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Artificial Intelligence Adoption and Financial Reporting Quality: The Mediating Role of Accounting Process Automation

Md Aman Ferdoush Afridy[1*], Tasmin Rahman[2], Amena Akter Rima[3], Md Hasibul Islam Santo[4]

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ABSTRACT

AI is making a dent in the work that accountants do, and the link between AI and the quality of financial reporting stems in part on how organisations integrate AI into their daily routines. The purpose of this study is to investigate the correlation between adoption of artificial intelligence and financial reporting quality as well as the mediation effect of accounting process automation. The analysis sample consists of 360 respondents from professionals in the fields of accounting, financial reporting, financial management, internal audit and accounting systems oversight. Partial least squares structural equation modelling is used to analyze three reflective constructs with five indicators. Indicator reliability, internal consistency, convergent and discriminant validity are supported by measurement assessment. For structural inference 10,000 bootstrap resamples were used. Both artificial intelligence adoption and accounting process automation are positively associated with financial reporting quality, with an average beta value of 0.500, while artificial intelligence adoption is positively related to accounting process automation with an average beta value of 0.478. The direct link between the use of AI and Financial Reporting quality is also positive and significant (beta = 0.189). Regarding the specific indirect effect, it is found to be 0.239 (95% CI: 0.188 to 0.296), showing that there was a complementary partial mediation. The model accounts for 22.8% of the variance of accounting process automation and 37.6% of the variance of financial reporting quality. Predictive assessment gives positive values for all endogenous indicators, i.e. Q^2predict. The results indicated that accounting process automation is a significant mechanism in which AI is associated with perceived reporting quality in organisations. Practical recommendations include workflow integration, secure source data, exception management, staff capability and human accountable review. Organizations need to consider not only the level of technology adoption but also the enhancements in accounting processes and consistent accounting outputs when they consider investing in AI.

INTRODUCTION

Background and Research Context

Financial reporting takes organisational activity and makes it available as information to help with oversight, allocating resources and evaluating financial performance. It relies on the accuracy of transactions that are recorded, and the consistency of accounting procedures, and the degree of faithful representation of the underlying activities. Reports are reliable, starting with connected decisions and controls related to data capture, classification, reconciliation, adjustment, review and presentation (Temitayo Oluwaseun Jejeniwa *et al.*, 2024). Thus, technology has an impact on reporting quality via not only the processes used to create financial information but also via the analytical tools used for financial information.

AI adds classification, prediction, Doc Interpretation, Anomalies detection, and Intelligent Assistance. For accounting systems, they can be used to help extract information in documents, detect any suspicious transactions, and prepare analyses during reporting. The value of adoption in an organisation is achieved when these applications are being used on a regular basis and are established within the organisation's workflow (Alghazzawi, 2025). Even with comparable technical systems there may be degrees of adoption, such as a trial application, an isolated experiment, and an embedded accounting capability.

The automation of accounting processes involves performing accounting functions with less human effort. It covers automated transactions, integration with other systems, regular audits, recurring workflows, and steps that a transaction advances to the next. There's some automation that's AI-based and other automation that's based on set rules or accounting software that you've already used (Thongprim & Sincharoonsak, 2025). It is important to distinguish this as it is an organisational aspect and the implementation of AI and the automation of accounting work are also related aspects with different meanings. One organisation might simply automate tasks without implementing much AI, while another might implement AI without altering its own accounting

[1] Department of Economics and Management, Tianjin University, Tianjin, P.R. China
[2] Department of Economics, Eden Mohila College, Bangladesh
[3] Master's in Economics, Eden Mohila College, Bangladesh
[4] Department of Marketing, East West University, Bangladesh
[*] Corresponding author's e-mail: amanferdoushafridy@gmail.com

process.

This study focuses on the relation between these characteristics and the quality of financial reporting. Direct contributions to AI adoption are through interpretation and review. It could also play a more indirect role by facilitating more harmonised and regularised accounting procedures. The indirect one is pertinent when the reporting is based on multiple transactions and information is passed through multiple systems. In this context, the importance of AI can be realised through operational modes that minimise the need for re-entry, enable timely checks, and prioritise staff activities based on exceptions where professional judgment is needed (Ma *et al.*, 2025).

Research Problem and Analytical Focus

Technology investment is typically assessed by stages of implementation, availability of the system, or how many activities are served by the use of a digital application. These measures relate to deployment, and the link between deployment and quality of reporting needs to be explored. The availability of a technology does not necessarily mean that it is used on a regular basis and vice versa. It is therefore necessary to pay attention to both adoptions and an organisational mechanism where adoption is integrated into routine accounting work when understanding the outcomes of reporting.

A mediation model of artificial intelligence adoption, accounting process automation, and financial reporting quality is used to address the research problem. In the model, there is a direct relationship between adoption and reporting quality and an indirect relationship that goes through automation. The structure enables the analysis to determine if automation is an alternative explanation for the link between AI adoption and financial report quality. It still enables the direct relationship to be maintained once automation is added (Al-Okaily, 2025).

Financial reporting quality is defined in terms of perceived accuracy, faithful representation, dependability, consistency with supporting records, and overall quality. These attributes link the results of the report with the accounting process. The analysis is thus about professionals' evaluations of organisational practices and reporting outputs. In the present paper, financial reporting quality is understood based on these measured aspects and this is evident in the interpretation of the structural relationships.

Objectives and Contribution

The overall focus is to explore how the adoption of AI in accounting processes relates to the quality of financial reporting. They include examining the correlation between AI adoption and automation, examining the correlation between automation and reporting quality, direct correlation between AI adoption and reporting quality, and tests for indirect correlation between AI and reporting quality via automation. The principal research question is related to how artificial intelligence adoption influences the financial reporting quality by considering automation of accounting processes as a mediating factor.

LITERATURE REVIEW

Artificial Intelligence Adoption in Accounting

Artificial Intelligence Adoption is the well-defined application of AI products in the organisational accounting/financial reporting functions. Adoption is manifested as the frequency of use, integration into processes, grown beyond a one-shot, and becoming a part of day to day work (Temitayo Oluwaseun Jejeniwa *et al.*, 2024). The emphasis of this definition is upon actual organisational use. So it effectively removes adoption from the realm of general awareness, positive attitudes toward technology use or discussing application use later (Alghazzawi, 2025).

AI's accounting relevance is thus a consequence of the information needed in the accounting process. Accounting records involve a mixture of structured transactions' information and documents, explanations, estimates, and judgements in context. AI tools can help with various aspects of this information ecosystem (Thongprim & Sincharoonsak, 2025). Document extraction can assist in data capture, classification can aid in the organisation of transactions and anomaly detection can guide review toward transactions that are unusual. The intelligent assistance also can help with preparing explanations and analysis. These applications are part of adoption when they are integrated in the established accounting obligations (Ma *et al.*, 2025).

Accounting Process Automation

Accounting process automation refers to how much the accounting process can proceed using technology with minimal manual involvement. This can range from transaction processing through to moving information between systems, regular reconciliations, regular report generation, and workflow progression (Anantharaman *et al.*, 2023). Automation can eliminate redundant manipulation of the same data and create a uniform workflow for dealing with similar transactions. The relevance to reporting is based on the fact that the reliability of the information later provided depends on the dependable routine execution (Al-Okaily, 2025).

Automation involves more than the speed of individual tasks. A task that can be done swiftly without being connected to the rest of the accounting process. Process Automation, however, is focused on connecting activities, passing information around, and when employees are involved (Korol & Romashko, 2024). Auto-transfers can eliminate re-entry and predetermined workflow stages can create a clear pathway from transaction initiation to review. For exception handling, the focus can be on items that need to be interpreted, corrected, or approved. These operational traits make automation a potential link between the adoption of AI and reporting quality (Leocádio *et al.*, 2024).

Financial Reporting Quality

Financial reporting quality is defined as the degree to which the reports are capable of providing a true and fair view of the financial activities, position and performance of an organisation (Alshareef, 2025). The measure is based on faithful representation, quality of overall presentation, consistency with other presentations and evidence, accuracy of representation, and dependable information. These attributes offer a concise description of reporting quality, based on the link between financial information and the underlying activities reported (Rawashdeh *et al.*, 2023).

Accuracy relates to the consistency of the reports to financial events that occurred. Faithful representation is about whether the information represents the economic substance and financial condition being reported. Dependability relates to the trust that the users and preparers have in the information (Zhu *et al.*, 2025). The final report is consistent with underlying records and this relates the report to the accounting basis and evidence. The overall quality item indicates the overall perception of these characteristics by the respondent in the organisation's reporting context (Bogdan *et al.*, 2025).

An Explanation of Process Capability

The theoretical rationale behind the model views technology adoption as an organisational resource, the value of which is exhibited by the operating capability. The access to AI applications is potential functionality; the value for an organisation hinges on whether the applications are integrated in processes that generate value (Adnan *et al.*, 2024). Accounting process automation is one such system as it organises the flow and management of monetary information. Financial reporting quality is an outcome which is related to this capability (Abdelouahab *et al.*, 2025).

The process explanation is complemented by professional oversight. While the employees will be responsible for accounting policy, accounting for unusual transactions, significant estimates, and accounting approval, the automation can perform repeated steps. Intelligent applications can help to provide some information to those responsibilities but responsibility is an organisational issue (Omari & Al-Nimer, 2024). The model is thus about the interplay of adoption and automation on perceived quality of reporting in an accounting system where human judgement is involved. Does not assume that the greater amount of technology used eliminates the need for review (Adnan *et al.*, 2024).

Artificial Intelligence Adoption and Accounting Process Automation

Process automation can be correlated with AI adoption as this can enable intelligent applications to support activities that were once being repeated manually (Johri, 2025). Fields can be extracted from documents, for instance, to be used for the processing of transactions, and classification can be used for routing entries to an appropriate account or review queue. These capabilities can enable more work to be completed in known stages of the process with less manual effort, when built into accounting processes (Peng *et al.*, 2023).

H1 posits that there is a positive and significant relationship between the application of artificial intelligence and accounting process automation.

Accounting Process Automation and Financial Reporting Quality

Financial reporting quality can be facilitated by automation of the same process for comparable transactions and routine checks. Continuity of source systems and accounting records can be maintained via automatic transfers. Common information base can be used to create recurring schedules and automatic reconciliations can detect items that need to be followed up. These features combined can enhance the consistency of accounting records, supporting evidence, and information in reports (Lawrence Damilare Oyeniyi *et al.*, 2024).

The expected relationship has to do not just with the amount of automation but also the quality of how the process is executed. A workflow can play a key role in dependable reporting when it is able to process the right information, based on specific rules, document the exceptions and escalate unresolved items to the right staff (Beryl Odonkor *et al.*, 2024). Accurate reporting is then possible using automation for consistent execution and review. What this measure reflects is the level of automation, and the proposed relationship evaluates whether there is a relationship between the level of automation and the professional's rating of report quality (Nasra Saif Ahmed Al-Arfia *et al.*, 2026).

H2 posits that there is a positive and significant relationship between H2 and FRQ.

Direct and Mediated Relationships

There is a possible direct link between the use of AI and the quality of reporting as AI applications can help with analytical tasks and not just routine process execution (Al Najjar *et al.*, 2024). An accountant can let AI help them sort data for a review or flag data items that need investigation. Even when the rest of the process is still conducted manually, such support can affect the assessment of the reporting quality. The direct path displays the association between adoption and quality with process automation added to the model (Al-Shanti *et al.*, 2024).

H3 posits that the adoption of artificial intelligence has a positive and important direct impact on financial reporting quality.

The mediation proposition is a mixture of the first two relationships. Adopting AI will likely be correlated with wider automation, which will be correlated with better reporting quality. The indirect path hence stands for a process mechanism by which the adoption–quality relationship is manifested (Abdullah & Almaqtari, 2024). If the effect is positive and indirect, with another positive effect that of automation, some of the relationship would

be explained by automation, but the adoption would have an additional direct association with reporting quality (Nadi *et al.*, 2024).

H4 posits the role of the accounting process automation in the positive relationship between the adoption of AI and the quality of financial reporting.

Conceptual framework was provided in figure 1. The exogenous construct are the Artificial Intelligence Adoption while the Mediator Construct is the Accounting Process Automation and the Endogenous Construct is the Financial Reporting Quality. The framework comprises of three direct paths and a particular indirect path. This design tests a specific aspect of an adopted technology capability with respect to its alignment with reporting outcomes by performing accounting work (Alshareef, 2025).

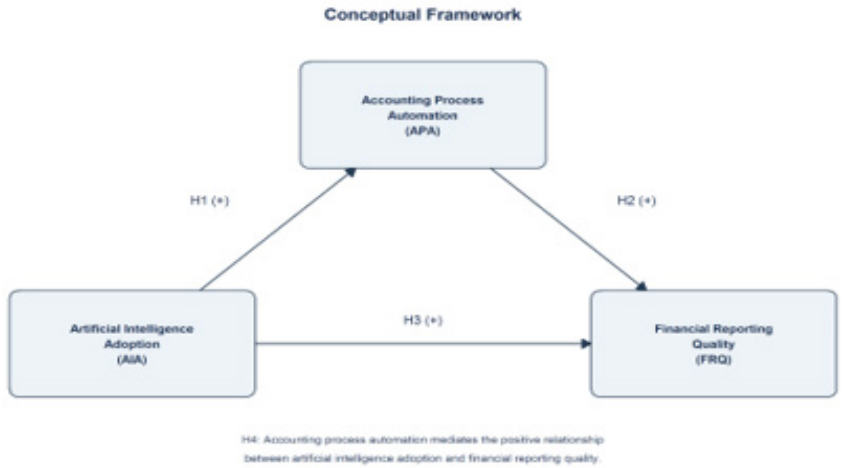

Figure 1: Conceptual framework

MATERIALS AND METHODS

Research Design and Analytical Material

This research adopts a quantitative survey approach to explore the connections between organisational adoption of AI, automation in accounting processes, and the quality of financial reporting. The analytical material includes the structured questionnaire and statistical results of the observations which are 360 in total. The questionnaire invites the respondents to judge the accounting and reporting practices in the organisation they are currently working, for the last 12 months or for the duration of their service if less than 12 months. This resulted in a design which captured the contemporaneous professional assessments of organisational practices (Wang *et al.*, 2024).

The analytical unit is the professional response about an organisation's accounting environment at an individual level. Respondents work in the fields of accounting, finance, financial reporting, internal audit, and accounting systems. They report on their findings and associations between the three constructs are estimated. The respondent profile, composed of organisational characteristics, and the specification of the structural model as expressed in the three main constructs are included. The interpretation of the model continues to reflect this assessment at respondent level in relation to organisational practices.

Eligibility and Questionnaire Structure

Candidates must be ≥ 18 years old, have a relevant professional role, will have to be familiar with the organisational accounting and reporting practices, and must have given their consent to participate in the project. Questionnaire allows for organisations at various levels of maturity with AI - including without AI applications. This can be a great attribute, instead of adopting just formal users. Respondents are told to indicate the response which they believe best describes the situation in their organisation (Schwalbe & Finzel, 2024).

The questionnaire includes consent and eligibility questions, respondent and organisational profile questions and the three construct scales. Profile details include Age, Gender, Education, Professional Qualification, Position, Relevant Experience, Organisational Tenure, Sector, Ownership entity, Size of the organisation, AI Adoption Stage and AI Training (Sharma *et al.*, 2021). The consent text outlines that it is voluntary, responses will be treated with confidentiality and analysed as a group, and personal or organisational names will not be asked for. These provisions present participant information and consent that will be part of the instrument.

Operationalisation of Constructs

Five items are used reflectively for each construct. Active use, regular use, workflow integration, use beyond trials and established use are used as measures of the adoption of AI. Accounting process automation is characterized by automatic transaction processing, automatic transfer of information, automatic checks and reconciliations, automatic recurring schedules and reports, and movement through predefined workflow scenarios. The quality of financial reporting is assessed

based on accuracy, faithful representation, dependability, consistency with evidence and overall quality.
Responses are on a five-point agreement scale (strongly disagree to strongly agree). Suggests a higher score reflects higher adoption or more pervasive automation or there is higher perceived reporting quality. Unable to assess responses are considered missing, not the neutral midpoint. This distinction is maintained so that the meaning of the level of agreement remains consistent: neither agree nor disagree is considered a substantive response and inability to assess is considered as unavailable information. The reported model uses all measurement items.

Data Screening and Descriptive Assessment
Data screening involves checking for eligibility, missing item responses and item score validity. The results found 360 imported records, all 360 were kept for analysis. No respondents are missing due to failed or missing eligibility responses, no measurement items or no valid measurement scores. No complete 15 item response patterns are repeated within the screening table. These checks can be used to determine how many observations are used during the measurement and structural assessments, without assuming a response rate from missing recruitment data.
Descriptive analysis refers to information that provides a summary of the respondent characteristics and the measurements item distribution. For profile categories, frequencies and percentages are used. Means, standard deviations, minimum and maximum values observed, skewness, and excess kurtosis are reported for each item. These statistics provide information about the location of each response and its spread prior to conclusions regarding relationships among the latent constructs. The assessment also differentiates difference in the means of the agreements from the structure association estimated between constructs (Aithal & Aithal, 2020).

Measurement and Structural Model Assessment
The measurement model of reflexivity and the suggested structural relations are evaluated using the PLS-SEM approach. Outer loadings and the outer loadings squared are used for the assessment of indicator reliability. Indicators to assess internal consistency are Cronbach's alpha, rho_A and composite reliability. Average variance extracted is investigated for convergent validity. The criteria adopted in the analysis are the reported loading value of 0.708, the reliability value > 0.70, and the average variance extracted > 0.50. In order to determine the discriminant validity, the heterotrait–monotrait ratio of the correlations and bootstrap confidence intervals are used. For the reported assessment a threshold of 0.85 is used for both point estimates and upper confidence limits. Inner variance inflation factors are used to evaluate structural collinearity, and the values given here are compared to the value of three. Based on these procedures, the distinctiveness of the constructs and the appropriateness of interpreting their unique contributions to the model can be inferred (Braun *et al.*, 2021).
10,000 bootstrap resamples are used for structural inference. Path coefficients, their standard errors (bootstrap), t statistics, normal-approximation p values, and 95% bootstrap confidence intervals have been reported. In interpreting the hypothesis, you have to look at whether the sign of the coefficient is positive or negative and if the confidence interval does or does not include the zero value. The R^2 and adjusted R^2 are used to understand how much the variance has been explained and f^2 explains the contribution of each predictor to its respective outcome (Holtom *et al.*, 2022). There is separation between statistical significance, explanatory contribution and substantive interpretation.

Mediation & Predictive Assessment
The effectiveness of mediation is tested in the particular indirect relationship between AI adoption and financial reporting quality via accounting process automation. The direct and total effects are also reported. If the 95% CI does not contain 0 in the positive direction, it is considered positive indirect effect that supports the proposed mediation relationship. When both direct and indirect effects are large and both are positive or negative, then the pattern is called complementary partial mediation. The indirect share of the total relationship is descriptively computed in order to provide an understanding of the relative contribution of the estimated paths (Becker, 2022). Predictive assessment is based on the provided PLSpredict outcomes for the 10 indicators that are endogenous to the model. Q^2predict assesses improvement against a benchmark (mean) and root mean squared error and mean absolute error assess errors in prediction. PLS prediction errors are compared with those of a linear model benchmark. This distinction, explaining variation in the model vs predicting held-out observations, is the same in the interpretation. The predictive claims are made because the indicator results are reported, and not made solely on the basis of the extent to which the structural coefficients are significant.

RESULTS AND DISCUSSION

Screening and Analytical Sample
Table 1 summarises sample retention. The 360 imported records satisfy all the eligibility and measurement criteria used in the analysis. Thus, the final sample is the full range of records going into screening. The uniformity enables any later tables to refer to a common sample size and it prevents that changes in the analytical basis occur between the descriptive and structural results. There are no repeated complete measurement response patterns and all observed Item scores are within the range of agreed Item scores.

Table 1: Data screening and sample retention

Screening step	N
Initial records imported	360
Excluded: failed or missing eligibility responses	0
Eligible records	360
Excluded: missing measurement-item responses	0
Excluded: invalid measurement-item scores after missing exclusion	0
Final observations retained	360
Repeated 15-item response patterns retained	0

Respondent and Organisational Characteristics

The respondent profile covers a range of age groups, roles, experience and organisational settings. Respondents aged 25–34 account for 36.94%, while those aged 35–44 account for 35.28%. These groups make up 72.22% of the sample. There are an equal amount of male (59.44%) and female (37.22%) respondents, and an additional category of other identity and non-disclosure. About 45.83% and 46.39% of the respondents are Bachelor's and Master's degree holders, respectively, which means that most of the respondents have University level education.

Accounting and Finance Officers/Executives account for 28.89% of the sample, senior officers/Executives for 26.11% and Accounting or Finance managers for 22.50%. The financial controllers, heads of finance and CFOs make up 7.50%. Perspectives on controls and system operation are also provided by internal audit and accounting systems professionals. 34.17% of the respondents have more than 10 years of relevant professional experience, and 21.67% report their experience as 7 - 10 years. Thus, the sample consists of the operational accounting views as well as longer professional experience (Anantharaman *et al.*, 2023).

The other sectors of organisation affiliation are represented by manufacturing (25.00%), banking, financial services and insurance (17.22%) and trading or retail (16.39%). There are 55.56% private domestic organisations. 25.56% of the organisations have 500 or more workers, and 25.00% have 100–249 workers. The material for analysis is distributed across the different types of organisations as can be seen in the following distributions. However, they do not necessarily suggest that the same relationships have been separately determined for each sector (or each size category).

36.11% of respondents report AI implementation in selected activities and 17.22% across multiple activities. Therefore, 53.33% state that it is implemented beyond the pilot stage. Another 22.22% say they use them on a

Table 2 : Respondent and organisational profile

Characteristic	Category	n	%
Age	18-24	30	8.33
	25-34	133	36.94
	35-44	127	35.28
	45-54	58	16.11
	55 or above	12	3.33
Gender	Male	214	59.44
	Female	134	37.22
	Another identity	4	1.11
	Prefer not to disclose	8	2.22
Education	Higher secondary or equivalent	10	2.78
	Diploma	15	4.17
	Bachelor's degree	165	45.83
	Master's degree	167	46.39
	Doctoral degree	3	0.83
Professional qualification	CA	41	11.39
	CMA	30	8.33
	ACCA	51	14.17
	Other completed professional qualification	15	4.17
	Currently pursuing a professional qualification	92	25.56

	None	131	36.39
Position	Accounting/finance officer or executive	104	28.89
	Senior officer/executive	94	26.11
	Accounting/finance manager	81	22.50
	Controller/head of finance/CFO	27	7.50
	Internal audit professional	26	7.22
	Accounting systems/ERP professional	24	6.67
	Other relevant position	4	1.11
Experience	Less than 1 year	17	4.72
	1-3 years	68	18.89
	4-6 years	74	20.56
	7-10 years	78	21.67
	More than 10 years	123	34.17
Organisational tenure	Less than 1 year	104	28.89
	1-3 years	115	31.94
	4-6 years	75	20.83
	7-10 years	46	12.78
	More than 10 years	20	5.56
Sector	Manufacturing	90	25.00
	Banking/financial services/insurance	62	17.22
	Trading/retail	59	16.39
	IT/telecommunications	44	12.22
	Professional or other services	40	11.11
	Government/public administration	23	6.39
	NGO/development	26	7.22
	Other	16	4.44
Ownership	Private domestic	200	55.56
	Public/state-owned	40	11.11
	Foreign-owned/multinational	49	13.61
	Joint venture	32	8.89
	NGO/non-profit	33	9.17
	Other	6	1.67
Employees	Fewer than 50 employees	45	12.50
	50-99 employees	59	16.39
	100-249 employees	90	25.00
	250-499 employees	74	20.56
	500 or more employees	92	25.56
AI stage	Not adopted and not planned	31	8.61
	Under consideration/planning	57	15.83
	Pilot or trial use	80	22.22
	Implemented in selected activities	130	36.11
	Implemented across several activities	62	17.22
AI training	No training	102	28.33
	Informal/self-directed learning only	112	31.11
	Formal training only	66	18.33
	Both formal and informal/self-directed learning	80	22.22

pilot or trial basis, 15.83% state they are considering or planning to adopt them and 8.61% say they don't adopt or plan to adopt them. This distribution aligns with the representation of organisations at varying points on the AI journey in the questionnaire and offers sufficient diversity to analyze the use of AI in organisations.

There is also a diversity of training experiences. There is 31.11% informal or self-directed learning and 28.33% no training. Only 18.33% reported that they had a formal training and 22.22% stated that their training was both formal and informal. These figures point to an organisational capability problem that is pertinent to suggestions for implementation. They do not create a training effect in the structure model, but they do explain why employee training is something that is worthy of managerial attention when organisations are aiming to incorporate AI with reliable accounting practices (Alshareef, 2025).

Descriptive Characteristics of the Measurement Items

Means, standard deviations, and distributional characteristics for the items on each table are reported in Table 3. AI adoption means range from 3.081 to 3.236, automation means from 3.092 to 3.164, and reporting quality means from 3.017 to 3.108. The five item means are about 3.144 for adoption, 3.122 for automation, and 3.073 for the reporting quality. Each of these descriptive averages is a summary of _item responses_ and should not be confused with the standardised latent variable scores that are used in the latent variable structural estimation.

Table 3: Descriptive statistics of measurement items

Item	Mean	SD	Min–max	Skewness	Excess kurtosis
AIA1	3.236	1.177	1–5	-0.178	-0.808
AIA2	3.147	1.155	1–5	-0.224	-0.715
AIA3	3.086	1.110	1–5	-0.048	-0.657
AIA4	3.172	1.138	1–5	-0.193	-0.773
AIA5	3.081	1.176	1–5	-0.208	-0.859
APA1	3.164	1.214	1–5	-0.157	-0.868
APA2	3.092	1.233	1–5	-0.130	-0.955
APA3	3.100	1.240	1–5	-0.146	-0.906
APA4	3.100	1.195	1–5	-0.134	-0.973
APA5	3.156	1.191	1–5	-0.193	-0.867
FRQ1	3.067	1.204	1–5	-0.157	-0.902
FRQ2	3.081	1.218	1–5	-0.034	-0.892
FRQ3	3.092	1.226	1–5	-0.066	-0.980
FRQ4	3.108	1.245	1–5	-0.102	-0.993
FRQ5	3.017	1.240	1–5	-0.049	-0.956

Skewness values are slightly negative (from about −0.224 to −0.034). The values of excess kurtosis are also negative, and vary between approximately -0.993 and -0.657. These statistics refer to relatively large response distributions on the range of the bounded agreement scale. The loadings themselves do not verify the validity of the constructs or structural model; this is done via the measurement assessments and bootstrap inference (Lawrence Damilare Oyeniyi *et al.*, 2024). They do not add anything to the analysis other than record the empirical distribution of responses that enter the analysis.

Indicator Reliability

Outer loadings evidence each indicator is linked to the construct intended. The adoption loadings vary from 0.813 to 0.854, automation loading from 0.823 to 0.863,

Table 4: Indicator reliability

Construct	Item	Outer loading	Squared loading
AIA	AIA1	0.813	0.661
AIA	AIA2	0.827	0.684
AIA	AIA3	0.817	0.667
AIA	AIA4	0.854	0.729
AIA	AIA5	0.813	0.661
APA	APA1	0.843	0.711
APA	APA2	0.863	0.745

APA	APA3	0.841	0.708
APA	APA4	0.845	0.715
APA	APA5	0.823	0.677
FRQ	FRQ1	0.836	0.699
FRQ	FRQ2	0.865	0.748
FRQ	FRQ3	0.832	0.692
FRQ	FRQ4	0.864	0.747
FRQ	FRQ5	0.854	0.730

and the reporting quality loadings from 0.832 to 0.865. All loadings are higher than the given value of 0.708. The squared association loadings corresponding to each of the constructs span from about 0.661 to 0.748, demonstrating that each of the constructs explains more than 50% of the variance in each of its respective indicators.

Internal Consistency and Convergent Validity

The reliability and convergent validity results are shown in Table 5. The Cronbach's alpha values are 0.883 (AI Adoption), 0.898 (Automation), and 0.904 (Reporting Quality). The corresponding rho_A values are 0.886, 0.900, and 0.905. Composite reliability values are 0.914, 0.925, and 0.929. This consistency across measures lends internal consistency to each five-item scale and convergent evidence that the indicators measure what they are supposed to measure.

The CVEs of the three factors are 0.680 for adoption, 0.711 for automation and 0.723 for reporting quality. The values are all above 0.50 suggesting that a large percentage of the indicators' variance is accounted for in the construct. The results relate the conceptual measurement design with the empirical performance of measurement. Adoption has multiple representations of present/unestablished adoption of AI; automation has multiple representations of present/unestablished automation of task; and reporting quality has several assessments of reliable financial information. These findings suggest that it is reasonable to move on to the evaluation of the relations between these separate constructs.

Table 5 : Internal consistency and convergent validity

Construct	Alpha	rho_A	CR	AVE
AIA	0.883	0.886	0.914	0.680
APA	0.898	0.900	0.925	0.711
FRQ	0.904	0.905	0.929	0.723

Discriminant Validity and Structural Collinearity

Table 6 reports the results of the discriminant validity. The HTMT value from between the adoption and automation is 0.532 with a 95% CI of 0.446 to 0.613. The value for the adoption-reporting quality is 0.478 (0.387-0.565). The interval between automation and reporting quality is 0.579-0.721 with a value of 0.653. All point estimates and upper confidence limits are <0.85 and separation is empirical under the condition specified.

Table 6: Discriminant validity

Construct pair	HTMT	95% CI lower	95% CI upper
AIA–APA	0.532	0.446	0.613
AIA–FRQ	0.478	0.387	0.565
APA–FRQ	0.653	0.579	0.721

SVIFs for the adoption-automation relationship and each of its two predictors of reporting quality are 1.000 and 1.295, respectively. Both of these values are well below the criterion of three that was used in this study. The results show that there is no significant collinearity between the predictors in this model as a result of the combined effect of both adoption and automation. Thus, their independent effects can be considered as separate conditional relationships within the defined structural relationships (Nasra Saif Ahmed Al-Arfia *et al.*, 2026).

Table 7: Structural model collinearity

Predictor	Outcome	Inner VIF
AIA	APA	1.000
AIA	FRQ	1.295
APA	FRQ	1.295

Direct Relationships and Hypothesis Testing

The Direct path results are shown in table 8. A positive and significant relationship was found between the two variables of AI adoption and accounting process automation (β = 0.478, t = 12.382, 0.402 < β < 0.553). The findings corroborate H1. The higher the adoption, the higher the automation in the model in standardised terms. The coefficient supports the assumption that already existing AI application is related to accounting task organization towards more automation.

Similarly, the path between automation and reporting quality is positive and significant (β = 0.500, t = 11.823, p value = 0.414 – 0.580). Thus, H2 is considered to be supported. Automation shows a larger standardised coefficient than the other direct predictor of reporting quality. This discovery positions process execution at the heart of the reporting-quality explanation: organisations that are evaluated as more automated are also evaluated as producing more dependable and faithful financial information conditional on the amount of AI usage in the model.

Table 8: Direct relationships and hypothesis testing

Path	β	SE	t	p	95% CI	Decision
H1 AIA → APA	0.478	0.039	12.382	< .001	0.402–0.553	Supported
H2 APA → FRQ	0.500	0.042	11.823	< .001	0.414–0.580	Supported
H3 AIA → FRQ	0.189	0.045	4.199	< .001	0.104–0.280	Supported

The direct link of the adoption of AI on financial reporting quality remains positive even after controlling for automation (β = 0.189, t = 4.199, and confidence interval 0.104 - 0.280). The findings are in line with H3. It is less than the automation coefficient, but more than 0 is still within its confidence interval. This finding suggests that the linkage between adoption and quality of the reports is not fully captured by the "automation pathway. There are other methods of analysis or review that are based on AI and offer a viable conceptual reading of the relationship that remains, but those activities are not estimated separately.

The three emphasized direct routes create a pattern. There is a correlation between automation and adoption, automation and reporting quality, and adoption itself and reporting quality. These coefficients are conditional relationships of the estimated survey model. Their



Figure 2: Structural model with standardised coefficients and explained variance

substantive interpretation is focused on the differences between the professional judgments in the observations made, not the percentage change in accounting accuracy or the amount of financial misstatements measured. Leaving them as separate entities enables them to be used to guide the organisation's action without them being given an operational meaning they do not deserve (Beryl Odonkor *et al.*, 2024).

Explained Variance and Effect Sizes

It accounts for 22.8% of the variance in accounting process automation and 37.6% of the variance in financial reporting quality. The adjusted R^2 values are 0.226 and 0.373 respectively. When R^2 and adjusted R^2 are similar, the results of the explanation are not likely to change significantly when the number of predictors is considered. The explained variance for automation is due to one (only) adoption predictor. When it comes to reporting quality it signifies a combination of adoption and automation.

Effect sizes help to understand the unique contribution of the individual relationships. The f2 value for the adoption to predict automation is 0.295 and the value of automation to predict reporting quality is 0.308.

Table 9: Explained variance

Outcome	Predictors	R^2	Adjusted R^2
APA	1	0.228	0.226
FRQ	2	0.376	0.373

Both the provided results classify them both as medium. The Direct adoption-to-reporting-quality effect is small with an f2 value of 0.044. The results support the path-coefficient pattern as they indicate automation has a stronger influence on explaining reporting quality than the remaining direct adoption relationship.

Effect sizes help to understand the unique contribution of the individual relationships. The f2 value for the adoption to predict automation is 0.295 and the value of automation to predict reporting quality is 0.308. Both the provided results classify them both as medium. The Direct adoption-to-reporting-quality effect is small with an f2 value of 0.044. The results support the path-coefficient pattern as they indicate automation has a stronger influence on explaining reporting quality than the remaining direct adoption relationship.

Table 10: Structural effect sizes

Relationship	f^2	Interpretation
AIA → APA	0.295	Medium
APA → FRQ	0.308	Medium
AIA → FRQ	0.044	Small

Mediation Analysis

The specific indirect effect from AI adoption to reporting quality via automation is 0.239. The standard error is 0.028, the t value is 8.550 and the 95% confidence interval is 0.188 - 0.296. The interval is not closed at zero and is in favor of H4. The finding aligns with a positive process path in which the use of AI is positively linked to the use of accounting automation, and the use of accounting automation is positively associated with the perceived reporting quality.

Table 11: Mediation and total effect

Effect	β	SE	t	p	95% CI
Specific indirect effect	0.239	0.028	8.550	< .001	0.188–0.296
Direct effect	0.189	0.045	4.199	< .001	0.104–0.280
Total effect	0.428	0.041	10.327	< .001	0.348–0.509

Note: The specific indirect effect follows AIA → APA → FRQ. The direct effect follows AIA → FRQ. The total effect is their sum. All bootstrap assessments use 10,000 valid resamples; p values are normal approximations.

The total effect is 0.428, with a confidence interval of 0.348–0.509. The indirect component is even bigger than its direct component, which is 0.189. A rough approximation of the indirect fraction of the total effect is obtained by dividing the estimated indirect effect by the total effect, resulting in approximately 55.8%, with the direct effect accounting for approximately 44.2%. This decomposition provides an indication of the relative influences of the estimated paths. It is not an indicator of the reporting quality due to automation and nor is it an indicator of the percentage of all reporting outcomes in the organisation that are explained by the use of AI (Peng *et al.*, 2023).

The direct and indirect paths are positive and significantly different from zero so this mediation pattern is that of a complementary partial mediation. The direct relationship is complemented by an important role of automation in the adoption–quality relationship. This outcome provides the model with substantive meaning, beyond the paths themselves. It recognises process automation as a meaningful channel between technology adoption and reporting assessments and retains the contribution that is not being captured by that channel, associated with the use of AI.

Predictive Assessment

The Q^2predict values of all the ten endogenous indicators are positive. The range for accounting process automation values are between 0.135 and 0.182. Their grades for financial reporting quality are between 0.101 and 0.147. For all indicators evaluated, these results are showing improvement relative to the mean-based prediction benchmark. They offer information that anticipates the explanatory assessment and helps to support the confidence intervals reported for the structural relationships.

Lower PLS root mean squared error than linear model benchmark is found for four of five automation indicators, and for all five reporting quality indicators. The difference between the two is about 0.0013 and thus APA1 has a slightly higher PLS error. On that comparison nine of the ten indicators favour PLS. The level of the error differences is generally not high, and the predictive interpretation is based on the direction of the benchmark comparison trend rather than size of the error and therefore not interpreted as a significant practical forecasting gain (Adnan *et al.*, 2024).

M.A.E provides an alternative perspective on prediction performance. The PLS estimates reveal less error, in absolute terms, for eight of the ten indicators, with APA5 and FRQ2 preferring the linear benchmark. The two error measures thus offer a differentiated picture of the predictive performance (Peng *et al.*, 2023). Overall, the results provided support predictive relevance for

Table 12: Predictive assessment

Item	Q^2predict	PLS RMSE	LM RMSE	PLS MAE	LM MAE
APA1	0.155	1.117	1.116	0.914	0.919
APA2	0.182	1.117	1.122	0.936	0.939
APA3	0.142	1.150	1.161	0.948	0.956
APA4	0.135	1.112	1.118	0.929	0.939
APA5	0.170	1.086	1.090	0.907	0.906
FRQ1	0.101	1.143	1.153	0.952	0.968
FRQ2	0.125	1.141	1.142	0.953	0.949
FRQ3	0.135	1.143	1.151	0.969	0.976
FRQ4	0.147	1.152	1.162	0.954	0.962
FRQ5	0.128	1.160	1.169	0.958	0.967

the endogenous indicators and the model appeared to perform relatively competitively against the linear benchmark. This evaluation will still be limited to the indicators measured in the survey.

Integrated Discussion and Organisational Implications

The key finding is that there is a substantial intermediate position between AI adoption and financial reporting quality that is accounting process automation. The direct adoption association is statistically supported, however, the automation association is larger and the indirect pathway accounts for greater than half of the estimated total adoption association. The evidence thus points to an organisational explanation where the relevance of the reporting of AI, partially, relies on how technology is integrated into the daily accounting execution.

The results indicate that the focus of managerial evaluation can be the interconnection between applications and work flows. Prior to scaling an AI application, managers can determine points and people in the accounting process where the AI output is needed, and how items that need further review get to the reporting team. A classification tool for instance gives best results if proposed classifications can also connect with agreed upon accounting rules and a suitable review process. These implementation considerations map the process focus in the model to actual organisational decisions and do not assume that the survey actually operated in a certain software configuration.

Another implication that is relevant is called source-data governance. The rules and information available for automated processing will determine its operation. Organisations can facilitate reliable accounting by providing for the accountability of master data, by controlling interfaces and by keeping supporting information traceable to documented transactions. These arrangements have a special significance in the context of automatic handling of information. They are to maintain the linkage between the source event, the accounting treatment, and the final report, that is encapsulated in the reporting-quality scale (Al-Shanti *et al.*, 2024).

The respondent profile also provides a real foundation on which to focus attention on staff capability. There is a high proportion of informal or no training reported and lower levels of formal learning. Responses to this that organisations can make would include role-specific development to include system outputs, exception assessment, documentation and accounting judgement. Staff needs to be trained to identify when an application can be used to do routine work and when it is a matter that needs further consideration. It can be assessed using actual work practices that show competencies rather than attendance only.

CONCLUSION

This research investigates the mechanisms by which AI aids financial reporting quality to the extent that AI is adopted by the accounting process automation. The results of the 360 returned questionnaires confirmed the reliability and validity of the three reflective constructs and evidence for all four hypotheses. Thus, there is a positive relationship between the use of AI and automation, and between automation and reporting quality; and a smaller positive direct association is observed between the use of AI and reporting quality once the mediator is present. The main result of the mediation is the central, concluding statement. The indirect effect is 0.239, the direct effect is 0.189 and the total effect is 0.428. They both have positive common direction and statistical support, which means they are complementary partial mediation. Hence, accounting process automation is an essential explanation for the relationship between the perceived reporting quality and use of the established AI. This model accounts for 22.8% of the variability in automation and 37.6% of the variability in reporting quality and has a positive Q^2predict for all the endogenous indicators.

Organisations must link AI investment decisions to well-defined accounting processes. Implementation plans should identify the tasks to be supported, as well as the information needed and the outputs to be produced and who would review and approve. Priority might be given to activities where there is regular information handling and routine checking which provides a clear opportunity for

consistent execution. The goal should be to put in place reliable procedures for providing financial information from adopted applications.

The accounting manager should have a methodical approach to handling exceptions and have automated workflows that are traceable. Any unresolved differences, unusual entries and uncertain classifications are due to be reported to responsible persons via set up review channels. Documentation of sources, processing decisions, corrections and approvals should be available for report checking. These practices facilitate the links between automaticity and the accuracy, reliability and consistency with evidence of the reporting quality construct.

Process integration should go hand in hand with staff development. The training could be on how to interpret AI-supported outputs, how to assess exceptions, making accounting judgements and when extra judgement is needed. Process and reporting measures, such as completion of the reconciliation, exceptions, corrections and consistency of reports with supporting records, should also be monitored as measures of transformation. These are recommended management measures and not outcomes separately estimated in this study.

The results highlight how the accounting process is at the heart of the organisational value of AI. The reporting quality association is larger with established use and mediated reporting than it is with direct reporting, with the mediated reporting association accounting for larger estimates of the total association. A coordinated strategy across its use of applications, its workflow design, information governance and professional accountability can give it a practical direction as organisations seek to increase the reliability of their financial reporting.

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