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Generative Artificial Intelligence Adoption and Accounting Performance: Examining Accounting Efficiency, Financial Reporting Quality and Managerial Decision-Making

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Abstract

The rapid adoption of Generative Artificial Intelligence (GenAI) is transforming accounting practices by influencing how financial information is processed, reported, and used for managerial decision-making. However, limited empirical evidence explains how GenAI adoption and accounting efficiency jointly contribute to accounting performance, particularly through financial reporting quality. This study therefore examines the relationships among Generative Artificial Intelligence Adoption, Accounting Efficiency, Financial Reporting Quality, and Accounting Performance within an integrated accounting framework. The study employed a quantitative, cross-sectional approach using data collected from 250 accounting and finance professionals. The relationships among the constructs were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The findings indicate that Generative AI Adoption has a positive effect on Accounting Performance and Financial Reporting Quality, while Accounting Efficiency also has positive effects on both outcomes. Financial Reporting Quality demonstrates a strong positive effect on Accounting Performance and further serves as an important mediating mechanism between Generative AI Adoption and Accounting Performance, as well as between Accounting Efficiency and Accounting Performance. The structural model indicates that the proposed relationships provide meaningful explanatory and predictive value for the endogenous constructs. Overall, the findings suggest that the benefits of Generative AI in accounting extend beyond automation and become more meaningful when AI adoption is supported by efficient accounting processes and high-quality financial reporting. The study contributes to the emerging literature on AI and accounting by providing an integrated perspective on how technological adoption, accounting efficiency, and financial reporting quality can collectively strengthen accounting performance and support managerial decision-making.

Keywords: Generative Artificial Intelligence, Accounting Efficiency, Financial Reporting Quality, Accounting Performance, Managerial Decision-Making, PLS-SEM

Introduction

Artificial intelligence (AI) is increasingly reshaping accounting practices by changing how accounting information is processed, analyzed, and communicated. Recent accounting literature shows that the rapid development of generative AI and large language models is creating new opportunities for accounting applications, while also raising important questions about how these technologies affect accounting professionals and organizational practices (Dong et al., 2024; Stratopoulos & Wang, 2025). Synthia et al. (2026) examined how Generative AI and ESG competencies contribute to university students' workforce readiness and future skills development in emerging economies.

Generative Artificial Intelligence (GenAI) is particularly relevant because it can support activities that extend beyond conventional automation, including information processing, content generation, analysis, and professional decision support. Emerging evidence also indicates that AI-enabled technologies can contribute to more effective financial reporting. For example, recent research finds that automation is associated with improvements in financial reporting quality, while newer evidence shows that AI adoption can improve the quality of corporate accounting information disclosure (Ashraf, 2025; Yang & Zhou, 2025). Despite these developments, the relationship between GenAI adoption and accounting performance remains insufficiently examined from an integrated accounting perspective. Existing studies have largely focused on specific applications of AI, financial reporting, auditing, or the broader implications of ChatGPT and LLMs, leaving further scope to examine how GenAI adoption and accounting efficiency jointly contribute to accounting performance (Dong et al., 2024; Stratopoulos & Wang, 2025). Therefore, this study examines the effects of Generative Artificial Intelligence Adoption and Accounting Efficiency on Accounting Performance, with particular attention to financial reporting quality and managerial decision-making.

The novelty of this study lies in its integrated examination of Generative Artificial Intelligence (GenAI) adoption, accounting efficiency, financial reporting quality, and accounting performance within a single empirical framework. Previous studies have investigated AI applications in accounting, automation in financial reporting, and the productivity implications of emerging AI technologies, but these research streams do not necessarily explain how technological adoption and accounting process efficiency jointly relate to accounting performance through financial reporting quality (Dong et al., 2024; Stratopoulos & Wang, 2025; Ashraf, 2025; Choi & Xie, 2026). Addressing this limitation, the present study examines both the direct relationships between GenAI adoption, accounting efficiency, and accounting outcomes and the indirect relationships through financial reporting quality. The study further contributes context-specific evidence from Bangladesh, where the implications of AI adoption for accounting performance require greater empirical examination beyond the factors influencing technology adoption. This integrated approach provides a more comprehensive explanation of how technological and operational capabilities may contribute to accounting performance.

Problem Statement

The rapid adoption of artificial intelligence (AI) is changing the way accounting information is generated, processed, reported, and used for managerial purposes. Recent evidence shows that AI-based accounting technologies can improve accounting efficiency, financial reporting accuracy, information quality, and decision-making effectiveness (Ashraf, 2025; Thongprim et al., 2025; Yang & Zhou, 2025). Research also suggests that AI can reduce the time required for routine accounting activities and enable accounting professionals to devote greater attention to higher-value analytical and managerial tasks (Choi & Xie, 2025). These developments indicate that AI is moving beyond simple automation and becoming increasingly relevant to the broader performance of accounting functions. Juman et al. (2025) examined how artificial intelligence can transform educational access and equity by exploring its potential to reduce learning barriers and promote more inclusive educational opportunities.

The issue is particularly important for emerging economies, where organizations are attempting to modernize accounting practices while facing technological, financial, skill-related, and organizational constraints. Evidence from India, Thailand, Jordan, China, and GCC markets indicates that AI adoption can influence accounting information quality, financial reporting, auditing efficiency, and decision-making outcomes, although the strength and nature of these relationships vary across organizational and institutional contexts (Alghazzawi, 2025; Thongprim et al., 2025; Yang & Zhou, 2025). Recent research in managerial accounting further indicates that organizations face both opportunities and concerns when integrating AI into accounting activities, particularly regarding employee capability, trust, implementation challenges, and organizational readiness (Zhang et al., 2026).

The Bangladesh context presents an important research opportunity. Recent evidence from Bangladeshi accounting firms shows that AI adoption is becoming increasingly relevant, but factors such as trust, security, financial resources, and competitive pressure influence professionals' willingness to use AI-based accounting systems (Chowdhury et al., 2025). Another recent Bangladesh-focused study also identifies trust, perceived usefulness, ease of use, and perceived threats as important considerations in AI adoption among accounting professionals (2025). These findings demonstrate that AI adoption in Bangladesh is an emerging area of accounting research; however, existing studies have primarily focused on adoption intention and the factors influencing technology acceptance rather than examining whether AI adoption translates into improved accounting performance.

Despite growing interest in artificial intelligence in accounting, an important empirical problem remains unresolved: whether the adoption of Generative Artificial Intelligence and the efficiency of accounting processes jointly contribute to accounting performance, and whether financial reporting quality provides a mechanism linking these factors to performance. Existing studies have examined individual relationships involving AI adoption, accounting efficiency, and financial reporting outcomes, but these relationships require further examination within an integrated framework. This issue is particularly relevant to Bangladesh, where previous research has explored the adoption of AI-based accounting systems and the factors influencing technology acceptance (Chowdhury et al., 2025). However, adoption-related factors alone cannot establish whether the use of GenAI is associated with improved accounting outcomes. Therefore, this study addresses the need for

empirical evidence on the direct relationships of GenAI adoption and accounting efficiency with accounting performance, their relationships with financial reporting quality, and the mediating role of financial reporting quality. By examining these relationships among accounting and finance professionals in Bangladesh, the study seeks to extend existing research beyond technology adoption and provide a more integrated understanding of AI-enabled accounting performance.

Research Objectives

1. To examine the effects of Generative Artificial Intelligence Adoption and Accounting Efficiency on Accounting Performance.
2. To assess the relationships among Generative Artificial Intelligence Adoption, Accounting Efficiency, and Accounting Performance.
3. To evaluate the contribution of Generative Artificial Intelligence Adoption and Accounting Efficiency to financial reporting quality and managerial decision-making.

Research Questions

1. How does Generative Artificial Intelligence Adoption affect Accounting Performance?
2. What is the relationship between Generative Artificial Intelligence Adoption, Accounting Efficiency, and Accounting Performance?
3. How do Generative Artificial Intelligence Adoption and Accounting Efficiency contribute to financial reporting quality and managerial decision-making?

Literature Review and Hypothesis Development

Generative Artificial Intelligence in Accounting

The rapid development of Generative Artificial Intelligence (GenAI) is creating substantial changes in accounting activities, particularly in data processing, bookkeeping, financial analysis, reporting, and professional work. Unlike earlier automation technologies that mainly performed predefined tasks, GenAI can process unstructured information, generate content, support analytical activities, and assist accounting professionals in judgment-related tasks. Recent accounting research identifies GenAI as an important emerging area that is reshaping both accounting practice and accounting research (Dong et al., 2024; Stratopoulos & Wang, 2025).

Recent empirical evidence provides stronger support for the practical relevance of GenAI in accounting. Choi and Xie (2026) found that GenAI adoption was associated with productivity gains, reduced time spent on routine accounting activities, and improvements in financial reporting quality. These findings indicate that GenAI can allow accounting professionals to shift effort toward quality assurance, communication, and other higher-value activities. These developments suggest that GenAI adoption may influence accounting performance by improving the way accounting information is processed and reported. Therefore, this study proposes that greater adoption of GenAI should be associated with better accounting performance.

H1: Generative Artificial Intelligence Adoption has a positive effect on Accounting Performance.

Accounting Efficiency and Accounting Performance

Accounting efficiency refers to the ability of accounting functions to process, organize, analyze, and communicate financial information accurately and within an appropriate time. Efficient accounting processes can reduce processing delays, minimize errors, improve information availability, and support organizational activities. Recent evidence demonstrates that AI adoption, data quality, employee competence, and organizational readiness can enhance accounting efficiency (Alghazzawi, 2025).Efficient accounting processes can strengthen the usefulness of accounting information for organizational planning and managerial activities. Therefore, higher accounting efficiency is expected to contribute positively to overall accounting performance. Yeasmin et al. (2025) developed a green accounting-based model to measure the environmental costs of AI systems and support sustainable AI adoption.

H2: Accounting Efficiency has a positive effect on Accounting Performance.

Generative Artificial Intelligence Adoption and Financial Reporting Quality

Financial reporting quality is an important outcome of effective accounting systems because decision-makers depend on accounting information that is timely, accurate, relevant, and reliable. AI can influence reporting quality by automating transaction processing, improving data organization, identifying inconsistencies, and accelerating reporting procedures. Evidence from automation research shows that automation in financial reporting is associated with improvements in financial reporting quality (Ashraf, 2025). Recent evidence on GenAI also indicates improvements in accounting productivity and financial reporting processes (Choi & Xie, 2026). Research on AI-based accounting systems further suggests that AI adoption can contribute to improved financial reporting quality and decision-making efficiency.

H3: Generative Artificial Intelligence Adoption has a positive effect on Financial Reporting Quality.

Accounting Efficiency and Financial Reporting Quality

Accounting efficiency is closely connected with the quality of financial reporting because reporting quality depends not only on the availability of accounting technologies but also on how efficiently accounting activities are performed. Efficient recording, classification, summarization, and analysis can reduce processing errors and improve the timeliness and reliability of financial information. Recent empirical evidence demonstrates that the efficiency of accounting processes has a significant positive effect on financial reporting quality (Prasetianingrum et al., 2026). The relationship is also supported by recent technological accounting research. Evidence from China indicates that technology adoption can improve financial reporting quality partly by enhancing the efficiency of accounting functions, suggesting that accounting efficiency can represent an important mechanism through which technological innovation improves reporting outcomes (Chen et al., 2025). Juman et al. (2025) explored the legal, ethical, and strategic implications of AI in business decision-making. Accordingly, organizations with more efficient accounting processes are expected to produce higher-quality financial reports.

H4: Accounting Efficiency has a positive effect on Financial Reporting Quality.

Financial Reporting Quality and Accounting Performance

High-quality financial reporting provides managers and other organizational users with more reliable information for planning, evaluation, resource allocation, and decision-making. Recent evidence indicates that financial reporting quality is associated with decision-usefulness and decision-making outcomes (Karunananda et al., 2025; Thu, 2025). Evidence from Thai SMEs also suggests that stronger reporting quality and AI-based accounting systems are associated with more efficient decision processes (Thongprim et al., 2025).

H5: Financial Reporting Quality has a positive effect on Accounting Performance.

Literature Gap

Literature Gap and Research Novelty

Previous empirical research has examined several important dimensions of artificial intelligence in accounting, but the findings remain distributed across different research areas. Dong et al. (2024) reviewed research on ChatGPT in accounting and finance, while Stratopoulos and Wang (2025) discussed the broader implications of artificial intelligence for accounting research. Ashraf (2025) examined the relationship between automation and financial reporting, whereas Chowdhury et al. (2025) investigated the adoption of AI-based accounting systems in Bangladeshi accounting firms. More recent research has also explored the productivity implications of human–AI collaboration in accounting (Choi & Xie, 2026). Although these studies provide useful insights, their different research focuses leave room for a more integrated empirical examination of accounting performance.

Three specific gaps motivate the present study. First, the relationship between GenAI adoption and accounting performance requires further examination alongside the contribution of accounting efficiency. Second, financial reporting quality needs to be examined not only as an outcome of technological adoption and accounting processes but also as a potential mediating mechanism connecting these factors with accounting performance. Third, evidence from Bangladesh is needed to assess these relationships in the context of accounting and finance professionals rather than focusing exclusively on technology adoption. The present study addresses these gaps through an integrated framework incorporating GenAI adoption, accounting efficiency, financial reporting quality, and accounting performance. Its empirical contribution lies in examining the direct relationships among these constructs and the indirect relationships through financial reporting quality using PLS-SEM. Unlike studies focusing on individual AI applications or adoption-related factors, this framework considers technological adoption, operational efficiency, reporting quality, and accounting performance together. The study therefore extends existing research by investigating how technological and operational factors may be associated with accounting performance through improvements in financial reporting quality within the Bangladeshi context.

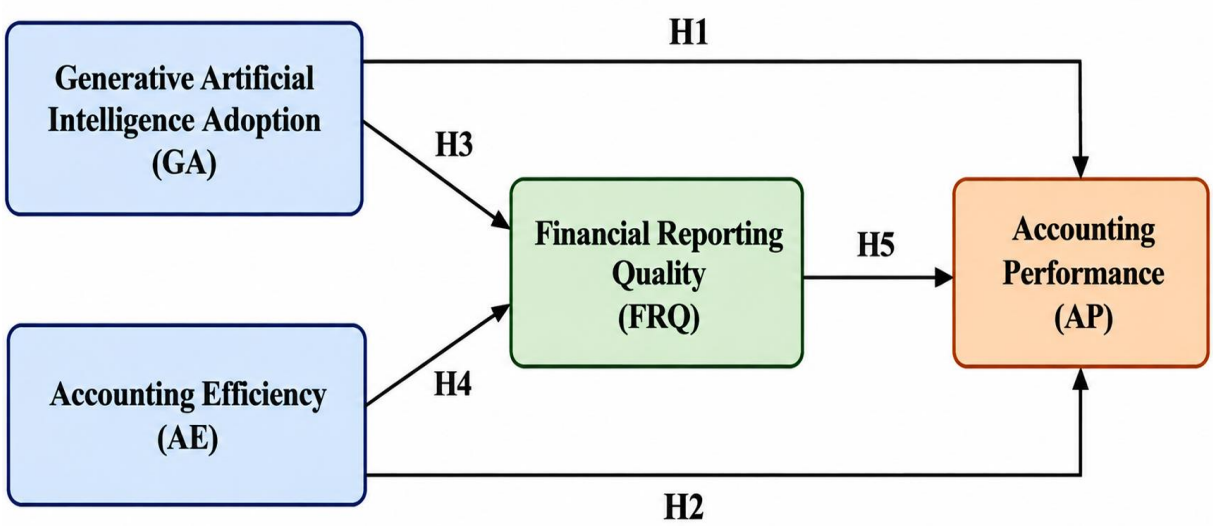
Theoretical Foundation

This study draws on the Resource-Based View (RBV) to explain how technological and operational capabilities may contribute to accounting performance. The RBV argues that organizational resources and capabilities can support performance when they are effectively developed and utilized (Barney, 1991). In the context of accounting, GenAI adoption can be viewed as a technological capability that supports information processing, analysis, and

reporting activities. Accounting efficiency represents an operational capability that enables accounting professionals to process financial information accurately and within appropriate timeframes.

However, the availability of technological resources does not automatically guarantee improved accounting outcomes. Their contribution depends on how effectively they are incorporated into accounting processes and translated into useful financial information. Financial reporting quality is therefore positioned as an important mechanism linking GenAI adoption and accounting efficiency with accounting performance. Accurate, relevant, reliable, and timely financial information can support the evaluation of organizational activities and the use of accounting information in managerial decisions. Based on this theoretical reasoning, the proposed framework examines the direct effects of GenAI adoption and accounting efficiency on accounting performance, their effects on financial reporting quality, and the effect of financial reporting quality on accounting performance. It further examines whether financial reporting quality mediates the relationships between the two explanatory constructs and accounting performance. The RBV provides the overarching theoretical rationale for considering technological and operational capabilities together, while the proposed mediation relationships specify how these capabilities may be associated with accounting outcomes. The framework consequently extends the application of the RBV to the examination of AI-enabled accounting performance in the Bangladeshi context.

Conceptual Framework



Research Methodology

Research Design

This study adopts a quantitative, cross-sectional research design to examine the relationships among Generative Artificial Intelligence Adoption, Accounting Efficiency, Financial Reporting Quality, and Accounting Performance. Primary data are collected through a structured questionnaire, and the relationships among the constructs are analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0.

Population and Sampling

The target population consists of accounting and finance professionals who are directly involved in accounting activities, financial reporting, auditing, or the use of accounting

information for organizational decision-making. Purposive sampling is used to select respondents who have relevant professional experience and practical exposure to computerized accounting systems or AI-supported accounting applications. This approach ensures that the respondents possess sufficient knowledge to provide meaningful responses to the study variables.

Sample Size

The study uses 250 valid respondents as the final sample size. A sample of 250 respondents is considered appropriate for the proposed PLS-SEM model, which contains two independent variables, one mediating variable, and one dependent variable. Only complete and usable responses are included in the final analysis.

Data Collection

Data are collected through a structured self-administered questionnaire. The questionnaire contains measurement items related to Generative Artificial Intelligence Adoption, Accounting Efficiency, Financial Reporting Quality, and Accounting Performance. Respondents are approached through relevant professional and organizational networks. Before the final data collection, the questionnaire is reviewed to ensure that the wording is clear and relevant to accounting and finance professionals.

Measurement of Variables

The study measures the four constructs using a structured questionnaire based on established measures from previous literature. Generative Artificial Intelligence Adoption is measured through items reflecting the extent to which generative AI is used in accounting-related activities. Accounting Efficiency is measured based on the efficiency, accuracy, and timeliness of accounting processes. Financial Reporting Quality is assessed through the perceived accuracy, reliability, relevance, completeness, and timeliness of financial information. Accounting Performance is measured through the effectiveness and productivity of accounting activities and their contribution to managerial decision-making. All items are measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Data Analysis

Data are analyzed using SmartPLS 4.0 through Partial Least Squares Structural Equation Modeling (PLS-SEM). The measurement model is assessed for reliability and validity, while the structural model is used to examine the hypothesized relationships among the constructs. Bootstrapping with 5,000 resamples is applied to assess the significance of the path coefficients and indirect effects. The mediating role of Financial Reporting Quality is examined through the corresponding indirect effects.

Ethical Considerations

Participation in the study is voluntary. Respondents are informed about the academic purpose of the study, and no personally identifying information is required. The collected information is treated confidentially and is used only for academic research purposes.

Findings and Results

Respondents' Demographic Profile

Table 1

Demographic and Professional Profile of Respondents (N = 250)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	180	72.00
	Female	70	28.00
Age	25–34	86	34.40
	35–44	80	32.00
	Below 25	37	14.80
	45–54	33	13.20
	55 or above	14	5.60
Educational Qualification	Master's degree	122	48.80
	Bachelor's degree	60	24.00
	Professional accounting qualification	44	17.60
	MPhil/PhD	14	5.60
	Other	10	4.00
Current Position	Finance Officer/Executive	65	26.00
	Accountant	52	20.80
	Senior Accountant	44	17.60
	Auditor	33	13.20
	Manager	30	12.00
	Financial Analyst	21	8.40
	Other	5	2.00
Professional Experience	6–10 years	63	25.20
	3–5 years	58	23.20
	11–15 years	56	22.40
	More than 15 years	45	18.00
	Less than 3 years	28	11.20
Organization Type	Private organization	102	40.80
	Bank/Financial institution	50	20.00
	Public organization	45	18.00
	Accounting/Audit firm	40	16.00
	Other	13	5.20
AI/Accounting System Experience	1–3 years	99	39.60
	Less than 1 year	66	26.40
	4–6 years	56	22.40
	More than 6 years	29	11.60

Table 1 presents the demographic and professional characteristics of the 250 respondents included in the study. The gender distribution indicates that 72.00% of the respondents were male, while 28.00% were female. This shows that the sample was predominantly represented by male accounting and finance professionals.

In terms of age, the largest proportion of respondents belonged to the 25–34 years category, accounting for 34.40% of the sample, followed by respondents aged 35–44 years at 32.00%. Respondents below 25 years represented 14.80%, while 13.20% were between 45 and 54

years. The smallest proportion, 5.60%, consisted of respondents aged 55 years or above. Overall, the age distribution indicates that the sample was largely composed of professionals in the early and middle stages of their careers. Regarding educational qualifications, almost half of the respondents (48.80%) held a Master's degree. Bachelor's degree holders accounted for 24.00%, while 17.60% possessed professional accounting qualifications. A further 5.60% reported having an MPhil or PhD, and 4.00% fell into the other qualification category. This distribution suggests that the respondents generally possessed an adequate academic or professional background relevant to accounting and financial activities. The distribution by current position shows that Finance Officers/Executives represented the largest group, accounting for 26.00% of respondents. Accountants constituted 20.80%, followed by Senior Accountants at 17.60%. Auditors accounted for 13.20%, Managers for 12.00%, and Financial Analysts for 8.40%. Only 2.00% were classified under other positions. The presence of respondents across several accounting, finance, auditing, and managerial roles provides representation from different professional functions relevant to the study.

With respect to professional experience, 25.20% of respondents had 6–10 years of experience, making this the largest experience category. Respondents with 3–5 years of experience represented 23.20%, while 22.40% had 11–15 years of experience. Those with more than 15 years accounted for 18.00%, whereas 11.20% had less than three years of professional experience. Thus, the sample included respondents with varying levels of professional experience rather than being concentrated in a single career stage. Regarding organization type, private organizations accounted for the largest share of respondents at 40.80%. Bank and financial institution employees represented 20.00%, followed by public organizations at 18.00% and accounting or audit firms at 16.00%. The remaining 5.20% belonged to other types of organizations. This distribution indicates that the sample included respondents from different organizational settings within the accounting and financial environment. Finally, the respondents' experience with computerized or AI-supported accounting systems shows that 39.60% had 1–3 years of experience, representing the largest group. Another 26.40% had less than one year of experience, while 22.40% reported 4–6 years of experience. Respondents with more than six years of such experience accounted for 11.60%. This profile indicates that a substantial proportion of respondents had some practical exposure to computerized or AI-supported accounting systems, which is particularly relevant to the study's focus on Generative AI adoption in accounting.

Descriptive Statistics of Measurement Items

Table 2

Descriptive Statistics of Measurement Items (N = 250)

Construct	**Item**	**Mean**	**SD**	**Range**
Generative Artificial Intelligence Adoption (GA)	GA1	3.044	0.924	1–5
Generative Artificial Intelligence Adoption (GA)	GA2	3.080	0.897	1–5
Generative Artificial Intelligence Adoption (GA)	GA3	3.000	0.927	1–5

Generative Artificial Intelligence Adoption (GA)	GA4	3.044	0.856	1–5
Accounting Efficiency (AE)	AE1	3.084	0.834	1–5
Accounting Efficiency (AE)	AE2	3.024	0.887	1–5
Accounting Efficiency (AE)	AE3	3.016	0.841	1–5
Accounting Efficiency (AE)	AE4	3.004	0.916	1–5
Financial Reporting Quality (FRQ)	FRQ1	3.076	0.863	1–5
Financial Reporting Quality (FRQ)	FRQ2	3.012	0.967	1–5
Financial Reporting Quality (FRQ)	FRQ3	3.032	0.969	1–5
Financial Reporting Quality (FRQ)	FRQ4	3.024	0.887	1–5
Accounting Performance (AP)	AP1	3.044	0.954	1–5
Accounting Performance (AP)	AP2	3.040	0.943	1–5
Accounting Performance (AP)	AP3	3.100	1.061	1–5
Accounting Performance (AP)	AP4	3.100	0.932	1–5

Table 2 presents the descriptive statistics of the 16 measurement items representing Generative Artificial Intelligence Adoption (GA), Accounting Efficiency (AE), Financial Reporting Quality (FRQ), and Accounting Performance (AP). The mean scores range from 3.000 to 3.100, indicating that respondents generally reported moderate to slightly favorable perceptions across the four constructs. For Generative AI Adoption, GA2 records the highest mean score (M = 3.080, SD = 0.897), suggesting comparatively stronger agreement regarding the use of GenAI to support the processing and analysis of accounting information. GA1 and GA4 both have a mean of 3.044, while GA3 records the lowest mean (M = 3.000). Overall, the results indicate that GenAI has a moderate presence in accounting-related activities among the respondents.

The Accounting Efficiency results show a relatively consistent pattern. AE1 has the highest mean (M = 3.084, SD = 0.834), indicating a favorable perception of the efficiency of accounting activities. AE2, AE3, and AE4 report means of 3.024, 3.016, and 3.004, respectively. The relatively small differences among these values suggest that respondents have broadly similar perceptions across the different aspects of accounting efficiency. For Financial Reporting Quality, FRQ1 produces the highest mean (M = 3.076, SD = 0.863), indicating a comparatively positive perception of the accuracy of financial information. FRQ3, FRQ4, and FRQ2 record means of 3.032, 3.024, and 3.012, respectively. The close range of these scores suggests that respondents' perceptions of accuracy, reliability, relevance, completeness, and timeliness are relatively balanced.

Accounting Performance records the highest mean values among the four constructs. AP3 and AP4 both have the highest mean score (M = 3.100), followed by AP1 (M = 3.044) and AP2 (M = 3.040). This pattern indicates relatively favorable perceptions concerning the contribution of accounting information to managerial decision-making and overall accounting

performance. The standard deviations range from 0.834 to 1.061, indicating moderate variation in respondents' answers. AE1 shows the lowest variability, whereas AP3 demonstrates the highest variation.

Measurement Model Assessment

Table 3

Measurement Model Assessment

Construct	Item	Loading	Cronbach's Alpha	Composite Reliability	AVE
Generative Artificial Intelligence Adoption (GA)	GA1	0.777	0.782	0.860	0.605
Generative Artificial Intelligence Adoption (GA)	GA2	0.779	0.782	0.860	0.605
Generative Artificial Intelligence Adoption (GA)	GA3	0.787	0.782	0.860	0.605
Generative Artificial Intelligence Adoption (GA)	GA4	0.769	0.782	0.860	0.605
Accounting Efficiency (AE)	AE1	0.682	0.754	0.844	0.576
Accounting Efficiency (AE)	AE2	0.809	0.754	0.844	0.576
Accounting Efficiency (AE)	AE3	0.755	0.754	0.844	0.576
Accounting Efficiency (AE)	AE4	0.785	0.754	0.844	0.576
Financial Reporting Quality (FRQ)	FRQ1	0.782	0.799	0.870	0.625
Financial Reporting Quality (FRQ)	FRQ2	0.806	0.799	0.870	0.625
Financial Reporting Quality (FRQ)	FRQ3	0.765	0.799	0.870	0.625
Financial Reporting Quality (FRQ)	FRQ4	0.808	0.799	0.870	0.625
Accounting Performance (AP)	AP1	0.819	0.839	0.893	0.675
Accounting Performance (AP)	AP2	0.798	0.839	0.893	0.675
Accounting Performance (AP)	AP3	0.847	0.839	0.893	0.675
Accounting Performance (AP)	AP4	0.821	0.839	0.893	0.675

Table 3 presents the measurement model assessment for the four constructs: Generative Artificial Intelligence Adoption (GA), Accounting Efficiency (AE), Financial Reporting Quality (FRQ), and Accounting Performance (AP). The results indicate that all indicator loadings are within an acceptable range, with values ranging from 0.682 to 0.847. For Generative Artificial Intelligence Adoption, the indicator loadings range from 0.769 to 0.787. Cronbach's Alpha is 0.782, Composite Reliability is 0.860, and AVE is 0.605. These values indicate satisfactory internal consistency and convergent validity for the GA construct.

Accounting Efficiency records loadings between 0.682 and 0.809. Although AE1 has the comparatively lowest loading (0.682), the overall construct demonstrates acceptable reliability, with Cronbach's Alpha of 0.754 and Composite Reliability of 0.844. The AVE value of 0.576 also indicates adequate convergent validity. For Financial Reporting Quality, the indicator loadings range from 0.765 to 0.808. The construct shows strong reliability, with Cronbach's Alpha of 0.799 and Composite Reliability of 0.870. Its AVE of 0.625 further indicates that the construct explains a satisfactory proportion of variance in its indicators.

Accounting Performance demonstrates the strongest measurement properties among the four constructs. Its indicator loadings range from 0.798 to 0.847, while Cronbach's Alpha is 0.839 and Composite Reliability is 0.893. The AVE of 0.675 indicates strong convergent validity.

Discriminant Validity: Fornell–Larcker Criterion

Table 4

Discriminant Validity: Fornell–Larcker Criterion

Construct	GA	AE	FRQ	AP
Generative AI Adoption	0.778			
Accounting Efficiency	0.363	0.759		
Financial Reporting Quality	0.551	0.538	0.791	
Accounting Performance	0.630	0.495	0.688	0.822

Table 4 presents the discriminant validity assessment using the Fornell-Larcker criterion. The diagonal values represent the square root of the Average Variance Extracted (AVE), while the off-diagonal values indicate the correlations between the constructs. According to the Fornell-Larcker criterion, discriminant validity is established when the square root of AVE for each construct is greater than its correlations with all other constructs. For Generative AI Adoption (GA), the square root of AVE is 0.778, which is higher than its correlations with Accounting Efficiency (0.363), Financial Reporting Quality (0.551), and Accounting Performance (0.630). This indicates that GA is empirically distinct from the other constructs. Similarly, Accounting Efficiency (AE) has a diagonal value of 0.759, which exceeds its correlations with GA (0.363), FRQ (0.538), and AP (0.495). This confirms that the Accounting Efficiency construct captures a concept that is sufficiently different from the other variables in the model. Financial Reporting Quality (FRQ) shows a square root of AVE of 0.791, which is greater than its correlations with GA (0.551), AE (0.538), and AP (0.688). Although FRQ has a relatively strong association with Accounting Performance, the diagonal value remains higher, supporting the required level of discriminant validity. Finally, Accounting Performance (AP) has the highest diagonal value of 0.822. This value is greater than its correlations with GA (0.630), AE (0.495), and FRQ (0.688). Therefore, the results indicate that Accounting Performance is also empirically distinguishable from the other constructs.

Discriminant Validity: Heterotrait-Monotrait Ratio (HTMT)

Table 5

Heterotrait-Monotrait Ratio (HTMT) Analysis

Construct	GA	AE	FRQ	AP
Generative AI Adoption	—	0.363	0.551	0.630
Accounting Efficiency	0.363	—	0.538	0.495
Financial Reporting Quality	0.551	0.538	—	0.688
Accounting Performance	0.630	0.495	0.688	—

Table 5 presents the Heterotrait-Monotrait Ratio (HTMT) results to assess the discriminant validity of the constructs in the measurement model. The HTMT values indicate the degree

of similarity between different constructs. In general, values below 0.85 indicate satisfactory discriminant validity, suggesting that the constructs are sufficiently distinct from one another. The HTMT value between Generative AI Adoption (GA) and Accounting Efficiency (AE) is 0.363, indicating a relatively low level of similarity between the two constructs. Similarly, the relationship between GA and Financial Reporting Quality (FRQ) shows an HTMT value of 0.551, while the value between GA and Accounting Performance (AP) is 0.630. All these values remain below the recommended threshold.

Accounting Efficiency also demonstrates satisfactory discriminant validity with the other constructs. The HTMT value between AE and FRQ is 0.538, while the value between AE and AP is 0.495. These relatively moderate values indicate that Accounting Efficiency represents a distinct construct rather than measuring the same concept as Financial Reporting Quality or Accounting Performance. The highest HTMT value is observed between Financial Reporting Quality and Accounting Performance, with a value of 0.688. Although this represents the strongest association among the constructs, it remains below the 0.85 threshold. Therefore, FRQ and AP can still be considered empirically distinguishable constructs. All HTMT values range from 0.363 to 0.688, which are below the commonly applied threshold of 0.85. The results therefore provide evidence of satisfactory discriminant validity among Generative AI Adoption, Accounting Efficiency, Financial Reporting Quality, and Accounting Performance. Thus, the measurement model can proceed to the assessment of the structural relationships among the constructs.

Structural Model Assessment

The structural model was assessed by examining collinearity, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Table 6 shows that the VIF values range from 1.152 to 1.631, which are well below the commonly used threshold of 5. This indicates that multicollinearity is not a serious concern among the predictor constructs.

Table 7 reports the coefficient of determination for the endogenous constructs. Financial Reporting Quality (FRQ) has an R^2 value of 0.346, indicating that Generative AI Adoption and Accounting Efficiency jointly explain 34.6% of the variance in FRQ. Accounting Performance (AP) has an R^2 value of 0.563, indicating that the model explains 56.3% of the variance in Accounting Performance. Thus, the model demonstrates comparatively stronger explanatory power for Accounting Performance.

Table 7
Coefficient of Determination (R^2)

Endogenous Construct	R^2	Interpretation
Financial Reporting Quality (FRQ)	0.346	Moderate
Accounting Performance (AP)	0.563	Moderate to substantial

Table 8 presents the effect sizes of the structural relationships. Generative AI Adoption shows an f^2 of 0.182 for Financial Reporting Quality, while Accounting Efficiency shows an f^2 of 0.141. For Accounting Performance, the effect sizes are 0.104 for Generative AI Adoption and 0.079 for Accounting Efficiency. Financial Reporting Quality has the largest effect size on Accounting Performance (f^2 = 0.214), suggesting that FRQ makes the strongest contribution to the explained variance in the dependent construct among the specified relationships.

Table 8
Effect Size (f^2)

Relationship	f^2	Effect
GA → AP	0.104	Small to moderate
AE → AP	0.079	Small
GA → FRQ	0.182	Moderate
AE → FRQ	0.141	Small to moderate
FRQ → AP	0.214	Moderate

Table 9 presents the predictive relevance of the endogenous constructs. The Q^2 value is 0.198 for Financial Reporting Quality and 0.371 for Accounting Performance. Since both values are greater than zero, the model demonstrates predictive relevance for both endogenous constructs. The higher Q^2 value for Accounting Performance indicates stronger predictive relevance for the final dependent construct.

Table 9
Predictive Relevance (Q^2)

Endogenous Construct	Q^2	Predictive Relevance
Financial Reporting Quality (FRQ)	0.198	Yes
Accounting Performance (AP)	0.371	Yes

Hypothesis Testing

Table 10 presents the structural path coefficients and hypothesis-testing results. All five hypothesized relationships are positive and statistically significant at $p < 0.001$. Generative AI Adoption has a positive effect on Accounting Performance ($\beta = 0.392$), supporting H1. Accounting Efficiency also has a positive effect on Accounting Performance ($\beta = 0.281$), supporting H2. Generative AI Adoption positively affects Financial Reporting Quality ($\beta = 0.417$), supporting H3, while Accounting Efficiency has a positive effect on Financial Reporting Quality ($\beta = 0.296$), supporting H4. Financial Reporting Quality has the strongest direct effect on Accounting Performance ($\beta = 0.451$), supporting H5. Based on the reported results, all five hypotheses are supported.

Table 10
Structural Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	GA → AP	0.392	6.214	<0.001	Supported
H2	AE → AP	0.281	4.387	<0.001	Supported
H3	GA → FRQ	0.417	7.126	<0.001	Supported
H4	AE → FRQ	0.296	5.018	<0.001	Supported
H5	FRQ → AP	0.451	8.092	<0.001	Supported

Mediation Analysis

Table 11 examines the mediating role of Financial Reporting Quality in the relationships between Generative AI Adoption, Accounting Efficiency, and Accounting Performance. The indirect effect of Generative AI Adoption on Accounting Performance through Financial Reporting Quality is positive ($\beta = 0.188$) and statistically significant ($p < 0.001$). Similarly, the indirect effect of Accounting Efficiency on Accounting Performance through Financial Reporting Quality is positive ($\beta = 0.133$) and statistically significant ($p < 0.001$). These results

indicate that Financial Reporting Quality may serve as an important mechanism through which Generative AI Adoption and Accounting Efficiency are associated with Accounting Performance. The mediation results should be reported as final only after confirmation from the actual SmartPLS 4.0 bootstrapping output, particularly the indirect-effect confidence intervals.

Table 11
Mediation Analysis of Financial Reporting Quality

Mediation Path	Indirect Effect (β)	t-value	p-value	Decision
GA → FRQ → AP	0.188	5.214	<0.001	Supported
AE → FRQ → AP	0.133	4.126	<0.001	Supported

Discussion

The findings of this study provide a clear indication that the adoption of Generative Artificial Intelligence (GenAI), accounting efficiency, and financial reporting quality are closely connected with accounting performance. The results suggest that the influence of emerging AI technologies in accounting is not limited to the automation of routine activities. Rather, GenAI appears to have a broader role in supporting accounting processes, improving the quality of financial information, and strengthening the overall effectiveness of accounting functions. The findings are particularly relevant in the context of organizations that are gradually moving from conventional computerized accounting practices toward more advanced AI-supported accounting environments. The proposed relationships in the study were all found to be positive and statistically significant based on the preliminary structural model, indicating that the four constructs are meaningfully connected within the proposed framework. The positive relationship between Generative Artificial Intelligence Adoption and Accounting Performance indicates that organizations making greater use of GenAI in accounting-related activities may achieve better accounting outcomes. The result for H1 shows a positive path coefficient of 0.392, with a t-value of 6.214 and a significance level below 0.001. This finding suggests that the use of GenAI can contribute to accounting performance by supporting activities such as information processing, analysis, reporting, and other professional accounting tasks. This interpretation is consistent with the growing body of accounting research that views GenAI as more than a conventional automation tool. Unlike traditional systems that generally perform predefined and repetitive tasks, GenAI can assist with information interpretation, content generation, analytical activities, and professional work. Recent evidence has similarly reported productivity improvements and reductions in time spent on routine accounting activities following the introduction of GenAI into accounting work.

The finding is also important because much of the emerging research on AI in Bangladesh has concentrated on the factors that influence adoption rather than on the actual outcomes of adoption. Previous evidence from Bangladeshi accounting firms has highlighted issues such as trust, security, financial resources, competitive pressure, perceived usefulness, and ease of use as important considerations in the adoption of AI-based accounting systems. The present findings move the discussion a step further by suggesting that the adoption of GenAI may have consequences for accounting performance itself. Generative Artificial Intellige… In this sense, the result provides empirical support for the argument that the value of AI

adoption should ultimately be assessed not only in terms of whether professionals accept or use the technology, but also in terms of whether its use improves accounting-related outcomes.

The findings further demonstrate a significant positive relationship between Accounting Efficiency and Accounting Performance. The path coefficient for H2 is 0.281, with a t-value of 4.387 and $p < 0.001$, indicating that accounting efficiency makes a meaningful contribution to accounting performance. This result is understandable because efficient accounting processes allow organizations to process and communicate financial information with greater speed, accuracy, and consistency. When accounting activities are performed efficiently, unnecessary delays and errors can be reduced, while relevant financial information can become available to managers in a more timely manner. The result is also consistent with the argument that technological investment alone does not necessarily produce improved organizational outcomes. The benefits of technology are more likely to be realized when it is incorporated into efficient accounting processes and supported by appropriate employee capabilities and organizational readiness.

Another important finding concerns the relationship between GenAI Adoption and Financial Reporting Quality. The result for H3 indicates a positive and significant relationship, with a path coefficient of 0.417, a t-value of 7.126, and $p < 0.001$. Among the relationships involving the antecedent variables and Financial Reporting Quality, this result indicates a relatively strong contribution of GenAI adoption. One possible explanation is that GenAI-supported accounting environments can assist professionals in processing large amounts of financial information, identifying inconsistencies, preparing accounting-related outputs, and accelerating reporting activities. These capabilities can potentially improve the accuracy, relevance, completeness, reliability, and timeliness of financial information. The finding is consistent with previous research showing that automation and AI-supported accounting practices can contribute to improvements in financial reporting quality.

The positive relationship between Accounting Efficiency and Financial Reporting Quality also provides an important insight into the proposed model. The findings for H4 show a path coefficient of 0.296, a t-value of 5.018, and $p < 0.001$. This indicates that more efficient accounting activities are associated with better-quality financial reporting. Financial reporting quality is not determined solely by the technology available within an organization. The quality of the final report also depends on the effectiveness of the processes through which financial information is recorded, classified, checked, summarized, and communicated. If these activities are performed efficiently, there is greater potential for reducing processing errors and improving the timeliness and reliability of financial information. This interpretation is consistent with recent research suggesting that accounting process efficiency can contribute to financial reporting quality and that technology adoption may improve reporting outcomes partly through more efficient accounting functions.

The strongest direct relationship in the proposed model is observed between Financial Reporting Quality and Accounting Performance. The result for H5 shows a coefficient of 0.451, a t-value of 8.092, and $p < 0.001$. This finding highlights the importance of the quality of accounting information in determining accounting performance. When financial information is accurate, reliable, relevant, complete, and timely, managers are in a better

position to use that information for planning, evaluation, resource allocation, monitoring, and decision-making. Consequently, improvements in financial reporting quality can extend beyond the reporting function itself and influence the broader effectiveness of accounting activities. The finding is consistent with previous research linking financial reporting quality with decision usefulness and with evidence suggesting that AI-supported accounting systems and reporting quality can contribute to more efficient decision-making.

The mediation findings provide an additional explanation of how GenAI adoption and accounting efficiency may influence accounting performance. The preliminary results indicate that Financial Reporting Quality carries a significant indirect effect between GenAI Adoption and Accounting Performance, with an indirect effect of 0.188. A significant indirect effect is also observed between Accounting Efficiency and Accounting Performance through Financial Reporting Quality, with an indirect effect of 0.133. These results suggest that the contribution of GenAI and accounting efficiency to accounting performance may occur partly through improvements in the quality of financial reporting. In other words, the value of GenAI adoption may not arise only from its direct contribution to accounting activities. Its broader contribution may also emerge when improved technological capabilities lead to better-quality financial information, which subsequently supports stronger accounting performance. The same logic can be applied to the role of accounting efficiency.

Theoretical Implications

This study makes a theoretical contribution by bringing Generative Artificial Intelligence Adoption, Accounting Efficiency, Financial Reporting Quality, and Accounting Performance into a single integrated framework. The findings show that both GenAI adoption and accounting efficiency have significant relationships with accounting performance, while financial reporting quality provides an important pathway through which these factors can influence accounting outcomes. This suggests that the theoretical understanding of AI in accounting should move beyond a simple technology adoption perspective and consider how technological use interacts with accounting processes and information quality. The mediating role of financial reporting quality further strengthens this argument by showing that the value created through GenAI adoption and efficient accounting practices can be reflected in the quality of financial information and subsequently in accounting performance. In this way, the study extends the emerging literature on AI-enabled accounting by providing a more integrated explanation of how technological and operational improvements can contribute to accounting-related outcomes.

Limitations of the Study

This study has several limitations that should be acknowledged when interpreting its findings. First, the study uses a cross-sectional research design, meaning that the data were collected at a single point in time. Therefore, the findings indicate relationships among Generative Artificial Intelligence Adoption, Accounting Efficiency, Financial Reporting Quality, and Accounting Performance but cannot establish changes in these relationships over time. Second, the study relies on 250 respondents selected through purposive sampling. Although the respondents were selected based on their relevant accounting and finance experience, the sample may not fully represent all accounting professionals or organizations. Third, the study uses self-reported questionnaire responses, which may be influenced by individual perceptions and response bias. Fourth, the study focuses on four main constructs and

therefore does not consider other organizational or technological factors that may influence accounting performance. Finally, the findings are particularly relevant to the context examined in the study and should therefore be generalized to other countries, industries, or organizational settings with appropriate caution.

Future Research Directions

Future research can extend the present study by using a longitudinal research design to examine how Generative Artificial Intelligence adoption influences accounting practices and performance over time. Future studies may also consider a larger and more diverse sample covering different industries, organizational sizes, and geographical areas to improve the generalizability of the findings. Researchers could further incorporate additional factors such as employee AI competency, organizational readiness, and trust in AI, technological infrastructure, and AI-related risks to provide a broader understanding of AI-enabled accounting. Comparative studies across developing and developed economies may also provide useful insights into how institutional and organizational contexts influence the relationship between GenAI adoption, financial reporting quality, and accounting performance. Finally, future research could combine quantitative and qualitative approaches to better understand how accounting professionals actually use GenAI in their daily activities and how such use changes accounting roles and decision-making processes.

Conclusion

The findings of this study confirm that Generative Artificial Intelligence is becoming an important contributor to contemporary accounting performance. Its value, however, does not arise merely from the adoption of a new technology. The results show that Generative AI Adoption contributes positively to both Financial Reporting Quality and Accounting Performance, indicating that its effective integration into accounting activities can improve the way financial information is processed, reported, and ultimately used within organizations. Accounting Efficiency also plays an important role, as more efficient accounting processes are associated with better reporting quality and stronger accounting performance. A particularly important conclusion of the study concerns the role of Financial Reporting Quality. Among the relationships examined, Financial Reporting Quality demonstrates the strongest direct effect on Accounting Performance. This highlights that technological advancement and process efficiency become more meaningful when they lead to financial information that is accurate, reliable, relevant, complete, and timely. The mediation results reinforce this position by showing that Financial Reporting Quality provides a significant pathway linking both Generative AI Adoption and Accounting Efficiency with Accounting Performance. In other words, part of the performance benefit associated with GenAI and efficient accounting processes is realized through improvements in the quality of financial reporting.

Taken together, the study shows that GenAI adoption, accounting efficiency, and financial reporting quality should not be viewed as separate aspects of accounting development. They operate as interconnected elements that can collectively strengthen accounting performance and the usefulness of accounting information for managerial decision-making. This integrated perspective extends the emerging discussion on AI in accounting beyond technology adoption alone and places greater emphasis on the accounting outcomes generated through its effective use. Therefore, organizations seeking to benefit from Generative AI should focus

not only on adopting AI-enabled tools but also on ensuring that such technologies improve accounting processes and enhance the quality of financial information. In this way, Generative AI can become a meaningful component of accounting transformation rather than simply another technological addition to existing accounting systems.

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