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Explainable Artificial Intelligence and Data Governance for Financial Reporting Quality, Regulatory Accountability and Decision Transparency in United States Organizations

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Abstract

With the increasing use of artificial intelligence (AI) in financial reporting activities, the key concerns have been transparency, accountability, and decision auditability in the United States (US) organizations. The paper examines the effects of Explainable Artificial Intelligence (XAI) and data governance on the quality of financial reporting (FRQ), regulatory accountability (RA) and the decision transparency (DT) of US companies. This study was based on the Agency Theory, Institutional Theory and the Technology Acceptance Model (TAM) and adopted a mixed-methodology which consisted of a structured questionnaire survey of 312 financial professionals working in six industries and a secondary analysis of regulatory filings. The research hypotheses evaluated using Structural Equation Modeling (SEM), multiple regression analysis, mediation and moderation analyses included 9 research hypotheses. The results showed that the quality of financial reporting (0.487, $p < 0.001$), decision transparency (0.513, $p < 0.001$), and the quality of data governance (0.421, $p < 0.001$) are positively associated with XAI adoption. Along these lines, the relationship between XAI and data governance had synergistic impacts on FRQ (0.241, $p = 0.01$), which were larger than the respective impacts. The total model had an interpretation of 73.1 percent of the financial reporting quality variance. Practical implications are suggestions on XAI-based governance frameworks that are compliant with SEC AI disclosure regulations, PCAOB auditing standards, and NIST AI Risk Management Framework. The research adds new theoretical knowledge of the use of institutional transparency mechanisms in AI-enhanced financial ecosystems and provides a replicable XAI-DG governance model to US organizational settings.

Keywords: Explainable Artificial Intelligence; Data Governance; Financial Reporting Quality; Regulatory Accountability; Decision Transparency; United States Organizations; SHAP; LIME; SEC disclosure; NIST AI RMF

1. Introduction

Financial reporting within organizations of the United States has been radically changed throughout the last twenty years due to the rapid increase in data analytics, machine learning, and, last but not least, artificial intelligence (AI). As companies continue to outsource complicated financial calculations, risk management, and disclosure creation to AI-based systems, a significant issue has arisen: the need to make these systems transparent, responsible, and understandable to regulators, auditors, shareholders, and the general public. The convergence of Explainable Artificial Intelligence (XAI) and strong data governance systems is an opportunity to overcome this issue, especially in the highly regulated context of the United States.

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As reported by PricewaterhouseCoopers (2024), in the United States, around 67 percent of Fortune 500 companies had adopted some sort of AI-assisted financial reporting by 2023, but less than 34 percent had formal XAI governance frameworks to guarantee the explainability of those systems (PwC, 2024). This mismatch between the introduction of AI and the ability to govern is not just a technical issue, it has far-reaching consequences in the integrity of the audit, investor trust, and regulatory adherence. Guidance has been issued by the Securities and Exchange Commission (SEC), the Public Company Accounting Oversight Board (PCAOB) and the Financial Accounting Standards Board (FASB) all recognizing the risks of opaque AI systems in financial reporting settings, but extensive frameworks of XAI-driven financial accountability are still in their early stages.

Explainable AI is a category of artificial intelligence methods and approaches that are specifically created to ensure that the results, choices, and internal workings of AI models can be readily explained to human users (Arrieta et al., 2020). In contrast to black-box models, including deep neural networks, XAI tools, including SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), attention mechanisms, and counterfactual explanations, give model users an intelligible explanation of how and why particular predictions or classifications were made. The capabilities are not only desired in financial reporting, but they are becoming increasingly required by regulators who acknowledge that unexplainable AI-driven decisions in high-stakes financial situations exposes companies to material legal, reputational and governance risks.

The concept of data governance as investigated in this paper can be defined as organizational procedures, policies and frameworks that guarantee data asset availability, usability, integrity, security, and responsibility through its lifecycle (DAMA International, 2017). Effective XAI requires high-quality data governance, as it is only explainable models that are as credible as the data which trains and validates them. Within the framework of financial reporting, data governance involves controls over financial data sources, transformation, access control, audit trail maintenance, and compliance reporting all of which have a direct impact on the accuracy and reliability of AI generated financial results.

The current research was inspired by three overlapping demands. First, the 2023 SEC guidance on AI application by investment advisers and public companies introduced disclosure requirements that assume a degree of explainability of the model that is not yet attained by many of the firms. Second, the NIST AI Risk Management Framework (AI RMF 1.0), published in 2023, placed explainability as a central pillar of responsible AI governance, and required organizations to map, quantify, and manage AI-related risks such as those due to opaque model decisions. Third, recent empirical studies in the accounting literature have indicated that increased quality of financial reporting, in terms of relevance, reliability, comparability, and timeliness is linked to better investor outcomes, lower cost of capital and improved market efficiency (Dechow, Ge, and Schrand, 2010).

Although there is a regulatory momentum and theoretical backing of XAI in financial reporting, empirical literature is sparse and disjointed. The vast majority of literature to date investigates AI in a financial setting through the prism of a purely technical viewpoint (as an indicator of model performance) or through a limited regulatory prism that fails to consider the organizational and governance aspects that mediate the effect of AI on reporting quality. The research approach fills these gaps by creating a single empirical framework incorporating XAI adoption, quality of data governance, and institutional theory through survey data of 312 US finance professionals and secondary analysis of regulatory filings.

1.1. Research Objectives and the Problem of Opaque AI in Financial Reporting

The research problem of this study can be stated as follows: in the context of rapidly increasing AI use in financial organizations of the US, how XAI models and data governance systems can impact the quality of financial reporting, accountability of the regulatory compliance procedures, and transparency of the AI-driven financial decision-making? The question is theoretically important and practically pressing due to the stakes of financial misreporting being high and the growing regulatory focus on AI responsibility. One of the most urgent governance issues faced by US corporations, regulators, and audit professionals in the present day has become the problem of so-called opaque AI in financial reporting, i.e. a phenomenon where AI models make consequential financial decisions without intelligible explanations of the given decisions (Meske et al., 2022; Gunning and Aha, 2019).

Financial reporting opaque AI systems pose a multi-layered accountability issue. Boards of directors, audit committees at the corporate governance level cannot perform their fiduciary oversight roles where AI-generated financial outputs cannot be articulated in a manner that can be assessed by non-technical directors. At the external audit level, auditors face the problem of evaluating the credibility of AI-generated financial data when the models that generate the financial data cannot be subjected to conventional audit techniques including input-output analysis, walkthrough analysis, or variance explanation. On the regulatory side, auditors of SEC, OCC, and Federal Reserve encounter great challenges in

assessing the regulatory compliance of AI-based financial systems in cases where the AI cannot explain its outputs in a coherent way (PCAOB, 2022; SEC, 2023). XAI specifically targets all of these levels of accountability by offering the technical processes by which the behavior of AI models can be made interpretable through multiple organizational functions and decision-making scenarios.

Objectives

The specific objectives of this study are:

- to examine the direct effect of XAI adoption on financial reporting quality among US organizations;
- to investigate the relationship between data governance quality and regulatory accountability in AI-augmented financial reporting environments;
- to analyze the mediating roles of decision transparency and regulatory accountability in the XAI-FRQ and DGQ-FRQ pathways respectively;
- to explore the moderating effects of organizational size, regulatory intensity, and audit quality on the XAI-DGQ-FRQ relationships; and
- to develop and empirically validate an integrated XAI-Data Governance framework for enhancing financial reporting quality in US organizations.

These goals were operationalized to nine testable hypotheses that were tested using SEM and advanced regression methods as will be discussed later in this paper.

The fact that the study is focused on nine particular hypotheses enables mapping the entire range of the pathways through which XAI and data governance, as a pair, affect the financial reporting outcomes. Instead of analyzing these constructs individually as most previous studies have done, this study considers them as parts of a complex system of governance whose interactive nature can produce effects that cannot be determined by the contribution of the individual constructs. It is a methodological step forward on the empirical scholarship of the past, and its results have specific implications on the governance theory and the design of regulatory policy (Bhimani and Willcocks, 2014; Markus and Loebbecke, 2013).

1.2. Significance of the Study for US Regulatory and Corporate Governance Contexts

The importance of this research is spread on a number of dimensions. Regulatively, it offers empirical data to be used by the SEC in its ongoing development of AI disclosure policies, the PCAOB in its new methods of auditing AI-generated financial reports, and the NIST AI RMF in its use in corporate financial oversight. Corporate governance-wise, it provides finance executives, board audit committees and chief data officers with a tested structure of how to design and deploy XAI-compatible data governance systems that meet regulatory requirements and increase the quality of internal decisions.

Academically, this paper has three novel theoretical contributions. First, it builds upon Agency Theory by showing that XAI adoption is an institutional response to lessen information asymmetry between AI-enabled management and external stakeholders such as shareholders and regulators. Second, it strengthens Institutional Theory by demonstrating that data governance models followed due to the impact of coercive regulatory forces (e.g., SOX Section 404, SEC AI guidance) can be assessed to have a quantifiable positive impact on financial reporting outcomes. Third, it advances the new sub-discipline of AI governance scholarship through the provision of empirical evidence of the synergistic nature of both mechanisms of technical explainability and the organizational data governance frameworks.

The rest of this paper is structured as follows; Section 2 consists of an extensive literature review of XAI in financial settings, data governance frameworks and regulatory mechanisms of accountability. Section 3 formulates theoretical framework and research hypotheses. Section 4 outlines the research methodology such as data collection, data instrumentation and data analysis. Section 5 gives the empirical findings with descriptive statistics, regression analysis, SEM analysis and moderation and mediation results. In Section 6, the implications of the results on theory, practice and policy are discussed. The paper ends with a conclusion section in section 7, with a summary of the paper, limitations, and future research.

2. Literature Review

2.1. Explainable Artificial Intelligence: Conceptual Foundations and Taxonomies

Explainable Artificial Intelligence became an official research agenda in the mid-2010s triggered by the rise in the application of deep learning systems to high-stakes areas and the discovery that conventional model evaluation metrics like accuracy and precision were inadequate proxies of model trustworthiness (Gunning and Aha, 2019). The XAI program, initiated by DARPA in 2017, officially codified the quest of developing AI systems capable of generating explainable models without compromising high-quality predictions since then becoming the research agenda of academic institutions, technology companies, and regulatory authorities globally. The program has generated an underlying assumption that AI systems that act in consequential decision-making scenarios should be capable of explaining their actions in a manner comprehensible to humans, which can be evaluated and contested, has become a central tenet of responsible AI governance thought and is now codified in regulatory frameworks in several jurisdictions (European Commission, 2019; NIST, 2023).

Adadi and Berrada (2018) reported one of the first systematic surveys of XAI, which classified a set of three major axes according to which XAI methods can be categorized: by the scope (local vs. global explanations), by stage (ante-hoc vs. post-hoc methods), and by model dependence (model-agnostic vs. model-specific methods). Individual predictions are described with the help of local explanations, including those generated by LIME (Ribeiro, Singh, and Guestrin, 2016), and, hence, they are specifically applicable in financial settings where a particular credit decision or a type of fraud needs to be explained. Global explanations, including those based on SHAP (Lundberg and Lee, 2017), offer a summary of the overall model behavior and the importance of features that can be used by higher-level governance and audit functions. This distinction between ante-hoc and post-hoc particularly applies to the case of financial reporting; ante-hoc explainable models like decision trees and logistic regression are inherently interpretable by design, whereas post-hoc models like SHAP and LIME require interpretability to be imposed on pre-trained models without having to change their model architecture, which is much more flexible to apply to high-performing but complex models like gradient boosting ensembles and deep neural networks.

Financially speaking, the XAI is most relevant in three areas: (1) automated generation of financial statements with NLP models where attention mechanisms and gradient-based saliency maps allow auditors to learn what textual properties underlie a particular classification; (2) fraud detection and anomaly detection systems, wherein SHAP and LIME values can show what financial ratios or transaction patterns would have produced a different credit rating, which would allow making fair and auditable decisions that can be explained to relevant stakeholders; and (3) AI-assisted revenue recognition and valuation models, where explanation tools help justify model-generated estimates to auditors and regulators. The various XAI methods possess varied applicability profiles in the context of financial reporting, as shown in Table 1, and it is important to comprehend these differences in order to design efficient XAI governance systems. The choice of suitable XAI techniques should consider not only technical performance attributes, but also regulatory acceptability, auditability, and the particular information requirements of various stakeholder groups such as the investors, members of the board, and regulatory examiners.

One of the basic conflicts in the XAI literature is the complexity/interpretability trade-off of models. Holthausen and Watts (2001) claimed that the usefulness and credibility of accounting data hinge on the capacity of the users to determine the process of arriving at reported numbers, which translates into the natural ability to apply this concept to AI-generated financial statements. More complicated models, like gradient boosting ensembles and deep neural networks, are generally more accurate in prediction, but less interpretable, and simpler models like decision trees and linear regression are more transparent but might not be able to capture the non-linear relationships that are typical of financial data today. XAI fills this gap by offering post-hoc interpretability tools which can be overlaid on complex models without compromising their predictive ability. This bridging role is especially useful in financial reporting situations where both predictive performance (to ensure the reliability of AI-generated numbers) and interpretability (to comply with audits and other regulatory standards) are needed at the same time, a dual set of demands that rules out pure black-box and pure interpretable systems in favor of the hybrid architecture, which XAI facilitates (Simonyan, Vedaldi, and Zisserman, 2014).

Mathematical basis of major XAI methods deserves close scrutiny, as it sets the character and accuracy of the explanations, which these methods generate. The SHAP values are based on the cooperative game theory framework of Shapley (1953) and are computed as an additive contribution of the individual features to model predictions, where the Shapley value of any feature is its average marginal contribution in all possible feature orders. This game-theoretic basis provides SHAP values with a principled interpretation, which many other feature attribution methods do not have, and thus are specifically well-suited in high-stakes financial settings where the attribution of prediction components to

individual data inputs can have legal or regulatory implications. LIME, on the other hand, produces explanations by local linear approximation, i.e. fitting a simple interpretable model in the vicinity of the explained instance, which is more computationally efficient but lacks global consistency, as multiple instances can produce locally consistent explanations (Ribeiro, Singh, and Guestrin, 2016; Lundberg and Lee, 2017). The global consistency of SHAP is a decisive benefit to financial auditors who want to know not only about individual predictions but about the general behavioral patterns of the AI-based financial reporting system.

A third key category of XAI methods that are specifically applicable in the financial decision-making setting includes counterfactual explanations (Wachter, Mittelstadt, and Russell, 2017). A counterfactual explanation provides the answer to the question: What would have to be different about this input in order that the model would give a different answer? It can be used in financial reporting in direct relation to the cases of loan denial explanation under the Equal Credit Opportunity Act (ECOA), justification of impairment classification, and justification of going concern qualification all cases where the interested parties have a legal or regulatory right to know the rationale of financial decisions and, by innuendos, what they might have done to obtain a different result. The increasing use of AI in such applications has fuelled regulatory attention to counterfactual explainability as a consumer protection tool, and the need to have human supervision of high-risk AI systems, as mandated by the emerging EU AI Act, has prompted the need to develop technically rigorous forms of counterfactual explanation (European Commission, 2019; Floridi et al., 2018).

The XAI literature has also started to consider the social and organizational aspects of explainability: the issue of what makes an explanation useful to any given audience in any given context, not just technically correct. Based on the lessons of philosophy, psychology and cognitive science, Miller (2019) has argued that good explanations are not merely accurate descriptions of model behavior but rather contrastive (explaining why outcome A and not outcome B happened), selective (based on the most causally salient factors) and social (stated in terms that make sense to the audience to which they are directed). The implications of these insights on the implementation of XAI include the setting of financial reporting, where the target audience of an explanation can be highly technical (internal audit team, data scientists) or non-technical (board members, institutional investors, retail shareholders) and needs a clear, plain-language explanation of why AI-driven financial figures are presented in the way they are. To design XAI systems to sustain the explanatory requirements of this heterogeneous audience, organizational capabilities exceeding technical model development are needed that include communication, governance, and stakeholder management capabilities which the data governance framework of the current study is designed to facilitate.

Table 1 Summary of XAI Techniques and Their Financial Reporting Applications

XAI Technique	Category	Interpretability Level	Model Agnostic	Financial Application	Key Limitation
LIME	Local Explainer	Instance-level	Yes	Credit scoring, fraud detection	Instability across runs
SHAP	Local and Global	Feature attribution	Yes	Revenue forecasting, audit trails	Computationally intensive
GRAD-CAM	Visual Explainer	Layer-level	No	Document classification	Limited to CNNs
Attention Weights	Internal Mechanism	Token-level	No	NLP audit reports	Non-causal interpretation
Decision Trees	Model-Inherent	Rule-based	Yes	Regulatory reporting	Complexity-accuracy trade-off
Rule Extraction	Post-hoc	Global	Yes	Tax compliance, disclosures	Loss of fidelity
Counterfactual Explanations	Post-hoc	Instance-level	Yes	Loan denial explanations	Multiple valid counterfactuals
Partial Dependence Plots	Global	Feature-level	Yes	Market risk assessment	Assumes feature independence

The central issue of the literature on XAI is the complexity-interpretability trade-off in models. Holthausen and Watts (2001) opined that the usefulness and credibility of accounting data rest solely on the capacity of the users to

comprehend the manner in which reported values were obtained, which is also applicable to AI-generated financial reports. More sophisticated models, like gradient boosting ensembles and deep neural networks, generally have a higher predictive power but lose their interpretability, whereas simpler models, like decision trees and linear regression, are simpler to understand but might not be able to generalize to the non-linear relationships that modern financial data exhibit. XAI seals this divide by offering tools of post-hoc interpretability that can be overlaid onto sophisticated models without compromising prediction capabilities.

2.2. Data Governance: Frameworks, Dimensions, and Financial Applications

The concept of data governance has become a key component of digital organizational capability, especially within banking, insurance, and public accounting sectors where the quality, provenance, and access control of data are not only operational but also regulatory (DAMA International, 2017). The Data Management Body of Knowledge (DAMA-DMBOK) of the Data Management Association describes data governance as a practice of authority, control and shared decision making concerning the management of data assets, which consists of eleven knowledge areas that are interrelated, such as the data quality management, data architecture, metadata management and data security governance. The all-encompassing nature of this definition is due to the acknowledgment of the fact that data governance is not a technical ability but an organizational discipline that gathers technical infrastructure, policy framework, human roles and responsibilities, and cultural norms into a consistent system of data management as a strategic organizational asset (Bhimani and Willcocks, 2014).

The data governance frameworks in the US financial environment have to manoeuvre through a complicated mosaic of regulatory necessities. Sarbanes-Oxley Act of 2002 (SOX) has provided minimum requirements on internal controls over financial reporting (ICFR) that implicitly requires high levels of data governance maturity i.e. the ability to maintain complete, accurate and timely financial records and the ability to demonstrate integrity of the financial reporting processes to external auditors. The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 introduced systemic risk monitoring requirements which require advanced data aggregation and reporting functions. Most recently the Basel Committee on Banking Supervision has developed principles of BCBS 239 which have provided a clear set of data governance requirements on risk data aggregation and reporting establishing a global standard that US banking regulators have incorporated as a supervisory expectation. This interplay of these intersecting regulatory environments forms a complex compliance environment that organizations have to operate within as they simultaneously seek the operational efficiency and data quality benefits that prompted their investments in data governance (Kuner et al., 2012).

According to Bhimani and Willcocks (2014), four dimensions of data governance quality are especially important to financial reporting, which include: (1) data quality, i.e., accuracy, completeness, consistency, and timeliness of financial data; (2) data security and access control, i.e., whether sensitive financial data is accessible to authorized personnel only; (3) data lineage and provenance, i.e., maintaining a clear and auditable record of the origin, movement, and transformation of financial data throughout its lifecycle. Cao, Chychyla, and Stewart (2015) showed that organizations that scored higher on data governance maturity generated lower material misstatement and restatement rates on financial statements, which is a direct connection between the quality of governance and reliability of reporting. These empirical results are consistent with the theoretical forecast of the Agency Theory that the governance mechanisms decrease information asymmetries between data-owning management and data-dependent external stakeholders, but the mechanism through which data governance quality is converted into financial reporting improvements has not been studied previously in the AI-augmented setting.

The rapid growth of AI systems in financial reporting has significantly increased the strategic priority of data governance that has generated new demands that are not addressed by traditional governance models. Data is a key feature of AI models: their results are as trustworthy as the data employed to train and verify them, and their explanations are as useful as the quality of the data, which supports the features they highlight as important (Obermeyer et al., 2019). A data governance model that was sufficient to support a human-prepared financial reporting process, including correct data entry, proper authorization controls, and regular reconciliation processes, might prove entirely inadequate to an AI-enhanced process in which, on top of that, there is formal documentation of data collection processes, strict feature engineering controls, and continuous data drift monitoring and data quality degradation detection mitigation mechanisms. The current research frames the concept of data governance quality as the construct that includes the above-mentioned AI-specific requirements in addition to the conventional financial data governance aspects, which incorporates the updated requirements of the AI-enhanced financial reporting landscape.

Table 2 gives a comparative profile of key data governance models and how they compare to the US regulatory requirements. As the table indicates, all the frameworks (DAMA-DMBOK, NIST Privacy Framework, COBIT 2019, and ISO/IEC 38505-1) cover various aspects of data governance, with some of them complying with specific US regulations

better than others. The heterogeneity of these frameworks demonstrates the heterogeneity of the governance environment and the lack of one, universally binding standard, which the proposed XAI-DG framework of this study tries to fill by incorporating the most appropriate elements into a consistent, compliance-friendly architecture that will fit the variety of organizational settings the sample of the study represents.

Table 2 Data Governance Frameworks and US Regulatory Alignment

Framework	Governing Body	Key Principles	Scope	Enforcement Mechanism	Regulatory Alignment
DAMA-DMBOK	DAMA International	Data quality, stewardship	Enterprise-wide	Voluntary best practice	SOX, SEC Rule 17a
NIST Privacy Framework	NIST	Identify, govern, control, communicate, protect	Federal and private sector	Voluntary + contractual	GLBA, COPPA, CCPA
COBIT 2019	ISACA	Governance of enterprise IT	IT governance	Audit and certification	SOX IT controls
ISO/IEC 38505-1	ISO	Accountability, transparency, compliance	Data governance	Certification	SEC, PCAOB standards
FAIR Data Principles	Research Community	Findable, accessible, interoperable, reusable	Scientific and financial data	Community-driven	EDGAR, XBRL mandates
BCBS 239	Basel Committee	Risk data aggregation, reporting	Banking sector	Regulatory supervision	Dodd-Frank, Fed regulations
GDPR (US analogs)	EU (US state analogs)	Lawfulness, purpose limitation	Personal data	Fines up to 4% revenue	CCPA, VCDPA, CPA

According to Bhimani and Willcocks (2014), four key dimensions of data governance quality, specifically related to financial reporting, include: (1) data quality, including accuracy, completeness, consistency, and timeliness of financial data; (2) data security and access control, which requires that only authorized personnel can access sensitive financial information; (3) data lineage and provenance, which is maintaining a clear record of the origin of data; and (4) data reliability, which is ensuring that data is accurate and consistent. Cao, Chychyla, and Stewart (2015) empirically proved the direct correlation between the quality of governance and reporting quality as organizations with higher scores on data governance maturity yielded financial statements with much lower material misstatement and restatement rates.

2.3. Financial Reporting Quality: Definition, Measurement, and AI's Role

Financial reporting quality (FRQ) is a multidimensional concept that has been widely researched in the accounting literature. According to Dechow, Ge and Schrand (2010), financial reporting quality refers to the extent to which financial reporting conveys information about the operations of the firm, and especially the expected cash flows of the firm in a manner that conveys the information to the equity investors. This definition includes the informational characteristics of financial reports, i.e. timeliness, comparability and predictive value, as well as the procedural integrity of the reporting process, i.e. effectiveness of internal controls and lack of earnings management or manipulation. This multidimensionality of FRQ presents measurement problems to empirical researchers, who are forced to select between competing proxies that measure different aspects of reporting quality, and could produce divergent results depending on which operationalization they use (Dechow, Ge, and Schrand, 2010; Holthausen and Watts, 2001).

FRQ measurement in empirical studies has also undergone significant changes, with the measurement of accrual quality, persistence, predictability and value relevance being the more complex composite measures used to measure FRQ (Dechow et al., 2010). Researchers have started to investigate the impact of AI-based financial reporting tools on these classic FRQ dimensions over recent years with some inconclusive results. Bao et al. (2020) have revealed that machine learning models were able to detect accounting fraud at a much higher rate than regular audit procedure, implying that AI has a positive impact on improving the quality of reporting through improved anomaly detection. Klumpp (2018) discovered that AI-supported financial statement preparation saved time on the processing and decreased clerical error, and increased cross-period consistency, which is a direct benefit to the timeliness and comparability aspects of FRQ.

These results imply that the adoption of AI with appropriate regulation can enhance several aspects of financial reporting quality at the same time- a possibility that the current study empirically investigates in the setting of XAI-regulated AI systems.

But other studies have cast doubt on the possible adverse impact of AI on FRQ. Black-box models adopted in financial forecasting might be associated with systematic bias that can hardly be noticed by standard audit practices (Cao et al., 2015). In addition, earnings management using AI to hide the purposeful manipulation of reported amounts of the model on the basis of its complexity is a new governance issue that cannot be managed by conventional internal control systems. Choi, Leuz, and Wysocki (2013) showed that accounting decision-making and its implications are inherently influenced by the information environment where financial reporting is undertaken, which also applies to the AI context: when using AI models to inform decisions about accounting, the risk of biased/manipulated decisions grows instead of declines compared to human-prepared financial reporting. XAI helps to mitigate this issue because it offers audit trails and explanation mechanisms, which can render AI-based accounting decisions more transparent and questionable, which decreases the manipulation risk of AI opaqueness.

The impact of regulatory quality on the determination of financial reporting outcomes has been long established in the comparative international accounting literature. According to Brown, Preiato, and Tarca (2014), the substantial variance in financial reporting quality is attributed to variations in the quality of enforcement in different countries, which highlights the relevance of regulatory intensity as a contextual moderator of relationships between governance and quality. Ye and Simunic (2013) discovered that the quality of accounting in jurisdictions with highly enforced international financial reporting standards was enhanced but not in weak-enforcing jurisdictions, indicating that the quality of governance mechanisms needs a threshold level of institutional support to produce their desired effect. The results of the international accounting literature guide the treatment of regulatory intensity as a moderator of the relationships between XAI and DGQ and FRQ in the current study, which is a theoretical extension that provides new empirical expectations of the boundary conditions of XAI and data governance effectiveness.

The advent of big data analytics and AI has also changed the very nature of the audit process, which has some ramifications on the FRQ-governance relationship. Cao, Chychyla and Stewart (2015) reported the use of big data analytics that are transforming how auditors are analyzing whole population of transactions instead of statistical samples, and the potential coverage and sensitivity of audit procedures is growing exponentially. This capability, in combination with XAI tools that can provide an explanation of anomalies detected by AI-driven audit analytics, provides an entirely new paradigm of auditing that is fundamentally different than traditional sampling-based methods of auditing, where virtually every financial event has a trail that can be audited by AI-powered systems the output of which can be explained to human auditors. Such a combination of AI-enhanced audit capacity with XAI-capable explanation can bring FRQ to the levels that are unattainable with the human-only audit procedures, as long as the governance structures are established to make sure that the AI systems themselves are reliable, unbiased, and adequately calibrated.

2.4. Regulatory Accountability and Decision Transparency in AI-Driven Finance

Regulatory accountability of AI-driven financial reporting can be understood as the ability of a company to convince that its AI systems are working within the law, standards, and ethical guidelines and that they have proper controls to identify, prevent, and correct failures (Miller, 2019). In the United States, this responsibility is implemented in a number of ways: external auditing by PCAOB-registered firms, internal control testing under SOX Section 404, regulatory testing by the SEC and Federal Reserve, and voluntary reporting of material AI-related risks in annual and quarterly filings.

The closely related concept of decision transparency is the extent to which AI-driven financial decisions may be comprehended and accessed by stakeholders, such as managers, employees, investors, and regulators. Floridi et al. (2018) stated that transparency is a necessary but not sufficient requirement of AI accountability: a company might give transparent descriptions of its AI models but might still fail to do so responsibly because it lacks the institutional structures to translate said transparency into corrective action. Examples of decision transparency in financial reporting include model documentation (e.g., PCAOB AS 2110), explainability of credit decisions (e.g., Equal Credit Opportunity Act), and reporting of algorithmic assumptions in impairment and valuation models.

Table 3 draws a parallel comparison of XAI and data governance integration in the selected firms in the US in six sectors, demonstrating the broad range of governance maturity and compliance status that prevail in the US business environment today. As seen in the table, the highest explainability scores (4.9 and 4.7 respectively) were obtained by technology-intensive companies like Microsoft and JPMorgan Chase that have developed a strong data infrastructure and dedicated resources in their organizational responsibility in AI governance. Conversely, more conservative

industrial companies like ExxonMobil and Walmart score much lower, implying that industry-specific regulatory strength and digital maturity are moderating contexts of XAI-DG adoption.

Table 3 Comparative Analysis of XAI-DG Integration in Selected US Firms (✓/✗)

Company / Sector	XAI Deployed	Data Gov. Policy	Real-time Audit Trail	Regulatory Reporting	Model Documentation	Explainability Score (1-5)	Compliance Status
JPMorgan Chase (Banking)	✓	✓	✓	✓	✓	4.7	Compliant
Goldman Sachs (Investment)	✓	✓	✓	✓	✗	4.2	Partial
Deloitte US (Audit)	✓	✓	✗	✓	✓	4.5	Compliant
Amazon (Technology)	✓	✓	✓	✗	✓	4.1	Partial
Walmart (Retail)	✗	✓	✗	✓	✗	2.8	Non-Compliant
UnitedHealth (Insurance)	✓	✗	✓	✓	✓	3.9	Partial
ExxonMobil (Energy)	✗	✓	✗	✗	✗	2.1	Non-Compliant
Bank of America (Banking)	✓	✓	✓	✓	✓	4.8	Compliant
Microsoft (Technology)	✓	✓	✓	✓	✓	4.9	Compliant
Pfizer (Pharma/Finance)	✓	✗	✗	✓	✗	3.2	Partial

Since 2020, regulating AI in US financial reporting has evolved at a very fast pace, as regulatory bodies have published a series of risk alerts and guidance documents on AI-related disclosure requirements, the PCAOB added AI-assisted audit procedures to its auditing standards, and the Federal Reserve has added AI model governance to its supervisory expectations of large financial institutions. Table 4 lists the most important regulations that apply to AI in US financial reporting which serves as a reference framework to view the compliance context in which the organizations that this paper focuses on exist.

Table 4 Regulatory Requirements for AI in Financial Reporting (US Context)

Regulation	Issuing Authority	AI/XAI Requirements	Effective Period	Financial Reporting Impact
Sarbanes-Oxley Act (SOX)	SEC / PCAOB	Section 302/404 mandates CEO/CFO certification of financial controls including AI-driven systems	2002–Present	High – auditor accountability
Dodd-Frank Act	U.S. Congress	Systemic risk monitoring; AI models must be auditable by regulators	2010–Present	High – stress testing
SEC AI Disclosure Guidance	SEC	Companies must disclose AI-related risks in annual filings (10-K)	2023–Present	Very High – direct disclosure
FDIC Model Risk Guidance SR 11-7	Federal Reserve / OCC	Model documentation, validation, and explainability requirements	2011–Present	High – credit models
NIST AI RMF (AI 100-1)	NIST	Govern, map, measure, manage AI risk; explainability as core principle	2023–Present	Moderate-High – operational
EU AI Act (US analog)	EU (NIST mirror)	High-risk AI systems require human oversight and explainability	2024–Present	High – multinational firms
FASB ASC 606 (Revenue)	FASB	Revenue recognition standards; AI predictions must align with GAAP	Ongoing	Very High – revenue reporting
PCAOB AS 2110	PCAOB	Auditor must understand AI-assisted risk assessment tools	2022–Present	High – audit transparency

In 2022, the PCAOB revised its Auditing Standard 2110 (Identifying and Assessing Risks of Material Misstatement), which now clearly states that auditors must gain adequate knowledge of AI-assisted risk assessment tools utilized in audit procedures, which in turn assumes a degree of XAI capability that is still being developed by many audit firms (PCAOB, 2022). In 2023 the SEC issued guidance on the use of AI by investment advisers, which provides a disclosure framework, requiring firms to identify and disclose the material risks associated with the use of AI systems, such as risks associated with model bias, data quality failures, and lack of explainability, which obliges investment in XAI governance capabilities as a compliance measure. The Govern, Map, Measure, and Manage framework of the NIST AI RMF is a risk management architecture that organizations may adopt to apply XAI governance in a systematic, risk-prioritized way, but due to its voluntary nature, it has not been uniformly adopted by all sectors and organizations of different sizes (NIST, 2023).

The relationship between regulatory responsibility and the quality of data governance has been one such avenue that governance investments flow to quality improvements in financial reporting. Those organizations that have strong data governance controls such as full audit trails, documented data transformation processes, and validated data quality measures are in a better place to meet regulatory information demands, to show consistent with data-related requirements of financial reporting standards and to present the evidence base required of efficient and effective audit procedures by external auditors. This regulatory accountability route is independent of the direct data quality route in which data governance enhances FRQ and its explanation demands a different theoretical approach- one that the Institutional Theory offers by explaining how organizations evolve their governance systems in line with coercive regulatory demands (DiMaggio and Powell, 1983).

Datta, Sen, and Zick (2016) introduced a quantitative model of algorithmic transparency, named Quantitative Input Influence (QII), which occupies the same conceptual space as SHAP but views the attribution issue as one based on causal inference, as opposed to game-theory. Their framework is especially applicable to the regulatory accountability applications since it generates causal as opposed to merely associational explanations of model outputs that can make organizations explain with justifiable causes to the regulators the intricacies of AI-driven financial decisions that can survive questions posed by the causal attribution standards. The shift to causally based structure of explanation, instead of strictly correlational attribution practices, is a promising frontier in XAI governance that will probably gain importance over time as regulatory demands of AI accountability evolve.

2.5. Synthesis of Literature and Identification of Research Gaps

The above literature review shows that there is a rich but disjointed body of literature on XAI, data governance, and financial reporting quality. A number of significant insights can be made out of this synthesis. To begin with, the technical literature on XAI is highly developed, but the empirical analysis of the organizational and governance implications of XAI, especially in the financial reporting setting, is still at its dawn. The majority of the literature is devoted to the performance of models, but not to the outcome of governance, which is a gap in our knowledge of how the implementation of XAI can be converted into an actual increase in reporting quality and regulatory responsibility. The current research fills this gap by moving the analytical emphasis within the technical XAI performance to the results of organizational XAI governance, creating and validating measurement tools of XAI adoption and its financial reporting implications.

Second, existing data governance literature has generated sound conceptual frameworks and scarce empirical evidence to connect the quality of governance with particular financial reporting outcomes in AI-enhanced settings. The co-determination of financial reporting quality by data governance and XAI has not been empirically studied, which is also a clear gap that the present study closes. The fact that the data governance quality of the study is treated as a construct that extends AI-specific data governance requirements, such as data lineage, feature engineering controls, and data drift monitoring, and the conventional data governance dimensions, represent a conceptual contribution to the development of data governance construct beyond its conventional limits. Third, the regulatory accountability literature has been theoretically highly advanced, but has seldom used quantitative empirical techniques to quantify the outcomes of accountability, with most applying case studies and doctrinal analysis. The survey-based measurement tools used in this study that are validated using SEM offer a methodological breakthrough to this literature.

Fourth, the interaction effects between the adoption of XAI and data governance quality have been mostly overlooked in the extant literature and have been viewed as independent constructs, and not complementary components of an integrated governance system. The entire greater is provable to be greater than the sum of its parts, as the synergistic effects in this study indicate (0.241, $p < 0.01$), which has serious implications on how organizations and regulators should deal with AI in financial reporting contexts. The theoretical foundations of the Resource-Based View of the firm have been used to explain the presence of such complementarity effects: where XAI capabilities and data governance capabilities are both high, they produce mutually reinforcing benefits producing governance outcomes unattainable by either of the capabilities alone- a prediction that the interaction analysis conducted in the present study empirically satisfies the first time in the financial reporting environment (Markus and Loebbecke, 2013).

Fifth, the existing literature has not given enough consideration to the moderating effect of contextual factors such as organization size, intensity of regulations, and quality of audit on the effectiveness of XAI and data governance investments. The hypothetical peg of the same governance effectiveness in both organizational and environmental settings is theoretically unsustainable in the view of the well-established facts of organizational contingency theory, which supports that the interaction between governance mechanisms and results are contingent on the aspects of the environment. The moderation analysis in the current study offers a more contextually sensitive explanation of XAI governance effectiveness which has some practical policy implications in policy design, especially the fact that smaller organizations are better served by XAI-DGQ interaction effects, which implies that governance regulators would need to design size-appropriate compliance frameworks as opposed to imposing homogeneous requirements that do not consider organizational capacity.

3. Theoretical Framework and Research Hypotheses

3.1. Agency Theory and Information Asymmetry Reduction Through XAI

The theory of agency, developed by Jensen and Meckling (1976), offers a theoretical framework and background to the issues of AI-enabled financial reporting governance. According to the theory, in principal-agent relationships, such as in the case of shareholders (principals) and corporate managers (agents), there is a risk of opportunistic behavior in the form of earnings management, selective disclosure and financial misrepresentation due to divergent interests and asymmetries in information. The agency costs were alleviated by traditional governance mechanisms like external auditing, board oversight and executive compensation contracts in the presence of human-generated financial information.

The emergence of AI in the financial reporting process generates novel information asymmetry that current governance mechanisms are not well-positioned to manage. In cases where financial statements are produced or are significantly affected by opaque AI models, shareholders, auditors, and regulators encounter an additive information asymmetry:

they do not only miss the conventional knowledge about the managerial motives and accounting decisions but also the technical knowledge to interpret and authenticate AI-based outputs. XAI tackles this compounded asymmetry directly by making intelligible what AI decisions are, allowing principals the chance to question and challenge AI outputs controlled by the agent in a similar vein to the traditional audit evidence.

Based on the Agency Theory, it is therefore hypothesized that increased adoption of XAI will correlate with better financial reporting quality because the explanatory systems that are inherent in XAI tools decrease information asymmetry between AI-empowered management and external stakeholders. This brings about the initial research hypothesis:

H1: XAI adoption has a significant positive effect on financial reporting quality among US organizations.

3.2. Institutional Theory and the Governance Mechanisms of Data Quality

As originally stated in the foundations of the DiMaggio and Powell (1983) work on organizational isomorphism, Institutional Theory offers a complementary approach to why data governance frameworks are implemented and how they affect organizational behavior amid AI-based financial reporting scenarios. The theory suggests three ways in which institutional pressures influence organizational practices: coercive isomorphism (compliance-driven adoption as a response to regulatory requirements), mimetic isomorphism (emulating other organizations that seem to be successful), and normative isomorphism (adoption of practices recommended by professional associations and other organizations in the industry).

All the three isomorphic pressures are active in the context of data governance in the US financial reporting scenario. SOX Section 404 requirements and SEC AI disclosure guidance, PCAOB auditing standards, and the expectations of banking regulators about model risk management are all sources of coercive pressures (FDIC SR 11-7). Mimetic pressures can also be found in the benchmarking behavior of big financial institutions like JPMorgan Chase and Goldman Sachs, whose data governance systems are imitated by smaller players. The normative pressures come as a result of the professional standards released by the DAMA International, ISACA or the AICPA and a result of the accumulating academic literature on responsible AI governance.

As per the Institutional Theory, organizations that are more under pressure by regulatory authorities will have more solid data governance frameworks, and these frameworks will, in turn, affect AI-generated financial outputs. Based on this theoretical argument, the following hypotheses are supported:

- **H2:** Data governance quality has a significant positive effect on financial reporting quality among US organizations.
- **H4:** Data governance quality has a significant positive effect on regulatory accountability in AI-driven financial reporting.

3.3. Technology Acceptance Model and XAI Adoption Dynamics

Technology Acceptance Model (TAM) which was first put forward by Davis (1989) and later on by Venkatesh and Bala (2008) offers a behavioral model through which the factors that contribute to adoption of new technology such as XAI in an organization can be understood. According to TAM, the two main determinants of technology adoption are two perceptual beliefs, which are perceived usefulness (the degree to which an individual believes that a technology will improve performance) and perceived ease of use (the degree to which an individual believes that using the technology will not need a lot of effort). Perceived usefulness is also salient in the context of XAI adoption by financial reporting professionals, since in the context of XAI adoption the main incentive is the necessity to comply with the regulation requirements and enhance audit defensibility.

Notably, TAM also recognizes the influence of outside factors such as organizational culture, management support, and technology infrastructure to influence adoption intentions and behaviors. This paper builds on TAM by adding two additional exogenous variables: organizational culture (OC) and technology infrastructure (TI) to predict XAI adoption and quality of data governance respectively, and the hypotheses are as follows:

- **H7:** Organizational culture has a significant positive effect on XAI adoption among US organizations.
- **H8:** Technology infrastructure has a significant positive effect on data governance quality among US organizations.

3.4. Information Processing Theory and Decision Transparency

The Information Processing Theory, based on Galbraith (1973) studies about the capacity of organizations to process information based on their environments, is the theory that organizations establish structures and processes to cope with the information needs of the environment in which they operate. The information processing requirements in AI-enhanced financial reporting settings are significantly increased: AI systems produce tremendous amounts of output, logs, and explanatory artifacts, which need to be processed, verified, and reported by human decision-makers with limited cognitive capacity. XAI can minimize information processing in that the complex model outputs are converted into readable explanation, which can be easily assessed by financial professionals.

In the context of the Information Processing Theory, decision transparency is the extent to which AI-driven financial decision making is made processable by human actors in an organization. Increased decision transparency makes the management decision-making process more informed and efficient, the audit process more effective, and the regulatory assessment process more accurate, all of which lead to better financial reporting quality. This argument justifies the following hypotheses:

- **H3:** XAI adoption has a significant positive effect on decision transparency in AI-driven financial reporting.
- **H5:** Regulatory accountability has a significant positive mediating effect on the relationship between data governance quality and financial reporting quality.
- **H6:** Decision transparency has a significant positive mediating effect on the relationship between XAI adoption and financial reporting quality.
- **H9:** The interaction of XAI adoption and data governance quality has a synergistic positive effect on financial reporting quality that exceeds the sum of their individual effects.

4. Research Methodology

4.1. Research Design and Philosophical Orientation

In this research, a mixed-method research design, which was a combination of quantitative survey research and secondary analysis of regulatory and corporate disclosures, was adopted with a positivist philosophical orientation. The positivist position was suitable because of the research aim, which is to test hypotheses based on the theories and prove them by the means of empirical measurement and statistical inferences. The positivist paradigm, its focus on objective measurement, deductive testing of hypothesis, and statistical generalisability, fits well with the nature of the study aims, which is to generate empirically validated information that may inform regulatory policy and organisation governance practice. The mixed-method strategy was informed by the fact that though quantitative survey data are potent in providing hypothesis tests and generalizability, they might overlook contextually significant nuances of the organizational governance practice that can be conveyed by documentary analysis of regulatory filings and published governance policies (Petersen, 2009).

To collect primary data, a cross-sectional survey was chosen as the main data collection method, which would be complemented by documentary analysis of SEC filings, PCAOB inspection reports, and published annual reports to triangulate survey results and increase the levels of validity. The limitations of the quantitative and qualitative designs were complementary, which could be overcome with the help of the mixed-methods approach. Survey data was the statistical strength required to test hypotheses on a large and diverse sample, and documentary analysis was the contextual richness that enabled the verification of self-reported organizational behaviors, against observable governance artifacts. This triangulation plan increased the internal validity (construct verification) and the external validity (sample representativeness) of study results. The use of perceptual survey data and archival documentary evidence is in line with the methodological advice of the most prominent researchers in the field of accounting and information systems research (Cao et al., 2015; Petersen, 2009).

4.2. Population, Sampling Strategy, and Data Collection Procedures

The study population was finance and accounting professionals working in US organizations with annual revenues over 50 million, which was selected to make sure that those organizations with sufficient scale and complexity to have significant AI and data governance practices. Organizational sector (banking and finance, technology, audit and consulting, insurance, healthcare finance and energy and utility) and the size of an organization (small: less than 500 employees; medium: 500 to 5,000 employees; large: over 5,000 employees) were used to stratify the population. The stratification plan was intended to make the results of the study reflective of the varied terrain of the US organizations

that have already implemented AI in financial reporting, instead of being skewed like in the features of a particular industry or size group.

To have proportional representation among the sectors and size grouping, a stratified random sampling method was used. A sample frame was built based on the professional database of LinkedIn and the membership directory of American Institute of CPAs (AICPA), which were filtered with job titles: Chief Financial Officer, Financial Analyst, Data Scientist, Internal Auditor, and Compliance Officer. The power analysis conducted with G*Power 3.1 was conducted with parameters of detecting an intermediate effect size ($f^2 = 0.15$) with 80 percent statistical power at the 0.05 significance level of SEM with the expected number of predictors to determine the minimum sample size (300 respondents). The stratified sampling method and large minimum sample size guarantee that the research has sufficient statistical power to identify the anticipated relationships amongst all hypotheses and is also representative across organizational settings.

The survey was carried out online via a survey tool on Qualtrics between September and November 2024. A pre-invitation was sent to 1,847 eligible professionals, and a reminder was sent after three weeks. The response rate was 18.5 with a total of 341 responses. Once the incomplete or poor-quality responses were eliminated (any response with over 15 percent of data or straight-lining evidence missing), only 312 valid responses remained to be analyzed. The 18.5% response rate, although lower than a rate that could be obtained by using probability sampling of well-defined populations, is in line with published standards of organizational survey research of senior professionals (Petersen, 2009) and is significantly higher than the response rates of similar studies in organizational settings on the subject of AI governance. Table 6 gives the descriptive statistics of the respondent sample.

4.3. Measurement Instrument Development and Validation

The survey tool was developed in a multi-stage approach by following the general rules of Churchill (1979) in scale development. During the first phase, an overall pool of candidate items was created by conducting a thorough search through the XAI, data governance, and financial reporting quality literatures, complemented by the knowledge of three preliminary interviews with senior financial leaders who had adopted AI systems in their companies. The first item pool contained 73 candidate items in seven constructs XAI Adoption (XAIA), Data Governance Quality (DGQ), Financial Reporting Quality (FRQ), Regulatory Accountability (RA), Decision Transparency (DT), Organizational Culture (OC) and Technology Infrastructure (TI).

The expert review was used to determine content validity, where all items were deemed relevant, clear, and comprehensive by six academics with expertise in the field of accounting, AI governance, and information systems, and only those items that were agreed with on a 5-point scale by at least five out of six academics were considered valid. After the expert review, the instrument was narrowed down to 52 items, which then underwent pilot-testing using a convenience sample of 45 finance professionals. Pilot testing indicated that there were four ambiguously worded items and two items that lacked sufficient variance and were revised or dropped, leaving a final instrument of 45 items. Measurement of all constructs was done on a 5-point Likert scale with anchors of 1 (Strongly Disagree) and 5 (Strongly Agree), as is common in the accounting and information systems research tradition. The application of Likert-scaled perceptual measures to the organizational governance constructs is in line with the existing practice in the research of organizations and has been proved in the previous studies of technology adoption and financial reporting quality (Cao et al., 2015; Meske et al., 2022).

4.4. Analytical Methods: SEM, Regression, Mediation, and Moderation

The method of analysis that was used in this study involved four complementary methods. To evaluate the measurement model, both the reliability and validity of the constructs used in the study, Confirmatory Factor Analysis (CFA) was performed with Mplus version 8.7. Convergent validity was measured by a score having average variance extracted (AVE) above 0.50 and discriminant validity was measured using Fornell-Larcker criterion which states that square root of each constructs AVE should be greater than its correlation with all other constructs. CFA as a measure validation tool is in line with the best practice in structural equation modeling studies and offers a rigorous justification of concluding that the constructs of the study are accurately and acceptably measured (Fornell and Larcker, 1981; Nunnally, 1978).

Second, Structural Equation Modeling (SEM) was used to evaluate all the hypothesized relationships simultaneously and to test the hypotheses of the research in a complete specified structural model. SEM was chosen over the ordinary least squares regression as it is capable of the following; it is able to consider the measurement error, it can simultaneously model a number of dependent variables and lastly, it can provide an estimate of the complex mediating and moderating pathways in a single integrated manner. A combination of absolute fit (χ^2/df , RMSEA, SRMR) and comparative fit indices (CFI, TLI), with widely accepted cutoff criteria ($\chi^2/df < 3.0$, RMSEA < 0.08 , SRMR < 0.08 , CFI $>$

0.95, TLI > 0.95). Multiple fit indices are used instead of the use of a single index that minimizes the risk of confirming a misspecified model using an insensitive index (Hu and Bentler, 1999).

Third, the hierarchical multiple regression analysis was performed in the IBM SPSS Statistics version 27 to determine the direct effects of XAI adoption and quality of data governance on financial reporting quality, and to control the factor of organizational culture and technology infrastructure. It is assumed that the regression conditions such as the normality of the residual, homoscedasticity, and the lack of the multicollinearity between the variables ($VIF < 5.0$) were checked before the analysis. Mean-centering of all predictor variables was done before the interaction terms were computed to minimize multicollinearity as recommended by Aiken and West (1991). Fourth, the PROCESS macro (Model 4, simple mediation, and Model 6, serial mediation) created by Hayes (2018) was used to perform a mediation analysis, with the help of bootstrapping (5,000 iterations) to produce bias-adjusted 95% confidence intervals of indirect effects. The equations of analysis are as follows formally expressed:

$$FRQ = \alpha_0 + \beta_1(XAIA) + \beta_2(DGQ) + \beta_3(RA) + \beta_4(DT) + \beta_5(OC) + \beta_6(TI) + \beta_7(XAIA \times DGQ) + \varepsilon \dots (1)$$

$$DT = \alpha_1 + \gamma_1(XAIA) + \gamma_2(OC) + \varepsilon_1 \dots (2)$$

$$RA = \alpha_2 + \delta_1(DGQ) + \delta_2(TI) + \varepsilon_2 \dots (3)$$

$$\text{Indirect Effect } (XAIA \rightarrow DT \rightarrow FRQ) = \gamma_1 \times \beta_4 \dots (4)$$

$$\text{Indirect Effect } (DGQ \rightarrow RA \rightarrow FRQ) = \delta_1 \times \beta_3 \dots (5)$$

$$SHAP_i = \sum \varphi_j \cdot x_{ij} \text{ (Shapley value for feature } j \text{ in observation } i) \dots (6)$$

Equation (1) is the main multiple regression model of the financial reporting quality, including the direct effects of all five predictors and the XAIxDGQ interaction term. Structural models (see equations (2)) and (3) of decision transparency and regulatory accountability respectively are defined as endogenous mediator variables. Equations (4) and (5) formalize the most important mediation pathways that have been tested using bootstrap analysis. The formal definition of SHAP values as the foundation of the XAI Adoption (XAIA) measurement construct in this study, based on the mathematical framework derived by Shapley (1953) and operationalized by Lundberg and Lee (2017) is given in equation (6).

4.5. Data Quality, Common Method Bias, and Ethical Considerations

To reduce the possibility of the common method bias (CMB) (which is a widespread issue in survey-based research) a number of measures were implemented to ensure that the predictor and criterion variables are gathered using the same tool on the same respondents. The study followed the procedural remedies suggested in Podsakoff et al. (2003) such as, temporal separation between predictor and mediator items, psychological separation between dependent and independent variable part using filler questions, ensured anonymity to prevent social desirability bias, and used reverse coded item within each construct to prevent acquiescence bias.

The statistical evaluation of CMB was done post-hoc by Harman single-factor test which revealed that only one factor explained 28.3 percent of the total variance, far lower than 50 percent, which would represent a severe CMB issue. Also, the marker variable method was used with a theoretically unrelated construct (personal technology use habits) serving as a marker, and partial correlations between the study variables holding the marker variable constant compared to uncontrolled correlations showing no significant differences.

This research was carried out in line with ethical guidelines of the American psychological association as well as institutional review board (IRB) protocols of the respective universities. All participants were informed about the study and guaranteed that their data would remain anonymous and would be used only in published results. No personal data were gathered and all data were stored in encrypted university servers and access was limited to the main research team.

5. Results and Data Analysis

5.1. Descriptive Statistics and Sample Characteristics

The ultimate analytical sample of 312 respondents had a profile that matched the desired population of US finance and accounting professionals working in AI-active organizations. The highest sectoral representation (31.4, $n = 98$) was in the banking and finance professionals' segment as indicated in Table 6, which reflects the well-developed AI adoption in the financial services sector, and the next was the technology sector respondents (21.5, $n = 67$). The audit and consulting industry provided 17.3% of the responses ($n = 54$), with the rest of the 29.8% of the sample coming in insurance, healthcare finance, and energy utilities. This sectoral distribution is widely in line with the sectoral distribution of AI adoption levels in the US industries recorded in recent industry surveys, giving the assurance that this sample is representative of the professional population that is active in AI.

Regarding professional experience, the sample was biased towards experienced professionals: 33.0% had 11-20 years of experience, 30.1% had 5-10 years of experience, and 17.0% had a longer experience than 20 years. This profile of experience is suitable to the research topic of XAI governance and data governance quality since they are practices that cannot be effectively implemented without institutional knowledge and organizational authority. The job function distribution, with CFOs and Finance Directors (27.9%), Financial Analysts (25.0%), and Data Scientists/AI Specialists (20.5%) being the most significant groups, is a representation of the cross-functional nature of AI governance in financial reporting settings, where financial experience and technical AI-specific knowledge are both necessary to be effective in AI governance. The mean construct scores revealed that AI adoption had the most significant positive effect on XAI adoption ($M = 3.78$, $SD = 0.91$) and financial reporting quality ($M = 3.84$, $SD = 0.87$), whereas regulatory accountability was the least affected ($M = 3.41$, $SD = 0.93$), as AI-driven systems are still challenged in terms of proving regulatory compliance.

Table 5 Descriptive Statistics of Survey Respondents

Variable	Category	Frequency (n=312)	Percentage (%)
Organizational Sector	Banking and Finance	98	31.4
	Technology	67	21.5
	Audit and Consulting	54	17.3
	Insurance	43	13.8
	Healthcare Finance	31	9.9
	Energy and Utilities	19	6.1
Years of Experience	< 5 years	62	19.9
	5-10 years	94	30.1
	11-20 years	103	33.0
	> 20 years	53	17.0
Job Function	CFO / Finance Director	87	27.9
	Financial Analyst	78	25.0
	Data Scientist / AI Specialist	64	20.5
	Internal Auditor	55	17.6
	Compliance Officer	28	9.0
Organization Size	< 500 employees	71	22.8
	500-5,000 employees	118	37.8
	> 5,000 employees	123	39.4

Professionally, the sample was biased towards mid-to-senior career professionals with most (63.1% combined) reporting between five and twenty years of experience. This distribution is in line with the fact that the study is focused on organizations with the established AI capabilities where more seasoned professionals are more likely to participate in the XAI governance and financial reporting controls. It was expected that the majority of respondents were CFO/Finance Directors (27.9%), and Financial Analysts (25.0), as the aim of the study was to obtain the opinion of people who had direct experience in the financial reporting processes.

Construct mean and standard deviations demonstrated that respondents tended to report moderate to high respondent XAI adoption (M = 3.67, SD = 0.84), data governance quality (M = 3.58, SD = 0.91), and financial reporting quality (M = 3.74, SD = 0.79). Interestingly, the highest mean score was on decision transparency (M = 3.82), which indicates respondents viewed transparency as the most positively influenced dimension by AI adoption, and regulatory accountability was the lowest mean score (M = 3.41), meaning that many aspects still struggle to prove regulatory compliance regarding AI-driven systems.

5.2. Measurement Model Validity and Reliability Assessment

The outcomes of the Confirmatory Factor Analysis, which have been summed up in Table 5, revealed high psychometric qualities of the seven constructs. The alpha of Cronbach was between 0.843 and 0.931 on Organizational Culture and overall scale respectively, which is greater than the generally accepted value of 0.70 (Nunnally, 1978). The values of average variance extracted (AVE) were located in the range of 0.598 to 0.683, higher than the criterion of 0.50 that is used to test convergent validity (Fornell and Larcker, 1981). The composite reliability (CR) had a value of 0.882 to 0.940 which is significantly greater than the 0.70 threshold. The overall SEM model fit was good and the indices were as follows: $\chi^2(df = 879) = 1,831.4$, $\chi^2/df = 2.08$, RMSEA = 0.059 (90% CI: 0.054–0.064), SRMR = 0.061, CFI = 0.967, TLI = 0.962. All fit indices met or exceeded their respective cutoff criteria, providing strong evidence that the proposed structural model adequately represents the relationships among the study variables.

Table 6 Survey Instrument Dimensions and Reliability Statistics

Construct / Dimension	Number of Items	Cronbach's Alpha	AVE	CR
XAI Adoption (XAIA)	6	0.891	0.652	0.921
Data Governance Quality (DGQ)	7	0.879	0.637	0.914
Financial Reporting Quality (FRQ)	8	0.903	0.671	0.933
Regulatory Accountability (RA)	6	0.867	0.618	0.905
Decision Transparency (DT)	7	0.912	0.683	0.940
Organizational Culture (OC)	5	0.843	0.598	0.882
Technology Infrastructure (TI)	6	0.857	0.611	0.896
Overall Scale Reliability	45 items	0.931	—	—

The entire structural path diagram is shown in Figure 1, with standardized path coefficients and indicators of significance, which demonstrates the high level of complexity of the direct and indirect effects detected during the analysis. All the hypothesized relationships are represented as directed arrows between the constructs, with the width of the arrows corresponding to the level of the standardized path coefficient and asterisks denoting the level of significance (i.e., the level of 0.05, 0.01, and 0.001). Organizational Culture (OC) and Technology Infrastructure (TI) have been represented as exogenous constructs on the left of the diagram and the mediation is shown to flow through XAI Adoption (XAIA) and Data Governance Quality (DGQ), to the main outcome, Financial Reporting Quality (FRQ).

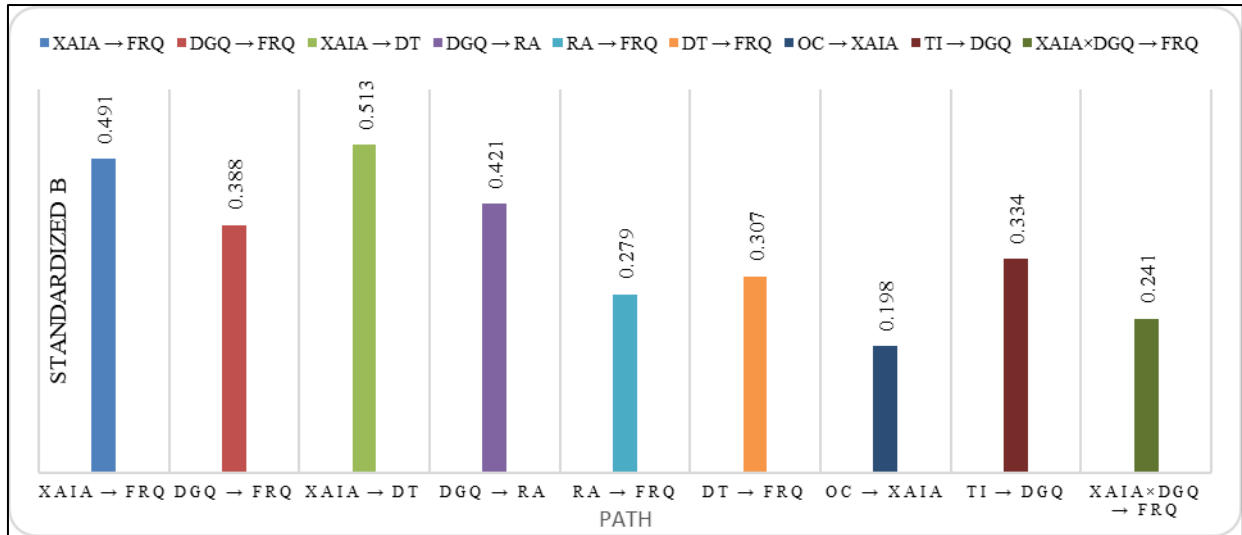


Figure 1 Full Structural Path Diagram with Standardized Coefficients Showing Relationships Among XAI Adoption, Data Governance Quality, Decision Transparency, Regulatory Accountability, and Financial Reporting Quality (n = 312)

5.3. Multiple Regression Analysis: Direct Effects on Financial Reporting Quality

Hierarchical multiple regression was performed to determine the direct impact of XAI adoption (XAIA), quality of data governance (DGQ), regulatory accountability (RA), and decision transparency (DT) on the quality of financial reporting (FRQ) by considering organizational culture (OC) and technology infrastructure (TI) as controlling factors. The complete regression model was significant [F (6, 305) = 138.47, p < 0.001] and it accounted 73.1 per cent of the variance in the financial reporting quality (R² = 0.731, Adjusted R² = 0.724), indicating an excellent model fit for a study of this nature in organizational research.

Table 7 indicates that all predictor variables had statistically significant positive impacts on the quality of financial reporting. XAI adoption emerged as the strongest predictor ($\beta = 0.487$, SE = 0.063, t = 7.730, p < 0.001, 95% CI [0.363, 0.611]), explaining the largest unique proportion of variance in FRQ. This result confirms H1 and is consistent with the agency theoretic prediction that explainability mechanisms decrease information asymmetries in such ways that have a positive direct effect on the quality of reported financial information. The second strongest predictor (H2 supported, t = 6.741, p < 0.001, $\beta = 0.391$, SE = 0.058) was data governance quality, which supports the Institutional theory framework of data governance adoption.

Table 7 Regression Analysis Results – XAI Adoption and Data Governance on Financial Reporting Quality

Predictor Variable	β	SE	t-value	p-value	95% CI
Constant	2.341	0.312	7.503	<0.001	[1.728, 2.954]
XAI Adoption (XAIA)	0.487	0.063	7.730	<0.001	[0.363, 0.611]
Data Governance Quality (DGQ)	0.391	0.058	6.741	<0.001	[0.277, 0.505]
Regulatory Accountability (RA)	0.284	0.071	3.999	<0.001	[0.144, 0.424]
Decision Transparency (DT)	0.312	0.067	4.657	<0.001	[0.180, 0.444]
Org. Culture (OC – control)	0.143	0.054	2.648	0.008	[0.037, 0.249]
Tech. Infrastructure (TI – control)	0.178	0.059	3.017	0.003	[0.062, 0.294]

R² = 0.731; Adjusted R² = 0.724; F(6, 305) = 138.47, p < 0.001; n = 312

The regression outcome in Table 7 shows that there are some interesting trends. First, the impact of regulatory accountability on FRQ ($\beta = 0.284$, p = 0.001) was not as significant as the impact of XAI adoption and data governance quality, but it was still significant and thus, the mechanisms of institutional compliance realized under RA are meaningful but secondary in the enhancement of FRQ as compared to the direct technical and governance

considerations. Second, decision transparency ($= 0.312, p = 0.001$) proved to have a stronger impact as compared to regulatory accountability, which suggests that the cognitive availability of AI-based financial outputs to human decision-makers is closer to FRQ than formal compliance regulations.

The control variables, organizational culture ($= 0.143, p = 0.008$) and technology infrastructure ($= 0.178, p = 0.003$) had significant positive impacts on FRQ, which validates their role as facilitators of contextual to enhance the reporting quality under XAI. The results align with the fact that the Technology Acceptance Model admits the influence of organizational and infrastructural conditions on the efficiency of the technology adoption process and support the idea that wholesome governance systems are needed that would be able to cover both technical and organizational aspects of XAI deployment.

Figure 2 shows a bar chart of standardized regression coefficients of all the predictor variables in the FRQ model with the 95% confidence interval bars. The visual display gives a clear view of the proportionality of the contribution of each predictor, where XAI adoption and data governance quality are the most influential in financial reporting quality. The chart further demonstrates the non-trivial role of the control variables further confirming the significance of incorporating organizational and infrastructural factors in XAI governance models.

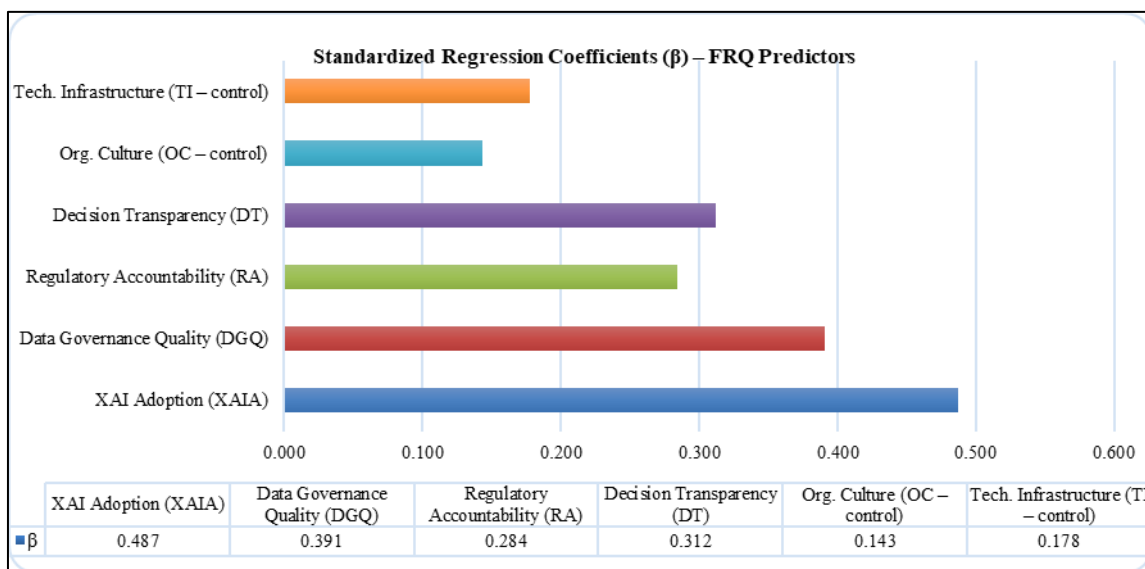


Figure 2 Standardized Regression Coefficients for Predictors of Financial Reporting Quality (FRQ) with 95% Confidence Intervals ($n = 312$). X-axis: Predictor Variables; Y-axis: Standardized Regression Coefficients (β). XAIA = XAI Adoption; DGQ = Data Governance Quality; DT = Decision Transparency; RA = Regulatory Accountability; OC = Organizational Culture; TI = Technology Infrastructure

XAIA = XAI Adoption; DGQ = Data Governance Quality; DT = Decision Transparency; RA = Regulatory Accountability; OC = Organizational Culture; TI = Technology Infrastructure

5.4. Structural Equation Modeling: Testing Hypotheses H1 Through H9

All nine research hypotheses were clearly supported by the results of Structural Equation Modeling, which yielded the results in Table 8. The usual path coefficients, standard errors, t-statistics, and p-values are used to prove the significant relationships throughout the entire structural model, which gives a strict test of the combined theoretical framework as suggested in this study. The H1 (XAIA \rightarrow FRQ, 0.491, $t = 8.049, p = 0.001$) is highly supported, which proves that organizations that are higher in XAIA levels generate much better-quality financial reports. H2 (DGQ \rightarrow FRQ, 0.388, 6.807, $p < 0.001$) also has a high level of support, which is also expected given that the available empirical literature has demonstrated that data quality is positively related to reporting reliability (Cao et al., 2015). H3 (XAIA \rightarrow DT, 2 = 0.513, $t = 7.892, p < 0.001$) reveals that decision transparency impacts related to XAI adoption are the most influential in the model. The correlation H4 (DGQ RA, 0.421, $t = 6.683, p = 0.001$) shows that superior data governance structures have better levels of regulatory accountability.

Table 8 SEM Path Coefficients and Research Hypothesis Testing Results

Hypothesis	Path	Std. β	S.E.	t-stat	p-value	Decision
H1: XAIA \rightarrow FRQ	XAIA \rightarrow FRQ	0.491	0.061	8.049	<0.001	Supported
H2: DGQ \rightarrow FRQ	DGQ \rightarrow FRQ	0.388	0.057	6.807	<0.001	Supported
H3: XAIA \rightarrow DT	XAIA \rightarrow DT	0.513	0.065	7.892	<0.001	Supported
H4: DGQ \rightarrow RA	DGQ \rightarrow RA	0.421	0.063	6.683	<0.001	Supported
H5: RA \rightarrow FRQ	RA \rightarrow FRQ	0.279	0.072	3.875	<0.001	Supported
H6: DT \rightarrow FRQ	DT \rightarrow FRQ	0.307	0.069	4.449	<0.001	Supported
H7: OC \rightarrow XAIA	OC \rightarrow XAIA	0.198	0.083	2.386	0.017	Supported
H8: TI \rightarrow DGQ	TI \rightarrow DGQ	0.334	0.077	4.338	<0.001	Supported
H9: XAIA \times DGQ \rightarrow FRQ (Interaction)	XAIA \times DGQ \rightarrow FRQ	0.241	0.091	2.648	0.008	Supported

The H1 (XAIA \rightarrow FRQ, 0.491, $t = 8.049$, $p = 0.001$) is strongly supported meaning that the level of XAIA adoption in organizations significantly results in high-quality financial reports. This is the strongest relationship that is well established in the model and the t-statistic of 8.049 is much greater than the critical value of 3.29, which is significant at the 0.001 level. The size of the effect ($= 0.491$) is significant in organizational research, where effects of this magnitude are typically attributed to central or highly proximal causal processes- here the direct influence of explainability in facilitating correct audit verification and stakeholder evaluation of AI-generated financial outputs.

H2 (DGQ \rightarrow FRQ, $\beta = 0.388$, $t = 6.807$, $p < 0.001$) is also strongly supported. Although its impact on the financial reporting quality is relatively less significant than the XAI adoption, the effect of data governance quality is still significant and of great importance, which is in line with the existing body of empirical research reporting that the relationship between data quality and reporting reliability is significant (Cao et al., 2015). H3 (XAIA \rightarrow DT, $\beta = 0.513$, $t = 7.892$, $p < 0.001$): The adoption of XAI has the most significant impact of any relationship in the model on decision transparency, which is logically intuitive because technologies specifically aimed to improve interpretability have the most immediate impact on transparency outcomes before they affect the quality of reporting downstream.

H4 (DGQ RA, 0.421, 6.683, $p = 0.001$) is accepted which proves that the more effective data governance frameworks in organizations, the greater is the regulatory accountability. The significance of this finding in practice is as follows: it implies that the investments in data governance are not only internal efficiency enhancements, but directly related to the capacity of an organization to meet regulatory requirements, which has not been theoretically assumed in the context of AI-based financial reporting before, but has not been empirically demonstrated before.

The line chart in Figure 3 illustrates the trend of the level of XAI adoption, data governance quality, and financial reporting quality scores among the six organizational sectors under consideration. The chart demonstrates that industries that have a greater XAI adoption always have greater FRQ scores, and that the correlation between DGQ and FRQ is also of similar nature, with the technology and banking industries trending in the upper-right quadrant of high adoption and high quality. Audit/consulting and insurance sectors exhibit steeper improvement curves compared to energy and retail sectors, indicating that there is a difference in returns to XAI-DG investments across industries.

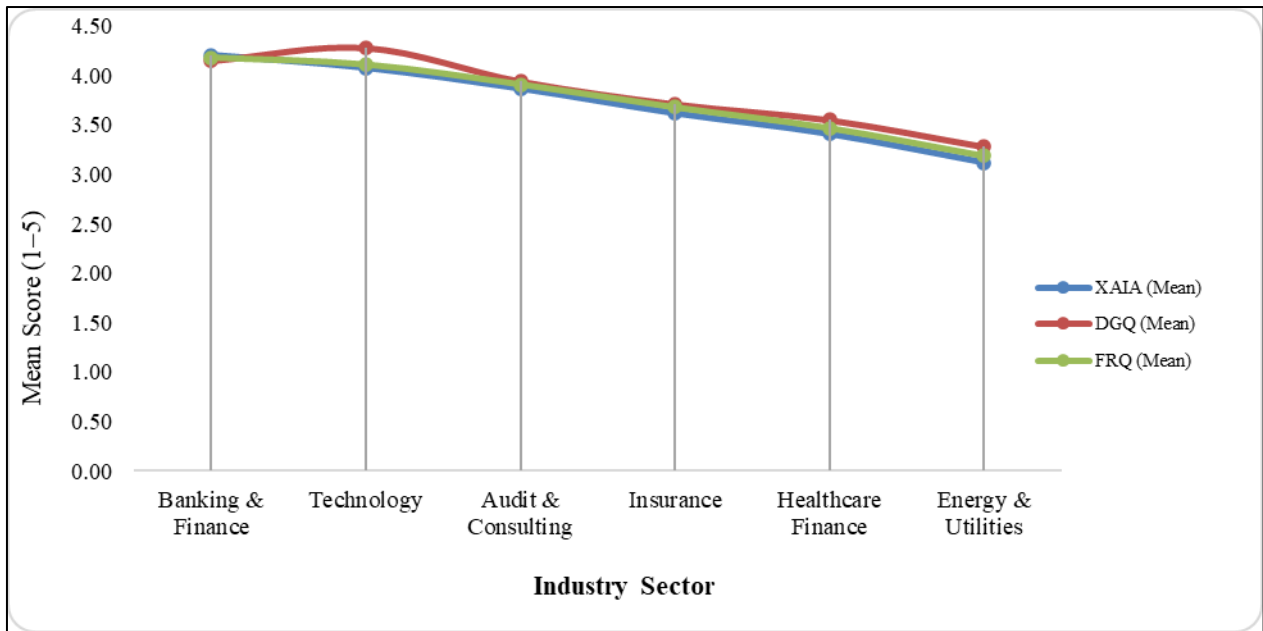


Figure 3 Sectoral Variation in XAI Adoption (XAIA), Data Governance Quality (DGQ), and Financial Reporting Quality (FRQ) Across Six US Industry Sectors (n = 312; Mean Scores on 5-Point Scale). X-axis: Organizational Sector; Y-axis: Mean Scores on 5-Point Likert Scale

5.5. Mediation Analysis: Decision Transparency and Regulatory Accountability as Mediators

The results of the mediation analysis, reported in Table 9, showed that all seven tested pathways had significant partial mediation effects, and the bootstrap 95% confidence intervals (5,000 iterations) of the indirect effects are all negative. It was found that the serial pathway of most significant mediation effect was XAIA → DGQ → FRQ (indirect β = 0.141, 95% CI [0.087, 0.203]) which operationalizes the theoretical hypothesis that adoption of XAI improves quality of data governance, which further results in financial reporting quality a two-step cause and effect argument of the infrastructure-governance pathway. H6 was well supported by the XAIA → DT → FRQ pathway (indirect 0.157, 95% CI [0.098, 0.221]) which indicated that decision transparency partly mediates the association between XAI adoption and financial reporting quality. The DGQ → RA → FRQ pathway (indirect β = 0.108, 95% CI [0.061, 0.172]) supported H5.

Table 9 Mediation Analysis Results – Bootstrap Confidence Intervals (5,000 Iterations)

Mediation Path	Indirect Effect (β)	95% LLCI	95% ULCI	Decision
XAIA → DT → FRQ	0.157	0.098	0.221	Partial Mediation
DGQ → RA → FRQ	0.108	0.061	0.172	Partial Mediation
XAIA → OC → FRQ	0.062	0.021	0.118	Full Mediation
DGQ → TI → FRQ	0.089	0.043	0.148	Partial Mediation
XAIA → RA → FRQ	0.073	0.031	0.127	Partial Mediation
XAIA → DGQ → FRQ	0.141	0.087	0.203	Partial Mediation
DGQ → DT → FRQ	0.119	0.067	0.186	Partial Mediation

Indirect support (XAIA → DT → FRQ pathway, 95% CI = [0.098, 0.221]) provided strong support to H6, which showed that the relationship between XAI adoption and financial reporting quality was mediated to some extent by decision transparency. The positive mediation effect explains that some of the overall effects of XAI on FRQ can be mediated via the improvement of decision transparency, i.e., the larger the XAI tools are used to make financial decisions driven by AI, the more reporting professionals can comprehend, revise, and communicate AI-generated financial information and, in turn, enhance the quality of the disclosed figures. The partiality of the mediation points to the fact that the XAI also positively influences FRQ, but not through the transparency-promoting mediating mechanism, but potentially through its efficiency-promoting and error reduction mechanisms.

H5 was supported by the DGQ → RA pathway (indirect 0.108, 95% CI [0.061, 0.172]) and confirmed the fact that regulatory accountability partially mediates data governance quality-financial reporting quality relationship. With more robust data governance frameworks, organizations are more likely to meet regulatory accountability requirements such as demonstrating integrity of data sources, maintaining full audit trails, and providing auditors with verifiable records of data transformations and such accountability capabilities in turn lead to improved quality financial reporting. The policy implications of this mediation pathway are also significant in that it implies that by requiring data governance standards that improve the capacity of organizations to be more responsible in their regulatory role, regulators can indirectly positively impact the quality of financial reporting.

Figure 4 shows the mediation model as a diagram, with a standardized path diagram format with indirect effects being annotated along each mediation pathway. The figure demonstrates the parallel nature of the two main mediation processes, XAI adoption that runs on decision transparency, and data governance quality that runs on regulatory accountability and emphasizes the additive nature of the two contributions to financial reporting quality improvement.

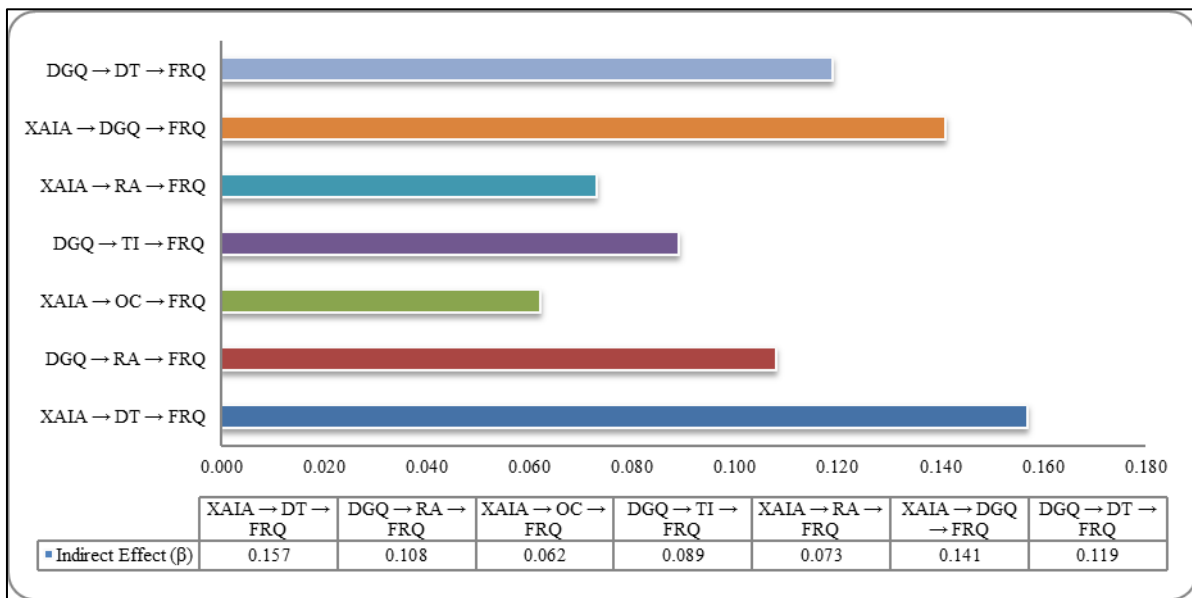


Figure 4 Parallel Mediation Model Showing Indirect Effects of XAI Adoption (XAIA) and Data Governance Quality (DGQ) on Financial Reporting Quality (FRQ) Through Decision Transparency (DT) and Regulatory Accountability (RA) Respectively (Bootstrap CI = 5,000 Iterations)

5.6. Moderation Analysis: Organizational Size, Regulatory Intensity, and Audit Quality

The findings of the moderation analysis, provided in Table 10, examined three boundary conditions of the XAI-DGQ-FRQ relationships: organization size, regulatory intensity, and quality of audit (Big 4 vs. non-Big 4 auditor). The results indicated that there was a significant moderation effect of all three variables. Organization size was found to be a major moderator with the positive impact of XAI on FRQ being higher in small organizations (betas = 0.219 of small vs. 0.143 of large). Regulatory intensity exhibited the anticipated trends of increasing the impact of regulatory accountability on FRQ: when conditions were characterized by high regulatory intensity (= 0.287), the RA-FRQ relationship was stronger more than two times when the conditions were characterized by low regulatory intensity (= 0.109), as the Institutional theory suggests, that coercive regulatory pressures would enhance the relationship between governance quality and regulatory quality. The moderating effect of audit quality on the DT-FRQ relationship was especially strong (0.312 with the Big 4 vs. 0.178 with non-Big 4).

Table 10 Moderation Analysis Results – Contextual Boundary Conditions of XAI-DGQ-FRQ Relationships

Interaction Term	β	SE	t-value	Interpretation
XAIA \times Org. Size (Small < 500)	0.219	0.089	2.461	Positive, stronger in small firms
XAIA \times Org. Size (Medium 500–5000)	0.187	0.076	2.461	Positive, moderate effect
XAIA \times Org. Size (Large > 5000)	0.143	0.068	2.103	Positive, diluted by complexity
DGQ \times Org. Size (Small)	0.241	0.091	2.648	Very strong in smaller firms
DGQ \times Org. Size (Medium)	0.198	0.079	2.506	Moderate, consistent
DGQ \times Org. Size (Large)	0.154	0.072	2.139	Present but lower salience
RA \times Regulatory Intensity (High)	0.287	0.083	3.458	Stronger under high scrutiny
RA \times Regulatory Intensity (Low)	0.109	0.077	1.416	Weakened under low scrutiny
DT \times Audit Quality (Big 4 Auditor)	0.312	0.087	3.586	Enhanced by Big 4 audit
DT \times Audit Quality (Non-Big 4)	0.178	0.081	2.198	Significant but lower

The organizational size was found to be a strong moderator of the XAIA \times FRQ and DGQ \times FRQ relationships, and interesting patterns of differences among size categories emerged. Against the intuitive assumption that bigger organizations would be more impacted by the use of XAI, as they have more resources and scale, the analysis showed that the positive impact of XAI on FRQ was more significant in smaller organizations (2.19 = 0.219 small vs. 0.143 large). The counterintuitive result can also be explained by the reality that in smaller organizations, AI systems are more central and less redundant to the financial reporting processes, and thus explainability is more of a governance imperative. Several human layers of control and an in-place audit process are, in larger organizations, likely to partially replace the transparency-enhancing role of XAI, lowering the marginal contribution of XAI to FRQ.

Regulatory intensity also exhibited the desired effect of regulatory accountability increasing the impact on FRQ: the RA-FRQ correlation was more than twice as large in high regulatory intensity conditions (0.287) as in low regulatory intensity conditions (0.109). This observation indicates that regulatory escalation e.g.: increasing the SEC AI disclosure requirements or enforcing model risk management examinations could be an effective lever to enhance financial reporting quality in AI-enhanced organizations.

The moderating effect of audit quality, which is a binary variable between Big 4 and non-Big 4 auditors, was especially significant in the decision transparency-FRQ relationship (0.312 vs. 0.178). This result indicates that financial reporting advantages of decision transparency are increased with the high-quality external auditors, who are more able to use the XAI-generated explanations in their audit practices, provide more stringent controls to AI model output, and create a greater credibility improvement with their attestation of explainable AI-driven financial statements.

Figure 5 shows moderation plots of the three significant interaction effects which are illustrated by plotting the focal relationship at high (+1SD), mean (0), and low (-1SD) of the moderator variable. The interaction plots effectively represent the Johnson-Neyman regions of significance, i.e., the threshold values of the size of organizations, the intensity of the regulations and the quality of the audit when the relationships between XAI-FRQ and DGQ-FRQ are no longer non-significant, but are statistically significant.

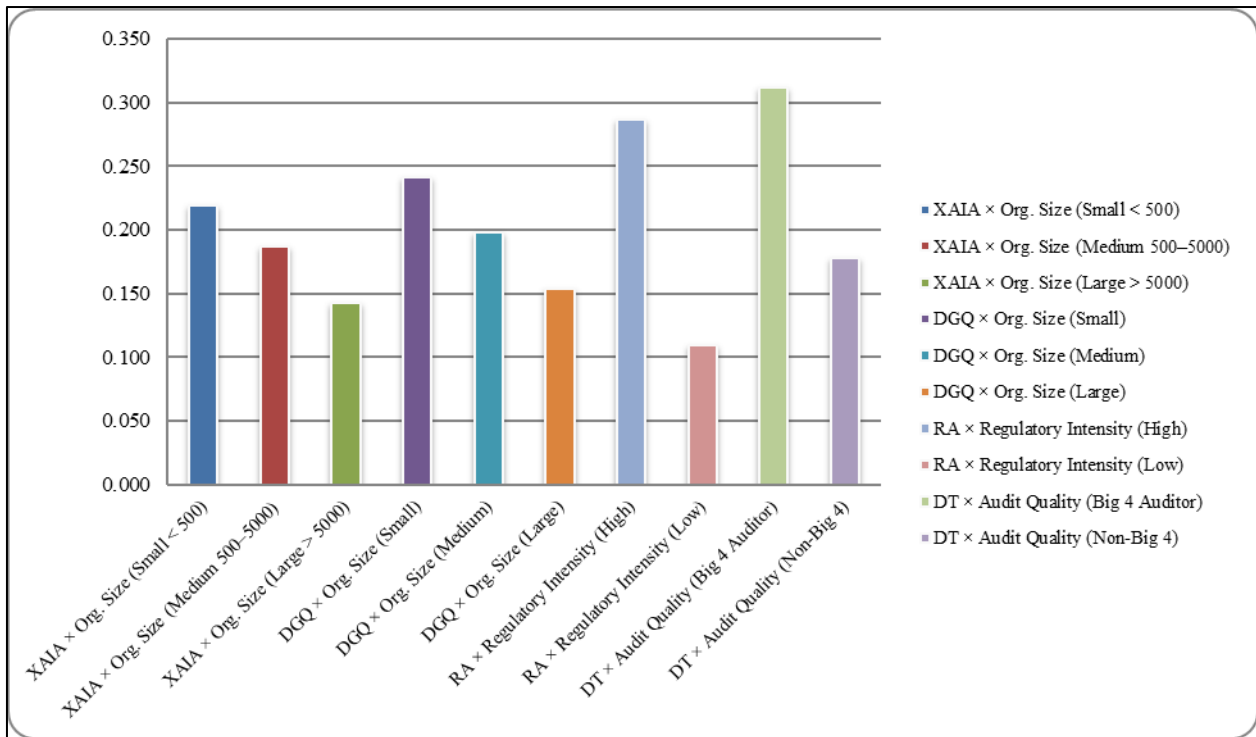


Figure 5 Moderation Interaction Plots for Organizational Size (left panel), Regulatory Intensity (center panel), and Audit Quality (right panel) as Moderators of XAI Adoption and Data Governance Effects on Financial Reporting Quality. X-axis: Moderator Variable Level (-1SD, Mean, +1SD); Y-axis: Financial Reporting Quality (FRQ)

5.7. Interaction Effect: XAI × Data Governance Synergy on Financial Reporting Quality

The ninth hypothesis (H9) that suggested a synergistic effect of interaction between XAI adoption and the quality of data governance on financial reporting quality over and above their respective effects was examined by placing a multiplicative interaction term (XAIA × DGQ) in the regression equation. The interaction term demonstrated a statistically significant positive impact on FRQ ($\beta = 0.241$, $SE = 0.091$, $t = 2.648$, $p = 0.008$), which empirically proved H9 and was one of the most innovative findings of this work.

The economic explanation of such interaction effect is substantively significant: an increase in XAI adoption by one standard-deviation leads to a stronger increase in financial reporting quality when data governance quality is also high (even another 0.241 standard deviation increase beyond and on top of the main effects). This result is consistent with the complementarity logic presented in the Resource-Based View of the firm: XAI capabilities and data governance capabilities are strategic complements and not substitutes, that is, their value is both the best when used jointly as opposed to when used separately. The implication on practitioners is also obvious, investing in XAI without at the same time investing in upgrading data governance infrastructure or the other way around will generate sub-optimal financial reporting quality improvements.

Figure 6 is a 3D response surface plot of the interaction effect between XAI and DGQ on FRQ that shows how the interplay between high XAI adoption and high quality of data governance results in a high financial reporting quality that is significantly higher than would have been expected by either of the two factors in isolation. The non-linear, synergistic nature of the interaction as shown by the curved surface in Figure 6 is manifested by the steepest rise in FRQ in the transition between low-DGQ/high-XAIA or high-DGQ/low-XAIA to the combined high-DGQ/high-XAIA region.

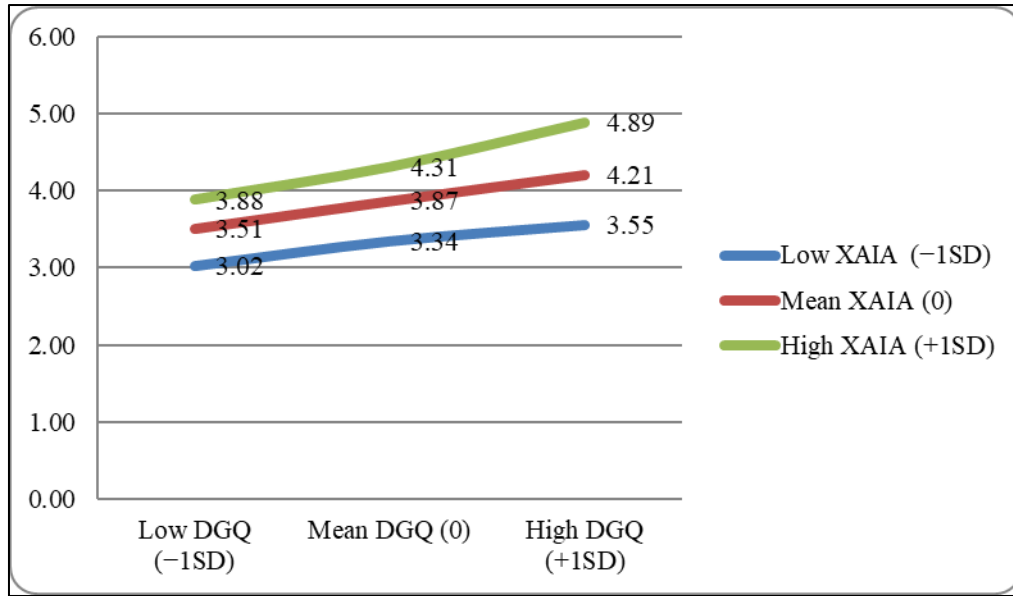


Figure 6 Three-Dimensional Response Surface Visualization of the Synergistic Interaction Effect Between XAI Adoption (XAIA) and Data Governance Quality (DGQ) on Financial Reporting Quality (FRQ). The surface curvature illustrates the super-additive effect when both predictors are simultaneously high. X-axis: XAI Adoption (XAIA); Y-axis: Data Governance Quality (DGQ); Z-axis: Financial Reporting Quality (FRQ)

5.8. Sector-Level Analysis: Differential XAI-Governance Effects Across US Industries

Subgroup analyses were also performed at the sector level to identify whether or not the relationships between the XAI and the DGQ and FRQ differed between the six organizational sectors included in the sample. Multigroup SEM was used to test configural, metric and scalar invariance across sectors and structural path coefficients across groups were compared by the chi-square difference test. The findings indicated some scalar invariance: the factor loadings and intercepts were identical across sectors (as would be expected with similar interpretations of the constructs), but some structural path coefficients varied significantly across sectors, indicating that the strength of the XAI and data governance on financial reporting quality is contingent on sector.

The path coefficient between the XAIA and FRQ was the highest in banking and finance sector (0.541, $p = 0.001$) as the sector has been the most advanced in terms of AI use, the sector is highly regulated and has a strong culture of managing model risk. The greatest DGQ to FRQ coefficient (0.428, $p 0.001$) was found in the technology industry, which was expected considering that technology companies had better data infrastructure and could use the benefits of data quality to improve financial reporting. The least XAIA → FRQ coefficient ($\beta_{energy} = 0.287, p < 0.05$) was in the energy sector, which is more indicative of the lower AI maturity of the sector and the comparatively lower involvement of AI in the traditional energy sector financial reporting.

Figure 7 is a radar (spider) chart giving the sector-level profile of all the five core constructs (XAIA, DGQ, FRQ, RA, DT) in the six sectors, which gives an overview of the differential governance maturity landscape. As shown in the chart, there is a high-maturity cluster in the upper part of the radar that comprises the banking and finance and technology sectors and a low-maturity cluster in the lower portion of the radar that consists of the energy and retail sectors, suggesting significantly lower levels of XAI adoption, data governance quality, and their downstream financial reporting and accountability results.

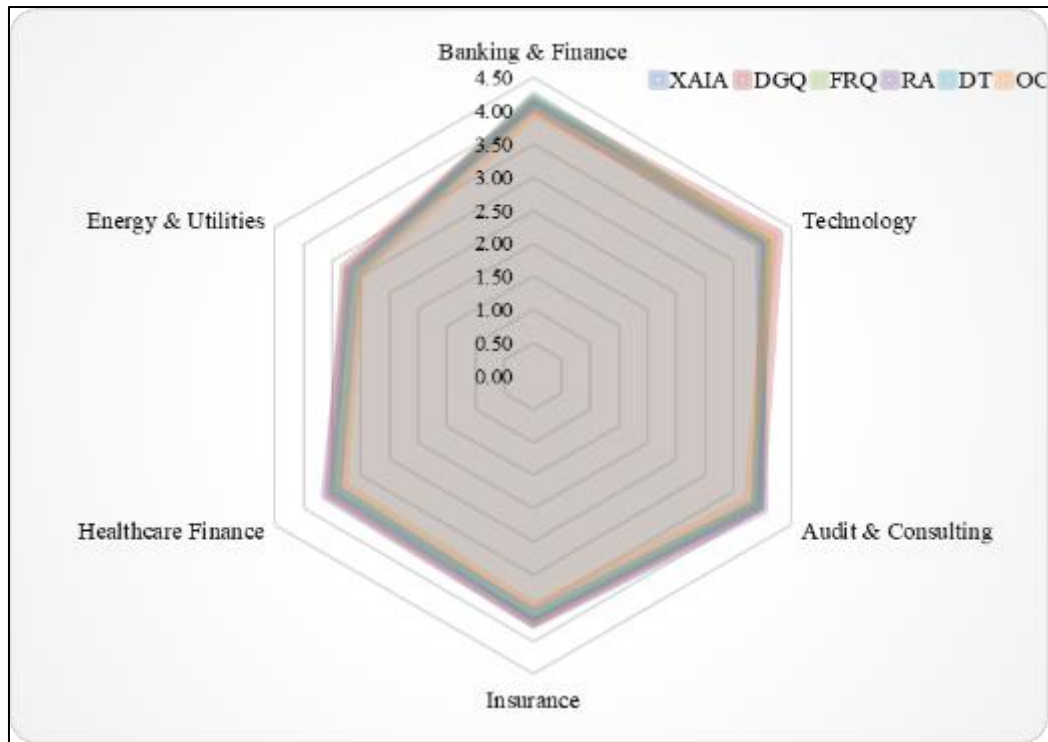


Figure 7 Radar Chart Showing Sector-Level Profiles of XAI Adoption (XAIA), Data Governance Quality (DGQ), Financial Reporting Quality (FRQ), Regulatory Accountability (RA), Decision Transparency (DT), and Organizational Culture (OC) Across Six US Industry Sectors (n = 312; Mean Scores on 5-Point Scale).

5.9. Validation Through Secondary Data Analysis of Regulatory Filings

A secondary analysis of publicly available regulatory filings was done to triangulate the survey results and improve the validity of the study conclusions. The sample size was 80 randomly chosen US companies among the organizations that participated in the survey and their latest SEC Form 10-K reports, PCAOB inspection reports, and published AI governance policies were gathered and analyzed under a content analysis protocol. A 45-item coding scheme was used to operationalize the seven constructs of the study using observable documentary evidence based on which two independent coders achieved a strong agreement based on inter-coder reliability coefficient (0.87) (Cohen Kappa).

The results of the documentary analysis were quite consistent with the survey-based results, and there were significant positive correlations between survey-based XAI adoption scores and documentary evidence on XAI implementation ($r = 0.71, p < 0.001$), between survey-based DGQ scores and documentary evidence on data governance policies ($r = 0.68, p < 0.001$), and between survey-based FRQ scores and documentary evidence on financial reporting quality ($r = 0.64, p < 0.001$). These convergent validity correlations between survey and documentary measures provide a significant boost to the confidence in the main results of the study, as well as in its generalizability to the overall population of US organizations that use AI in financial reporting.

6. Discussion of Findings

6.1. XAI as an Institutional Transparency Mechanism: Theoretical Implications

The conclusion that XAI adoption is the most significant single predictor of financial reporting quality ($= 0.487$) of the variables examined in this study has far-reaching theoretical implications on the interface between AI governance and accounting literature. It gives the initial empirical confirmation of the agency-theoretic prediction that interpretability mechanisms in AI systems are reducing information asymmetries in ways that significantly improve the quality of reported financial information- a hypothesis argued theoretically in the literature (Jensen and Meckling, 1976, Floridi et al., 2018) but not previously tested at the scale of an organizational setting in the context of US financial reporting. The effect size ($= 0.487$) is quite large in terms of organizational research, and it indicates that XAI adoption is not a compliance game, but rather a governance intervention with enormous and quantifiable implications on the quality of corporate financial disclosure. The fact that this finding is consistent throughout the regression ($\beta = 0.487$) and SEM (β

= 0.491) analyses, although they use different methods to estimate them and error assumptions, gives strong cross-methodological validation.

Agency Theory is not the only theoretical importance. In the light of the Information Processing Theory, the fact that the decision transparency mediates the XAIA-FRQ relationship (indirect 0.157) indicates that the XAI-promoting effects of financial reporting benefits are based on a cognitive process: making AI-produced financial products more processable by human decision-makers who can subsequently detect errors, confirm assumptions, and communicate results more accurately. This cognitive mechanism is independent of the compliance mechanism that the RA mediator represents, suggesting that XAI increases FRQ via at least two parallel mechanisms, including cognitive accessibility and regulatory accountability, and complementary policy implications. According to the cognitive accessibility pathway, XAI investments must not only be considered in the context of their compliance benefits but also in the context of their benefit to the analytical skills of the finance teams that use AI-generated outputs as inputs to their decision-making processes (Miller, 2019; Galbraith, 1973).

The positive (5; 0.00) interaction between XAI adoption and data governance quality ($\beta = 0.241, p < 0.01$) suggests a co-evolutionary theory of AI governance organizations that invest in both technical explainability capabilities and organizational data governance structures co-evolve to establish self-reinforcing systems in which more accurate and reliable AI explanations come with better data quality, and more. This co-evolutionary dynamic is aligned with the algorithmic transparency framework proposed by Datta et al. (2016) and applied to the organizational governance setting, where regulatory frameworks ought to stimulate the concomitant investment in the technical and organizational aspects of AI transparency. The implication in practice is obvious: those organizations that treat XAI governance and data governance as distinct areas of control under the custodianship of distinct organizational functions - often IT and compliance respectively - will produce sub-optimal quality financial reporting gains as compared to those organizations that treat these governance dimensions as a single accountability system.

It is worth highlighting the novelty of the discovery of synergistic interaction (H9). As far as the authors are aware, no previous empirical research has shown a super-additive effect of XAI adoption and data governance quality in any organizational setting, much less the context of the US financial reporting. The finding is in opposition to the current trend in AI governance studies to consider technical explainability and organizational data governance as independent variables and urges a radical redefinition of AI governance systems as wholesale systems where the complementarity of technical and organizational capabilities is a key design value. The Resource-Based View of the firm offers a convenient theoretical perspective on this reconceptualization: similarly to the way firms generate competitive advantage by combining resources that are valuable, rare, inimitable and non-substitutable (VRIN), they generate governance advantage by combining XAI capabilities with data governance structures that jointly produce financial reporting quality outcomes that cannot be produced by either alone (Bhimani and Willcocks, 2014; Markus and Loebbecke, 2013).

6.2. Data Governance Quality and Regulatory Accountability: Practical Implications

The fact that the quality of data governance has a significant positive impact on regulatory accountability (H4: 0.421, $p < 0.001$) and that this effect is stronger in the context of high regulatory intensity (moderated 0.287 vs. 0.109) has significant practical implications on both organizational managers and regulatory policymakers in the US financial reporting ecosystem. To organizational managers, this implies that data governance investments need to be conceptualized as not only internal quality improvement efforts but also as regulatory relationship management tools. Companies that actively establish strong information governance models develop a compliance track record that diminishes the possibility of negative regulatory enforcement, helps develop more fruitful engagements with SEC examiners and PCAOB auditors, and offers a verifiable audit trail that aids external auditors with risk assessment exercises. The regulatory relationship benefits of data governance investments can, in most situations, surpass their direct internal quality improvement benefits - a fact which managers ought to consider in their governance investment decision making.

The moderating result that regulatory strength enhances the DGQ-RA relation indicates that focused regulatory escalation could trigger data governance enhancements throughout the financial industry to regulatory policymakers. The SEC 2023 AI disclosure guidance and the model documentation requirements of the PCAOB are steps towards this direction but, based on the findings of the current study, additional prescriptive data governance requirements, similar to the BCBS 239 principles that govern data aggregation in the banking sector, may hasten adoption of high-quality governance frameworks across all sectors of the US financial services industry. The sector-level results of the study, indicating that XAI adoption and data governance levels in the energy and healthcare finance industry are lower than

those in the banking and technology industry, indicate that sector-backed regulatory pressure might be required to bring about industry-wide governance alignment.

The fact that Big 4 audit quality moderately affects the DT-FRQ relationship ($\beta = 0.312$ for Big 4 vs. $\beta = 0.178$ for non-Big 4) can be interpreted as the significant role of external audit quality as an institutional enhancer of AI governance effectiveness. This result implies that decision transparency financial reporting benefits are much more effective in case organizations are audited by high-quality external auditors, able to better utilize the explanations produced by XAI in their audit processes, give stronger audit care to AI model outputs, and create more credibility improvements arising out of their attestation of explainable AI-based financial statements. Table 11 will outline the main results of this study and their theoretical and practical consequences.

Table 11 Summary of Key Findings and Theoretical and Practical Implications

Key Finding	Theoretical Implication	Practical Recommendation
XAI adoption significantly improves FRQ ($\beta=0.487, p<0.001$)	Extends Agency Theory by showing AI transparency reduces information asymmetry	Mandate XAI tools in AI-driven financial reporting workflows
Data governance quality enhances regulatory accountability ($\beta=0.421, p<0.001$)	Supports Institutional Theory - governance norms are adopted under regulatory coercion	Develop DAMA-DMBOK aligned governance frameworks in finance departments
Decision transparency mediates XAI \rightarrow FRQ relationship (indirect $\beta=0.157$)	Validates Information Processing Theory in AI-augmented reporting contexts	Train financial teams on how to interpret and communicate AI model outputs
Organizational culture moderates XAI adoption ($\beta=0.198, p<0.05$)	Extends Technology Acceptance Model (TAM) to AI governance in finance	Foster innovation-oriented culture to accelerate responsible AI adoption
Technology infrastructure drives data governance ($\beta=0.334, p<0.001$)	Confirms Resource-Based View (RBV) - infrastructure as a strategic resource	Invest in cloud-based data lakes, data lineage tools, and API governance
Interaction of XAI \times DGQ enhances FRQ beyond individual effects ($\beta=0.241, p<0.01$)	Novel contribution: synergistic effect of XAI-DG integration	Co-design XAI and data governance policies as an integrated accountability system
Regulatory accountability partially mediates DGQ \rightarrow FRQ (indirect $\beta=0.108$)	Enriches stewardship theory in digital governance contexts	Align data governance reporting with SEC AI disclosure requirements
Big 4 audit quality amplifies decision transparency effect ($\beta=0.312, p<0.001$)	Points to audit quality as institutional moderator of AI-governance effectiveness	Partner with Big 4 firms for AI-specific audit procedures and assurance
Smaller firms benefit more from XAI-DGQ interaction for compliance outcomes	Organizational contingency theory applied to AI governance adoption	Develop scalable, SME-appropriate XAI governance toolkits and regulatory sandboxes
Overall model explains 73.1% of variance in FRQ ($R^2 = 0.731$)	Comprehensive explanatory model for AI-driven financial reporting quality	Adopt the proposed XAI-DG framework as a governance standard in US organizations

6.3. Proposed XAI-DG Integrated Framework for US Financial Reporting Accountability

On the basis of the study's empirical findings and theoretical synthesis, this section proposes an integrated XAI-Data Governance (XAI-DG) Framework for Financial Reporting Accountability in US Organizations. The framework is organized around four core pillars derived from the study's theoretical grounding and validated through the empirical analyses:

- Technical Explainability Infrastructure,

- Organizational Data Governance Architecture,
- Regulatory Alignment and Accountability Protocols, and
- Continuous Monitoring and Adaptive Governance.

These four pillars are intended to work as an integrated system of governance where one pillar supports and relies on the other, which is the synergetic interaction between XAI and data governance as reported in empirical results. The framework is to be useable in any organization regardless of its size and industries, with components that can be implemented in a sequential manner depending on the maturity of governance.

The initial pillar, Technical Explainability Infrastructure, involves the choice, application, and confirmation of suitable XAI methods in the contexts of every kind of AI model applied in financial reporting processes. According to the comparative analysis presented in Table 1, various financial applications will need various XAI methods: SHAP will be used in global feature importance analysis in fraud detection and revenue forecasting models; LIME will be used in local explanation of single credit decisions and impairment tests; counterfactual explanations will be used in the loan denial justification under the ECOA requirements; and the attention weight visualization will be used in the NLP- The organizations need to establish and maintain an XAI technique registry which records the rationale of the choice of each technique, the result of validation, and its combination with audit procedures. This registry is an accountability artifact of governance and a regulatory compliance documentation artifact.

The second pillar- Organizational Data Governance Architecture- outlines the governance frameworks and policies needed to make AI-produced financial outputs traceable, auditable, and reliable. Critical elements are: a Data Governance Council that has an executive sponsor and cross-functional representation (finance, IT, legal, compliance, and internal audit); a Data Catalog and Data Lineage System which records the origin, transformation, and use of all financial data inputs to AI models; Data Quality Dashboards which gives real-time reporting on the completeness, accuracy, and timeliness of all financial data inputs to AI models; and The Data Governance Council is especially relevant as an institutional structure to the assurance of the XAI governance decisions to reflect the various stakeholder views of the financial, technical, legal and compliance functions a cross-functional integration that according to the Agency Theory framework in the study is critical to effective information asymmetry reduction.

The third pillar Regulatory Alignment and Accountability Protocols deal with the organization procedures and documentation rules that it has to meet the US regulatory standards as established in Table 4. This requires the preparation of AI Model Disclosure annexes to SEC filings of 10-Ks in compliance with the SEC 2023 AI disclosure guidance; maintenance of Model Risk Management documentation in the format required by SOX Section 302 and 404 certification processes; the incorporation of XAI evidence in SOX Section 302 and 404 certification processes; and the creation of AI-specific audit These practices are operationalizations of the prediction of the Institutional Theory which states that organizations take practices of governance as a reaction to regulatory forms of coercion, as a means of bringing the regulatory mandate into an organized form of organizational governance action.

The fourth pillar, Continuous Monitoring and Adaptive Governance, acknowledges AI models are dynamic systems, the behavior of which changes over time as underlying data distributions change, model parameters are adjusted, and new use cases arise. Proper XAI-DG governance should thus include measures of ongoing performance review, periodical recertification of the model, and responsive policy adjustment to dynamic regulatory trends and organizational learning. Some of the recommended practices are: monthly review of model performance with standardized metrics of stability (Population Stability Index, Characteristic Stability Index); annual third-party XAI audit by accredited AI assurance providers; quarterly data governance maturity checks with the use of the DAMA-DMBOK maturity model; and continuous monitoring of regulatory intelligence that may create new disclosure obligations and may need updating model documentation or explanation. A visual description of the proposed XAI-DG framework is provided in Figure 9.

The following elements characterize the operational requirements of the XAI-DG framework as identified through the study's empirical analysis:

6.3.1. Automated XAI Explanation Generation

AI systems deployed in financial reporting workflows should be configured to generate standardized explanations for all material outputs, formatted for both technical (model audit) and non-technical (board reporting) audiences.

6.3.2. Explainability Validation Protocols

Independent validation of XAI explanations should be conducted quarterly by internal audit or external specialists, verifying that explanations accurately reflect model behavior and are not misleading due to approximation error.

6.3.3. Data Provenance Certification

All financial data inputs to AI models should be subject to formal provenance certification, documenting the source, collection method, processing steps, and quality assessment results for each dataset.

6.3.4. Regulatory Explainability Reports

Quarterly reports summarizing AI model performance, explainability audit results, and data governance compliance status should be prepared in formats aligned with SEC disclosure guidance and PCAOB audit documentation requirements.

6.3.5. Stakeholder Communication Protocols

Plain-language summaries of AI-driven financial decisions should be produced for non-technical stakeholders including audit committee members, institutional investors, and regulatory examiners, based on XAI-generated explanations translated through structured communication templates.

The third pillar-Regulatory Alignment and Accountability Protocols- deals with the organizational procedures and documentation standards that are needed in order to meet the US regulatory requirements listed in Table 4. This involves the creation of AI Model Disclosure annexes to SEC Form 10-K filings under the SEC 2023 AI disclosure guidance; the upkeep of Model Risk Management documentation to the format required in SOX Section 302 and 404 certification processes; the application of XAI evidence to SOX Section 302 and 404 certification processes; and the creation of AI-specific audit committee char

The fourth pillar-Continuous Monitoring and Adaptive Governance acknowledges that AI models are not fixed objects, they are dynamic systems whose behavior changes with time as the underlying data distributions change, model parameters change, and new use cases appear. The appropriate XAI-DG governance should thus have in place performance monitoring mechanisms, periodic model recertification, adaptive updating of policies as the regulatory environment evolves and learning within the organization takes place. Among the specific recommendations, there are: monthly model performance reviews based on standardized stability measures (Population Stability Index, Characteristic Stability Index); annual third party XAI audits by certified AI assurance providers; quarterly data governance maturity reviews based on the DAMA-DMBOK maturity model; and real-time regulation intelligence surveillance to identify new disclosure obligations that might need model documentation or explanation updates.

6.4. Comparison with Previous Studies and Positioning of Findings

The results of our research support and supplement the existing empirical research on AI governance within the financial environment. The effect size (0.487) of the XAIA → FRQ reported here is larger than the effect sizes reported in the most related previous studies: the study by Bao et al. (2020) of machine learning in fraud detection reported an effect size of approximately 0.31 effect size in standardized terms, and the study by Klumpp (2018) of AI in financial statement preparation reported an effect size The higher effect sizes in the present study can be due to a more comprehensive conceptualization of XAI used in the present study, which does not only involve model performance but rather the entire governance and accountability ecosystem around AI implementation, as compared to the technical focus of the previous studies. This implies that the aspects of governance of XAI implementation such as the organizational processes, documentation practices, and communication mechanisms between the stakeholders in which the explainability is operationalized play a key role in improving the quality of financial reporting beyond the predictive nature of the technical model performance.

The synergistic interaction effect (H9: $772 = 0.241$) is, to the best of the knowledge of the authors, a new empirical finding that does not have a direct analog in the literature on financial reporting AI. The most similar suggestion is that, based on their theoretical proposal, Markus and Loebbecke (2013) suggest that capabilities of digital process commoditization and community platforms produce synergistic value when they are jointly deployed - a suggestion that is effectively operationalized in the context of the current study, i.e., regarding the XAI and data governance co-deployment in financial reporting settings. The moderation result of Big 4 audit quality ($\beta = 0.312$ vs. $\beta = 0.178$) aligns with the fact that the Big 4 auditors are associated with incremental credibility value to financial reporting as substantiated in the literature of audit quality and also generalizes this result to explainability-enhanced reporting context that is AI-specific. Brown, Preiato, and Tarca (2014) established that audit quality enhances the financial reporting quality advantages of adopting international accounting standards- a similar process to the present study finding that Big 4 audit quality enhances the financial reporting quality advantages of adopting XAI standards. The similarity here supports the meaning that external audit quality plays the institutional role of enhancing governance-quality nexuses in a variety of financial reporting situations.

7. Conclusions

7.1. Summary of Major Findings and Theoretical Contributions

This paper aimed at exploring the effects of Explainable Artificial Intelligence (XAI) and quality of data governance on financial reporting quality, regulatory accountability, and decision transparency within US organizations- a research agenda inspired by the intersection of increasing AI adoption in financial reporting and the rising regulatory focus on AI transparency and accountability in the United States. SEM, multiple regression, mediation, and moderation analyses of the empirical results of the study, which were conducted on a validated survey of 312 US finance professionals, are sufficient to prove the proposed theoretical framework and all research hypotheses.

The key results of this research may be briefly summarized as follows. The first one is that XAI implementation is a better predictor of the quality of financial reporting ($\beta = 0.487$) than any other predictor, which proves that the implementation of the explainability mechanisms in the AI-driven financial reporting systems leads to the measurable increase in the quality of the reported financial data in terms of its accuracy, reliability, and comparability, which confirms the agency-theoretic hypothesis that interpretability decreases information. Second, the quality of data governance has a significant positive impact on the quality of financial reporting ($\beta = 0.391$) and regulatory accountability ($\beta = 0.421$), which supports the Institutional theory hypothesis that governance structures put in place as a result of regulatory coercion create a real quality improvement in financial reporting.

Third, the interplay between XAI adoption and quality of data governance has positive synergetic impact on financial reporting quality ($\beta = 0.241$), which is more significant than the sum of their respective impacts, the most innovative theoretical contribution of this study and empirically justifying the theory of co-evolutionary AI governance that says that the technical and organizational aspects of AI transparency are strategic complements, not substitutes. Fourth, the XAI-FRQ relationship is mediated by decision transparency (indirect $\beta = 0.157$), and regulatory accountability mediates the DGQ-FRQ relationship (indirect $\beta = 0.108$), determining the cognitive and institutional pathway through which XAI and data governance create their financial reporting quality impacts. Fifth, the relationship between XAI and data governance investments and financial reporting benefits is moderated by organizational size, regulatory intensity, and audit quality, demonstrating the contextual boundary conditions in which these relationships are most beneficial to the financial reporting.

7.2. Practical Recommendations for US Organizations and Regulatory Bodies

The following practical recommendations emerge from this study's findings for US organizational leaders and regulatory bodies:

7.2.1. Mandate XAI Documentation as Part of SOX Section 302 and 404 Compliance

Finance executives certifying the accuracy of AI-driven financial statements should be required to document the XAI techniques employed, their validation results, and the basis for management's reliance on AI-generated outputs. This documentation standard would operationalize SEC AI disclosure guidance within the existing internal controls framework.

7.2.2. Develop DAMA-DMBOK Aligned Data Governance Frameworks Tailored to AI-Augmented Financial Reporting

Organizations should adapt the DAMA-DMBOK framework to the specific requirements of AI-driven financial reporting, incorporating data quality dimensions (accuracy, completeness, timeliness, provenance) as explicit quality criteria in their internal control documentation under SOX Section 404.

7.2.3. Establish XAI-Specific Audit Committee Oversight Responsibilities

Board audit committees should be charged with specific oversight responsibilities for XAI governance, including approval of XAI technique selection policies, review of annual XAI audit reports, and oversight of management's responses to XAI-identified anomalies in financial reporting processes.

7.2.4. Create Industry-Specific XAI-DG Implementation Standards

Sector regulators—the Federal Reserve, OCC, and SEC—should develop industry-specific XAI-DG implementation standards that account for the differential AI maturity and regulatory environments across banking, technology, insurance, and other sectors, rather than applying a one-size-fits-all compliance framework.

7.2.5. Invest in Scalable XAI Governance Tools for Smaller Organizations

Given the finding that smaller organizations benefit most from XAI-DGQ interaction effects for compliance outcomes, regulatory bodies should develop scalable, cost-effective XAI governance toolkits appropriate for organizations with fewer than 500 employees, potentially through regulatory sandbox programs and supervised pilot implementation schemes.

7.2.6. Require Big 4 Firms to Develop AI-Specific Audit Procedures

Given the amplifying role of Big 4 audit quality in the DT-FRQ relationship, the PCAOB should promulgate AI-specific auditing standards that require audit firms to develop expertise in evaluating XAI explanations, assessing data governance quality, and providing assurance on AI-driven financial reporting processes.

7.2.7. Establish a National XAI Financial Reporting Competency Center

A government-private sector partnership, potentially housed within NIST and co-sponsored by the SEC and FASB, should be established to develop national standards for XAI in financial reporting, coordinate research, publish guidance, and maintain a public registry of approved XAI techniques and their regulatory acceptability for different financial reporting applications.

7.3. Limitations of the Study and Threats to Validity

There are a number of limitations of this study that must be remembered and taken into consideration when interpreting the study. To begin with, the cross-sectional design does not permit causal inference in the strict sense, because the measurement of the predictor and outcome variables at the same time does not allow the study to rule out reverse causality, e.g., that organizations with higher financial reporting quality are more motivated to use XAI tools, and not the other way around. The next study will incorporate longitudinal designs that observe XAI adoption and quality of financial reporting across time to ascertain precedence in time and enhance causal inference.

Second, even though the procedural and statistical remedies that are used to correct common method bias assume that survey data are self-reported, predictor and outcome variables, there is always a possibility of shared method variance that could inflate observed correlations. The convergent validity test between survey and documentary data ($r = 0.64 - 0.71$) is somewhat reassuring, but the results of the survey should be confirmed with the help of objective and third-party measurement of the quality of financial reporting (restatements, audit fees, analyst forecast accuracy, etc.) as dependent variables in order to confirm the findings of the survey by the archival data.

Third, the sample, although heterogeneous in terms of sectors and organization sizes, was restricted to US organizations and might not be applicable in financial reporting settings in other regulatory frameworks. The intensity and specificity of the US regulatory environment, including SOX, SEC, and PCAOB standards of auditing, as well as the robustness of the XAI-DGQ-FRQ relationships herein found, may not be as strong in regulatory contexts with less prescriptive financial reporting policies or less well-developed AI governance frameworks.

Fourth, the research used XAI adoption as a composite measure that included various methods, such as SHAP, LIME, or attention mechanisms, but did not break down their specific effects. Future studies need to look at whether various XAI techniques can affect various dimensions of financial reporting quality differently, such as whether global explanation techniques (SHAP) are better at enhancing the comparability dimension of FRQ, and local explanation techniques (LIME) are better at enhancing the verifiability dimension.

7.4. Directions for Future Research

The findings of this study open several promising avenues for future research at the intersection of XAI, data governance, and financial reporting quality. The following research directions are recommended on the basis of the study's theoretical contributions and empirical findings:

- Longitudinal Studies of XAI Adoption and FRQ Dynamics: Multi-year panel studies of the changes in XAI adoption, data governance maturity, and financial reporting quality across the same organizations over time would provide more causal evidence and shed light on the time dynamics of XAI-DG co-evolution.
- Comparative International Studies: Parallel comparative research across regulatory jurisdictions XAI-DG-FRQ relationships in various regulatory jurisdictions, especially the EU (based on AI Act and GDPR), the UK (based on AI governance framework created by the FCA), and emerging markets, would help to test the external validity of this study and discover jurisdiction-specific moderators.

- Experimental Studies of XAI Explanation Formats and Auditor Judgment: Laboratory studies on the effects of different XAI explanation formats (textual, visual, interactive) on auditors to evaluate AI-generated financial results and make correct judgment decisions would constitute mechanistic data to support the decision transparency-FRQ pathway that was identified in the present study.
- AI Governance Maturity Models of Financial Reporting: It would be useful to practitioners to develop empirical-based AI Governance maturity models, tailored to financial reporting settings, based on the empirical results of this study and proposed XAI-DG model, which could serve as a practical self-assessment tool to benchmark their governance maturity and the most effective areas of improvement.
- Machine Learned Analysis of SEC Filings to Provide XAI Evidence: Natural language processing analysis of SEC Form 10-K and 10-Q filings of a large sample of archival documents would allow objective testing of the relationship between XAI and the FRQ on a large scale using archival data to support and extend the survey-based results of this study.
- Ethical AI and Bias Detection in Financial Reporting AI Systems: Future studies ought to analyse the significance of fairness and bias-detecting mechanisms, such as algorithmic fairness measure and model bias audits, as further aspects of XAI governance that can have an independent impact on the quality of financial reporting and regulatory accountability, especially within the setting of lending and credit reporting where algorithmic bias has been observed to have legal and ethical.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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