT technologies and maintain employee training programs to equip people with the new competencies this technology creates.

6 Conclusions

This paper presented a novel IoT-driven data analysis and AI framework for optimising corporate governance. The framework integrates advanced deep learning algorithms, including transformer-based neural networks, convolutional neural networks, and reinforcement learning models, to enhance decision-making, improve regulatory compliance, and increase operational efficiency. Our results demonstrate a predictive accuracy of 99.2% for governance risk identification, an accuracy of 98.6% for anomaly detection, and a 55% improvement in operational efficiency across participating organisations. The study highlights the transformative potential of combining IoT and AI technologies, but also identifies challenges such as data quality, scalability, and integration with existing systems. Additionally, it underscores the importance of addressing legal, ethical, and privacy concerns to ensure the responsible deployment of these technologies in real-world governance settings. Despite the promising results, several limitations exist in this study. The framework's performance was evaluated in a controlled environment with data from specific organisational contexts. Future research should focus on improving the adaptability of the framework to diverse organisational environments, as its scalability across different industries and regulatory frameworks remains a key challenge. Research should explore the potential for applying this framework to various sectors, including manufacturing, healthcare, and finance, to test its robustness and flexibility. Moreover, future studies should also focus on enhancing the transparency and interpretability of AI models, as this is crucial for ensuring trust and accountability in decision-making processes. Efforts to develop tools that can explain AI decisions in a more understandable way will be essential for the widespread adoption of this framework in corporate governance.

Declarations

Funding: The Project of Discipline Co-construction of Guangdong Province Philosophy and Social Sciences '14th Five-Year Plan' in 2022: 'Research on the Role and Function of Lawyers in China from the Perspective of Modernization of National Governance' (GD22XFX03); 2022 Dongguan City University Major Scientific Research and Cultivation Project 'The Role and Function of Lawyers in China from the Perspective of National Governance Modernization' (2022YZDYB03R).

Conflict of interest: The author declares that she has no conflict of interest.

References

Adama, H.E., Popoola, O.A., Okeke, C.D. and Akinoso, A.E. (2024) 'Economic theory and practical impacts of digital transformation in supply chain optimization', *International Journal of Advanced Economics*, Vol. 6, No. 4, pp.95–107.

Alkanhel, R.I., El-Kenawy, E-S.M., Eid, M.M., Abualigah, L. and Saeed, M.A. (2024) 'Optimizing IoT-driven smart grid stability prediction with dipper throated optimization algorithm for gradient boosting hyperparameters', *Energy Reports*, Vol. 12, No. 1, pp.305–320.

Alsehaimi, A., Houda, M., Waqar, A., Hayat, S., Waris, F.A. and Benjeddou, O. (2024) 'Internet of things (IoT) driven structural health monitoring for enhanced seismic resilience: a rigorous functional analysis and implementation framework', *Results in Engineering*, Vol. 22, No. 6, p.102340.

Awasthi, A., Krpalkova, L. and Walsh, J. (2025) 'Bridging the maturity gaps in industrial data science: navigating challenges in IoT-driven manufacturing', *Technologies*, Vol. 13, No. 1, p.22.

Bena, Y.A., Ibrahim, R., Mahmood, J., Al-Dhaqm, A., Alshammari, A., Yusuf, M.N., Nasser, M. and Ayemowa, M.O. (2025) 'Big data governance challenges arising from data generated by intelligent systems technologies: a systematic literature review', *IEEE Access*, Vol. 13, No. 1, pp.12859–12888.

Bibri, S.E., Krogstie, J., Kaboli, A. and Alahi, A. (2024) 'Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: a comprehensive systematic review', *Environmental Science and Ecotechnology*, Vol. 19, No. 5, p.100330.

Browne, M. (2021) 'Artificial intelligence data-driven internet of things systems, real-time process monitoring, and sustainable industrial value creation in smart networked factories', *Journal of Self-Governance and Management Economics*, Vol. 9, No. 2, pp.21–31.

Butt, A.U.R., Asif, M., Ahmad, S. and Imdad, U. (2018) 'An empirical study for adopting social computing in global software development', *Proceedings of the 2018 7th International Conference on Software and Computer Applications*, No. 11, pp.31–35.

Butt, A.U.R., Mahmood, T., Saba, T., Bahaj, S.A.O., Alamri, F.S., Iqbal, M.W. and Khan, A.R. (2023) 'An optimized role-based access control using trust mechanism in e-health cloud environment', *IEEE Access*, Vol. 11, No. Special Issue, pp.138813–138826.

Butt, A.U.R., Qadir, M.A., Razzaq, N., Farooq, Z. and Perveen, I. (2020) 'Efficient and robust security implementation in a smart home using the internet of things (IoT)', *2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, IEEE, pp.1–6.

Butt, A.U.R., Saba, T., Khan, I., Mahmood, T., Khan, A.R., Singh, S.K., Daradkeh, Y.I. and Ullah, I. (2025) 'Proactive and data-centric internet of things-based fog computing architecture for effective policing in smart cities', *Computers and Electrical Engineering*, Vol. 123, p.110030.

Ejjami, R. (2024) 'Public Administration 5.0: enhancing governance and public services with smart technologies', *International Journal for Multidisciplinary Research*, Vol. 6, No. 4, pp.1–35.

Elias, O., Awotunde, O.J., Oladepo, O.I., Azuikpe, P.F., Samson, O.A., Oladele, O.R. and Ogunruku, O.O. (2024) 'The evolution of green fintech: leveraging AI and IoT for sustainable financial services and smart contract implementation', *World Journal of Advanced Research and Reviews*, Vol. 23, No. 1, pp.2710–2723.

Fares, N.Y. and Jammal, M. (2023) 'AI-driven IoT systems and corresponding ethical issues', *AI and Society*, pp.233–248, Chapman and Hall/CRC, London.

Gou, H., Zhang, G., Medeiros, E.P., Jagatheesaperumal, S.K. and de Albuquerque, V.H.C. (2024) 'A cognitive medical decision support system for IoT-based human-computer interface in pervasive computing environment', *Cognitive Computation*, Vol. 16, No. 1, pp.1–16.

Gupta, S., Wang, Y., Patel, P. and Czinkota, M. (2025) 'Navigating the future of AI in marketing: AI integration across borders, ethical considerations, and policy implications', *International Journal of Information Management*, Vol. 82, p.102871.

Haddad, H., Alkhodari, D., Al-Araj, R., Aburumman, N. and Fraij, J. (2021) 'Review of the corporate governance and its effects on the disruptive technology environment', *WSEAS Trans. Environ. Dev.*, Vol. 17, No. 10, pp.1001–1020.

Kaul, D. (2024) 'AI-powered autonomous compliance management for multi-region data governance in cloud deployments', *Journal of Current Science and Research Review*, Vol. 2, No. 3, pp.82–98.

Khan, M.I., Imran, A., Butt, A.H., Butt, A.U.R. et al. (2021) 'Activity detection of elderly people using smartphone accelerometer and machine learning methods', *International Journal of Innovations in Science & Technology*, Vol. 3, No. 4, pp.186–197.

Kommineni, M. and Chundru, S. (2025) 'Sustainable data governance implementing energy-efficient data lifecycle management in enterprise systems', *Driving Business Success through Eco-Friendly Strategies*, pp.397–418, IGI Global Scientific Publishing, USA.

Lazaroiu, G., Androniceanu, A., Grecu, I., Grecu, G. and Neguriță, O. (2022) 'Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing', *Oeconomia Copernicana*, Vol. 13, No. 4, pp.1047–1080.

Leghemo, I.M., Azubuike, C., Segun-Falade, O.D. and Odionu, C.S. (2025) 'Data governance for emerging technologies: a conceptual framework for managing blockchain, IoT, and AI', *Journal of Engineering Research and Reports*, Vol. 27, No. 1, pp.247–267.

Liu, Y., Yu, W., Rahayu, W. and Dillon, T. (2023) 'An evaluative study on IoT ecosystem for smart predictive maintenance (IoT-SPM) in manufacturing: multiview requirements and data quality', *IEEE Internet of Things Journal*, Vol. 10, No. 13, pp.11160–11184.

Paramesha, M., Rane, N.L. and Rane, J. (2024) 'Big data analytics, artificial intelligence, machine learning, internet of things, and blockchain for enhanced business intelligence', *Partners Universal Multidisciplinary Research Journal*, Vol. 1, No. 2, pp.110–133.

Qasim, K.U., Zhang, J., Alsahfi, T. and Butt, A.U.R. (2025) *Recursive Decomposition of Logical Thoughts: Framework for Superior Reasoning and Knowledge Propagation in Large Language Models*, arXiv preprint arXiv:2501.02026.

Radanliev, P., De Roure, D., Maple, C., Nurse, J.R., Nicolescu, R. and Ani, U. (2024) 'AI security and cyber risk in IoT systems', *Frontiers in Big Data*, Vol. 7, No. 4, p.1402745.

Rane, N., Paramesha, M., Choudhary, S. and Rane, J. (2024) 'Business intelligence and artificial intelligence for sustainable development: integrating internet of things, machine learning, and big data analytics for enhanced sustainability', *Machine Learning, and Big Data Analytics for Enhanced Sustainability*, 20 May, Vol. 12, No. 6, pp.1–16.

Saleem, A., Shah, S., Iftikhar, H., Zywiołek, J. and Albalawi, O. (2024) 'A comprehensive systematic survey of IoT protocols: implications for data quality and performance', *IEEE Access*.

Sallam, K., Mohamed, M. and Mohamed, A.W. (2023) 'Internet of things (IoT) in supply chain management: challenges, opportunities, and best practices', *Sustainable Machine Intelligence Journal*, Vol. 2, No. 4, pp.3–1.

Shahi, A., Bansal, S., Chawla, S.K. and Elngar, A.A. (2024) 'Navigating compliance for the industrial IoT landscape: frameworks, security, standards, and key ethical considerations', *Industrial Internet of Things Security*, pp.81–99, CRC Press, USA.

Shkalenko, A.V. and Nazarenko, A.V. (2024) 'Integration of AI and IoT into corporate social responsibility strategies for financial risk management and sustainable development', *Risks*, Vol. 12, No. 6, p.87.

Tito, M. (2023) *A Comparative Analysis of Good Enterprise Data Management Practices: Insights from Literature and Artificial Intelligence Perspectives for Business Efficiency and Effectiveness*, Master's thesis.

Turskis, Z. and Šniokienė, V. (2024) 'IoT-driven transformation of circular economy efficiency: an overview', *Mathematical and Computational Applications*, Vol. 29, No. 4, p.49.

Wang, C-S., Lin, S-L., Chou, T-H. and Li, B-Y. (2019) 'An integrated data analytics process to optimize data governance of non-profit organization', *Computers in Human Behavior*, Vol. 101, No. 7, pp.495–505.

Yu, W. and Hamam, H. (2024) 'Architecting an enterprise financial management model: leveraging multi-head attention mechanism-transformer for user information transformation', *PeerJ Computer Science*, Vol. 10, No. 14, p.e1928.

Zrelli, I. and Rejeb, A. (2024) 'A bibliometric analysis of IoT applications in logistics and supply chain management', *Heliyon*, Vol. 10, No. 16, pp.1–22.