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Impact of AI Disclosure on the Financial Reporting and Performance as Evidence from US Banks

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Abstract: Purpose: This study examines the impact of artificial intelligence disclosure within the US banking sector. It may explore the implications of AI disclosure on issues like financial reporting, transparency, accountability, and ethical considerations within the banking sector. Design/methodology/approach: Using a blend of qualitative and quantitative analyses, the researchers utilized SEC and NASDAQ databases to scrutinize AI disclosures within the top 10 banks. The sample comprised 100 annual reports, and through multiple regression analysis, the research discerned a noteworthy enhancement in performance metrics. Findings: The study found that AI influences financial performance only when moderated by the interaction of shareholders, the board of directors, and independent board members. The findings indicate a rising trend of AI disclosure in financial reports. The study indicates that AI disclosure impacts NII, TEXP, and P/E. Additionally, the study indicated a conflict of interest between agents and principals. Large shareholders tended to favor more AI disclosures, whereas the board of directors either did not support or adopted a more conservative stance on disclosure. Research limitations/implications: This study acknowledges a limitation in the dataset; initially comprising 100 annual reports, it was later refined to meet regression analysis assumptions. Despite this limitation, the study's insightful results contribute significantly to our understanding of the dynamic relationship between AI disclosure and the performance of top-tier banks in the USA. Originality/Value: By investigating the impact of AI disclosure, the study aims to provide insights into the broader considerations associated with artificial intelligence disclosures in the US banking sector. This study also analyzes how stakeholders respond to the disclosed information about artificial intelligence.

Keywords: AI; disclosure; financial performance; financial reporting; banks

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1. Introduction

In the rapidly evolving technological landscape, US banks striving for competitiveness must adopt a proactive approach. Recognizing the dynamic nature of customer preferences, banks have consistently enhanced their services. To stay ahead in the competitive landscape, banks have integrated technology into their operations, and the latest frontier is artificial intelligence. Thanks to computer hardware and software advancements, artificial intelligence empowers banks to efficiently process extensive data sets, leading to the development of innovative business solutions (Kaya et al., 2019).

AI refers to computer programs that can acquire and apply knowledge independently without human involvement. These systems analyze information and draw conclusions based on their observations of the world. As "they learn from their previous judgments",

their performance improves over time (Kaya et al., 2019), making AI an emerging technology that can give companies a competitive edge (Harrington & Voehl, 2010). AI integration positively influences different dimensions of the business, such as financial performance, marketing performance, and customer satisfaction. Companies that integrate AI into their operations realize an increase in financial performance (Alsheibani et al., 2018; Davenport & Ronanki, 2018) and expect a "38% increase in profitability by 2035" (Purdy & Daugherty, 2017). Also, research shows that AI improves marketing effectiveness by processing customers' data regarding their preferences, which enables AI to enhance market segmentation (Enholm et al., 2022). AI can collect information about customers' behavior, which helps companies provide a better customer experience (Riikkinen et al., 2018; Schmidt et al., 2020), thus increasing customer satisfaction.

The integration of AI technology in companies will profoundly impact their management and governance since AI considers decision-making and evaluation in its analysis, which will necessitate significant changes in corporate governance (Omar et al., 2017). One proposed solution is to establish positions such as "Chief AI Officer" and "Risk AI Officer" (Schäfer et al., 2022). However, opinions among AI experts are divided, with some believing that such roles could exist within large organizations, while others speculate that they may emerge in the future (Schäfer et al., 2022). Nevertheless, the suggestion to introduce new governance positions to manage AI in companies represents an eye toward the future.

Furthermore, without proper regulation, AI could contribute to agency problems within organizations by mitigating or amplifying information asymmetry, allowing agents to use it for their benefit. One of the signals that agents use to inform shareholders is disclosures in the annual reports. Thus, AI disclosures can be used to send a signal to shareholders. Accordingly, the study aims to explore AI disclosures' impact on banks' performance while considering the agency between shareholders and agents.

Previous studies regarding AI and technology disclosure examined the effect of such disclosures on financial performance, using it as an indicator for AI adoption (Finkenwirth, 2021; Alkaraan et al., 2022; Shiyyab et al., 2023; Shehadeh et al., 2024).

Finkenwirth (2021) used AI terms mentioned in the German financial institutions' annual reports from 2016 to 2019 to assess the effect of AI disclosures on ROA, ROE, and P/E. Alkaraan et al. (2022) used textual analysis of UK firms' annual reports from 2013 to 2018 to identify the disclosures of technology practices (CITTI4.0) and how such practices effect UK companies ROA and ROE. On the other hand, Shiyyab et al. (2023) studied AI disclosures, and Shehadeh et al. (2024) studied digital transformation disclosures within the Jordanian banks' context. While previous studies focused on German financial institutions, UK firms, and Jordanian banks, this study examines AI disclosure in the US banking sector.

Previous studies were limited to certain geographical and environmental contexts, and the sample was not extended across different countries. This study is different from the previous ones. First, there are differences in business culture, institutional setting, and regulatory environment. Culture in the US fosters competition and individualism (Eckhardt, 2001). Since business culture differs in previous studies and some scholars indicate that culture influences financial reporting (Doupnik & Tsakumis, 2004), the current study examines a different sample with different financial reporting standards.

Additionally, the corporate governance system in the US is power concentrated in which the CEO acts as chairman, is more shareholder-focused than stakeholder-inclusive, is highly regulated, and lacks mandatory CSR disclosure requirements (Aguilera et al., 2006). Furthermore, listed firms in the UK, Germany, and Jordan are required to use IFRS reporting standards (IFRS Foundation, 2024), while listed firms in the US are required to use US GAAP. The difference in the regulatory setting would affect how listed companies disclose their information, as GAAP is more rule-based while IFRS is principal-based.

Hence, the current study is the first to examine AI disclosures' influence on measurable financial outcomes within the US GAAP context.

Second, similar to Shiyyab et al. (2023), our analysis included broader financial performance metrics beyond ROA and ROE, including total expenses, interest income, and P/E. Third, unlike Shiyyab et al. (2023), our study is the first to assess the moderation effect of AI disclosures with the board of directors (the board of director's size and the independent board members) and AI disclosures with large shareholders on financial performance. While Alkaraan et al. (2022) examine the interaction between CITI4.0 disclosures and ESG, it is important to note that the corporate governance system in the UK is a dual leadership structure that separates the chairman and the CEO roles. UK's leadership integrates CSR into corporate governance, and the role of institutional investors is a key driver of this integration (Aguilera et al., 2006). Furthermore, Alkaraan et al.'s (2022) study is not limited to AI as it is a component of the Industry 4.0 paradigm; also, the study excludes financial institutions from the sample.

In light of this, this study aims to investigate the impact of artificial intelligence disclosures in the US banking sector and how these disclosures are perceived by bank governance and shareholders. Using a sample of 100 financial reports from the top 10 US banks, the study uncovered evidence of a potential conflict of interest between agents and principals. Notably, AI influences financial performance only when moderated by the interaction of shareholders, the board of directors, and independent board members.

The motivation to focus on the top ten banks stems from the scale of their operations, which necessitates the use of AI technology. Previous studies (e.g., Bayo-Moriones & Lera-López, 2007; Ramdani et al., 2009) suggest that larger firms have more significant needs and resources to adopt new technologies, enabling them to manage associated risks better. Financial resources and firm size are pivotal in AI adoption, as Hradecky et al. (2022) found that these factors drive faster implementation of AI. As company size grows, so does task complexity, necessitating innovative solutions to streamline operations (Chenhall & Langfield-Smith, 1998). Thus, larger organizations are likely to adopt AI at a quicker pace. Additionally, the second motivation lies in the fact that boards of directors in financial institutions face severe information overload (Chao, 2017), and AI can enhance information flow (Srinivas et al., 2019). Finally, the financial sector is heavily regulated, and these stringent regulatory measures result in more effective governance in the banking industry.

This study is structured after the introduction: Section 2 provides a literature review. Section 3 provides the theoretical framework. Section 4 provides results and data analysis. Section 5 explains the results and provides the findings. Section 6 discusses the results and findings. Section 7 provides the implications, contributions, limitations, and conclusion.

2. Literature Review

2.1. AI Disclosure and Financial Reporting

Financial disclosure is a critical component of financial reporting, mandated by regulatory bodies across the globe, as it openly communicates financial data to an organization's stakeholders. As a result, businesses that incorporate AI into their operations must consider pertinent financial disclosures, including disclosures related to AI-related terms. Such disclosures are essential for clearly conveying how AI assists in their operations and clarifying the extent to which such technology is critical to their performance. Conversely, the inappropriate disclosure of financial data that do not align with reporting standards can harm a company's performance and create financial instability (Chen & Zhang, 2022).

Content analysis of AI discourse in public companies in Malaysia indicated that fewer than 20 companies mentioned the words "Artificial intelligence", "machine learning", and "Big data" (Omar et al., 2017). On the other hand, Spanish companies' annual reports

mentioned "Artificial intelligence", "machine learning", "Deep Learning", and "Big data" 704 times (Bonsón et al., 2021), which suggests that AI disclosure is on the rise. The increasing trend of AI disclosure is also indicated in German financial institutions, Jordanian banks, and UK companies; it has been reported that "in 2019, 31% of the companies mentioned AI-related words in their annual reports." (Finkenwirth, 2021) in Germany, and Jordan ASE-listed banks showed an incremental increase in AI disclosures from 73 words in 2014 to 733 in 2022 (Shiyyab et al., 2023). Additionally, UK-listed companies are consistent with this trend and showed an accelerated increase in CITTI4.0 disclosures from 2013 to 2018 (Alkaraan et al., 2022).

Analysis of AI-related term disclosure in the financial reporting of German financial institutions through qualitative and quantitative analysis revealed that the effect of AI disclosure on financial performance measures such as "ROA", "ROE", and P/E were insignificant; nevertheless, some evidence suggests that companies pioneering in AI disclosures practices in the annual reports have a better financial performance than late adopters (Finkenwirth, 2021). On the other hand, in Jordan, AI term disclosures significantly affect performance measures such as ROA, ROE, and NII and significantly reduce total expenses (Shiyyab et al., 2023). However, AI disclosures in Jordanian banks are uneven; while some banks extensively mention AI words in their annual reports, others show a minimal disclosure, indicating varying adoption stages (Shiyyab et al., 2023).

Companies use AI disclosure as a strategic component of their digital transformation journey. These disclosures signal the degree of involvement in the transformation process and how such transformation improves their financial performance. For instance, corporations that extensively disclose CITTI4.0 tend to exhibit a better financial outcome (Alkaraan et al., 2022). Similarly, banks with higher digital transformation generally exhibit better financial performance, such as improved ROA and ROE (Shehadeh et al., 2024).

Accordingly, does AI-related disclosure in the top US banks show the same trend as Jordanian banks and companies in Germany, Malaysia, the UK, and Spain?

It is logical to assume that when companies expand their use of AI in their operations, AI disclosure in financial reporting should increase accordingly. Hence, AI-related terms disclosures can be used to analyze the entity's performance after implementing AI. The existing literature on AI and banks' performance suggests that using AI leads to better performance.

2.2. AI Function in the Banking Sector and the Financial Performance

The banking industry has shown considerable acceptance and implementation of artificial intelligence, setting it apart from other sectors (Husain et al., 2022). Banks have always been early adopters of technology, and installing the first ATM in London in 1967, about 56 years ago, is a prime example (Kaya et al., 2019). The introduction of ATMs revolutionized the way routine transactions were performed, allowing bankers to focus on more critical tasks such as customer service, issuing credit cards, and selling investment loans (Kaya et al., 2019). Stanford Federal Credit Union was the first bank to provide customers with online banking in 1994, and in 1995, Presidential Bank was the first to allow customers to access their online bank accounts (England, 2022). This technological advancement has reduced the number of customers visiting bank branches, allowing them to perform various transactions online without physically interacting with bankers (Kaya et al., 2019). Consequently, banks have become more dependent on online platforms than bank branches.

Banking corporations need to incorporate AI into their business strategy to maintain their competitive edge (Singh, 2020). In today's world, banks strive to reduce costs, meet margins, and exceed customer expectations through personalized experiences (Singh, 2020).

AI integration in various financial service applications can contribute to banks' performance. Chatbots and voice assistants can be used for customer support (Kaya et al., 2019; Singh, 2020; Umamaheswari & Valarmathi, 2023), while robo-advisors can provide investment advice (Kaya et al., 2019; Singh, 2020). AI can also be used for identification (Kaya et al., 2019; Umamaheswari & Valarmathi, 2023), detecting fraudulent activities (Kaya et al., 2019; Singh, 2020; Umamaheswari & Valarmathi, 2023), and risk and credit assessment (Kaya et al., 2019; Singh, 2020).

Chatbots and AI voice assistants provide customers with fast and efficient solutions without human interaction. They use neutral language and tone, avoiding offensive tones and reducing the risk of human error (Singh, 2020). As a result, customers using chatbots might use them to receive offers and discount recommendations (Bhattacharya & Sinha, 2022). Robo-advisors offer automated financial advice, asset management, and portfolio management without human intervention (Kaya et al., 2019; Singh, 2020). AI-powered systems can quickly and accurately vet customer documents through algorithms that analyze and compare information from various sources, including the Internet, and any discrepancies in the customer's identity can be reported (Kaya et al., 2019; Umamaheswari & Valarmathi, 2023). AI can also prevent the risk associated with credit transactions by analyzing past transaction patterns and blocking any fraudulent transactions before they occur (Kaya et al., 2019). Additionally, it can assess customers' creditworthiness by analyzing the documents they provide (Singh, 2020).

Studies have proven that AI integration in banks positively impacts performance. In Jordan, implementing AI in Jordanian commercial banks increases job performance (Abusalma, 2021). Similarly, financial performance in banks was found to be higher with AI programs (Setiawan et al., 2021). Another example from South Korea shows that AI has a positive impact on business performance through "information system risk management" and "corporate entrepreneurship" (Lee, 2020). Additionally, AI positively affects "customer satisfaction", "service quality", "competitive advantage", and "employee efficiency" (Elegunde & Oladimeji, 2020). Furthermore, AI can decrease technical inefficiency (Mor & Gupta, 2021) by eliminating repetitive tasks and reducing the demand for less skilled workers. This allows employees to focus on more important tasks (Kaya et al., 2019), reducing their workload (Satheesh & Nagaraj, 2021). As a result, employees can provide customers with more advanced, high-quality services like "chatbots", "mobile banking", "augmented reality" (Satheesh & Nagaraj, 2021), and smart wallets (Umamaheswari & Valarmathi, 2023).

Accordingly, the first hypothesis:

Hypothesis 1: *The disclosure of AI-related terms indicates that applying AI in banks' operations improves banks' performance by positively affecting one or more performance measures (ROA, ROE, NII, and P/E).*

Using AI helps reduce the expenses associated with a larger workforce and increases profitability (Kaya et al., 2019). Furthermore, AI in banks leads to cost reduction (Ali et al., 2022; Kochhar et al., 2019) through enhancing risk management (Ali et al., 2022). Hence, incorporating AI into bank operations can improve efficiency and accuracy, leading to innovative solutions that can revolutionize the financial landscape.

Accordingly, the second hypothesis:

Hypothesis 2: *The disclosure of AI-related terms indicates that the application of AI in banks' operations negatively affects TEXP.*

It is interesting to see how organizations are starting to embrace AI technology, even though the future is uncertain. Companies must be transparent about using AI to build trust with stakeholders. According to research, incorporating AI in business operations has many positive effects, making it a promising avenue for growth. Therefore, it is worth exploring AI disclosure in bank operations, as it can benefit companies, regulators, and stakeholders alike.

3. Theoretical Framework

In the face of growing organizational complexity, it becomes crucial to grasp the dynamics between principals and agents and the challenges that stem from conflicting interests. A comprehensive understanding of delegation, decision-making processes, control mechanisms, and incentive structures is instrumental in developing governance frameworks that effectively align owners' interests with those entrusted with the organization's management.

The agency theory perspective is "the separation of ownership and control" (Shleifer & Vishny, 1997), initially developed by Stephen Ross and Barry Mitnick, with both scholars making significant contributions to its development. Ross's perspective considers agency relationships as challenges related to compensation contracting and incentives. Conversely, Mitnick's institutional theory of agency underscores the role of institutions in addressing imperfections within agency relationships and adapting to them over time (Mitnick, 2019).

Agency theory emphasizes the relationship between the agent (managers or fund managers) and the principal (Shareholders or clients). According to the theory, individuals are egoists who work for their best interests, and there is an information gap between the agents and principals (Linder & Foss, 2013). The agents and principals use the available information to create contracts and determine how to act; as a result, agents have more power as they have access to more information and are able to make decisions (Linder & Foss, 2013). Agency conflict can lead to agency loss, which is maximized when agents work for their interests. The more alignment in interest between the agent and principal, the lower the agency loss will be (Kopp, 2023). Agency problems can have devastating consequences, leading to agency costs that affect the efficiency of company governance and reduce the company's market value (Andrijašević & Pašić, 2018). One example of agency problems is the ENRON company, where the managers and directors attempted to hide financial losses to maintain high stock prices and avoid falling due to increased debt by using tricky accounting tactics (Segal, 2023).

The problem of information asymmetry between the agents and the owners can be resolved through signaling, as the signaling theory suggests that firms use disclosures to signal the quality of their value to investors. Shehata (2014) and Cotter et al. (2011) state that voluntary disclosures are one of the signals managers use to inform investors, and they argue that managers in high-quality firms use voluntary disclosures to differentiate themselves from lower-quality firms. Cotter et al. (2011) argue that poor companies tend to conceal or delay voluntary disclosures due to the magnitude that such disclosures have on the market, as bad news always has a higher impact than good news (Hooghiemstra, 2010).

Beyond examining the impact of AI disclosures on financial performance, it is crucial to understand how bank governance and shareholders influence these disclosures. Since AI implementation directly affects shareholders and the board of directors, applying agency theory can clarify whether these parties align in their support for AI usage and its disclosure in the annual reports or if conflicting interests exist between them.

Hence the question:

Is there a disagreement between shareholders and the board of directors regarding AI disclosure? If so, is that attributable to the information gap between both parties?

AI has the potential to significantly enhance governance within the banking industry. The Federal Reserve's "Proposed Guidance on Supervisory Expectations for Boards of Directors" highlights that "Boards of large financial institutions face significant information flow challenges, especially in preparing for and participating in board meetings. Absent actively managing its information flow, boards can be overwhelmed by the quantity and complexity of information they receive" (Chao, 2017). AI technology offers a powerful solution to this problem, effectively reducing information complexity by streamlining information processing and flow for boards of directors (Srinivas et al., 2019).

Prior studies' findings on AI and technology disclosures are consistent with the agency and signaling theory perspective. Alkaraan et al. (2022) found that firms with higher profitability are more willing to disclose CITTI4.0 initiatives in their annual reports, and those firms with higher ESG performance strengthen the relationship, consistent with the signaling theory that governance of highly profitable firms uses disclosures to signal their success and attract further investment. Additionally, Shiyyab et al. (2023) found that AI disclosures correlate positively with board size and board independence, consistent with the theory, where firms voluntarily disclose favorable information (e.g., AI adoption) to exhibit operational efficiency and financial performance.

However, while the aforementioned studies align with the signaling perspective, larger or independent boards might still dilute the effectiveness of such disclosures in improving specific financial performance measures due to inefficiencies in decision-making or conflicting interests within diverse governance structures. Shehadeh et al. (2024) found that gender diversity in governance is inversely associated with digital transformation. Stakeholders often hold differing opinions on technological innovation, and adopting new technologies can intensify these disparities (Enholm et al., 2022). While Srinivas et al. (2019) found that AI helps boards manage information overload and reduce complexity, many interviewed directors expressed reservations about its use. They believed the complexity of AI systems necessitates extensive training, leading to unfavorable attitudes toward its implementation. While higher ESG practices in the UK advocate for increasing CITTI4.0 disclosures (Alkaraan et al., 2022), the institutional setting in the US differs in that emphasis on CSR practices disclosures is less and not mandatory (Aguilera et al., 2006). Therefore, in firms with less CSR emphasis, their governance might influence the magnitude of AI disclosure. More importantly, "In the absence of appropriate AI governance practices, negative and unintended consequences can occur" (Enholm et al., 2022). Additionally, while larger and independent boards encourage transparency in AI disclosures (Shiyyab et al., 2023), directors and top management may view the adoption of AI as a significant risk that comes with substantial costs (Omar et al., 2017), as poor AI implementation and inadequate AI governance will lead organizations to incur significant costs (Higgins et al., 2024). Therefore, it might amplify cost-related impacts due to their comprehensive oversight.

Hence, the third and the fourth hypotheses are:

Hypothesis 3a: *The size of the board of directors weakens the association between AI-related term disclosures and one or more financial performance measures (ROA, ROE, NII, and P/E).*

Hypothesis 3b: *The size of the board of directors strengthens the association between AI-related term disclosures and TEXP.*

Hypothesis 4a: *The size of the independent board of directors weakens the association between AI-related term disclosures and one or more financial performance measures (ROA, ROE, NII, and P/E).*

Hypothesis 4b: *The size of the independent board of directors strengthens the association between AI-related term disclosures and TEXP.*

The bank's governance may adopt a more cautious and negative stance toward AI disclosures. This reluctance likely stems from potential setbacks in AI implementation that could impact operational performance, and disclosing such information may invite increased scrutiny of their performance.

In contrast, shareholders view AI implementation as a tool for boosting efficiency and cutting costs (Dedrick et al., 2013), seeing it as a strategic avenue to enhance returns on investment (Güngör, 2020). However, concentrated ownership is negatively correlated with AI-related disclosures in Jordan banks, which means that the dominant shareholders show reluctance about AI disclosures (Shiyyab et al., 2023). However, the institutional setting in the US differs in that it is more shareholder-focused than stakeholders-inclusive, and the institutional investors are more short-term-oriented (Aguilera et al., 2006). Therefore, driven by a focus on economic value, shareholders are incentivized to invest in and support AI technology, recognizing its potential to maximize profitability.

Hence, the fifth hypothesis:

Hypothesis 5a: *The increase in large shareholders strengthens the association between AI-related term disclosures and one or more financial performance measures (ROA, ROE, NII, and P/E).*

Hypothesis 5b: *The increase in large shareholders weakens the association between AI-related term disclosures and TEXP.*

Therefore, shareholders are likely to favor AI-related term disclosures, as such transparency would enhance their credibility with other stakeholders, positioning them as forward-thinking and aligned with cutting-edge technological advancements.

4. Research Methodology

This study implements qualitative and quantitative data analysis based on the annual reports of the leading banks in the United States, particularly the top 10 banks, in terms of total assets from 2013–2022.

Step 1: Create an index with the most used AI-related terms.

The most used AI terms in the financial services sector in the United States include "Computer vision, Physical robotics", "Natural language text understanding", "Virtual agents or conversational interfaces", "Natural language speech understanding", "Robotic process automation", "Machine learning", "Autonomous vehicles", and "Natural language generation" (Cam et al., 2019). However, a recent study by Shiyyab et al. (2023) developed a term index for the most frequent AI-related terms in financial disclosures from previous literature (refer to Appendix A, Table A3). This index will be adopted to analyze banks in the United States, as it provides a comprehensive list of AI-related disclosure terms that are divided into three main categories: "Digital awareness, transformation, and capabilities", "AI application, product, service, and process", and "AI information challenges and cyber security threats."

Step 2: Generate the frequency table using the term index.

In step 2 of the analysis, the term index is used to calculate the frequency of AI terms in the annual reports. For this purpose, the content analysis software "MAXQDA 24.0.0" will be used to perform content analysis. Once calculated, the frequency will be used to measure the dependent variables as an independent variable at the next step in the regression model.

Step 3: Regression models

Previous literature used financial performance measures to study the impact of AI-related term disclosure on financial performance (Finkenwirth, 2021; Shiyyab et al., 2023). For this study, bank performance will be measured based on several factors, including return on assets, return on equity, P/E, net interest income, and total expenses. ROA and ROE are metrics that measure the bank's management effectiveness, indicating its overall performance (McClure, 2024). Higher ratios of ROA and ROE indicate better management effectiveness.

On the other hand, adopting AI in banking operations can help reduce expenses (Kaya et al., 2019; Kochhar et al., 2019; Ali et al., 2022) as AI can mimic human brain function, performing various tasks such as customer service through chatbots, sales automation through analyzing customers' behavior and performing predictive market analysis, data mining, and financial management (Kunduru, 2023), which can save time and resources. Researchers found that 63% of respondents reported revenue increases in companies that use AI in their operations, with most of the increase often coming from marketing and sales (Cam et al., 2019). Alternatively, 44% reported a cost decrease (Cam et al., 2019).

Investors often use the P/E ratio to assess a bank's stock performance and decide whether to invest (Fernando, 2023). Additionally, net interest income is a crucial performance indicator for banks since it reflects the revenue generated from lending and borrowing interest rates. Ultimately, using AI can positively enhance performance metrics such as ROA, ROE, P/E, and net interest income and negatively affect total expense, leading to higher performance outcomes for banks.

It is essential to account for various internal and external factors that shape AI practices and disclosure decisions, as these can differ based on each bank's unique characteristics (Shiyyab et al., 2023). These variations create distinct incentives for managers to adopt AI and disclose related activities. To address this, controlling for crucial aspects such as bank governance, ownership structure, and relevant economic variables is important, ensuring a comprehensive analysis of the factors influencing AI adoption and disclosure.

Extensive research in prior literature has examined the impact of board size and board independence on performance within the banking sector (Staikouras et al., 2007; Belkhir, 2009; Isik & Ince, 2016; Weerink, 2019; Majeed et al., 2020)—accordingly, our analysis accounts for both board size and independence.

Public companies' conflicts between shareholders and creditors can escalate into agency capital costs; therefore, it is crucial to control for ownership structure factors, including the large share ratio—calculated as the percentage of major shareholders owning 5% or more—and the debt ratio, measured by long-term debt over total liabilities. Additionally, the study accounts for key economic factors, such as bank size, the age of the bank since its establishment, and the impact of the COVID-19 years.

$$BK.\ Performance_{\ t} = Constant + ß1 * AIFQ_{\ t-1} + ß2 * BSIZE_{\ t-1} + ß3 * DEBT_{\ t-1} + ß4 * BDSIZE_{\ t-1} + ß5 * INDPB_{\ t-1} + ß6 * LARSHE_{\ t-1} + ß7 * AGE_{\ t-1} + ß8 * YEAR + e \quad (1)$$

Model specifications:

AIFQ = the number of AI-related terms mentioned in each annual report

BSIZE = bank size, which is the natural log of assets

DEBT = long-term debt to total debt ratio

BDSIZE = number of board of directors

INDPB = the proportion of independent board members

LARSHE = percentage of accumulated shareholders who own more than 5% of total shares

AGE = the age of the bank. Number of years from the date of establishment

YEAR = dummy variable 1: COVID year and years after COVID, 0: Other

The interaction effect:

Analysis of the interaction effect is crucial to evaluate the perspectives of the board of directors, independent board members, and shareholders on AI disclosures in annual reports. Equation (2) illustrates the regression model incorporating these interaction effects.

$$BK.\ Performance_{\ t} = Constant + ß1 * AIFQ_{\ t-1} + ß2 * BSIZE_{\ t-1} + ß3 * DEBT_{\ t-1} + ß4 * BDSIZE_{\ t-1} + ß5 * AI{*}DB_{\ t-1} + ß6 * INDPB_{\ t-1} + ß7 * AI{*}INDB_{\ t-1} + ß8 * LARSHE_{\ t-1} + ß9 * AI{*}SHE_{\ t-1} + + ß10 * AGE_{\ t-1} + ß11 * YEAR + e \quad (2)$$

Model specifications:

*AI*BD* = AI-related terms disclosures interaction with board size.

*AI*INDB* = AI-related terms disclosures interaction with independent board members

*AI*SHE* = AI-related terms disclosures interaction with large shareholders.

Figure 1 illustrates the main effect of AIFQ and the interaction effect of AIFQ with other variables.

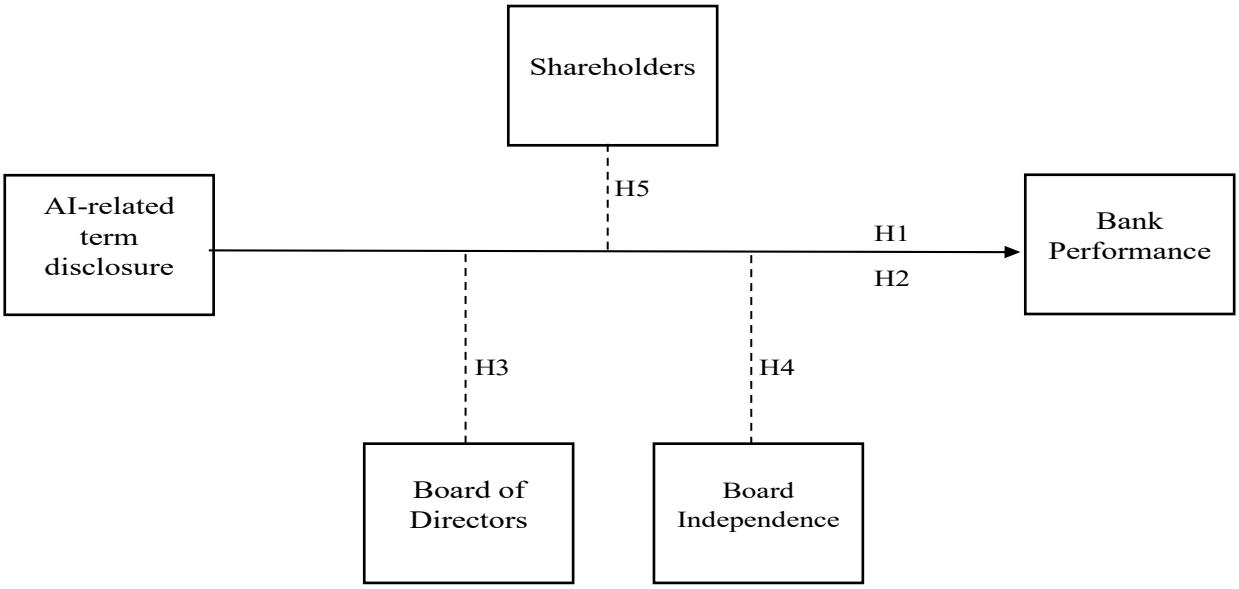


Figure 1. Research model.

5. Data Analysis and Results

The data were collected from 100 annual reports and proxy statements for the leading ten banks in the USA (Appendix A, Table A1). The selected banks were ensured to be American banks. Therefore, the 10th bank on the list (TD Bank) was not selected because it is a subsidiary bank affiliated with TD Bank NA, the parent headquarters in Canada. Instead, the 11th bank on the list, Charles Schwab Corp, was included in the sample size.

5.1. Qualitative Analysis Through MAXQDA

Step 1: Coding the AI-term index.

In Step One, the AI-related term index (Appendix A, Table A3: AI-related term index) is coded into MAXQDA software.

Step 2: Generate the frequency table using MAXQDA.

Annual reports uploaded to MAXQDA to analyze the frequency of AI-term disclosures. Table 1 below shows the related AIFQ by bank and year.

Table 1. AI-related term frequency.

Bank	*AI-Frequency by Bank*	*Year*	*AI-Frequency by Year*
Chase	274	2013	72
Bank of America	244	2014	97
Citibank	233	2015	152
Wells Fargo	295	2016	158
Goldman Sachs	203	2017	154
Morgan Stanley	90	2018	228
US. Bancorp	131	2019	241
PNC	226	2020	271
Truist Financial	111	2021	263
Charles Schwab Corp	48	2022	219
Total	**1855**		**1855**

The qualitative analysis shows that AIFQ disclosure in the annual reports is progressively increasing yearly, reaching its peak in 2020 by 271. The increased use of AI in bank operations explains such a progressive increase. Later, in 2021 and 2022, the AIFQ decreased by 263 and 219, respectively. Such a decrease is reasonable, as in 2020, during COVID-19, the use of online and mobile banking services that require AI increased. Wells Fargo and Chase Bank have the highest reported AIFQ, with 295 and 274, constituting 15.65% and 14.77% of the total sample, respectively. On the other hand, Morgan Stanley and Charles Schwab Corp have the least reported AIFQ by 90 and 48 times, constituting approximately 5% and 2.6% of the AI frequency sample, respectively. (Appendix B, Figures A1 and A2 shows AIFQ by bank and year.)

5.2. Analysis and Results

First, researchers rigorously ensured that all variables in the dataset followed a normal distribution, eliminating any outliers beyond the −3 to +3 standard deviation range. The process was achieved by normalizing the fractional ranks of each variable using SPSS, ensuring the dataset was fully optimized for analysis. Subsequently, multiple regression analyses were conducted for each dependent variable, applying both Equations (1) and (2).

5.3. Descriptive Statistics

Table 2 presents the descriptive statistics for the study variables. The mean value of AIFQ is 18.562, revealing that the frequency of AI-related term disclosures per year is low. The highest count of AI-related terms in a single year is 50, recorded by Chase Bank in 2016, while the lowest is a mere 2, disclosed by US Bancorp in 2013 (see Appendix C, Table A4). The mean board size is 14.064, reflecting a notably large board structure, with an average of 12.248 independent board members, signifying that the vast majority are independent.

The mean percentage of large shareholders is 0.205, indicating that approximately 20% of bank shareholders are large shareholders, suggesting their substantial influence over bank decisions. The average bank age is 138.5 years, underscoring that the banks in the sample are well-established, with significant market experience. In terms of size, the average total assets per bank amount to roughly 1.27 billion, reflecting their substantial financial standing. Lastly, the mean debt ratio is 0.129, signifying that, on average, banks carry around 13% debt, highlighting a relatively modest reliance on debt financing.

Table 2. Descriptive statistics **.

	N	Minimum	Maximum	Mean	Std.	Skewness		Kurtosis	
						Stat	Std. Error	Stat	Std. Error
BSIZE	99	18.58	22.67	20.629	0.849	0.000	0.243	−0.319	0.481
DEBT	99	−0.01	0.27	0.129	0.058	0.000	0.243	−0.319	0.481
BDSIZE	100	8.33	20.25	14.064	2.396	0.165	0.241	−0.058	0.478
INDPB	99	6.81	17.31	12.248	2.196	0.046	0.243	−0.393	0.481
LARSHE	99	−0.01	0.42	0.205	0.089	0.000	0.243	−0.319	0.481
AGE	99	35.98	241.02	138.500	42.532	0.000	0.243	−0.318	0.481
AIFQ	99	−10.25	45.42	18.562	11.882	0.006	0.243	−0.348	0.481
ROA	99	0.002	0.018	0.010	0.003	0.000	0.243	−0.319	0.481
ROE	99	0.02	0.18	0.100	0.033	0.000	0.243	−0.319	0.481
TEXP	99	15.008	19.284	17.146	0.887	0.000	0.243	−0.319	0.481
PE	99	−6.62	36.73	15.052	8.993	0.000	0.243	−0.319	0.481
NII	99	13.86	19.00	16.429	1.065	0.000	0.243	−0.319	0.481
YEAR*	100	0	1	0.30	0.461	0.886	0.241	−1.240	0.478
Valid N (listwise)	87								

* All variables have been normalized via SPSS using fractional ranks and normal distribution function, except the (Year) variable. ** Numbers are rounded to the third decimal point. BSIZE: LN total assets, DEBT: debt ratio, BDSIZE: number of board members, INDPB: number of independent board members, LARSHE: the percentage of owners who own 5% and more, AGE: bank age, AIFQ: AI-related term frequency, YEAR: dummy variable represent COVID-19 years, ROA: return on assets, ROE: return on equity, TEXP: LN total expenses, PE: prices–earnings ratio, NII: LN total interest income.

5.4. Correlation Analysis

The correlation analysis in Table 3 reveals an alarming degree of multicollinearity, with the moderating variables *AI*INDB* and *AI*BD* showing a staggering correlation coefficient of 0.949 and BDSIZE and INDPB displaying a similarly high coefficient of 0.931. These coefficients are exceptionally high, indicating severe multicollinearity, significantly violating the assumption (Kim, 2019). The VIF scores from the regression output confirmed the extent of collinearity between the variables. Specifically, the variables BDSIZE, INDBP, *AI*BD*, and *AI*INDB* all have VIF scores exceeding the critical threshold of 10 (see Appendix C, Table A5). As a result, BDSIZE alone was deemed adequate to represent the bank's governance, necessitating a separate regression analysis for INDBP and AI*INDB.

AIFQ exhibits a significant positive correlation with BSIZE and AGE, indicating that larger and older banks correlate with higher AI-related terms disclosures. Additionally, the COVID-19 years demonstrate a clear positive correlation with AIFQ, further reinforcing the fact that COVID-19 years correlate with more AI-terms disclosures. Conversely, BDSIZE shows a negative correlation with AIFQ, suggesting that larger boards correlate with more AI disclosures.

Moreover, AIFQ is positively and significantly correlated with TEXP and NII, implying that increased AI-related disclosures are aligned with rising total expenses and net interest income. However, it negatively correlates with P/E, indicating that banks with higher AI disclosures have lower price-to-earnings ratios.

Table 3. Correlation.

	AIFQ	*BSIZE*	*DEBT*	*BDSIZE*	*INDPB*	*LARSHE*	*AGE*	*YEAR*	*ROA*	*ROE*	*TEXP*	*NII*	*PE*	*AI*BD*	*AI*INDB*	*AI*SHE*
AIFQ																
BSIZE	0.616 **															
DEBT	0.167	0.202 *														
BDSIZE	−0.224 *	−0.350 **	−0.194													
INDPB	−0.068	−0.237 *	−0.323 **	0.931 **												
LARSHE	−0.085	−0.073	0.007	0.037	−0.073											
AGE	0.566 **	0.262 **	0.205 *	−0.112	0.026	−0.469 **										
YEAR	0.362 **	0.251 **	−0.235 *	0.022	0.006	0.191	0.124									
ROA	−0.021	−0.275 **	−0.242 *	0.179	0.297 **	−0.025	0.189	−0.136								
ROE	−0.073	−0.196	−0.414 **	−0.097	−0.017	0.298 **	−0.114	0.088	0.779 **							
TEXP	0.606 **	0.937 **	0.300 **	−0.353 **	−0.252 *	−0.149	0.359 **	0.116	−0.182	−0.190						
NII	0.580 **	0.700 **	−0.163	−0.127	0.086	−0.377 **	0.506 **	0.167	0.161	0.032	0.745 **					
P/E	−0.474 **	0.386 **	−0.338 **	0.184	−0.157	0.162	−0.502 **	−0.180	−0.271 **	−0.073	−0.501 **	−0.350 **				
AI*BD	−0.053	0.177	0.010	0.041	0.029	0.181	0.060	−0.098	−0.147	−0.121	0.107	0.026	−0.085			
AI*INDB	0.000	0.082	0.024	0.027	−0.001	0.266 **	−0.004	−0.038	−0.227 *	−0.133	0.134	0.012	−0.054	0.949 **		
AI*SHE	−0.021	−0.021	0.114	0.163	0.241 *	−0.511 **	0.237 *	−0.102	0.205 *	−0.096	0.033	0.175	−0.110	−0.060	−0.120	

$p < 0.10$, p * < 0.05, p ** < 0.01.

5.5. The Regression Analysis

a- The first regression without moderation (Equation (1))

Table 4a shows the summary of the regression models for Equation (1). The case of AIFQ effect without moderation.

Table 4. (a) Regression analysis—Equation (1); (b) regression analysis—Equation (2) (moderation); (c) regression analysis for removed variables.

(a)

	Model 1 (ROA) [a]	*Model 2 (ROE)* [a]	*Model 3 (NII)* [b]	*Model 4 (TEXP)* [b]	*Model 5 (P/E)* [a]
BSIZE	−0.001 *	−0.006	0.867 ***	0.977 ***	−1.818
DEBT	−0.019 ***	−0.294 ***	−5.004 ***	0.510	−32.722 **
BDSIZE	0.000	−0.002 *	0.046 **	0.003	−0.153
LARSHE	0.008 **	0.166 ***	−1.571 **	−0.475 *	−2.138
AGE	3.412×10^{-5} ***	0.000 **	0.008 ***	0.002	−0.080 **
AIFQ	1.600×10^{-5}	-5.681×10^{-5}	0.005	0.000	−0.063
YEAR	−0.002 **	−0.008	−0.374 ***	−0.176 **	−1.807
CONSTANT	0.020 *	0.299 **	−2.246	−3.069 ***	72.622 **
N	92	94	94	92	94
R SQUARED	0.299	0.361	0.863	0.963	0.404
ADJ. R SQ.	0.241	0.309	0.852	0.960	0.356
MODEL SIG	<0.001	<0.001	<0.001	<0.001	<0.001

(b)

	Model 1 (ROA) [a]	*Model 2 (ROE)* [a]	*Model 3 (NII)* [b]	*Model 4 (TEXP)* [a]	*Model 5 (P/E)* [a]
BSIZE	0.000	−0.002	0.917 ***	0.969 ***	−1.536
DEBT	−0.025 ***	−0.341 ***	−6.711 ***	0.725 *	−34.069 **
BDSIZE	0.000	−0.003 *	0.039 **	0.013	−0.091
LARSHE	0.018 ***	0.248 ***	−0.658	0.043	−0.413
AGE	4.143×10^{-5} ***	0.000 **	0.008 ***	-7.777×10^{-5}	−0.073 **
AIFQ	-1.639×10^{-6}	0.000	0.011 *	0.007 **	−0.083
YEAR	−0.002 ***	−0.013 *	−0.524 ***	−0.190 **	−1.998
AI*BD	−0.001 **	−0.008 **	−0.091 **	0.039	−0.655
AI*SHE	0.001 **	0.007 **	0.101 **	0.079 **	−0.185
CONSTANT	0.011	0.136	−3.247 **	−3.169 ***	65.114 **
N	92	93	94	89	93
R SQUARED	0.413	0.438	0.870	0.945	0.410
ADJ. R SQ.	0.349	0.377	0.856	0.939	0.346
MODEL SIG	<0.001	<0.001	<0.001	<.0001	<0.001

(c)

	Model 1 (ROA) [a]	*Model 2 (ROE)* [a]	*Model 3 (NII)* [b]	*Model 4 (TEXP)* [b]	*Model 5 (P/E)* [a]
INDPB	0.000 **	0.000	0.020	0.108 *	0.539
AI*INDP	−0.0001 **	−0.005	−0.037	−0.065 **	−0.456
AIFQ	-1.178×10^{-7}	0.000	0.053 ***	0.043 ***	−0.356 ***
CONSTANT	0.005 **	0.109 ***	15.201 ***	17.101 ***	14.942 **
N	95	97	96	92	97
R SQUARED	0.138	0.023	0.507	0.526	0.224
ADJ. R SQ.	0.110	−0.008	0.491	0.510	0.219
MODEL SIG.	0.004	0.531	<0.001	<0.001	<0.001

p * < 0.10, p ** < 0.05, p *** < 0.01; [a] OLS Regression. [b] WLS Regression.

Researchers employed ordinary multiple regression analysis for Models 1, 2, and 5. However, due to significant heteroscedasticity detected in Models 3 and 4, weighted least squares (WLS) regression was applied. Heteroscedasticity was tested using the Breusch and Pagan test, also known as the score test (Rosopa et al., 2013). The test yielded significant results, with p-values of <0.01 for the TEXP model and 0.002 for the NII model.

Consequently, WLS was chosen for its greater power and robustness in the presence of heteroscedasticity (Rosopa et al., 2013) to ensure more reliable and accurate results.

While all five regression models demonstrate a strong fit and are highly significant at $p < 0.01$, AIFQ consistently remains insignificant across all models, which indicates that the main effect of AIFQ on financial performance is insignificant, leading to the rejection of hypotheses 1 and 2. The R^2 values are notably high in Models 3 and 4, at 86.3% and 96.3%, respectively.

In Model 2, BDSIZE is negative and significant at <0.10, while in Model 3, it shows a positive and significant effect at <0.05. This suggests that larger boards of directors are negatively associated with ROE but positively linked to increases in net interest income. LARSHE is both positive and significant in Models 1 and 2 at <0.05 and <0.01, respectively, but turns negative in Models 3 and 4 at <0.05 and <0.10, which reveal that an increase in large shareholders is positively associated with higher ROA and ROE but is negatively associated with net interest income and total expenses.

b- The second regression with moderation (Equation (2))

Table 4b shows the summary of the regression models for Equation (2). The case of AIFQ effect with moderation.

The second regression analysis was conducted to assess the impact of moderators on AIFQ and financial performance. Ordinary least squares (OLS) multiple regression was applied to all models except for Model 3, where weighted least squares (WLS) regression was utilized due to significant heteroscedasticity. Each regression model demonstrated a robust fit, with significance levels at $p < 0.01$.

The earlier regression analysis without moderators revealed that the main effect of AIFQ was insignificant across all models. However, the introduction of the moderators dramatically shifted the significance of AIFQ in Models 3 and 4 to <0.10 and <0.05, respectively. Such an outcome indicates that AI-related term disclosure positively and meaningfully impacts net interest income and total expenses.

The moderator variable (AI*BD) shows a negative and significant effect at <0.05 across Models 1, 2, and 3, indicating that as the size of the board of directors increases, the association between AI-related term disclosure and financial performance becomes negative. Specifically, the relationship between AIFQ and ROA, AIFQ and ROE, and AIFQ and NII becomes increasingly negative, suggesting that larger boards tend to inhibit the positive impact of AI disclosures on these key financial metrics; thus, the results confirmed Hypothesis 3a and rejected Hypothesis 3b because AI*BD is insignificant in Model 4.

On the other hand, the interaction between AI-related term disclosure and large shareholders is positive and significant at <0.05 across Models 1, 2, 3, and 4. Such an outcome indicates that as large shareholders increase, the relationship between AIFQ and key financial metrics—ROA, ROE, and NII—strengthens, becoming increasingly positive. In other words, larger shareholder influence amplifies the beneficial impact of AI disclosures on financial performance, whereas it increases TEXP. Thus, the results confirm Hypothesis 5a while rejecting Hypothesis 5b.

c- The Third Regression-for the eliminated variables:

Table 4c shows the regression models for the removed variables.

All models demonstrate a strong fit except for Model 2, which is insignificant with a *p*-value of 0.531. AIFQ exerts a highly significant impact on NII, TEXP, and P/E at <0.01. However, the moderator variable (AI*INDB) shows a negative and significant effect in Models 1 and 4, indicating that as the proportion of independent board members increases, the influence of AIFQ on ROA and TEXP becomes increasingly negative. It suggests that

greater board independence diminishes the positive effects of AI-related disclosures on these financial metrics. Hence, the results confirm hypotheses 4a and 4b.

6. Findings

The results reveal that AI-related term disclosure has no impact across all five models in the initial regression analysis before introducing moderating variables. However, after incorporating the moderating effects of (*AI*BD* and *AI*SHE*) in the second regression, the significance of AIFQ's main effect shifts, positively affecting total expenses and net interest income. Likewise, in the third regression, the moderating variable (AI*INDB) alters AIFQ's main effect, positively impacting net interest income and total expenses while negatively affecting the price-to-earnings (P/E) ratio.

- *The second regression (moderating effect):*

In Models 1 and 2 (ROA and ROE), the interaction between the board of directors and AI disclosure is significant. Figures 2–5 show that the changes in the board of directors have an inverse effect on AI disclosures and ROA and AI disclosures and ROE, while changes in the proportion of large shareholders have a direct relationship with AI disclosure and ROE and AI disclosures and ROA. Accordingly, the board of directors and shareholders affect AI disclosure signals differently. Shareholders consider disclosure signals valuable when explaining performance measures such as ROA and ROE.

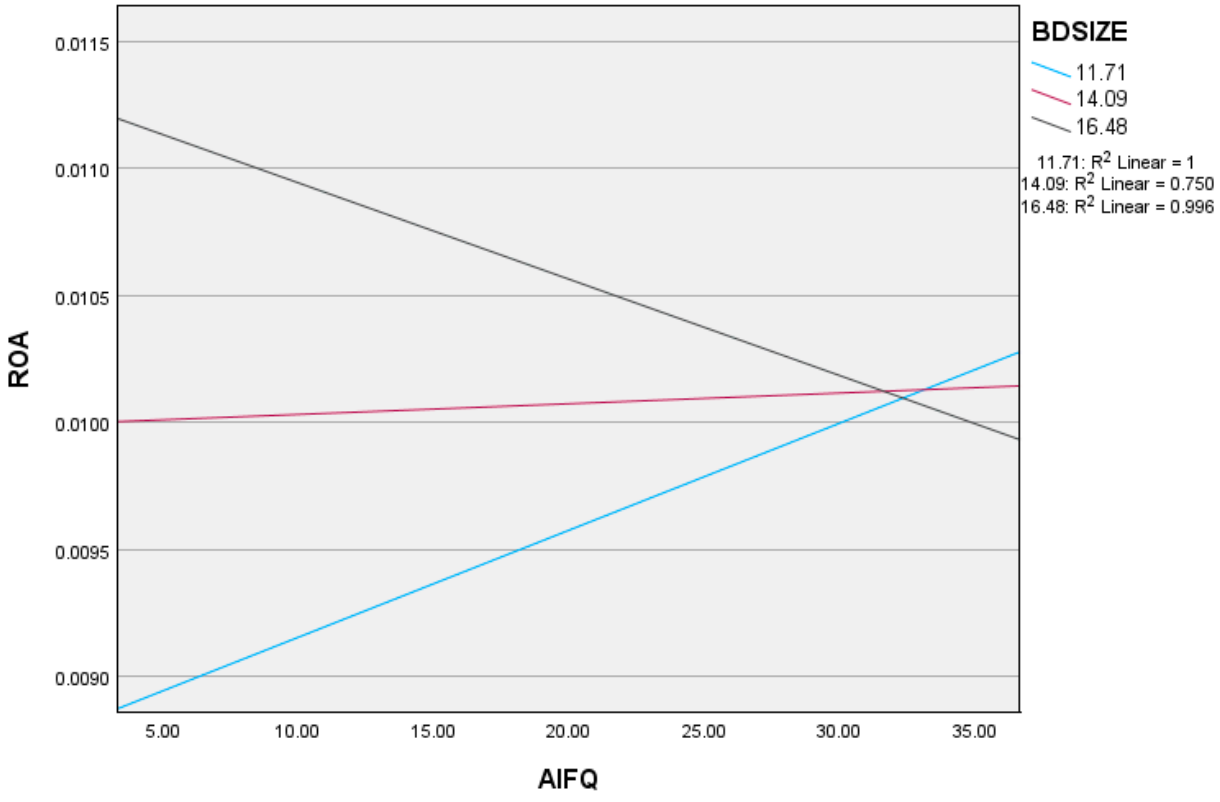


Figure 2. Model 1: AIFQ and BDSIZE moderation Graph.

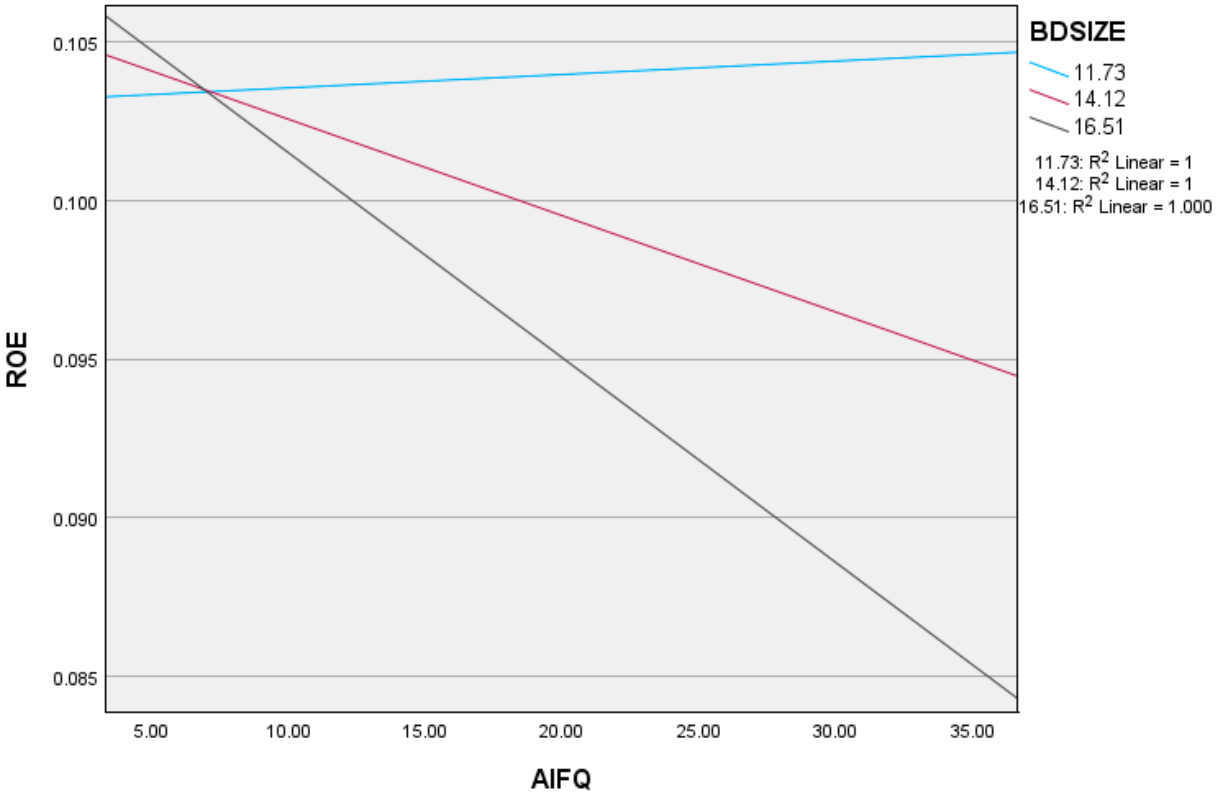


Figure 3. Model 2: AIFQ and BDSIZE moderation Graph.

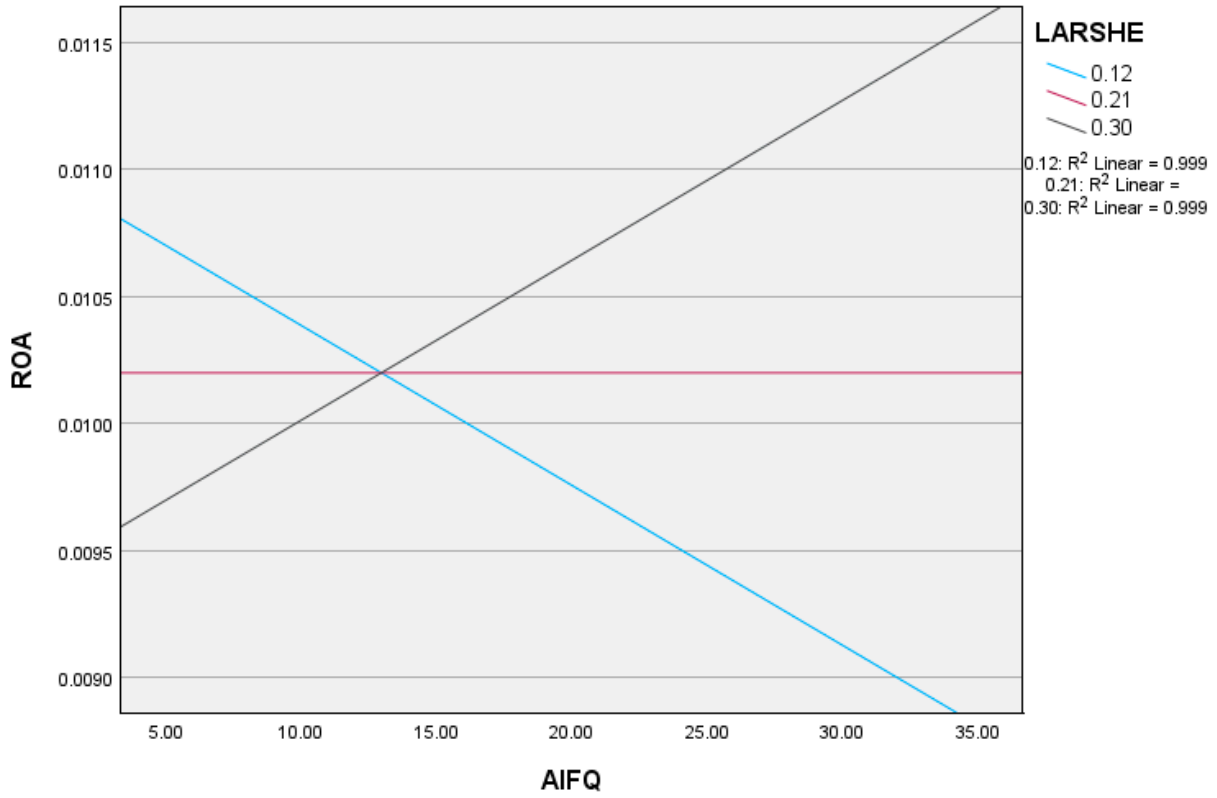


Figure 4. Model 1: AIFQ and LARSHE moderation Graph.

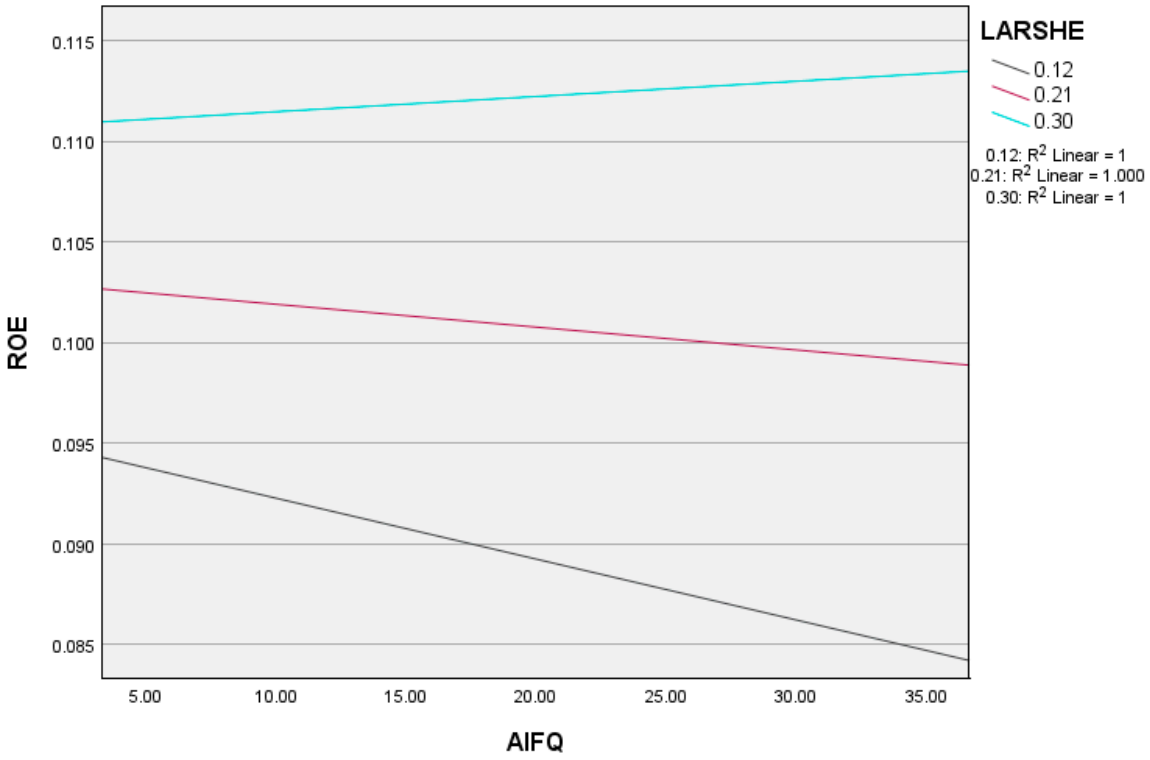


Figure 5. Model 2: AIFQ and LARSHE moderation Graph.

In Model 3 (NII), AIFQ positively affects net interest income (NII) at a *p*-value < 0.1. Notably, without the moderating effect, AIFQ had no impact on NII. However, Figure 6 shows that when interacting with the board of directors, the interaction between the board of directors and the AI disclosure is negative, suggesting that the board of directors does not view it as a significant signal that explains the positive influence of AI disclosure on net interest income.

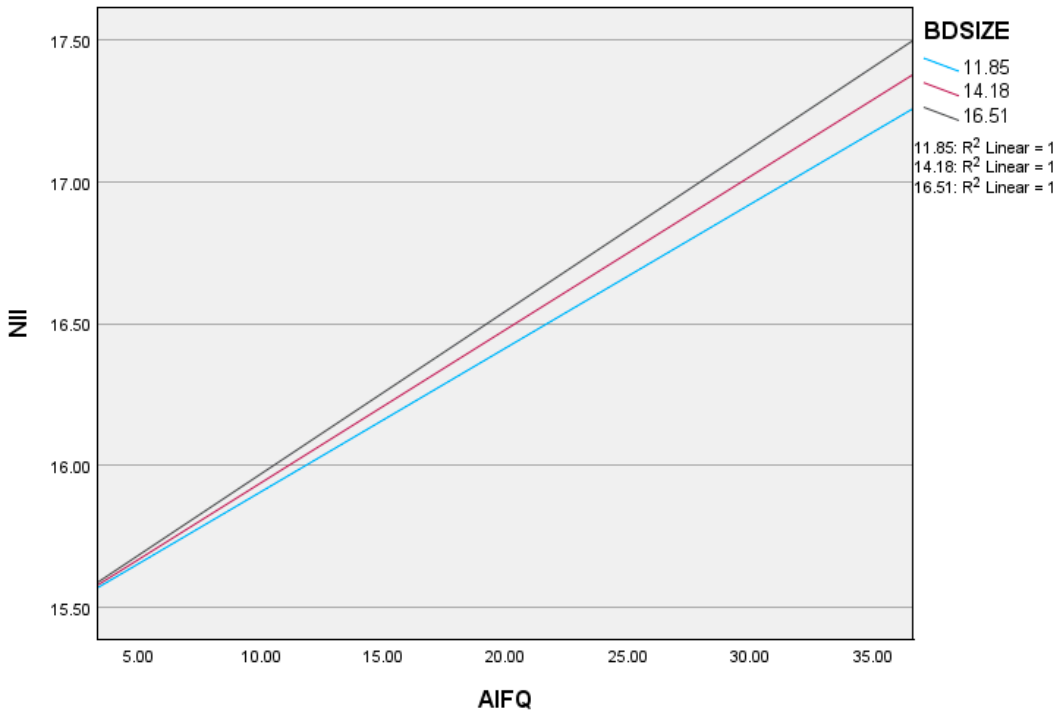


Figure 6. Model 3: AIFQ and BDSIZE moderation Graph.

Figure 7, On the other hand, as the influence of large shareholders grows, the positive association between AIFQ and NII strengthens. Therefore, it highlights the importance of AI disclosures to the shareholders as they consider it a signal explaining the changes in net interest income.

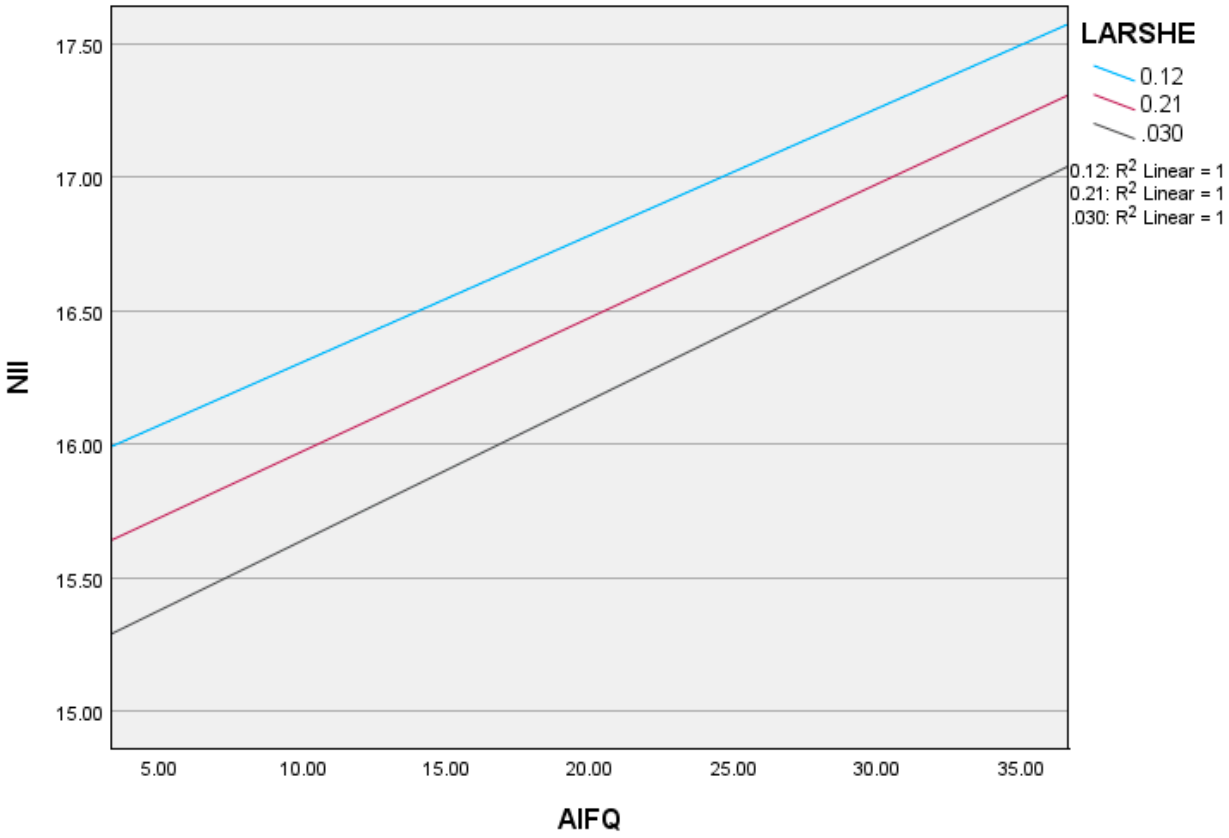


Figure 7. Model 3: AIFQ and LARSHE moderation Graph.

In Model 4 (TEXP), after introducing the moderating effect in the second regression, AIFQ has a positive effect on total expenses (TEXP) at a p-value < 0.05. Note that without considering moderation, AIFQ does not affect total expenses. However, in Figure 8, the interaction between AIFQ and large shareholders is significantly positive, while in Figure 9, the interaction between AIFQ and board size is insignificant. Hence, such a finding suggests that as the proportion of large shareholders increases, their interest in AI disclosures increases because such signals are crucial to explain the increase in expense, whereas changes in board size do not influence AI's effect on total expenses.

- *The third regression (eliminated variables):*

In Model 3 (NII), AIFQ is both positive and significant at a p-value < 0.01. However, in Figure 10, the interaction between AIFQ and board independence is insignificant, showing that changes in the level of board independence neither weaken nor enhance the positive effect of AI-related term disclosure on NII. Accordingly, such a finding suggests that the top ten banks' governance structures may not consider AI disclosure as a critical single to explain performance, especially the positive changes in net interest income.

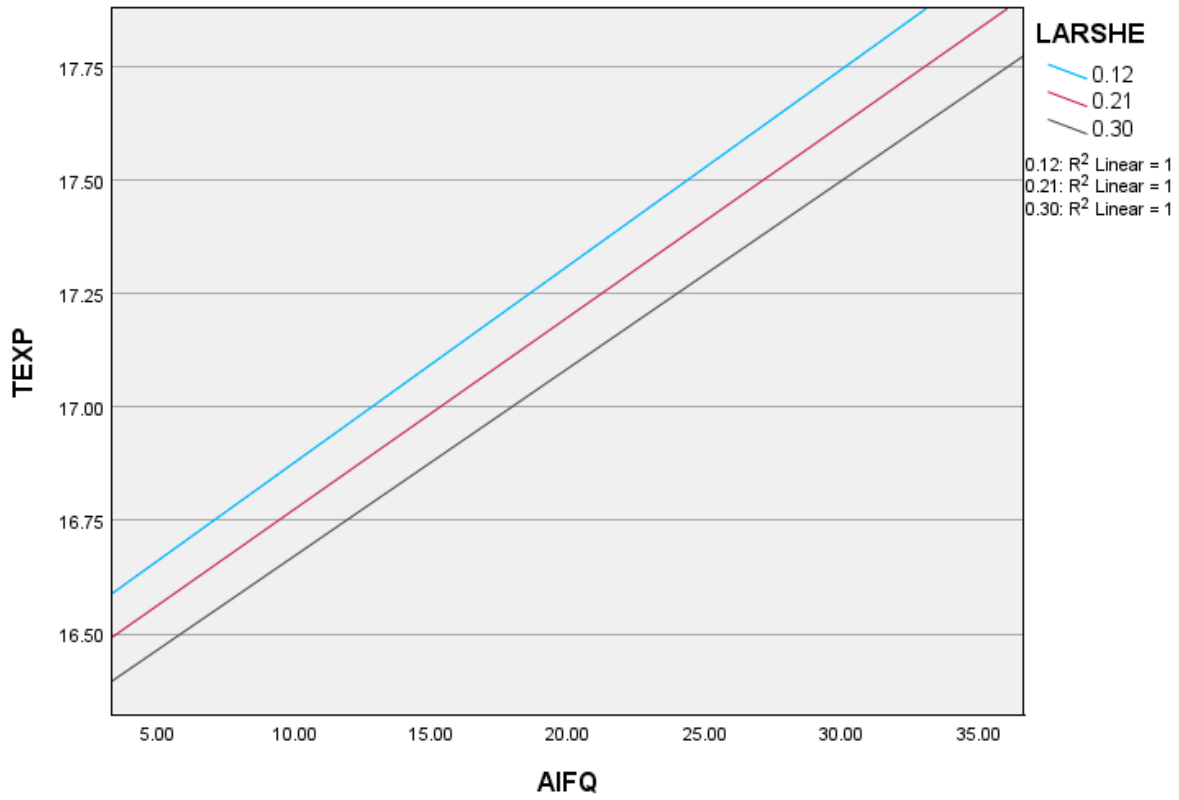


Figure 8. Model 4: AIFQ and LARSHE moderation Graph.

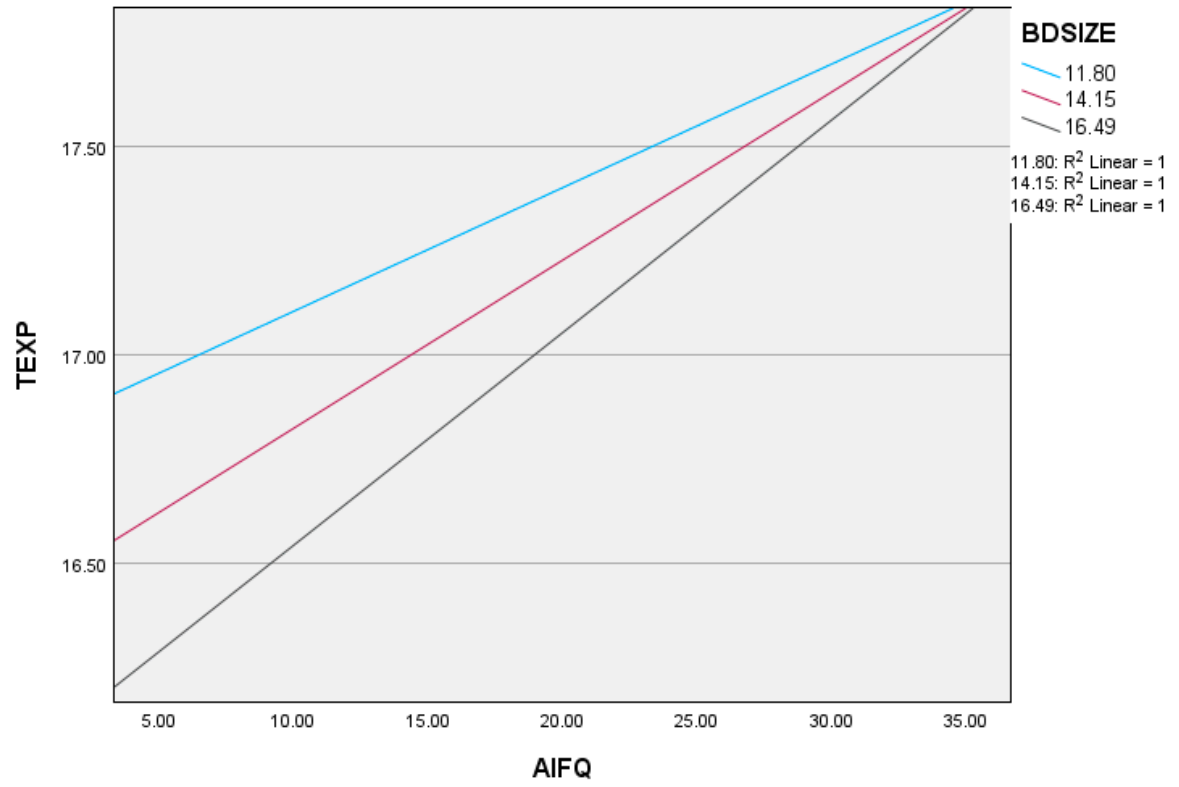


Figure 9. Model 4: AIFQ and BDSIZE moderation Graph.

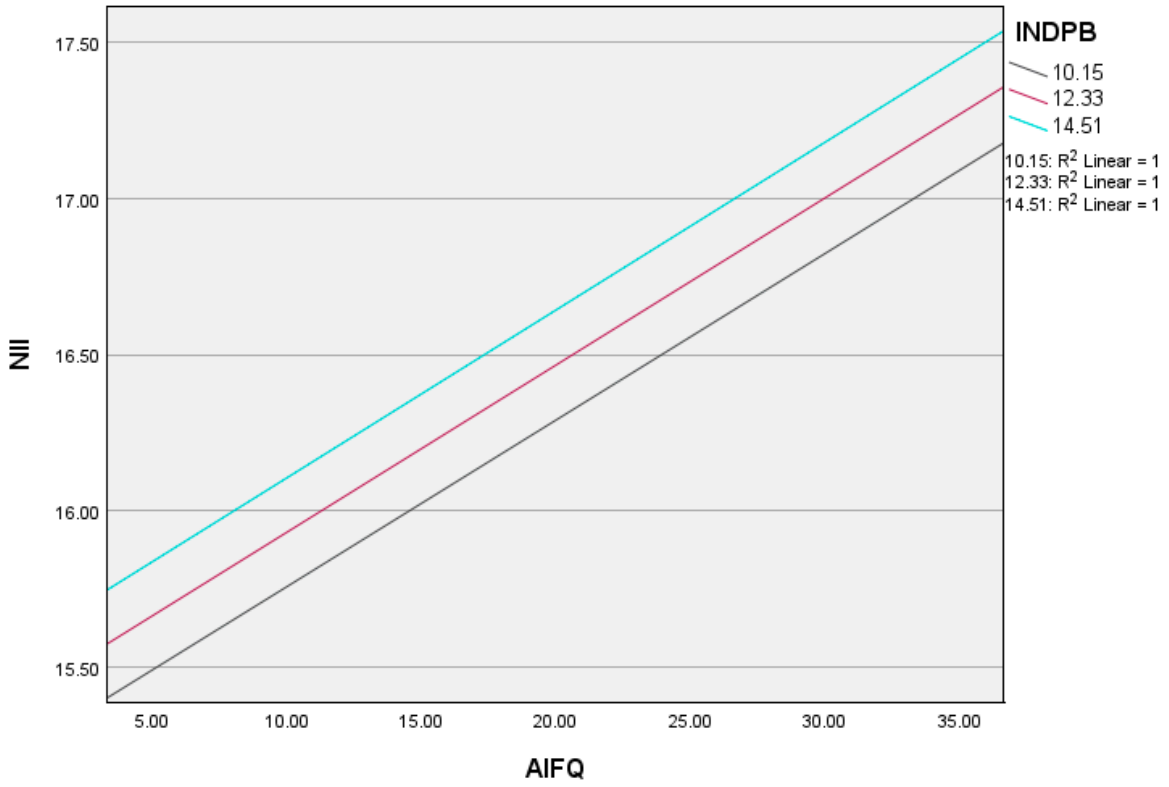


Figure 10. Model 3: AIFQ and INDPB moderation Graph.

In Model 4 (TEXP), the interaction between AI-related term disclosure and an independent board of directors reveals that increased board independence weakens the positive effect of AI-related term disclosure on total expenses (See Figure 11), indicating that independent board members are reacting negatively to AI disclosures as they view such signals less effective to explain the changes in total expenses.

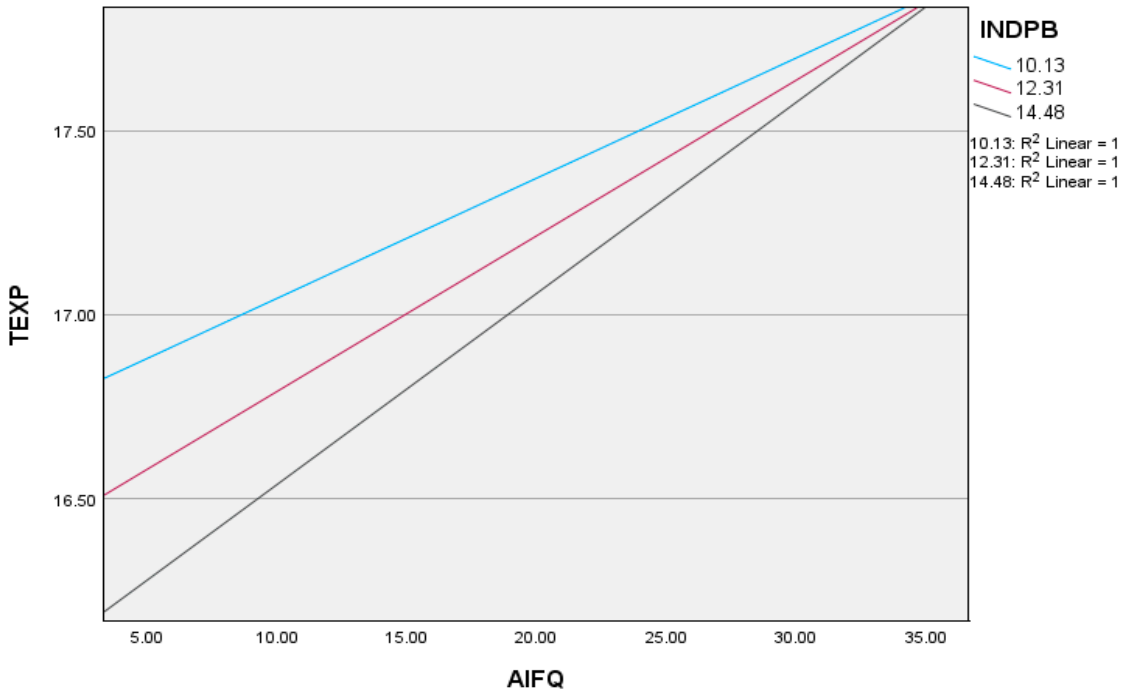


Figure 11. Model 4: AIFQ and INDPB moderation Graph.

- COVID-19 effect:

The independent variable, YEAR, is a dummy variable used to control the impact of COVID-19 during and after the pandemic, with 2020, 2021, and 2022 classified as COVID-19-affected years. Correlation analysis shows that the YEAR variable is significantly correlated with AIFQ (positive at $p < 0.05$), BSIZE (positive at $p < 0.05$), and DEBT (positive at $p < 0.1$). To capture COVID-19's effect on these variables, an independent sample *t*-test was conducted (See Appendix C, *t*-test section). Levene's Test for Equality of Variances was insignificant for AIFQ, BSIZE, and DEBT, confirming the homogeneity assumption. The one-sided *p*-value for all three variables was <0.01, indicating that the COVID-19 years significantly affected them.

The average bank size during COVID-19 was 20.959, compared to 20.493 before the pandemic. With a significant *p*-value, this indicates that banks' total assets increased during the pandemic. At the same time, the debt ratio was lower throughout the pandemic, with an average of 0.108 compared to 0.194 before 2020. This rise in assets and reduction in debt can be attributed to the federal government's increased money supply, strengthening banks' financial positions. Additionally, AI-related term disclosures saw a notable increase during 2020, 2021, and 2022, with an average of 25.05 terms, compared to just 15.741 terms before Covid. This surge reflects banks' heavy reliance on AI technology to meet customer needs during the pandemic.

7. Discussion

AI terms disclosure frequency in the annual reports in the US banks showed the same trend as in Jordanian banks, with the highest value of 2 and the lowest of 50. Figure A1 in Appendix B shows that such a variation in terms mentioned in the annual reporting exists. This is consistent with previous studies (e.g., Shiyyab et al., 2023; Shehadeh et al., 2024), in which banks show variations in disclosures. The variation in disclosures indicates that banks in the US do not engage in the same level of AI adoption and that the board of directors of those banks does not exhibit the same level of signaling across different banks. Additionally, the findings align with (Bonsón et al., 2021; Finkenwirth, 2021; Shiyyab et al., 2023; Shehadeh et al., 2024), indicating that AI term disclosures exhibit incremental growth in financial reporting. Figure A2 in Appendix B shows an increasing trend in the most recent year.

Although there is an increase in AI disclosures in US banks, findings indicate that such an increase does not affect financial performance, which contradicts the first and the second hypotheses. This is consistent with (Finkenwirth, 2021) and contradictory to (Alkaraan et al., 2022; Shiyyab et al., 2023; Shehadeh et al., 2024). Such a disparity between the current and prior studies might be attributed to the difference in the US institutional setting and business environment. As in the US, the CEO's power is concentrated, which leverages their influence over the board (Aguilera et al., 2006). Additionally, the difference in the accounting standards might cause a disparity between the current study results and prior studies.

This analysis shows that banks with larger and independent boards are less likely to view AI disclosures as less effective signals to explain financial performance or changes in such metrics. Accordingly, it confirms that bank governance may adopt a more cautious and negative stance toward AI disclosures because AI disclosure could draw unwanted attention to their performance instead of sending a positive signal to shareholders. This finding, as expected, is contradictory to (Alkaraan et al., 2022; Shiyyab et al., 2023), and it supports that the difference in the institutional setting and accounting standards would lead to different results. Alternatively, concentrated ownership and institutional investors in the US banks view AI disclosures as valuable signals to explain financial performance, which

is contradictory to (Shiyyab et al., 2023), as the institutional investors in the US are more short-term-oriented and driven by a focus on economic value to maximize their profitability.

Finally, COVID-19 analysis shows a negative effect in the first and second regression analysis, which inversely affects financial performance during COVID-19 years. This finding is consistent with (Shehadeh et al., 2024), in which COVID-19 negatively affects digital transformation initiatives in Jordan, and it contradicts (Shiyyab et al., 2023), in which COVID-19 did not affect financial performance. On the contrary, the study found that during COVID-19, the frequency of AI discourses increased in the annual reports.

This study highlights a different view between banks' governance and large shareholders. While bank agents' and principals' goals and objectives may appear aligned, the board of directors reacts negatively to AI disclosures, while shareholders react positively to AI disclosures. While a potential conflict of interest may exist, the disparity in perspectives could also stem from a knowledge gap, lack of information between the two parties, or CEOs' concentrated power in the US institutional setting. In direct decision-making, agents have immediate control, whereas principals remain more distanced from the bank's day-to-day operations (Linder & Foss, 2013). This separation likely contributes to the differing views on AI disclosures.

8. Limitations, Recommendations, and Conclusions

This study's findings have implications for financial reporting and disclosure. First, shareholders react positively to AI disclosures, believing they could help explain the bank's performance. Accordingly, banks could increase AI disclosures to signal the positive influences of AI in banks' operations. Second, the study showed that AI disclosures affect performance measures; therefore, regulators and policymakers could establish rules and guidelines for AI disclosures, ensuring that AI-related activities are disclosed in annual reports. Furthermore, the study findings could call for future mandatory disclosures by accounting governing bodies.

While the study's findings may not be generalizable due to the sample size, they substantially contribute to the literature on AI technology's role in major U.S. banks. It highlights how boards of directors and principals view AI disclosure in financial reports to signal financial performance, offering valuable insights into the effective use of AI in the banking sector.

The core idea of this study is that frequent AI-related term disclosures in annual reports indicate innovation and market competitiveness. Banks that extensively report AI usage invest in advanced technology, enhancing their competitive edge. The analysis of AI term disclosures among leading US banks indicates that these disclosures mirror the extent of AI integration in their operations. The lowest frequency of AI-related terms observed in annual reports is just 2, highlighting a need for greater attention (see Appendix C). Meanwhile, Wells Fargo has the highest AI disclosure, totaling 295 AIFQ mentions from 2013 to 2022.

The primary aim of this study is to assess how the board of directors, independent board members, and larger shareholders influence the relationship between AI-related term disclosures and financial performance and to determine whether their interaction mitigates or exacerbates agency problems. This study reveals that AIFQ alone does not affect financial performance. However, the moderating effects of the board of directors, independent board members, and larger shareholders significantly impact financial performance in some models.

The study's limitations include data collection methods, the study's timeframe, and the nature of the data. Data were gathered from bank annual reports, proxy statements, and websites. The limited sample size and short timeframe restricted the ability to expand the

sample. Additionally, the data required transformation to meet the normality assumption. Heteroscedasticity was identified as an issue in Models 3 and 4. In order to solve the issue, a score test was conducted to assess the significance of heteroscedasticity (see Appendix C, Table A6), and a weighted least squares regression model was applied accordingly.

Further analysis is recommended to validate the impact of AIFQ on US banks' financial performance and explore the moderating effects of board size, independent board members, and large shareholders. Future research should consider a larger sample size to improve the relevance and accuracy of the results. Given the data's inherent heterogeneity, transforming the data is essential for robust measurements. Employing a larger sample or alternative statistical methods may enhance the evaluation of the relationship between these variables.

The age of AI is here, and businesses need to capitalize on the benefits while minimizing the drawbacks. In the coming years, competition will be fierce among institutions developing and investing in AI technology. Banks, in particular, have already shown a keen interest in adopting this emerging technology through various banking services. However, given the preliminary stage of the technology, accounting regulations must consider its usage and disclosure. To this end, this study aimed to examine the impact of AI-related disclosures on the performance of top US banks, analyze trends in their financial reporting, and measure agency issues between related parties.

This study has two questions. As per the first question, does AI-related disclosure in the top US banks show the same trend as Jordanian banks and companies in Germany, Malaysia, the UK, and Spain? AI-related disclosures showed an increase in the top US banks' financial reports, similar to those in other countries. As for the second question, is there a disagreement between shareholders and the board of directors regarding AI disclosure? If so, is that attributable to the information gap between both parties? The board of directors and shareholders did not share the same view about AI disclosure; the shareholders' view was toward more disclosure than the board of directors, and apparently, their conflicting interest is attributable to the information gap.

Despite the small sample size, this study successfully addresses all research questions and concludes that AI disclosure affects net interest income, total expense, and prices-to-earnings ratio only by moderating the bank's governance and large shareholders. To further solidify these findings, it is recommended that future analyses employ a larger sample size or alternative statistical methods. Additionally, the study advocates for further exploration of AI disclosures across various industries to develop comprehensive accounting standards that regulate AI disclosures and practice.

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Appendix A

Table A1. List of banks included in the sample size.

Rank	*Bank Name*	*Headquarters*	*Total Assets*
1	JP Morgan Chase	New York City	$3868
2	Bank of America	Charlotte	$3123
3	Citigroup	New York City	$2423
4	Wells Fargo	San Francisco	$1876
5	Goldman Sachs	New York City	$1571
6	Morgan Stanley	New York City	$1164
7	US. Bancorp	Minneapolis	$680
8	PNC Financial Services	Pittsburg	$558
9	Truist Financial	Charlotte	$544
11	Charles Shwab Corp	Westlake, Texas	$511

Table A2. List of variables description.

AIFQ	The number of mentioned AI-related terms in each annual report
ROA	Return on Assets
ROE	Return on equity
NII	Net interest income
P/E	P/E ratio
TEXP	Natural log of total expenses
TNIEXP	Total non-interest expenses
BSIZE	Bank size, which is the natural log of assets
DEBT	Long-term debt to total debt ratio
BDSIZE	Number of board of directors
AI*BD	AI-related terms disclosures interaction with board size
INDPB	The proportion of independent board members
AI*INDB	AI-related terms disclosure interaction with independent board member
LARSHE	Percentage of shareholders who own more than 5% of total shares
AI*SHE	AI-related terms disclosure interaction with Large shareholders
AGE	The age of the bank. Number of years from the date of establishment
YEAR	Dummy variable 1: COVID year and years after COVID, 0: Other

Table A3. AI-related term Index.

Digital awareness, transformation, and capabilities	Digital transformation, fintech, financial technology, modern technology, AI digital strategy, latest technology, advanced technology, AI computing technology, digital infrastructure, digital library, electronic channel, electronic system, internet of things, 5 g technology, advanced technical experiences, digital platform, digital technology, 5 g networks, blockchain, smart connection, digital awareness, digital capabilities, digital culture, digital economy, digital futuristic, digital transition, augmented reality technology, technical platform, web technology, machine learning, deep learning, augmented intelligence, natural language processing (NLP).
AI application, product, service, and process	Robotics, robo-advisors, automation, digital banking, mobile banking, online banking, digital services, mobile apps, electronic payment, Internet banking service, mobile branches, mobile payment, robots, mobile ATMs, digital payment, digital identity, smartphones, smart bank websites, digital product, electronic service, intelligently analyses, digital wallet, electronic wallet, mobile device service
AI information challenges and cyber security threats	Information security, cyber security, electronic security, it risks security, electronic security policies, card security, cyber risk, electronic security, cybercrime, bank electronic security, customized electronic security methods, cyber breach, cyber resiliency, defense technology, cyber intelligence, electronic attack, global security, information security breaches, security vulnerabilities.

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Appendix B. Plots and Figures

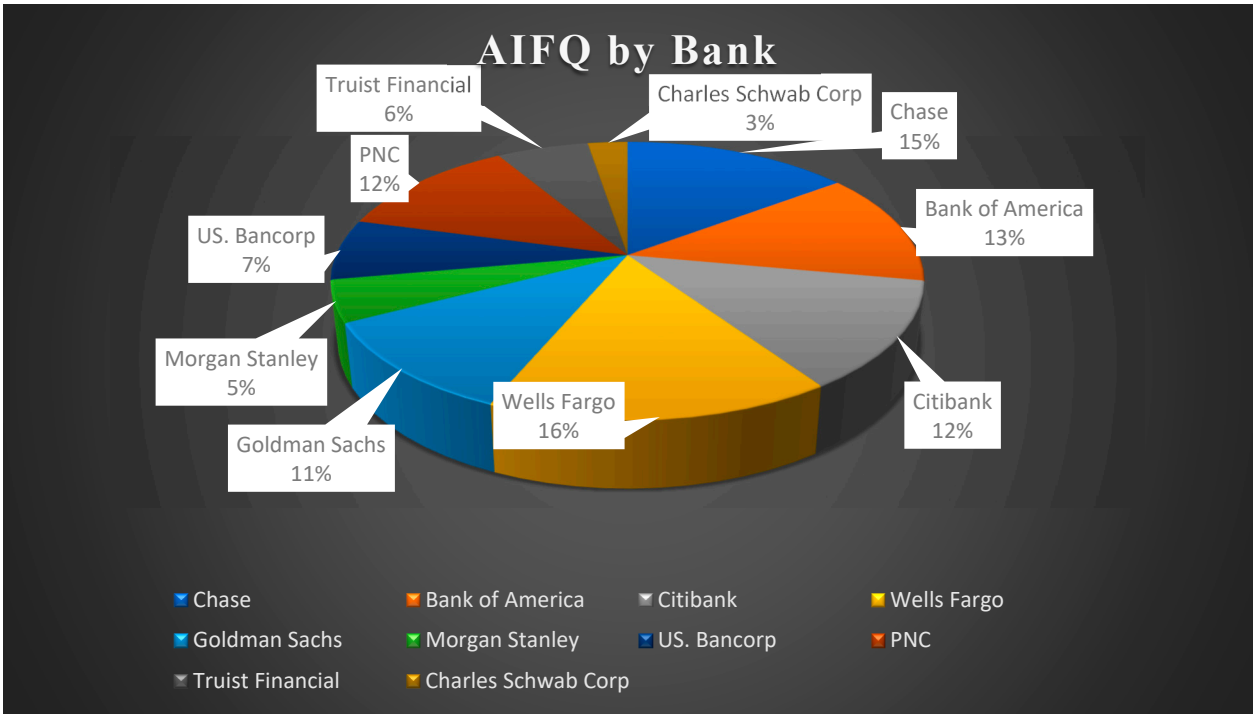


Figure A1. AI frequency by bank.

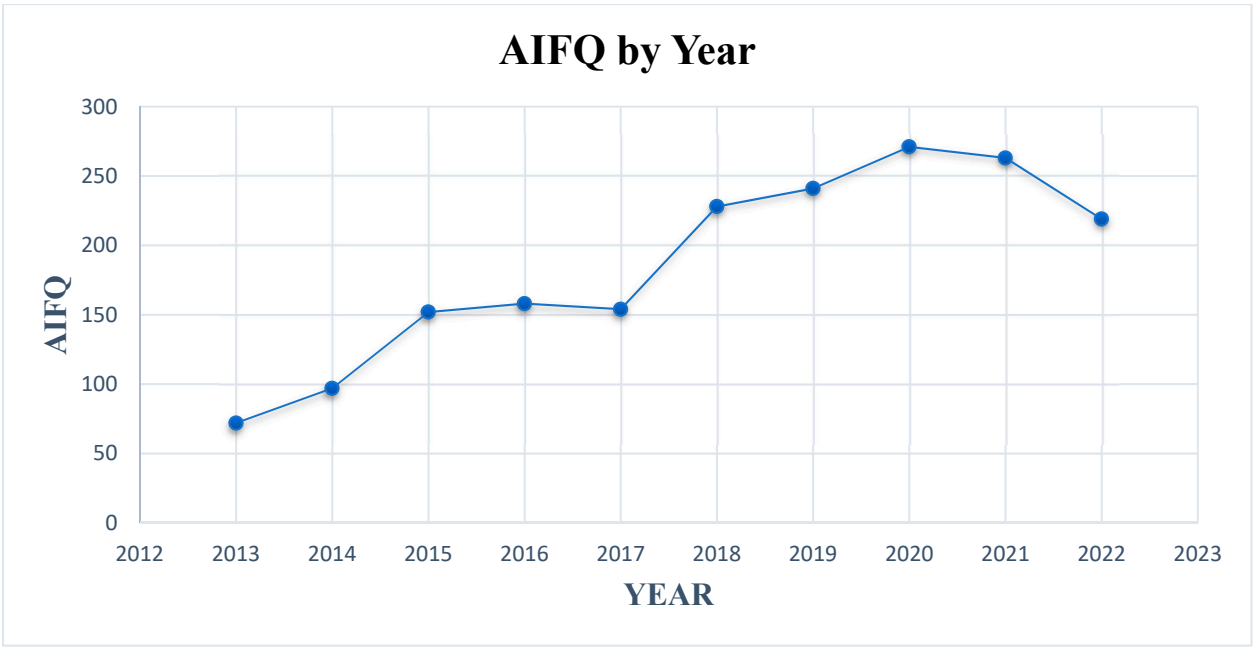


Figure A2. AI frequency by year.

Appendix C

Table A4. Banks AIFQ per single year.

Bank Name	*YEAR*	*AIFQ*
CHASE	2013	10
CHASE	2014	9
CHASE	2015	41
CHASE	2016	50
CHASE	2017	19
CHASE	2018	34
CHASE	2019	11
CHASE	2020	47
CHASE	2021	32
CHASE	2022	21
BANK OF AMERICA	2013	16
BANK OF AMERICA	2014	14
BANK OF AMERICA	2015	17
BANK OF AMERICA	2016	10
BANK OF AMERICA	2017	14
BANK OF AMERICA	2018	22
BANK OF AMERICA	2019	26
BANK OF AMERICA	2020	34
BANK OF AMERICA	2021	46
BANK OF AMERICA	2022	45
CITIBANK	2013	6
CITIBANK	2014	11
CITIBANK	2015	19
CITIBANK	2016	19
CITIBANK	2017	25
CITIBANK	2018	32
CITIBANK	2019	47
CITIBANK	2020	33
CITIBANK	2021	22
CITIBANK	2022	19
WELLS FARGO	2013	16
WELLS FARGO	2014	22
WELLS FARGO	2015	18
WELLS FARGO	2016	23
WELLS FARGO	2017	23
WELLS FARGO	2018	43
WELLS FARGO	2019	37
WELLS FARGO	2020	38
WELLS FARGO	2021	38
WELLS FARGO	2022	37
GOLDMAN SACHS	2013	5
GOLDMAN SACHS	2014	13
GOLDMAN SACHS	2015	10
GOLDMAN SACHS	2016	13
GOLDMAN SACHS	2017	23
GOLDMAN SACHS	2018	24
GOLDMAN SACHS	2019	31
GOLDMAN SACHS	2020	31
GOLDMAN SACHS	2021	34
GOLDMAN SACHS	2022	19
MORGAN STANLEY	2013	4
MORGAN STANLEY	2014	6
MORGAN STANLEY	2015	6
MORGAN STANLEY	2016	10
MORGAN STANLEY	2017	11
MORGAN STANLEY	2018	10
MORGAN STANLEY	2019	11

Table A4. *Cont.*

Bank Name	*YEAR*	*AIFQ*
MORGAN STANLEY	2020	11
MORGAN STANLEY	2021	10
MORGAN STANLEY	2022	11
USBANCORP	2013	2
USBANCORP	2014	5
USBANCORP	2015	9
USBANCORP	2016	6
USBANCORP	2017	10
USBANCORP	2018	19
USBANCORP	2019	24
USBANCORP	2020	20
USBANCORP	2021	26
USBANCORP	2022	10
PNC	2013	7
PNC	2014	8
PNC	2015	19
PNC	2016	16
PNC	2017	18
PNC	2018	27
PNC	2019	31
PNC	2020	34
PNC	2021	34
PNC	2022	32
TRUIST FINANCIAL	2013	3
TRUIST FINANCIAL	2014	6
TRUIST FINANCIAL	2015	7
TRUIST FINANCIAL	2016	6
TRUIST FINANCIAL	2017	6
TRUIST FINANCIAL	2018	11
TRUIST FINANCIAL	2019	19
TRUIST FINANCIAL	2020	17
TRUIST FINANCIAL	2021	17
TRUIST FINANCIAL	2022	19
CHARLES SCHWAB CORP	2013	3
CHARLES SCHWAB CORP	2014	3
CHARLES SCHWAB CORP	2015	6
CHARLES SCHWAB CORP	2016	5
CHARLES SCHWAB CORP	2017	5
CHARLES SCHWAB CORP	2018	6
CHARLES SCHWAB CORP	2019	4
CHARLES SCHWAB CORP	2020	6
CHARLES SCHWAB CORP	2021	4
CHARLES SCHWAB CORP	2022	6

Table A5. Multicollinearity test.

Variable	*Collinearity Statistics (VIF)*
YEAR	1.683
BSIZE	2.184
DEBT	2.513
BDSIZE	17.800 *
LARSHE	2.292
AGE	2.625
AIFQ	3.479
*AI*BD*	13.534 *
*AI*SHE*	1.727
*AI*INDB*	13.703 *
INDPB	19.158 *

* high collinearity.

Table A6. Score test.

Model	*REGRESSION W/O MODERATION P-VALUE*	*REGRESSION W/MODERATION P-VALUE*	*REGRESSION FOR ELIMINATED VARIABLES P-VALUE*
NII	0.002	0.011	<0.001
TEXP	<0.001	0.417	0.092

- **T-test:**

Table A7. Independent samples test ***.

		Levene's Test for Equality of Variances		*t-Test for Equality of Means*							
						Sig.				**95% Confidence Interval of the Difference**	
		F	*Sig.*	*t*	*df*	*One-Sided p*	*Two-Sided p*	*Mean Difference*	*Std. Error Difference*	*Lower*	*Upper*
BSIZE	Equal variances assumed	0.525	0.470	2.553	97	0.006 **	0.012 *	0.466	0.182	0.104	0.827
	Equal variances are not assumed.			2.651	56.982	0.005 **	0.010 *	0.466	0.176	0.114	0.817
AIFQ	Equal variances assumed	0.018	0.893	3.823	97	<0.001	<0.001	9.309	2.435	4.476	14.141
	Equal variances are not assumed.			3.832	55.542	<0.001	<0.001	9.309	2.429	4.442	14.175
DEBT	Equal variances assumed	0.463	0.498	−2.384	97	0.01 *	0.019 *	−0.030	0.012	−0.055	−0.005
	Equal variances are not assumed.			−2.565	65.921	0.006 **	0.013 *	−0.030	0.012	−0.053	−0.007

* $p < 0.05$, ** $p < 0.01$; *** Numbers are rounded to the third decimal point.

Table A8. Group statistics **.

	*Year **	*N*	*Mean*	*Std. Deviation*	*Std. Error Mean*
BSIZE	1	29	20.959	0.773	0.144
	0	70	20.493	0.846	0.101
AIFQ	1	30	25.050	11.088	2.024
	0	69	15.741	11.153	1.343
DEBT	1	30	0.108	0.050	0.009
	0	69	0.194	0.060	0.007

* Year is a dummy variable coded 1 as COVID-19 year and 0 before COVID-19 year. ** Numbers are rounded to the third decimal point.

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