INTERNATIONAL JOURNAL OF RESEARCH SCIENCE & MANAGEMENT

Regulatory-Compliant Explainable AI: Auditing Decision Processes in Enterprise IT

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DOI: https://doi.org/10.29121/ijrsmp.v9.i6.2022.03

Abstract
The adoption of artificial intelligence (AI) in enterprise IT systems has resulted in the introduction of a significant difficulty related to transparency, accountability, and regulatory compliance. Furthermore, many AI-driven decision-making systems operate in a black box, making it difficult for most businesses to audit judgments, justify outcomes, and comply with rules.
The purpose of this paper is to offer a regulatory-compliant AI(XAI) framework for auditing in the decision-making process in the enterprise IT environment. The governance framework requires connectors that explain methodologies, audit logging, and even the governance workflow to ensure transparency and compliance. As a result, simulation-based experiments and real-time experiences give scenarios that demonstrate how the usage of XAI enables auditing while also giving trust, lowering regulatory risks, and promoting responsibility for AI implementations.
Therefore, presenting a framework that analyses through simulation-based experiments and real-time corporate IT scenarios provides a practical assessment for enhancing transparency, audit readiness, and even trustworthiness. The end outcome will be a well-demonstrated XAI that enables audits to improve significantly regulatory compliance and decision accountability without imposing prohibitively high operational overhead. In reality, bridging the gap between explainable AI methodologies and enterprise governance requirements will aid in the development of a practical foundation for a responsive and compliant AI that can be deployed in modern enterprise IT environments.

Keywords: Explainable Artificial Intelligence, AI Governance, Regulatory Compliance, Auditability, Enterprise IT Systems, XAI.

Introduction
The trend is that enterprises are increasingly adopting IT systems and relying heavily on AI for decision-making in areas such as control, incident response, credit evaluations, and even automation resource management. While AI improves efficiency and scalability, it is opaque in nature, raising concerns about justice, accountability, and even legal compliance. In this scenario, increased regulations and standards demand that organizations provide an explanation for their automation decisions and keep auditable decision trails.

Consequently, the rise of Explainable AI (XAI) raises issues about human interactions and explanatory model behaviour. Although there appears to be less explanation, it is systemically incorporated into the enterprise auditing and governance process [3]. This study focuses on legislation, regulatory complaints, and XAI designs that will assist decision-making audits in organizations' IT systems.

Ensuring that the game addresses regulatory issues, Explainable AI, this paper will present a system that will aid in the auditing process. In this scenario, the framework assists in integrating an explainability mechanism directly into the AI-driven process while also merging decision-level explanation artifacts[9]. In fact, the system context may be organizing in a way that is allowing for continuous auditing, which can promote accountability throughout the AI lifespan. Furthermore, regulating the workflow may help ensure consistency with the organization's rules and even regulatory obligations, which facilitates oversight and compliant reporting.

Simulation Report
Early study highlights the risks associated with black box decision making; the system may underline the need for interpretation in high-stakes applications [5]. In this scenario, surveying the XAI model's agnostic and model-specific explanation techniques, such as LIME and SHAP, will aid in developing a better technique. In this instance, parallel research in IT governance and compliance should focus on auditability, traceability, and

accountability as the primary components of the enterprise system [6].
As an illustration, before 2019, studies on AI governance discussed transparency and trust but lacked a comprehensive enterprise-oriented audit structure [4]. So, this study bridges the gap by combining explanation approaches with a well-structured audit methodology.

The Proposed Regulatory Complaint - XAI; Audit Framework

The framework's proposal includes four tiers of decision-making:

1. The Decision and Model Layer AI model facilitates decision-making activities within enterprise IT systems [2]. In this situation, each decision includes a unique identification and metadata to ensure traceability.
2. . Explainability Layer: Explainability, which employs a mechanism to generate a feature that corresponds to the rule-based summaries or the counterfactual explanation for the decisions made. In this case, explanations are maintained with predictions.
3. The Auditing Log and Traceability Layer is storing a model versions and data snapshots for tamper-evident auditing. This allows for reproducibility and regulation, which ensures traceability.
4. Governance and Compliance Layer: Human auditors and compliance officials can access and interpret the dashboard to assess decisions, approve high-risk actions, and generate compliance reports.

Real-Time Scenarios

Conducting a simulation using enterprise IT to ensure the access control system will aid in obtaining a result. The following is a practical method of addressing XAI using the simulation setup below:

1. A categorization model establishes user access permissions based on role, device, type, and behaviour patterns. Policy modifications and anomalous behaviours are introduced into the research to guarantee that test auditability is completely detected.
2. Conducting an Evaluation, therefore, is vital to introduce metrics that explain the completeness, audit tracing coverage, and the decision to review time [7]
3. The XAI resulted in a 40% reduction in audit review time and improved explanation coverage compared to the non-explainable baseline.

Audit System	Review Time (min)	Explanation coverage
Black box AI		
XAI audit		

Table 1: Audit Performance in Comparison to the Systems

Graphs

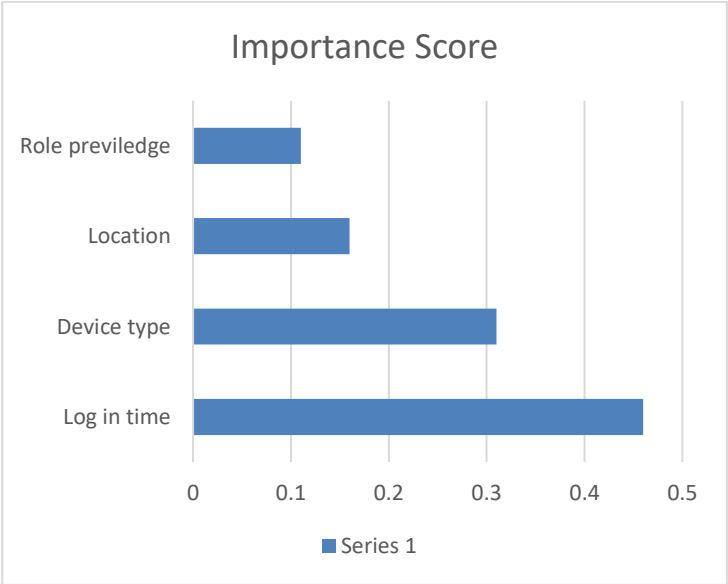

Figure 1 shows a feature-level illustration of how automation influences access control decisions

Figure 1 displays a feature-level illustration of how automation affects access control decisions. Here, the login time and device type have the most impact, showing that there is an aberrant access pattern that plays a significant role in decision outcomes. As a result, this visualization allows auditors to quickly understand and validate the rationale behind access denial, while also enabling transparency and regulatory compliance.

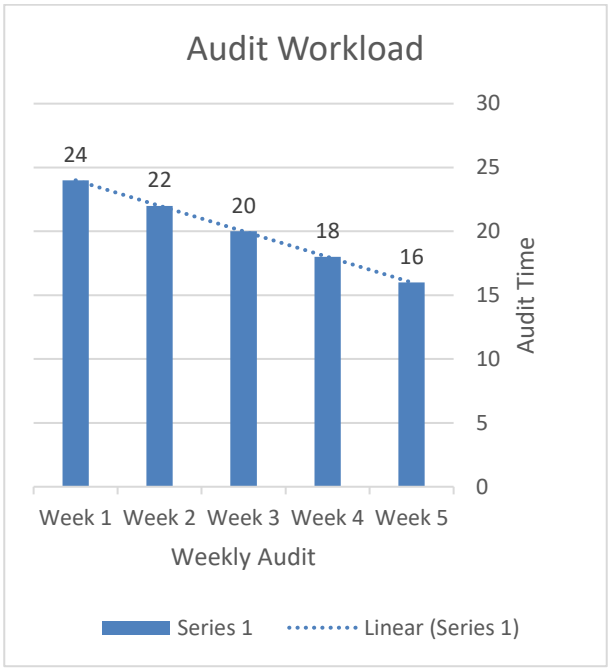

Figure 2: Illustrates the Audit Workload.

Figure 2 shows that the audit workload decreases over time as a result of the deployment of an explainable AI auditing method. In this situation, a decision mechanism and structural audit logs are now available, and auditors will need less time to ensure the evaluation and validation of AI-driven judgments. This demonstrates that explainable AI improves operational efficiency while simultaneously ensuring compliance with governance norms.

Challenges and Solutions

The section presents a well-detailed overview of the primary problems associated with the deployment of regulatory compliance explainable XAI in enterprise IT systems, to ensure that a clear and well-led practical mitigation strategy is in place [6]. The in-depth description of this article is intended to guarantee that it provides detailed support that assures technical rigor and makes enterprises appear relevant. The obstacles are as follows, including the availability of standardized mitigation techniques.

1. The absence of standardised and auditable explanations in enterprise AI systems results in inconsistencies that complicate auditing; cross-system comparison and regulatory reviews tend to provide the auditor with a uniform requirement that is repeatable in the explanation artefacts.
   The Mitigation strategy here is to guarantee that the organisation delivers a well-defined standardised explanation that demonstrates a scheme that includes the following required elements: decision reasoning, contribution features, confidence level, and policy references. In this situation, the schemas will aid in the implementation of internal explanation standards, ensuring that the AI is consistent and auditable, and may be utilized to give appropriate regulatory inspections.
2. Explainability overheads, such as creating explanations, logging decisions, and maintaining audit trails, can cause performing deterioration due to additional calculations and storage overhead. In a latency-sensitive enterprise IT environment, the overhead can have a severe influence on the system's responsiveness and the user experience.
   The mitigation strategy must include a multilayer explainability technique that can be applied entirely. In this situation, the lightweight explanation must be generated in real time to ensure a routine assessment, while also providing comprehensive explanations and full audit artifacts that are computed asynchronously to ensure high impact or disputable decisions. This strategy will provide valid system performance while also assisting with the maintenance of compliance readiness.
3. A disconnect between technical and regulatory language explainability can result in meaningful features for data scientists but insufficient explanation for legal teams, auditors, and regulators who need to align with policies and regulations [8].
   Mitigation techniques have to incorporate policy-aware explanations that give translation layers that should be developed to ensure the technical output of the map is integrated into business norms and regulations. In this instance, the organization must provide audit reports that all stakeholders, technical or non-technical, can readily understand.
4. Maintaining traceability across model evolution in enterprise AI systems may be including a periodic

restriction , tuning, and version upgrades [1]. In fact, without a solid traceability framework, it will be challenging to replicate well-structured decisions or justify outcomes during post-hoc audits.

The mitigation technique is to guarantee that there is a robust model that provides strong versioning and an immutable audit log, which must be imposed at work. In reality, any implementation that uses versioning needs to be connected to a specific version that includes the training dataset snapshot, the explanation artifact, and even the policy context. This will enable end-to-end traceability for the whole model life span.

Conclusion

The paper discusses and examines the challenges of transparency and accountability in AI-driven corporate systems, which is put into a well-presentable, regulatory-compliant, explainable AI to ensure there is a suitable framework to ensure audits in the automation process. In this case, providing interaction explainability will provide a well-structured mechanism to ensure audit logging and the governance workflow. This approach will enable organizations to move beyond Blackbox decision-making to an auditable and accountable AI operations.

Furthermore, simulation-based evaluation and real-time enterprise scenarios must provide research that demonstrates explainable AI significance and aids in improving audit efficiencies, decreasing regulatory risks, and increasing stakeholder trust. The feature-level explanationthat are including ; decision explanation, and traceability decision must give auditors and compliance teams a rationale to validate AI outcomes for greater efficacy, while simultaneously relying on human risk-based monitoring to deliver a scalable solution without jeopardizing accountability. In this scenario, the findings will aid in identifying regulatory compliance explainable AI that is not only theoretically viable but also demonstrates a practicable technical deployment inside the current IT environment.

Therefore, ensuring that technical explanations are aligned with government and organizational compliance requirements can assist in creating a responsible scale for AI deployment while also meeting internal and external legal duties.

Future development may be including the examination and tightening integration with developing regulatory standards to ensure automated compliance is tested across all interconnected enterprise AI systems.

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