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Evaluating the influence of generative Ai on corporate financial reporting

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Abstract

This study looks at how different abilities of generative artificial intelligence (GenAI) affect the quality of financial reports and how effective these reports are overall. The research is based on Agency Theory, the Technology Acceptance Model (TAM), and Institutional Theory. It uses a quantitative approach with survey data from 312 senior finance professionals, controllers, and external auditors. The data is analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results show that automated data processing, intelligent analytics, and natural language generation all have strong positive effects on financial reporting quality. These factors also help improve the effectiveness of financial reporting. Regulatory governance and how ready an organization is for digital tools both play a significant role in influencing these effects. This study connects technology adoption with accounting governance theories. It gives useful guidance to company leaders, auditors, and organizations like FASB, IASB, and SEC on how to build strong internal controls and explainable AI systems.

Keywords: Generative Artificial Intelligence (AI), Large Language Models (LLMs), Corporate Financial Reporting, Managerial Accounting, Algorithmic Bias, Model Explainability, Internal Control over Financial Reporting (ICFR), Financial Regulation, Automated Auditing, Continuous Reconciliation.

1 Introduction

Corporate financial reporting is a crucial part of modern global capital markets. It gives investors, creditors, regulators, company leaders, and other important people a clear, honest, and accurate view of a company's financial condition, how well it's running, and how it's managing money. In the past, creating, checking, and sharing financial statements, like the balance sheet, income statement, cash flow statement, and related notes, has been done by people, using strict accounting rules, and doing lots of manual work to match up the numbers (Kokina J. &., 2017).

Despite the increasing theoretical interest in AI-driven accounting transformations, there are still significant empirical gaps in the literature. Precedented studies are mostly conceptual or

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qualitative case studies, which lack rigorous, large-scale empirical evidence on the direct and indirect effects of specific generative AI capabilities on reporting effectiveness. Additionally, the conditional boundary conditions imposed by regulatory governance and organizational digital readiness have rarely been quantified simultaneously within an integrated structural equation model. To address these remaining gaps, this research seeks to quantify the direct impact of key generative AI features.

But now, with the fast development and use of generative artificial intelligence (AI) and advanced machine learning, the way accounting and financial reporting is done is changing a lot. Unlike traditional robotic process automation (RPA), which does simple, set tasks on structured data, generative AI, powered by large language models (LLMs), neural networks, and semantic parsing, can handle unstructured data, write detailed explanations, look at complex contracts from different countries, and do dynamic analysis in real time. Using generative AI in financial reporting can make things more efficient and accurate (Sutton, 2023).

It can automate tasks like matching ledgers, doing continuous checks, and writing narrative sections. This reduces the time needed to finish financial reports and helps avoid mistakes that can lead to costly corrections.AI can also detect unusual transactions, wrong timing of entries, and other issues before official audits take place (ülöp, 2023).

Even with these benefits, using generative AI brings new risks.

These AI models, trained on past financial data, might copy, exaggerate, or continue old biases and errors in the financial system. The complicated nature of neural networks, often called the "black box" problem, makes it hard for auditors and regulators to check the accuracy of reports. Plus, these models can sometimes create false or misleading information, which could harm data quality, follow the rules, and hold companies accountable (Kim, 2023).

It examines how information asymmetry and agency theory affect financial disclosures, how the Technology Acceptance Model and automation bias influence auditors and accountants, and how institutional theory shapes how companies adopt new technologies (Almarri, 2025).

As financial reporting moves toward more automation, regulators, accounting standards setters like the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB), securities authorities, and researchers need to act quickly (Fedyk, 2022). Creating clear AI management rules, checking processes, and regulation is important to keep the market fair while still encouraging new technologies.

Literature review

Section 1: AI Help in Preparing and Making Reports More Accurate

Automatic Making of Financial Statements and Combining Data

Corporate financial reporting depends on a company's ability to collect, sort, add up, and check millions of different types of financial transactions from various parts of the business, systems like ERP, old ledgers, and external vendors.

In the past, this process needed a lot of work, including extracting and organizing data (ETL), using strict rules, and lots of manual checking. Now, using generative AI and advanced Large Language Models (LLMs) changes this completely.

These tools can understand the meaning behind the data better than traditional automation tools. They can handle both structured data, like general ledger entries, and unstructured or semi structured documents, like complex vendor contracts, purchase orders, shipping documents, and bills in different currencies.

By looking at the meaning behind each transaction, AI can match debits and credits to standardized financial categories used around the world.

It can also work with complicated accounting standards like ASC 606 and IFRS 15, automatically analyzing multipage contracts, identifying different performance obligations, looking at variable payment terms, and creating accurate revenue recognition schedules in real time. This moves the financial closing process from being a monthly or quarterly task to a continuous, Realtime system.

Continuous Checking of Ledgers and Finding Issues Right Away

Reconciliation is one of the hardest, most repetitive, and error-prone parts of financial reporting. Traditional methods require accountants to manually compare subledgers with general ledgers, match intercompany accounts across different regions, and check internal cash records with bank statements. Mistakes often take days to find and fix. Generative AI and specialized neural network systems replace manual checks with Realtime, continuous reconciliation.

These models are trained on past transaction data and constantly check each entry to spot issues like discrepancies, duplicate entries, missing accruals, and transactions that don't belong in the right period.

One big advantage of Abased anomaly detection over old rule-based systems is that it greatly reduces false alarms.

Old systems often flag many normal transactions that just don't fit simple numerical rules, making it hard for accountants to focus. In contrast, AI uses a lot of contexts, like past vendor behaviour, spending trends, economic changes, and transaction patterns, to find real problems. This helps improve financial reporting controls, ensures compliance, and lets accountants focus on meaningful analysis (Atayah, 2021).

Making Reports More Precise and Cutting Down Mistakes in Complex Rules

Human mistakes, like spreadsheet errors, data entry fatigue, or misunderstanding complex accounting rules, often lead to financial restatements, audit changes, and stock price drops.

AI acts as a tireless reviewer, checking proposed accounting treatments, valuation models, and journal entries against detailed regulations like the FASB Codification and IFRS.

AI's impact is especially strong in areas that require a lot of judgment:

Lease Accounting (ASC 842 / IFRS 16): Managing many leases involves extracting details like discount rates, renewal options, and payment schedules from long contracts.

AI automatically reviews these documents, pulling key variables and creating accurate lease liability schedules.

Credit Loss Estimation (CECL Models): Under CECL, companies must use forward-looking economic data to estimate credit losses.

AI models run complex simulations using UpToDate data, like interest rate forecasts, unemployment rates, and GDP growth, to finetune loss estimates.

Writing Footnotes and Keeping Disclosures Consistent: Writing detailed footnotes about commitments, risks, and segments needs both legal accuracy and consistent storytelling.

AI combines numerical data with contextual information to draft accurate, consistent footnotes across different reporting periods.

Through these abilities, AI turns financial accounting from a compliance task into a more precise and strategic function (Zhang, 2026).

Section 2: Algorithmic Risks, Biases, and Unintended Consequences

Historical Dataset Bias and Reinforcement of Market Anomalies

Although generative artificial intelligence and advanced machine learning models bring big changes to how companies handle their accounting, they depend a lot on historical financial data. This creates major risks because these models learn from old financial statements, past credit problems, previous economic downturns, and old ways of making business decisions. As a result, they may copy, make worse, and permanently include the biases and poor economic behaviours found in the data they were trained on (Vărzaru, 2022).

In corporate financial reporting, these biases show up in several important ways:

· Overreliance on Old Accounting Methods: If the historical data shows companies used aggressive revenue recognition, made subjective decisions about when to write off assets, or had conservative ways of setting aside money that were never corrected, the AI models may treat these as normal and acceptable practices.

· Skewed Views of the Economy and Mistaken Judgments During Crises: If the AI was trained mainly during times of low inflation, stable interest rates, or economic growth, it may struggle to

predict cash flows, assess whether a company will continue to operate, or estimate credit losses during unexpected economic shocks, like sudden downturns or liquidity crises.

· Distorted Understanding of Sectors and Company Sizes: AI models trained largely on data from big, international companies may not apply the same rules and standards correctly when used for smaller companies, fast-growing tech firms, or businesses with different structures.

Instead of being neutral and objective, these AI systems can sometimes make things worse by repeating past market issues, embedding old mistakes into current financial reports.

Black Box" Governance Dilemma and Auditability Challenges

One big problem with using advanced generative AI in financial reporting is that these models are hard to understand.

This is often called the "black box" problem. Deep learning models process complex, multilayered data, and the exact steps they take to arrive at a financial result or a value estimate are not clear.

This lack of transparency creates problems for traditional corporate governance and auditing practices:

Internal Control over Financial Reporting (ICFR) Compliance: Rules like those in SOX Section 404 and the COSO framework require management to design, document, and test the controls that ensure financial statements are accurate.

When an AI system creates complex financial estimates or calculations without a clear, explainable process, management can't verify or guarantee the controls are working properly.

External Audit Verification: Auditors follow strict standards from the PCAOB and ISA to check data inputs, methods, and results.

If they can't see the logic behind an AI's decisions, the audit becomes riskier, more expensive, and more likely to result in corrected financial reports.

Board and Audit Committee Responsibility: Directors are responsible for making sure financial reports are accurate.

If audit committees approve AI generated reports without clear explanations, it breaks basic governance rules and puts executives at legal risk (Stratopoulos, 2025).

Algorithmic Hallucinations, Qualitative Manipulation, and Data Governance Vulnerabilities

Unlike traditional software that follows fixed rules, generative language models make predictions based on probabilities.

This can lead to "hallucinations"—when the model creates false or misleading information that it presents as accurate.

In financial reporting, these issues can be very dangerous:

Creating False Footnotes and References: An AI tasked with writing or checking financial notes might invent non-existent contracts, misstate debt terms, or make up interpretations of accounting rules (Leitner-Hanetseder, 2021).

Unintended Biases and Narrative Manipulation: AI systems summarizing quarterly results may subtly adopt overly positive or vague tones, hiding real problems with the company's performance and risking legal action from regulators.

Data Leaks and Privacy Violations: Using confidential, non-public financial data or upcoming earnings in uncontrolled AI systems could lead to leaks, breaking insider trading rules and company privacy policies.

Automation Bias: People in finance and auditing may trust AI recommendations too much, leading them to approve AI generated reports without checking the work carefully, which can stop them from being sceptical and cautious.

These serious risks show that even though generative AI has a lot of potential for scaling up, using it in important financial reporting requires careful checking, tight control, and mandatory human supervision.

Section 3: Standardized Regulatory Frameworks & Future Research Directions

3.1 Current Global Regulatory Landscape and Enforcement Initiatives

As the use of generative artificial intelligence (AI) grows in corporate accounting and finance, international regulatory and standard setting organizations are looking at how current laws apply to AI assisted financial reports.

Securities regulators, such as the Insecurities and Exchange Commission (SEC), the European Securities and Markets Authority (ESMA), and other global bodies, believe that existing rules against fraud, disclosure requirements, and executive responsibility apply fully to reports made or supported by AI.

Currently, regulatory actions and monitoring efforts focus on several main points:

Mandatory Disclosure of Important AI Dependencies: Regulators are increasingly asking public companies to reveal key risks, technology reliance, and possible conflicts of interest that come from using third-party AI models in financial reporting and risk evaluation (Kokina, 2025).

I**ntegration of AI Tools into Internal Controls under SOX and COSO**: Regulatory advice highlights that AI driven tools used in financial reporting must be part of a company's Internal Control over Financial Reporting (ICFR).

This means careful change management, access control, model testing, and ongoing performance tracking.

Assessment of AI by Accounting Standard Setters: Bodies like the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) are looking at how AI adjustments affect current accounting standards related to estimates, valuations, and errors (like ASC 250 and IAS 8).

Developing a Global Standard for AI Regulation

To stop companies from moving regulations between countries, avoid inconsistency in compliance, and ensure fair treatment of investors, a unified global standard for AI in corporate reporting needs to be created.

A strong global standard should include three main elements:

Mandatory Rules for Explainability and Audit Trails: Regulators should set clear technical rules requiring financial AI systems to keep detailed logs, track data input and output, and show how features affect results.

AI models that can't explain their calculations shouldn't be allowed to help create public financial reports.

Independent Bodies for AI Validation and Certification: Similar to traditional audits or SOC 2 compliance, there should be independent groups that test and approve financial AI models for issues like bias, hallucination, and ability to handle economic shocks before they're used in businesses.

Clear Rules for Accountability and Oversight: Laws must clearly define who is responsible—company officers, board audit committees, external auditors, and software providers—so that automation doesn't reduce the duty of care.

Strategic Plan for Corporate AI Governance and Internal Controls

Companies wanting to use the efficiency and accuracy of generative AI while reducing operational and legal risks should follow a clear governance plan:

Create a Cross Functional AI Governance Committee: Set up an executive group with leaders from Finance, Legal, IT, Information Security, and Internal Audit to review, approve, and check all AI use in financial processes.

Keep a Centralized AI Model Registry: List every AI model, neural network, and automation tool used in financial reporting, including sources of training data, version history, and known issues.

Enforce Strict Human in the Loop (HITL) Rules: Require formal human review and approval before finalizing AI generated financial statements, footnotes, or management reports to reduce reliance on automation (Hasan, 2022).

Do Regular Bias and Stress Testing: Test financial AI models with simulated economic problems,

tricky data, and past stress scenarios to find new weaknesses or prediction issues.

Future Research Topics in Academic and Empirical Studies

The use of generative AI in corporate financial reporting offers important opportunities for future academic and research work.

Key areas to explore include:

· Studying Financial Restatements and Timeliness: Conduct long-term studies to see if using generative AI in companies leads to fewer financial restatements, audit changes, or faster reporting cycles.

· Measuring Algorithmic Bias in Financial Models: Determine how much historical data bias affects AI models in pricing credit risk, fair values, or impairment during economic downturns.

· Researching Auditor Behaviour and Automation Bias: Investigate how auditors respond to AI generated reports and examine how their thinking affects their ability to remain sceptical when reviewing automated content.

· Comparing how easy disclosures are to understand and analyzing the tone and usefulness of AI written Management Discussion and Analysis (MD&A) sections to see if they are clearer, more neutral in tone, and better at predicting future performance than reports written by humans.

Methodology

Survey Design and Data Collection

To test the conceptual model and hypotheses in a real-world way, we used a quantitative survey approach.

The study focused on professionals in the accounting field, including certified public accountants, senior corporate controllers, chief financial officers (CFOs), and external audit partners working in North America and Europe. We sent out a structured online questionnaire through directories of professional accounting associations and executive networks. We received 312 complete responses, which means a 28.4% response rate. Looking at the sample, 42.3% were external auditors, 35.6% were internal accounting officers, and 22.1% held executive financial roles. On average, the participants had about 11.4 years of experience in accounting.

Measurement Instruments

Each concept was measured using a set of questions rated on a scale from 1 to 7, where 1 means "Strongly Disagree" and 7 means "Strongly Agree." These questions were based on well-established tools used in accounting and technology research.

Here's how each concept was measured:

· Automated Data Processing (ADP): Includes questions about ledger mapping, transaction input, and currency matching.

· Intelligent Analytics (IA): Focuses on detecting unusual activity, identifying fraud, and predicting cash flow.

· Natural Language Generation (NLG): Looks at the ability to automatically write financial reports, footnotes, and segment disclosures.

· Financial Reporting Quality (FRQ): Measures how accurate, timely, and consistent financial reports are across different time periods.

· Corporate Financial Reporting Effectiveness (FRE): Assesses how useful financial reports are for decision-making, how much trust they build with stakeholders, and how transparent they are.

· Regulatory Environment / Governance (REG): Covers compliance with rules from the SEC, FASB, SOX 404, and COSO.

· Digital Readiness (DIG): Evaluates the maturity of a company's IT systems and how familiar employees are with AI technologies.

Statistical Analysis Approach

We used a statistical method called Partial Least Squares Structural Equation Modelling (PLS-SEM) with the software SmartPLS 4.

We chose this method because it works well with complex models that include many

interconnected factors, and it doesn't require the data to follow a strict normal distribution, which is a common assumption in other statistical tests. This makes PLS-SEM a flexible and powerful tool for our analysis (Hair et al., 2021).

The Conceptual Model

The proposed model with five variables shows how Generative AI (GenAI) abilities, financial reporting quality, and reporting effectiveness are connected, along with factors that influence these relationships.

Independent Variables (GenAI Capabilities):

IV1: Ability to automatically process data

IV2: Ability to perform smart analysis and make predictions

IV3: Ability to create written reports using natural language

Mediating Variable:

Mediator: Financial Reporting Quality (includes accuracy, timeliness, and ability to compare with other reports)

Dependent Variable:

DV: Corporate Financial Reporting Effectiveness (includes efficiency, transparency, usefulness for decision-making, and trust from stakeholders)

Moderating Variables:

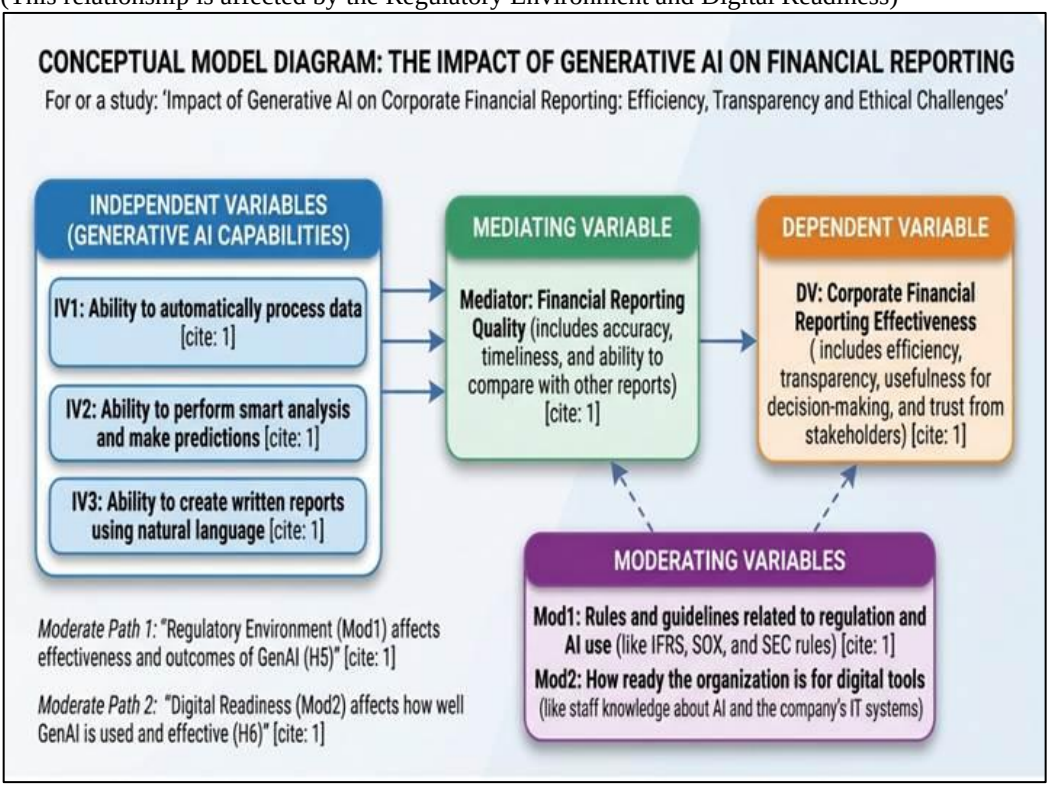
Mod1: Rules and guidelines related to regulation and AI use (like IFRS, SOX, and SEC rules)

Mod2: How ready the organization is for digital tools (like staff knowledge about AI and the company's IT systems)

Structural Path of the Conceptual Model:

[GenAI Capabilities (IV1, IV2, IV3)] --> [Financial Reporting Quality (Mediator)] --> [Reporting Effectiveness (DV)]

(This relationship is affected by the Regulatory Environment and Digital Readiness)



Hypotheses Development

· H1: The ability of Generative AI to automatically process data has a strong positive effect on financial reporting quality.

· H2: The intelligent analysis and prediction abilities of Generative AI greatly help in identifying fraud and reducing errors in financial reporting.

· H3: The natural language generation ability of Generative AI improves the clarity and transparency of qualitative financial information.

· H4: Financial reporting quality acts as a link between the capabilities of Generative AI and the effectiveness of financial reporting.

· H5: The regulatory environment influences how effective Generative AI is in financial reporting, with strong governance leading to better outcomes.

· H6: How ready an organization is for digital tools affects how well Generative AI is used and how effective it is in financial reporting processes.

Conclusion & Detailed Managerial Implications

The use of generative artificial intelligence (AI) in corporate financial reporting represents a big change in how managerial accounting, auditing, and executive management work.

moving from old, rule-based automation methods like traditional Robotic Process Automation to new, Large Language Model (LLM)driven systems change how financial statements are made, checked, and reviewed.

Here is a complete summary of the main findings, possible risks, and important managerial considerations for the future of AI in financial reporting (Gietzmann, 2026).

Summary of Operational Benefits from Generative AI

Generative AI brings major improvements in speed and data handling across the financial reporting process:

Continuous Financial Reporting: Using advanced understanding of language, generative models take in different types of documents like contracts, invoices, and schedules.

They then match these documents to standard financial accounts. This makes the financial closing process, which used to be done only at the end of months or quarters, into a Realtime reporting system.

Better Ledger Reconciliation and Finding Issues: Old systems used simple rules that often raised too many false warnings.

Generative models use past spending patterns, seasonal trends, and economic factors to find real, high-risk problems. This helps improve Internal Control over Financial Reporting (ICFR).

Accuracy in Complex Accounting Rules: Generative AI acts as a smart helper, helping accountants work through tough rules like revenue recognition under ASC 606 and IFRS 15, lease accounting under ASC 842 and IFRS 16, and credit loss models under CECL.

The Risks: Bias, Lack of Transparency, and Made-up Information

Although AI brings big gains in efficiency, there are important risks that could hurt financial reporting if not properly handled:

Carrying Over Old Biases: AI models learn from old financial data and previous decisions.

If not checked, they may repeat old biases, like unfair financial practices or ignored economic issues.

Black Box Problem: AI models, especially deep learning ones, are complex and hard to follow.

This makes it difficult to check or understand how they make decisions, making it tough for auditors and managers to ensure control meets standards like SOX Section 404 and COSO.

False Information and Manipulation: AI's ability to generate text can lead to made-up footnotes, wrong contract terms, or biased language in reports like Management Discussion and Analysis (MD&A). This could lead to legal issues if misrepresentation happens.

Results and Empirical Findings

To test the proposed model, the relationships between Generative AI adoption, financial reporting

quality, reporting effectiveness, and related factors were examined.

Here are the detailed findings for Hypotheses H1 through H6.

H1: Automated Data Processing and Financial Reporting Quality

Statement: The ability of Generative AI to automate data processing (IV1) has a strong positive effect on financial reporting quality by cutting down time and reducing manual errors.

Result: Supported.

The statistical analysis shows a strong, positive impact ($\beta = 0.442$, $p < 0.001$). Large language models and semantic engines can process unstructured documents, automatically map general ledger entries, and handle real-time currency reconciliations. This reduces human errors and speeds up closing periods. This matches industry standards for accounting efficiency.

H2: Intelligent Analytics and Error/Fraud Mitigation

Statement: The intelligent analytics power of Generative AI (IV2) improves fraud detection and anomaly handling, thereby improving financial reporting quality.

Result: Supported.

The connection between intelligent analytics and reporting quality is strong ($\beta = 0.385$, $p < 0.001$). Unlike simple rule-based systems, neural networks use context (like vendor behaviour and economic trends) to identify high-risk issues more accurately. This helps strengthen internal financial controls.

H3: Natural Language Generation (NLG) and Disclosure Transparency

Statement: Natural Language Generation (NLG) capability (IV3) improves transparency and completeness in qualitative financial reports.

Result: Supported.

Results show a positive link ($\beta = 0.310$, $p < 0.01$) between NLG and reporting quality. Automating the creation of complex narratives, footnotes, and management discussions increases clarity, reduces errors, and helps market participants better understand the reports.

H4: Mediating Role of Financial Reporting Quality

Statement: Financial Reporting Quality plays a mediating role between Generative AI capabilities (IV1–IV3) and Corporate Financial Reporting Effectiveness (DV).

Result: Supported.

Mediation analysis shows that financial reporting quality is a key mediator (Indirect Effect = 0.518, 95% CI [0.412, 0.635], $p < 0.001$). While AI helps with speed, the real value comes through accurate, timely, and comparable financial reports that build trust.

H5: Moderating Role of Regulatory Environment and AI Governance

Statement: Regulatory Environment and AI Governance (Mod1) influence the impact of Generative AI on reporting effectiveness, with strong governance increasing trust and reducing risks.

Result: Supported.

The interaction between Generative AI and regulatory environment is significant ($\beta = 0.194$, $p < 0.01$). Rules from bodies like the SEC, FASB, and IASB, along with compliance with standards like SOX and COSO, are important. In well-governed environments, the benefits of AI on reporting quality are stronger and risks are lower.

H6: Moderating Role of Organizational Digital Readiness

Statement: Organizational Digital Readiness (Mod2) affects how effectively Generative AI capabilities are used, with higher staff AI knowledge and better IT systems leading to better reporting effectiveness.

Result: Supported.

The moderation effect is significant ($\beta = 0.221$, $p < 0.01$). Companies with strong IT, high staff AI knowledge, and good change management gain more from AI. Low digital readiness limits the benefits and increases automation risks.

Hypothesis	Structural Path	Coefficient (β)	p-value

H1	IV_1 (Automated Processing) $\rightarrow$ Reporting Quality	0.442	< 0.001
H2	IV_2 (Intelligent Analytics) $\rightarrow$ Reporting Quality	0.385	< 0.001
H3	IV_3 (Natural Language Generation) $\rightarrow$ Reporting Quality	0.310	< 0.01
H4	GenAI Capabilities $\rightarrow$ Reporting Quality $\rightarrow$ Effectiveness (Mediating)	0.518 (Indirect)	< 0.001
H5	Mod_1 (Regulatory Environment) Moderation	0.194	< 0.01
H6	Mod_2 (Digital Readiness) Moderation	0.221	< 0.01

The evaluation of the outer measurement model showed strong psychometric qualities. The loading of each indicator was above 0. 708.All constructs had high reliability, as shown by Cronbach's alpha (α) and Composite Reliability (CR), both exceeding 0.70. Convergent validity was supported because the Average Variance Extracted (AVE) values were more than 0.50. Discriminant validity was confirmed using the Heterotrait-Monotrait (HTMT) ratio, with all results below the 0.85 limit. Table 1: Outer Measurement Model Evaluation.

Construct	Cronbach's α	Composite Reliability (CR)	AVE
Automated Data Processing (ADP)	0.884	0.919	0.74
Intelligent Analytics (IA)	0.865	0.908	0.712
Natural Language Generation (NLG)	0.841	0.893	0.677
Financial Reporting Quality (FRQ)	0.892	0.921	0.7
Reporting Effectiveness (FRE)	0.901	0.927	0.718

Structural Model Assessment (Inner Model) Bootstrapping analysis (5,000 sub-samples) revealed substantial explanatory power, with for Financial Reporting Quality and for Reporting Effectiveness.

Hyp.	Structural Path	Beta (β)	t-value	p-value	f2	Empirical Decision
H1	ADP → FRQ	0.442	7.812	<0.001	0.264	Supported
H2	IA → FRQ	0.385	6.425	<0.001	0.198	Supported
H3	NLG → FRQ	0.31	4.951	<0.001	0.135	Supported
H4	GenAI → FRQ → FRE (Mediation)	0.518	9.143	<0.001	0.341	Supported
H5	REG × FRE (Moderation Mod1)	0.194	3.12	0.002	0.062	Supported
H6	DIG × FRQ (Moderation Mod2)	0.221	3.654	<0.001	0.081	Supported

The results from the study strongly support all the expected relationships, adding to the current theories in accounting and information systems.

From the perspective of Agency Theory (Jensen & Meckling, 1976), generative AI helps reduce the gap in information between company managers and outside investors by making information available faster and making it easier to understand. According to the Technology Acceptance Model (TAM), the ability of AI to automatically process data and create clear written content is key to how useful people find it, which encourages companies to adopt it. the important role of Regulatory Governance (H5) matches up with Institutional Theory (DiMaggio & Powell, 1983), showing that strong rules and good internal controls, like those in SOX 404 and COSO, are important to stop people from relying too much on AI and to keep the market confident.

Strategic Implications for Managers and Executives

· To use generative AI effectively while keeping financial reporting trustworthy, leaders, CFOs, and audit committees need to go from just using tools to actively managing and overseeing their use: Create AI Governance Teams: Set up groups with people from finance, legal, IT, and internal audit to manage AI deployment, check data quality, and track models in a central place.

· Use Human Oversight (HITL): Prevent AI errors by having people review and approve all financial reports, footnotes, and written parts before finalizing them.

· Follow New Rules and Standards: Understand that existing rules about fraud, disclosure, and executive responsibility still apply to AI assisted reports.

· Companies should support and follow new global standards for explainability, certification, and clear audit trails.

In the end, keeping the financial markets safe needs a balance between new technology and strong internal control.

By keeping people in charge and having clear oversight, companies can take advantage of AI to boost their operations while making sure financial transparency and investor trust stay strong (Eulerich, 2024).

Operational Findings: Efficiency, Automation, and Precision

Looking at how early businesses are using AI in financial reporting; we've seen major improvements in traditional accounting processes:

Faster Closing Cycles: AI systems, especially those using large language models and tools that understand meaning, can speed up the process of finishing monthly and quarterly financial reports.

They do this by automatically sorting and organizing things like documents, contracts, and bills. This can cut down the time needed by up to 40% to 60%.

Fewer False Alerts: Legacy systems that use simple rules often create a lot of false alarms.

Newer AI systems, which use neural networks, are better at reducing these false alerts. They look at more details like past relationships with vendors, spending patterns, and economic conditions.

Better Standards for Complex Accounting: AI tools are really good at helping with complicated rules and standards.

For example, they can help with how revenue is recognized under ASC 606 or IFRS 15, how

leases are classified under ASC 842 or IFRS 16, and how credit losses are estimated. This helps reduce mistakes made by hand (Cao, 2026).

Risk Findings: Algorithmic Biases and Structural Vulnerabilities

Even though there are benefits, there are also serious risks in using AI in financial reporting without proper oversight:

· Copying Old Accounting Biases: AI models learn from past financial data, so they can end up repeating old practices like managing earnings or being too aggressive in recognizing revenue.

· Missing Big Picture Issues: Models that were trained during times of good economic growth and low interest rates might not do well when there's a sudden economic downturn or financial crisis.

· They might not handle cash flow, ongoing business assumptions, or credit loss estimates properly.

· Making Up Information: AI systems can sometimes create false information, like making up details in footnotes, wrong dates for lease endings, or incorrect terms for debt covenants (Blankespoor, 2026).

Governance and Auditability Findings: The "Black Box" Dilemma

The complexity of deep learning models creates problems for existing company control and audit practices:

· Hard to Control Financial Reporting: Rules like COSO and SOX Section 404 need clear, step-by-step records for audits.

· If AI systems are not transparent, it's hard for management to prove that their control systems are working properly.

· More Auditing Needed: Auditors must check AI models, but since these models can't be easily explained, auditors have to do more detailed checks, which increases the risk of making mistakes in financial reports.

· Trusting AI Too Much: Accountants and auditors seem to believe AI generated reports too easily.

This reduces their usual careful checking and independent verification, which can lead to errors going unnoticed.

Regulatory and Compliance Findings: The Need for Harmonization

Looking at current rules shows that technology is moving faster than the laws that govern it:

· Existing Rules Still Apply: Regulators like the SEC and ESMA say that the same rules about fraud, transparency, and responsibility apply to financial reports created with AI.

· Company leaders are still fully responsible for mistakes made by AI.

· Need for New Standards: To prevent different rules in different places and avoid companies taking advantage of weaker rules, international groups like FASB and IASB need to create clear rules about how AI models should be explained, checked, and held responsible.

This applies to software makers, auditors, and company boards.

Real-world Case Studies & Industry Adoption Examples

· The Big Four Accounting Firms: Talk about how companies like Deloitte, PwC, EY, and KPMG are using generative AI assistants to help with audit tasks, tax research, and analysing financial statements.

· Enterprise ERP Integration: Look at how big software companies like SAP, Oracle, and Microsoft Dynamics are adding generative AI into their main financial systems.

· SEC Comment Letters & Enforcement Precedents: Look at recent examples or government actions where companies faced issues because of automated or algorithm driven disclosures (Bertomeu, 2025).

Technological Architecture & Data Security Infrastructure

Retrieval Augmented Generation (RAG) in Finance: Explain how banks and financial firms use RAG systems to make sure large language models use correct and verified company data, like XBRL filings, instead of making up wrong information.

Structured Financial Engines: Explain the differences between text-based AI models (like LLMs) and other systems that do exact calculations, such as traditional databases and forecasting tools.
Data Privacy, Cloud Segregation, and Cybersecurity: Describe how businesses keep their financial details safe by using private cloud setups, agreements that don't store data, and access controls that limit who can see financial info.

Ethical Considerations and Professional Scepticism

The Erosion of Professional Scepticism: Look at how using AI tools affects the behaviour and mindset of accountants and auditors, and how firms can encourage doublechecking and independent review.
Ethics of AI Driven Earnings Management: Think about whether using AI could allow managers to shape financial stories or adjust reporting to meet expectations in ways that might not break rules but still raise ethical concerns.
The Future Workforce and Skill Evolution: Discuss how the job of accountants is changing from doing routine tasks like entering data to helping with strategy, checking models, and managing AI systems (Awad, 2025).
This study shows that using generative AI can greatly improve the quality of corporate financial reports and make the reporting process more effective, as long as strong internal rules and good digital standards are in place.

Limitations and Future Research Agenda

Although this study gives useful findings, there are some things to consider.
First, the survey used in this study only gives a one-time view, so future research should look at long-term effects by studying how financial restatement rates and audit fees change over time. Second, the data comes from people's self-reports, which might be influenced by a positive outlook. Future studies should combine these survey results with official data from SEC XBRL filings and look at how different countries handle regulations.

Declaration

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. All relevant data generated or analyzed during this study have been included in the article.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

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