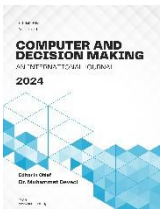
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AI-Automated Financial Reporting, Accounting Quality, Internal Controls, and Equity Market Valuations: Documentary Evidence from GCC-Listed Companies

Tauseef Malik[*1], Awni Rawashdeh[2]

[1]*FCMA (Fellow Member of The Chartered Institute of Management Accountants) UK, tauseefmalik1@outlook.com, ORCID: 0009-0001-4775-1720

[2]Department of Accounting, Faculty of Business, Applied Science Private University (ASU), Amman-Jordan, email: a_rawashdeh@asu.edu.jo, ORCID: 0000-0003-3382-1529

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ABSTRACT

GCC corporate reports disclose growing use of artificial intelligence (AI), but finance-specific adoption is often mixed with deterministic automation and wider enterprise initiatives. This study examines what eight GCC-listed issuers report about financial-reporting applications, accounting quality, internal controls, and equity-market valuation. A deductive comparative case design applies manual documentary content analysis to 43 distinct evidence IDs across 51 register rows from issuer reports. Predefined categories identify deployed finance-related AI, non-AI reporting automation, adjacent control uses, prospective applications, and market context. stc describes an AI-based IFRS advice assistant with reported productivity indicators; other issuers document regulatory reporting automation, governance, fraud monitoring or control-testing systems without consistently identifying financial-statement AI. An internal GPT pilot described at stc includes Internal Audit users but is not evidence that GPT conducted an audit. Market capitalisation disclosures do not identify AI-related valuation effects. Findings support more precise disclosure of tasks, deployment, human oversight, and measured outcomes; causal impacts cannot be inferred from these documents alone.

1. Introduction

1.1 Research Background

Artificial Intelligence (AI) can help accountants in standards research, reconciliation, exception review, and disclosure preparation tasks. These are different applications from rules-based robotic process automation (RPA), enterprise AI, and independent financial-statement audit. Distorting what issuer disclosures set forth is confusing. The listed companies in the GCC capital markets can be a good example, as they publish reports on digital transformation, corporate governance, and financial performance, albeit in varying degrees of detail. This study looks at real-world pledges made by eight issuers, rather than all AI initiatives being viewed as accounting automation. The relationship between AI adoption and accounting outcomes has been correlated with evidence from the GCC region, but this does not confirm any specific issuer's outcomes in accounting [1]. While automation can streamline repetitive reporting tasks, its impact on error rates and controls will vary based on how it's implemented and monitored. There is research on automation and internal control that can find benefits and risks to be monitored [2]. Accounting information system studies also differentiate between the accounting information's quality and the technology capability [3]. In the Saudi context, the literature shows that adopting AI is correlated with financial reporting quality; however, the measurements cannot be

* *Corresponding author.*
E-mail address: tauseefmalik1@outlook.com

replicated in these cases without similar observations [4].

1.2 Literature and Analytical Perspective

The study on accounting by researchers [5] suggests that the intensity of the use of AI and the internal-control systems is related to information quality. Explainable-AI scholarship emphasizes that traceability and accountability of the human, and not just the algorithmic output, are reliable [6]. There are opportunities and practical considerations for field research in auditing, such as confidentiality and validation [7]. The research on ChatGPT also shows that the process of language generation needs to be separated from the accounting process [8].

Linguistic use is recognized in published research because of the use of generative AI, but whether earnings quality improved remains elusive [9]. There are other empirical studies that have found a correlation between AI and disclosure quality [10]. The evidence of Palestinian industrial companies is for a different population and measurement system [11]. In a larger study, client AI usage has also been linked to audit quality [12]. These external results are information for interpretation but not case-level results of the selected GCC issuers. Key differences involved here are: Task specificity, Deployment state, Process indicators observed, and evidence of controls.

Investors may respond differently to certain disclosures and promotional stories regarding AI [13]. Firm-value work is a measure of technological capability versus language used to describe it [14]. AI washing research warns that enthusiasm for AI does not necessarily translate to economic gains [15]. This analysis then looks at whether the selected reports present any known link between a finance-related activity of AI and the reliability of financial statements, financial-statement control, or the market value of the financial statements.

A differentiation in analytical value is vital to the recommendation of deployment of AI in the reporting chain. An accounting guidance tool is before the transaction recognition and is upstream of the financial statement's preparation, whereas an automated control would be after the financial statements were prepared and only act on exceptions. The two views do not give any clear indication of which of the numbers is likely to be more accurate. An informative disclosure will identify the disclosure task, the reader responsible for the disclosure, and what is being disclosed. If it weren't for that, AI would not be specific: there would be different kinds of organisational activity that are grouped in the term.

1.3 Research Gap, Significance and Objectives

The research gap is not a lack of AI announcements; a lack of clarity at the level of cases regarding what technology was being implemented, which accounting activity it engaged with and what was demonstrated. Failure to implement the resources created by AI can destroy organisational value [17], while successful implementation can add value [16]. In addition, there are indications from disclosure research that the meaning of similar disclosures by AI can be different for the market [18]. A bounded documentary comparison is useful for the boards, auditors, and investors to help differentiate what actions lead to what consequences, but not necessarily a causal effect.

The goal is to do a comparison of eight listed companies from Saudi Arabia, UAE, Qatar, and Kuwait. What activities are clearly identified as being related to finance that are being undertaken using AI or automation? (2) What information is collected from these activities? (3) What information is being created or used because of these activities? (2) Are reporting quality and internal control processes and/or results documented? (3) What evidence is there that those activities are related to equity-market valuation? The contribution is not an estimated treatment effect or a representative assessment of all six GCC countries, but rather it is a specified evidence classification which is transparent.

2. Methodology

2.1 Deductive Documentary Research Design and Cases

The research method is a deductive qualitative multiple-case study, and the data analysis technique is manual content analysis of corporate documents. The following are case examples of listed companies and observation examples of their disclosures, linked to their sources. The 8 companies were purposively selected from Saudi Arabia, UAE, Qatar, and Kuwait as their issuer reports were accessible and had material relating to AI, reporting processes, or governance. This selection does not represent a typical sample from the GCC region, but rather includes contrasting disclosures, with an overrepresentation of banks, and Bahrain and Oman not represented. There is no statistical hypothesis testing, as there are predefined categories to guide comparison. Structured documentary analysis without interviews is supported by case-study guidance [21], while bounded

cases and observation units are important to the design [19] and are important for contextual interpretation [20].

2.2 Corporate Documentary Data and Extraction

There are 43 different source-linked evidence IDs in the attached Evidence Register (with 51 register rows) from eight different issuers. Materials are largely from financial years 2023–2025 and are only used in a subsequent context in one 2026 QNB governance statement. The following fields are extracted: issuer, country, year, evidence ID, source document and locator, disclosed activity or figure, analytic category, and restriction on interpretation. The observations are provided in annual reports, governance statements, and investor communications. Data are largely statements of choices, implementation and oversight, and are predominantly qualitative in nature. Data like requests/month, process count and market capitalisation are not pooled or correlated and are not modeled. No transcripts from interviews, proprietary audit files or external data sets of market events were used. The bounded cases are indicated in Table 1.

The companies were analysed as cases, and the individual statements in the annual and governance reports were the unit of analysis. The register shows details of the issuer, the year being reported on, the reporting source and locator, activity or reported figure, and the analytical category. The statements were considered as a single system, rather than two separate systems, because they discussed the same system. Automated reports do not confirm the accuracy of financial statements, but report on the activity of reporting processes.

The list of categories included the following pre-defined categories: AI-assisted financial reporting, accounting quality, internal controls, and equity-market valuation. The study distinguished the deployment of AI from rules-based automation, traditional analytics, and planned initiatives. Numbers were kept by each company and reported. Earnings per share was considered a financial-performance context, and the market capitalisation was considered an equity-valuation indicator, but not an outcome of AI. The comparison highlights similarities and differences among the practices disclosed, governance, and reported indicators; the comparison does not score companies or estimate the effects.

Table 1. GCC cases and documented reporting activities

Case	Issuer/country	Documented reporting or AI activity
G01	stc / Saudi Arabia	IFRS AI advisory; revenue-assurance invoice reconciliation (AI not specified)
G02	Al Rajhi / Saudi Arabia	200+ reports automated; AI role unspecified
G03	Emirates NBD / UAE	Enterprise AI; reporting oversight separately disclosed
G04	e& / UAE	Customer-billing AI; Internal Audit reviews AI risks
G05	QNB / Qatar	COMICS RPA/control testing; machine learning proposed
G06	Commercial Bank / Qatar	AI-enabled business workflows; AI policy approved
G07	NBK / Kuwait	AI fraud monitoring; management report automation
G08	KFH / Kuwait	Risk-report RPA; reconciliation automation

2.3 Directed Content Analysis and Quality Controls

Manual deductive coding applied five predefined categories: T0, enterprise AI capability; T1, accounting or financial-reporting activity; T2, internal controls and governance; T3, equity-market valuation; and T4, non-market financial context. The observations were grouped by the task category revealed in the evidence, and then by the strength of the evidence, which was explicitly finance-AI, automation with unspecified AI, adjacent control or business AI, prospective use, or contextual indicator. This is a directed Documentary Content Analysis, and the case comparison serves to interpret the cases within the assigned categories. It is not a systematic or narrative literature review, and numbers are not a statistical analysis. Modern thematic-methods instruction puts emphasis on the understanding of the relation between codes and interpretations [22]. It is also helpful to provide methodological guidance as to the choices made in coding [23]. A worked example is used to illustrate the importance of being explicit when making coding decisions [28]. The criticism of superficial topic summaries is a topic of critical thematic-methods scholarship [29].

A second manual reading was conducted to determine if the proposed label went beyond what was disclosed. The machine learning features were planned for but not coded as evidence of absence or failure when there is no evidence. The Evidence IDs enable the reader to follow each interpretation back to the place it was found in

the company passage. Dependability is limited by the fact of single-coder assessment, due to selective corporate reporting and inconsistent years. These limitations can be explicitly and methodologically stated with the help of the guidance provided in the case-study [24]. All claims in this study are not a representation of an issuer's technology performance, audit opinion, accounting error rate, or share-price response. Quality checks included source attribution, which was used to verify that the data would be representative of the population, cautious inference to ensure that the data were reasonable, and consistency between Tables 1 and 2. The same can be said for accounting scholarship, which focuses on the examination of the use of AI in writing [30].

There was no numerical score used to determine coding; there were explicit rules. Only if the disclosure also mentioned accounting or reporting and the use of AI was mentioned, could it be a disclosure of finance-related AI. If the source did not mention any AI aspects, RPA was defined as automation. Governance rather than operational deployment was coded for the approval of an AI policy. Market cap was used as a context of valuation but not as an AI effect without a link. The rules were applied in each of the eight cases.

Double counting of the same statement on the same system is not counted as two separate statements. The number of evidence entries does not imply that any frequency of the adoption of AI is implied. That's not an indication of other technologies or results.

3. Results

3.1 Disclosure Evidence Overview

The cross-case pattern has to do with the specificity of disclosures, not with the maturity of technology, as stc points out there's a finance-related generative-AI advisory task, and Al Rajhi mentions a lot of report automation but not that AI is at fault for writing the reports. Other cases are typically more about enterprise AI, risk monitoring, governance, or non-AI process automation. The evidence boundaries are provided below in Table 2. This classification is like that in a previous study which classified the technical aspect that was disclosed from the general statement of ability [27].

Table 2. Cross-case evidence and valuation limitations

Case	Financial reporting evidence	Internal controls evidence	Equity valuation evidence/limitation
stc	AI IFRS advice; reporting-quality effect not measured	Revenue-assurance reconciliation; AI role not specified	2024 market capitalisation: approximately SAR 200bn; no AI attribution
Al Rajhi	200+ automated reports; AI role unspecified	Anti-fraud technology and reporting governance	No AI-attributable market effect identified
Emirates NBD	Oversight of reporting; finance-specific AI not demonstrated	AI-supported cybersecurity monitoring	No AI-attributable market effect identified
e&	Customer billing assistant; not statutory accounting AI	Internal Audit coverage includes AI-related risks	Market-cap change reported; AI link untested
QNB	Financial reporting control assessment documented	COMICS uses RPA/analytics; ML features planned	No AI-attributable market effect identified
Commercial Bank	Financial-reporting control framework disclosed	Board approved AI Governance Policy	No AI-attributable market effect identified
NBK	Management-report automation; AI role unconfirmed	AI-assisted fraud detection	No AI-attributable market effect identified
KFH	RPA reconciliation; AI not specified	Risk-report automation; cyber-AI	Market-cap change reported; AI link untested

3.2 Accounting Quality and Reporting Processes

In 2024, stc shared an example of a digital co-worker on the IFRS, which is supported by AI and processes about 100 compliance requests every month. It said that it has achieved a 70% increase in the productivity of finance teams and resolved complex cases (G01-E01–E02) 33% quicker. These are issuers' self-reported workflow indicators and do not include any audited misstatement rates, nor measurements of the quality of the financial statements issued. The company also had a recon process and an organization-wide data quality indicator (G01-E04–E05) of 97%. It is not concluded from the documents that the reconciliation and the data quality programmes were a product of the IFRS assistant.

In 2023, Al Rajhi reported that over 200 strategic and regulatory reports were automated (G02-E01) but was unable to specify which one was the AI automating the reports. NBK presented the credit-administration report automation (G07-E03), and KFH presented the credit-reconciliations using RPA (G08-E03). Emirates NBD has provided information on audit-committee oversight of the integrity of reporting, but not any evidence of financial statements being created using AI (G03-E03–E04). The following observations are related to workflow design and/or governance. They don't exhibit a decrease in restatements, abnormal accruals, or errors due to AI.

When it comes to productivity, this should not be given as an improvement in the quality of earnings. Some inferences can be drawn from external research on disclosure quality to support a hypothesis for future testing [10], but this dataset does not replicate those tests. What is consistently found, however, is that the details of finance-related automation are quite different, ranging in terms of specificity and whether AI is mentioned as the technology involved.

The reported outputs cannot be combined into one measure. Some of the questions addressed here in the monthly IFRS are based on the workload of the advisories, while the production volume is reflected in the automated regulatory reports; the scope of the control activity is reflected in the reconciliations; and the scope of the enterprise-wide data-quality percentage is different. The indicators are not described using a common outcome definition, nor do they have a common denominator. They require further in-depth analysis but do not provide an overall rank of the eight companies based on accounting quality nor an overall rank of the benefit of AI.

3.3 Internal Controls and Governance

QNB's COMICS platform is said to enable documentation, analytics, sample selection, automated control testing, and management reporting using RPA (G05-E01). Its 2025 governance report talks about more machine-learning capabilities being "potential" (G05-E02), rather than operational. The importance of management assessment of internal control over financial reporting (G05-E03) is also discussed. These passages outline process setups, neither external nor independent of which assure AI models or enhancements to control effectiveness.

The Direct Carrier Billing Reconciliation System (G01-E04) by stc reconciles the content provider's invoice with the platform. This documents revenue assures but doesn't show an AI component or show an improvement in the effectiveness of the controls. Emirates NBD's AI-related cybersecurity monitoring (G03-E02), and e&'s Internal Audit coverage of AI-related risks. Commercial Bank has a policy on the governance of artificial intelligence (AI) in addition to its financial-control oversight (G06-E03-E04). AI-assisted fraud detection is captured in the NBK documents (G07-E01), and risk report automation and cyber-related areas of AI activity are described in the KFH documents (G08-E01; G08-E04).

There are no common assurance processes for AI to be included; these disclosures are related to various aspects of reporting, monitoring, and governance. Although there have been prior studies on the effects of AI on audit quality [12] and explainability [6] in general, none of them has confirmed that these eight companies have better control effectiveness. Therefore, the results presented are only for the activities and types of tools and process indicators reported.

3.4 Equity Market Valuation Evidence

The reason for the three issuers who have provided context in the register is that they have reported their market capitalisation level at the end of 2024 (stc: G01-E06), growth in market capitalisation (e&: G04-E04) and a year-on-year change (KFH: G08-E05). The observations do not provide an estimation of the impact of AI on value. In cases other than this, the parameters of earnings, profit, and return on equity are not related to

market valuation. No one offers an AI date-specific financial-reporting treatment, comparison benchmark, and identified investor response.

Lack of a causal connection isn't a conclusion that the disclosure of the target is insufficient or that AI is useless. Research on the content of the announcements and market response reveals the importance of the content of AI's narratives [13]. AI washing can be spotted by researchers who advise against using such catchy terms as hype for the benefit of the economy [15]. For this reason, the eight cases do not allow the attribution of share-price movements or valuation premiums for accounting with the aid of AI. The other type of design is a capital-market research design, which would be needed.

There is critical importance in equity market valuations in terms of timing. There are many factors that can change a company's market valuation in the same time frame as the annual report mentions AI, such as earnings expectations, interest rates, sector movements, and beyond. The disclosures reviewed do not include announcement and/or deployment dates with investor responses. The valuation analysis is therefore an 'as reported' analysis of valuation and is not attempting to measure abnormal returns or to measure causal effects or valuation premiums.

3.5 Cross-Case Discussion and Implications

There are 3 comparative patterns that arise. The first distinction is that there is much less effective AI than there is general enterprise AI. First, there's much less effective AI than there is general enterprise AI. Second, deterministic reporting or control automation can be applicable for reporting processes but shouldn't be considered AI. Third, the valuations of financial-reporting AI will not be apparent from the market reports. The differences reflect the challenge of information asymmetry (that is, it's easier for investors to see what has been announced than what has been validated in the model, the rate of exceptions, governance decisions, or control outcomes). The exercise is based on a comparison of statements by issuers and is not a re-audit of their systems.

Useful reporting would provide the name of the accounting task, class of the accounting tool, date of deployment, reviewer, and observed outcome. Audit committees should differentiate between AI tools and those that are used for the purpose of knowledge retrieval and those that are used in financial reporting or controls. These eight cases are framed by external research on the efficiency of investment and AI [25], which is not applicable to them. Similarly, based on stock market research of LLM deployments [26], no market effects have been found in the current sample.

A suggested explanatory route, rather than a causal sequence: a reporting task that is clearly defined and accompanied by an accountable review and validation can then be matched to an interpretation of the results by the investor. The information in the present documents only documents some of those steps. This sample is weighted to include only banks and does not include Bahrain and Oman as cases; therefore, it is not intended to estimate prevalence, but rather to compare analyses.

An IFRS assistant in the form of a question-and-answer tool may assist staff in finding or interpreting the IFRS, but it does not conclude that entries meet the recognition, measurement, and disclosure requirements of IFRS. RPA can be used to automate the reconciliation without considering how to maintain source-data quality, or how to override and handle exceptions. If either of these tools is used, the outcome evidence would need to be credible, which means that the process owner, process validation, control testing, and escalation records would need to be documented. These public disclosures, which were reviewed, have not provided those case-level operational records.

The issuer governance reports that were examined did not include model-validation results, remediation records, or independent performance tests. If the use of AI was not mentioned in the reviewed documents, then it was coded as 'not demonstrated in reviewed documents'. This is not to say that a company didn't have such a system; it is just that the documents made available up to this point were limited.

4. Conclusions

The study showed that eight companies in the Gulf Cooperation Council region listed on the stock exchange had 43 different source-linked evidence IDs in predefined categories of documentation. stc provided the most obvious finance-related evidence of an AI example that was linked to the source (company-reported workflow indicators). Other cases reported were either with respect to automation of reporting, enterprise AI, internal control monitoring, governance, or without a clear connection to statutory reporting and AI. No single case provided evidence that would support the notion that financial-reporting AI causes an increase in accounting quality (as evidenced by better audited accounting quality), an increase in effectiveness of tested controls, or

an increase in equity valuation.

The key contribution is an evidence hierarchy which divides the evidence into the following categories: announced technology, operational use, management-reported process indicators, assurance evidence, and market-level outcomes. A board disclosure would be more decision-useful if it includes tasks, dates, and limitations of the models and human authorisation. The results provide answers to the documentary questions of the study, and the impact estimation is left to work done with internal control tests, dated deployments, and observations of the market's events.

5. Strengths and Limitations

The advantage of the present study is that it enables comparison between eight issuers based on 43 distinct source-linked evidence IDs openly and transparently. The coding framework classifies finance-first AI from business-as-usual automation, enterprise AI, AI planning, and governance. By using Source IDs, traceability is maintained and by using cross case analysis, it is possible to see where descriptions support the narrower interpretation than what is indicated in the headline. There are still significant restraints: Reports from companies are selective, the individual cases vary in their coverage of sources, and the sample consists of banking companies. There were no private accounting data, separate model tests, audited error-rate changes, or event-study data available. As such, findings are about practices that have been disclosed, and evidence sets rather than about impacts that have been confirmed or the prevalence of practices across the GCC.

6. Future Recommendations

Future research should seek permission to review logs of the financial system, deployment dates, accounting closure dates, exception registers, and independent testing dates for control of the financial system. Interviews with reporting teams and internal auditors might help to make it clearer who is accountable for reporting, the processes for validation, and why certain technologies were chosen. The sample should include Bahrain and Oman, and more sectors should be included in a larger sample of the GCC. Research on equity market values should focus on identification of events related to implementation/disclosure, daily returns, and other events that might impact values. Going forward, one must differentiate between generative AI and deterministic RPA, between plan vs. operational and between claimed efficiency vs. measured accuracy. Failure in implementation, monitoring expenses, and governance protections also should be revealed in research.

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Data Availability Statement

The 43 distinct evidence IDs (51 register rows) obtained from published corporate documents are as follows: Annual Report 2024 of the stc Group; Al Rajhi Bank Annual Report 2023; Emirates NBD Annual Report 2025; e& Integrated Annual Report 2025; QNB Corporate Governance Report 2025; Commercial Bank Qatar Annual Report 2025; National Bank of Kuwait Sustainability Report 2025; and Kuwait Finance House Sustainability Report 2025. There were also additional issuer reports and results releases, as well as governance statements that were reviewed (the 2026 QNB statement was contextual only). The code for each observation and the limitations are shown on the accompanying Evidence Register in an Excel spreadsheet along with the document name, the year in which it was issued, and the URL and locator for the document. No accounting or audit records were acquired that would provide information that was confidential.

Conflicts of Interest

Conflict-of-interest declaration: [to be confirmed by all authors].

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Declaration of Generative AI Use

No generative AI or large language models were used in the development, writing, editing, or preparation of this manuscript. The authors are solely responsible for the manuscript’s content, verification of evidence, and compliance with the journal’s publication policies.

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