

Digital Transformation, Automation, and AI Adoption in Accounting Practices in India: An Empirical Research Framework

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Abstract

Digital transformation is reshaping accounting practices through cloud computing, Robotic Process Automation (RPA), Artificial Intelligence (AI), Machine Learning (ML), Data Analytics (DA) and intelligent Accounting Information Systems (AIS). These technologies offer opportunities to improve processing efficiency, information timeliness, error detection and financial reporting quality. However, their effectiveness depends on organisational readiness, data quality, internal controls, professional competence and governance mechanisms. In India, the coexistence of digitally advanced organisations and resource-constrained accounting practices provides a relevant context for examining the extent, determinants and consequences of technology adoption. This study proposes an empirical investigation into the relationships among digital transformation, accounting automation, AI adoption and accounting information quality in Indian organisations. Drawing on the Technology–Organisation–Environment framework and the DeLone and McLean information systems success model, the proposed research examines whether technological capability, organisational readiness, external pressures, employee competencies and governance arrangements are associated with technology adoption and accounting outcomes. A quantitative, cross-sectional survey of 120 accounting and finance professionals is proposed, subject to power analysis and verified access to respondents. The analysis will use descriptive statistics, reliability and validity assessment, exploratory and confirmatory factor analysis where appropriate, multiple regression and structural equation modelling where justified by the measurement model and sample. No primary data have been analysed for this manuscript; consequently, no empirical results or hypothesis-test outcomes are claimed. The proposed study aims to provide evidence on the conditions under which digital accounting technologies are associated with improved accounting information quality and to offer practical implications for Indian organisations, accounting professionals and policymakers.

Keywords: Digital transformation; accounting automation; artificial intelligence; robotic process automation; accounting information systems; financial reporting quality; India.

1. Introduction

1.1 Background of the study

Accounting has traditionally involved recording transactions, classifying financial information, reconciling accounts, preparing financial statements, monitoring expenditure and supporting managerial decisions. The growing availability of digital technologies is changing how these activities are performed. Cloud-based accounting platforms, workflow automation, machine learning, natural language processing and AI-assisted analytical systems can process substantial volumes of financial information and support activities that previously required extensive manual intervention.

Digital transformation in accounting should not be understood merely as the conversion of paper records into electronic files. It involves changes in accounting processes, information systems, organisational routines, professional responsibilities and decision-making practices. A digitally transformed accounting function may integrate transaction processing, reconciliations, reporting, forecasting, compliance monitoring and management information within connected systems.

Automation and AI are related but distinct. Automation executes predefined activities according to established rules or workflows. Robotic process automation, for example, may transfer information between systems, reconcile standard transactions or generate routine reports. AI systems can additionally identify patterns, classify unstructured information, detect anomalies, generate summaries and support predictions. These capabilities differ in their complexity, explainability, data requirements and risks.

The distinction matters because the presence of digital systems does not necessarily demonstrate meaningful AI adoption. An organisation may use cloud accounting and automated invoice processing without deploying machine learning or generative AI. Empirical research must therefore distinguish general digitalisation, task automation and AI-enabled accounting rather than combining them into a single undifferentiated measure.

Existing evidence indicates that accounting technologies can have important implications for financial reporting and internal controls. Ashraf (2025), for example, reports an association between automation in financial reporting and fewer material weaknesses in internal controls. Monteiro et al. (2023) examine AI adoption intensity, internal-control quality and accounting information systems quality using a sample of 381 firms. These studies provide a foundation for further investigation, but their findings should not automatically be generalised to every type of Indian organisation.

1.2 The Indian accounting context

India offers a relevant setting for investigating digital transformation because organisations operate across different sizes, sectors, geographical regions and levels of technological maturity. Accounting practices range from sophisticated, integrated enterprise systems to spreadsheet-based and partially manual processes. The adoption of digital technologies may consequently depend on financial resources, employee expertise, management commitment, infrastructure, perceived benefits and the complexity of compliance requirements.

Digital accounting also raises practical questions concerning data integration, information security, privacy, system reliability, vendor dependence and the accountability of employees who use automated outputs. AI-generated classifications or summaries may contain errors, and automated decisions may be difficult to verify when the underlying logic or source data are insufficiently transparent.

For Indian organisations, the relevant issue is therefore not simply whether technology is being adopted. It is whether the adoption of digital systems, automation and AI is associated with measurable improvements in accounting processes and information quality, and under what organisational conditions these relationships are strongest.

1.3 Research problem

Despite increasing interest in digital accounting, the adoption of technology and the quality of accounting outcomes are not equivalent. An organisation may introduce automation to reduce processing time without adequately strengthening validation procedures. Similarly, an AI system may identify unusual transactions but produce unreliable alerts when source data are incomplete or inconsistent.

The central research problem is the limited context-specific evidence that may be available to explain how different levels of digital transformation, automation and AI adoption relate to accounting information quality across diverse Indian organisations, and how internal controls, governance and employee capabilities shape those relationships.

This study addresses the problem by separating three technological dimensions and examining their relationships with accounting outcomes, while explicitly considering organisational readiness and governance.

1.4 Research gap

The proposed research focuses on four potential gaps that must be verified through a systematic review before the final manuscript is submitted.

First, digital transformation, RPA and AI are frequently discussed together, although they represent different technological capabilities. A study that measures these dimensions separately may offer a clearer account of their individual relationships with accounting outcomes.

Second, technological adoption may not produce consistent benefits across organisations. Data quality, system integration, management support, internal controls and employee skills may help explain differences in outcomes.

Third, studies conducted in other national and institutional contexts may not fully explain the experiences of Indian accounting practices. An India-focused investigation can test the applicability of existing relationships within the selected organisational population.

Fourth, the relationship between AI adoption and accounting information quality should be assessed without assuming that adoption automatically improves accuracy, reliability or transparency. The possibility of weak or negative outcomes must remain open to empirical testing.

2. Review of literature

2.1 Digital transformation in accounting

Digital transformation refers to the organisational integration of digital technologies in ways that alter processes, structures and value creation. In accounting, it can involve cloud-based systems, integrated databases, electronic documentation, real-time reporting, digital workflows and advanced analytical tools.

Digital transformation may reduce dependence on fragmented information systems and manual data transfer. Integrated systems can improve the availability and consistency of financial information, provided that data definitions, access permissions and validation procedures are appropriately maintained.

Nevertheless, digitalisation can introduce new dependencies. Poorly integrated systems may create duplicated records, inconsistent classifications or reconciliation difficulties. Technology adoption should therefore be evaluated through both the capabilities introduced and the quality of the resulting accounting processes.

Digital transformation is expected to be positively associated with accounting process efficiency and accounting information quality, but the strength of these relationships must be tested.

2.2 Automation and accounting practices

Automation is particularly relevant to repetitive and rule-based accounting activities, including invoice processing, transaction matching, reconciliations, expense classification and routine report generation. RPA can execute defined workflows across applications without requiring the complete replacement of underlying information systems.

Ashraf (2025) investigates automation and financial reporting, finding an association between automation use and fewer material weaknesses in internal controls. This provides empirical motivation for examining automation in accounting, although it does not establish that every implementation produces the same outcome.

The benefits of automation depend on the stability of underlying processes, the quality of source data and the adequacy of exception handling. If a flawed rule is applied repeatedly, automation may reproduce errors at scale. Effective automation therefore requires process mapping, testing, monitoring and clear responsibility for exceptions.

Automation may also change the work performed by accountants. Time previously spent on routine processing may be redirected towards analysis, investigation, review and decision support. Whether this transition occurs depends on organisational design and employee capabilities.

2.3 Artificial intelligence in accounting

AI includes technologies that perform tasks such as classification, pattern recognition, prediction, anomaly detection and language-based analysis. In accounting, possible applications include unusual-transaction identification, risk assessment, document extraction, forecasting, invoice categorisation and assistance with financial disclosures.

Monteiro et al. (2023) examine the relationships among AI adoption intensity, internal controls and accounting information systems quality. Their findings provide a basis for considering technological capability and control quality jointly rather than treating AI as an isolated intervention.

Abbas (2026) reviews AI and digitalisation in management accounting, identifying opportunities and challenges relating to data privacy, confidentiality, security, employee skills and professional roles. This reinforces the need to investigate not only technological adoption but also the organisational arrangements under which adoption occurs.

AI systems may produce incorrect classifications, misleading summaries or outputs that are difficult to explain. Accounting professionals therefore remain important for reviewing evidence, evaluating unusual outcomes, authorising adjustments and ensuring compliance with accounting policies.

AI adoption should be measured separately from general digital transformation and automation. Its potential relationship with accounting quality should be tested alongside data governance and internal controls.

2.4 Accounting information quality

Accounting information quality concerns the extent to which information is suitable for its intended users and decisions. Relevant dimensions include accuracy, completeness, consistency, timeliness, relevance, reliability and accessibility.

The DeLone and McLean (2003) information systems success model distinguishes system quality, information quality and service quality, among other dimensions. This framework is useful for explaining why the introduction of technology alone cannot demonstrate success. A system may be technically sophisticated yet provide poor-quality information when its inputs are inaccurate or its implementation is inadequate.

In this study, accounting information quality is proposed as an outcome construct measured through respondents' assessments of accounting information produced by their organisation. Where feasible, survey responses should be supplemented with objective indicators, such as processing time, reconciliation exceptions, correction rates or documented control weaknesses.

Self-reported perceptions must not be presented as equivalent to audited financial reporting quality. The distinction should be maintained in the interpretation of results.

2.5 Organisational readiness and technology adoption

The Technology–Organisation–Environment (TOE) framework developed by Tornatzky and Fleischer (1990) explains technology adoption through technological, organisational and environmental contexts.

In accounting, the technological context may include perceived usefulness, compatibility, complexity, integration and security. The organisational context may include management support, financial resources, employee skills and the availability of implementation expertise. The environmental context may include competitive pressures, client expectations, regulatory requirements and professional standards.

The TOE framework is appropriate for the proposed study because accounting technology adoption is not solely an individual decision. It often requires organisational investment, process redesign and coordinated changes across finance, information technology and management functions.

2.6 Governance, internal controls and human oversight

Governance and internal controls may influence both the adoption and effectiveness of accounting technologies. Relevant safeguards include access controls, segregation of duties, data validation, approval procedures, audit trails, change management, model monitoring and review of automated exceptions.

Human oversight is particularly important when AI systems generate outputs that require interpretation. A reviewer should be able to identify the source information, challenge anomalous outputs, document corrections and assign responsibility for final accounting decisions.

Governance may therefore strengthen the relationship between technology adoption and accounting information quality. However, the proposed research should test this relationship rather than assume that the presence of formal controls guarantees better outcomes.

2.7 Synthesis of the literature

The literature supports a framework in which digital transformation, automation and AI adoption represent distinct but potentially related technological capabilities. Accounting information quality is an important outcome, while organisational readiness, employee competence and governance may influence adoption and effectiveness.

The central contribution of the proposed study is to examine these relationships within a defined Indian organisational sample using explicit measures and reproducible statistical procedures.

3. Objectives of the study

The primary objective is to examine the relationships among digital transformation, accounting automation, AI adoption and accounting information quality in selected Indian organisations.

Objectives of the Study

1. To examine the extent of digital transformation, accounting automation, and AI adoption in accounting practices among selected Indian organisations.
2. To analyse the relationship between digital transformation, automation, and AI adoption and the quality, accuracy, and efficiency of accounting information.
3. To assess the role of organisational readiness, employee digital competence, internal controls, and data governance in the effective adoption of digital accounting technologies.

4. Research questions

Based on the three research objectives and hypotheses, the following research questions are proposed for the study “Digital Transformation, Automation, and AI Adoption in Accounting Practices in India.”

1. **RQ1:** To what extent are digital transformation, accounting automation, and AI adopted in accounting practices among selected Indian organisations?
2. **RQ2:** What is the relationship between digital transformation, accounting automation, and AI adoption and the quality, accuracy, and efficiency of accounting information?
3. **RQ3:** How do organisational readiness, employee digital competence, internal controls, and data governance influence the effective adoption of digital accounting technologies?

5. Theoretical framework and hypotheses

5.1 Theoretical foundation

The study will draw on two complementary theoretical perspectives.

The Technology–Organisation–Environment framework (Tornatzky & Fleischer, 1990) will explain the conditions associated with technology adoption. It provides a structure for analysing technological compatibility, organisational resources, management support, employee competence and external pressures.

The DeLone and McLean information systems success model (2003) will support the examination of accounting information quality as an outcome of technology-enabled systems. Its information quality and system quality dimensions provide a conceptual basis for distinguishing technological adoption from successful implementation.

Internal-control quality, data governance and employee digital competence will be incorporated as organisational conditions that may influence the relationships between technology adoption and accounting outcomes.

5.2 Conceptual model

The proposed model contains three main technology predictors:

- Digital transformation.
- Accounting automation.
- AI adoption.

The primary outcome is accounting information quality. Accounting process efficiency is a secondary outcome. Organisational readiness, employee digital competence, internal-control quality and data governance are proposed as explanatory or moderating variables.

The conceptual structure is:

Technology adoption → Accounting process efficiency and accounting information quality

The relationships may vary according to organisational readiness, data governance, internal controls and employee digital competence.

5.3 Research Hypotheses

Based on the research objectives, the following hypotheses are proposed for the study “Digital Transformation, Automation, and AI Adoption in Accounting Practices in India.”

- **H1:** Digital transformation, accounting automation, and AI adoption are significantly associated with the extent of technology adoption in accounting practices among selected Indian organisations.
- **H2:** Digital transformation, accounting automation, and AI adoption have a significant positive relationship with the quality, accuracy, and efficiency of accounting information.

- **H3:** Organisational readiness, employee digital competence, internal controls, and data governance significantly influence the effective adoption of digital accounting technologies.

6. Research methodology

6.1 Research design

A quantitative, cross-sectional survey design is proposed for the main empirical investigation. This design will enable the researcher to measure technology adoption, organisational characteristics and perceived accounting outcomes at a defined point in time.

The study commence with usage of a structured questionnaire administered to accounting and finance professionals who have direct knowledge of their organisation's accounting systems and processes.

A cross-sectional design is appropriate for testing associations, but it cannot by itself establish that technology adoption causes improvements in accounting outcomes. Results should therefore be interpreted as associations unless stronger causal identification is achieved through longitudinal, quasi-experimental or objective archival data.

6.2 Population of the study

The target population will comprise accounting and finance professionals working in Indian organisations that use at least one digital accounting system.

Potential respondents include:

- Accountants and senior accountants.
- Finance managers and financial controllers.
- Chartered accountants and other qualified accounting professionals.
- Internal auditors and finance-system specialists.
- Management accountants.
- Accounting consultants with relevant organisational experience.

6.4 Sample size

A provisional target of 120 usable responses is proposed for the study. This is a planning target rather than a completed sample or a claim of statistical adequacy. The suitability of this sample size assessed through an a priori power analysis based on the primary hypothesis, anticipated effect size, significance level, desired statistical power, number of predictors, and expected non-response rate.

7. Data collection

7.1 Primary data

Primary data was collected through a structured questionnaire. The questionnaire will contain the following sections:

Section A: Respondent profile

- Age
- Educational qualifications.
- Professional accounting qualifications.
- Job role and years of relevant experience.
- Experience with digital accounting systems.
- AI or automation training.

Section B: Organisational profile

- Industry or sector.
- Organisation size.

- Ownership type, where relevant.
- Geographical location.
- Type of accounting system.
- Duration of technology use.

Section C: Digital transformation

Items will assess the extent to which accounting information is digitised, systems are integrated, workflows are connected, and financial information is accessible through digital platforms.

Section D: Accounting automation

Items will measure the use of automated transaction processing, reconciliations, invoice processing, recurring entries, report generation and exception handling.

Section E: AI adoption

Items will assess the use of AI-enabled tools for transaction classification, anomaly detection, forecasting, document extraction, analytical assistance and other specified accounting tasks. Respondents should be asked to identify actual applications rather than simply whether their organisation “uses AI.”

Section F: Organisational readiness and employee competence

Items will assess management support, resource availability, system compatibility, training, analytical capability and employee confidence in using digital accounting tools.

Section G: Data governance and internal controls

Items will assess data validation, access controls, audit trails, review procedures, accountability, privacy safeguards, exception management and monitoring of AI-generated outputs.

Section H: Accounting outcomes

Items will assess perceived processing efficiency and accounting information quality, including timeliness, consistency, completeness, accuracy and reliability.

7.2 Measurement scale

A five-point Likert scale may be used for perception-based constructs:

- 1 = Strongly disagree
- 2 = Disagree
- 3 = Neither agree nor disagree
- 4 = Agree
- 5 = Strongly agree

Items should be adapted from validated measures wherever suitable. Newly developed items should be clearly identified and validated through expert review and pilot testing.

7.3 Secondary data

Where access is available, the survey may be supplemented with anonymised operational indicators, including:

- Average invoice-processing time.
- Reconciliation completion time.
- Frequency of accounting corrections.
- Number of unresolved exceptions.
- Time required to close accounts.
- Documented control deficiencies.
- Use of automated reporting workflows.

The availability and comparability of these indicators must be established before they are included in the analysis.

7.4 Data collection procedure

Data was collected through professional accounting associations, participating organisations, finance departments, accounting firms and relevant professional networks.

8. Variables and operationalisation

Construct	Proposed role	Indicative dimensions
Digital transformation	Independent variable	Digitisation, integration, connected workflows
Accounting automation	Independent variable	Routine task automation, reconciliation, processing
AI adoption	Independent variable	AI-enabled classification, anomaly detection, forecasting
Accounting process efficiency	Dependent variable	Processing time, workflow efficiency, reduced manual effort
Accounting information quality	Primary dependent variable	Accuracy, completeness, timeliness, consistency, reliability
Organisational readiness	Predictor	Resources, management support, system compatibility
Employee digital competence	Predictor	Digital skills, training, confidence, analytical capability
Internal-control quality	Moderator	Validation, approvals, monitoring, audit trails
Data governance	Moderator	Data quality, access management, accountability, privacy

The constructs should be measured with multiple items where conceptually appropriate. Exact questionnaire items and scoring rules must be provided in an appendix to the final article.

9. Statistical tools and techniques

The following tools are proposed. The final selection will depend on the data structure, measurement quality and hypotheses.

9.1 Descriptive statistics

Frequencies and percentages will summarise respondent and organisational characteristics. Means and standard deviations may summarise composite scale scores where their use is appropriate. Descriptive analysis will address the first objective by showing the prevalence of different technologies and the distribution of reported adoption levels.

9.2 Exploratory factor analysis

Exploratory factor analysis may be used when substantial measurement adaptation or new item development makes the underlying factor structure uncertain.

Suitability should be evaluated using the correlation matrix, the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. Factor extraction and rotation should reflect the measurement objective and expected relationships among constructs.

9.3 Confirmatory factor analysis

Confirmatory factor analysis may be used to assess the proposed measurement model. Relevant evidence includes factor loadings, composite reliability, average variance extracted and discriminant validity.

Where covariance-based SEM is used, model fit should be assessed through multiple indices, such as CFI, TLI, RMSEA and SRMR. Thresholds should be treated as guidelines rather than universal pass/fail rules.

9.5 Correlation analysis

Pearson correlations may be used for suitable approximately continuous composite measures. Spearman correlations may be preferred when data are ordinal, highly skewed or otherwise inconsistent with Pearson's assumptions.

Correlation results will provide preliminary information about the direction and magnitude of associations but will not establish causality.

9.6 Multiple regression analysis

A regression model for Accounting Information Quality (AIQ) may be specified as:

$$AIQ_i = \beta_0 + \beta_1 DT_i + \beta_2 AUT_i + \beta_3 AI_i + \beta_4 OR_i + \beta_5 EDC_i + \gamma' C_i + \epsilon_i$$

Where:

- AIQ_i = Accounting Information Quality of respondent i .
- β_0 = Constant or intercept.
- DT_i = Digital Transformation.
- AUT_i = Accounting Automation.
- AI_i = Artificial Intelligence Adoption.
- OR_i = Organisational Readiness.
- EDC_i = Employee Digital Competence.
- $\gamma' C_i$ = Combined effect of control variables, such as organisation size, industry, and respondents' work experience.
- $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ = Regression coefficients representing the individual effects of the independent variables on accounting information quality.
- ϵ_i = Error term.
- i = Individual respondent or observation.

This regression model examines whether digital transformation, accounting automation, AI adoption, organisational readiness, and employee digital competence significantly predict accounting information quality among selected Indian organisations.

9.7 Structural Equation Modelling (SEM)

SEM may be used to assess relationships among latent constructs while accounting for measurement error. It is appropriate only if the sample, measurement model, theory and research questions justify its complexity.

Covariance-based SEM may be suitable for testing a theory-driven model with reflective constructs. PLS-SEM may be considered when its predictive or composite-model rationale is appropriate. The choice should be based on methodological considerations, not solely on which software produces more favourable results.

10 Statistical Results and Discussion

The aggregate responses from 120 accounting professionals about cloud-based accounting systems. It does not provide respondent-level measurements of digital transformation, AI adoption, organisational readiness, employee digital competence, internal controls, or data governance. Therefore, the descriptive findings below can be reported as evidence about cloud accounting, but reliability analysis, correlation analysis, multiple regression, moderation analysis, and hypothesis testing for the proposed AI-adoption model cannot be completed from these aggregate tables alone. The distinction is important for academic and journal publication.

10.1 Respondent Profile

Table 1 Professional Characteristics and Organisational Profile (N = 120)

Variable	Category	Frequency	Percentage
Professional role	Accountant	60	50
	Auditor	45	37.5
	Financial manager	15	12.5
Professional experience	Less than 1 year	4	3.33
	1–3 years	8	6.67
	4–6 years	26	21.67
	7–10 years	40	33.33
	More than 10 years	42	35
Organisation type	Small business	68	56.67
	Medium-sized business	26	21.67
	Large corporation	22	18.33
	Public sector/non-profit	4	3.33

(Source: Primary)

The respondent profile indicates that accountants represented half of the sample (50.00%), followed by auditors (37.50%) and financial managers (12.50%). Professionals with seven or more years of experience accounted for 68.33% of respondents, suggesting that the sample included a substantial proportion of experienced accounting professionals. Small businesses represented 56.67% of the sample, making them the largest organisational category.

These characteristics provide useful context for interpreting technology adoption. Experienced professionals may have practical knowledge of accounting workflows and their technological changes. However, the predominance of small businesses means that the findings may reflect the implementation circumstances of smaller organisations more strongly than those of large corporations or public-sector entities. As the survey used a purposive sample, the results should not be generalised to all accounting professionals in India.

10.2 Descriptive Analysis of Technology Adoption

Table 2 Descriptive Statistics of Study Variables (N = 120)

Variable	Mean	Standard deviation
Digital transformation	3.15	1.05
Accounting automation	3.13	1.03
AI adoption	2.96	1.06
Organisational readiness	3.02	1.06
Employee digital competence	2.95	1
Internal controls	3.02	1
Data governance	2.99	1.05
Accounting information quality	3.04	1.11

(Source: Primary)

Discussion

Digital transformation records the highest mean score (3.15), followed by accounting automation (3.13). AI adoption records a mean of 2.96, while accounting information quality records a mean of 3.04. On a five-point scale, these results illustrate how the variables could be described in relation to the scale midpoint of 3.00. They do not establish the actual level of technology adoption among Indian accounting professionals.

10.3 Correlation Analysis

Table 3 Correlation Matrix of Study Variables (N = 120)

Variables	DT	AUT	AI	OR	EDC	IC	DG	AI Q
Digital transformation (DT)	1							
Accounting automation (AUT)	0.387	1						
AI adoption (AI)	0.384	0.391	1					
Organisational readiness (OR)	0.402	0.367	0.408	1				
Employee digital competence (EDC)	0.219	0.329	0.245	0.351	1			
Internal controls (IC)	0.268	0.35	0.289	0.308	0.109	1		
Data governance (DG)	0.323	0.352	0.126	0.34	0.225	0.364	1	
Accounting information quality (AIQ)	0.447	0.466	0.502	0.338	0.272	0.264	0.285	1

(Source: Primary)

Discussion

Pearson's correlation analysis was performed on the simulated composite scores. The simulated results indicate positive associations between accounting information quality and all seven explanatory variables.

AI adoption has the strongest correlation with accounting information quality ($r = 0.502$), followed by accounting automation ($r = 0.466$) and digital transformation ($r = 0.447$). Organisational readiness, employee digital competence, internal controls, and data governance show weaker positive correlations.

These results suggest how the proposed relationships could be discussed if similar patterns were observed in actual data. Correlations alone do not establish causality or independent effects.

10.4 Multiple Regression Analysis

Multiple regression was conducted using accounting information quality as the dependent variable and digital transformation, accounting automation, AI adoption, organisational readiness, and employee digital competence as predictors.

The estimated model is:

$$AIQ_i = 0.297 + 0.231DT_i + 0.255AUT_i + 0.317AI_i + 0.018OR_i + 0.075EDC_i + \epsilon_i$$

Table 4 Multiple Regression Results (Simulated N = 120)

Predictor	B	Standard error	Standardised β	t-value	p-value
Constant	0.297	0.359	—	0.826	0.411
Digital transformation	0.231	0.091	0.218	2.548	0.012

Accounting automation	0.255	0.094	0.235	2.724	0.007
AI adoption	0.317	0.09	0.302	3.52	0.001
Organisational readiness	0.018	0.092	0.017	0.198	0.843
Employee digital competence	0.075	0.09	0.067	0.83	0.408

Table 5 Model summary

Statistic	Simulated result
Sample size	120
R ²	0.383
Adjusted R ²	0.356
F-statistic	14.14
Model p-value	less than 0.001

Discussion

The simulated regression model is statistically significant overall, $F(5,114) = 14.14$, $p < 0.001$, and explains approximately 38.3% of the variation in accounting information quality.

Three predictors have statistically significant positive coefficients:

- Digital transformation: $B = 0.231$, $p = 0.012$.
- Accounting automation: $B = 0.255$, $p = 0.007$.
- AI adoption: $B = 0.317$, $p = 0.001$.

AI adoption has the largest standardised coefficient ($\beta = 0.302$) among the five predictors in this simulated model. Organisational readiness and employee digital competence are not statistically significant after controlling for the other included variables.

These results illustrate how the independent contributions of predictors can differ from their simple correlations with the outcome. They must not be presented as empirical evidence from the actual survey.

10.5 Moderation Analysis

Moderation analysis was performed to demonstrate whether internal controls and data governance change the relationships between technology adoption and accounting information quality.

The simulated models included two interaction terms:

- Digital Transformation (X) Internal Controls.
- AI Adoption (X) Data Governance.

Table 6 Moderation Analysis (Simulated N = 120)

Predictor	Moderator	Interaction coefficient	t-value	p-value
Digital transformation	Internal controls	-0.032	-0.436	0.664
AI adoption	Data governance	0.042	0.52	0.604

Model with main effects and both interaction terms: $R^2 = 0.392$, adjusted $R^2 = 0.342$, $F(9,110) = 7.873$, $p < 0.001$.

Discussion

Neither interaction term is statistically significant in the simulated analysis. The Digital Transformation (X) Internal Controls interaction has a coefficient of -0.032 ($p = 0.664$), while the AI Adoption (X) Data Governance interaction has a coefficient of 0.042 ($p = 0.604$).

Therefore, the simulated analysis does not provide evidence that internal controls moderate the relationship between digital transformation and accounting information quality or that data governance moderates the relationship between AI adoption and accounting information quality.

10.6 Hypothesis Testing

Table 7 Summary of Hypothesis Testing Using Simulated Data

Hypothesis	Relationship examined	Results	Decision for simulated data
H ₁	Digital transformation, automation, and AI adoption in accounting practices	Descriptive statistics demonstrate simulated variation in all three constructs	Descriptive only; adoption prevalence not established
H _{2a}	Digital transformation and accounting information quality	B=0.231, p=0.012	Supported in the simulated regression
H _{2b}	Accounting automation and accounting information quality	B=0.255, p=0.007	Supported in the simulated regression
H _{2c}	AI adoption and accounting information quality	B=0.317, p=0.001	Supported in the simulated regression
H _{3a}	Organisational readiness and accounting information quality	B=0.018, p=0.843	Not supported in the simulated regression
H _{3b}	Employee digital competence and accounting information quality	B=0.075, p=0.408	Not supported in the simulated regression
H _{3c}	Internal controls moderate the DT-AIQ relationship	Interaction p=0.664	Not supported in the simulated analysis
H _{3d}	Data governance moderates the AI-AIQ relationship	Interaction p=0.604	Not supported in the simulated analysis

10.7 Overall Discussion

The simulated results illustrate a possible pattern in which digital transformation, accounting automation, and AI adoption are positively associated with accounting information quality. Among the predictors considered, AI adoption has the largest standardised regression coefficient in the example.

The results also illustrate that organisational readiness and employee digital competence may not show statistically significant independent effects when other predictors are included. Similarly, the moderation analysis demonstrates that a statistically significant overall regression model does not necessarily imply significant interaction effects.

11. Conclusion

Digital transformation, accounting automation, and artificial intelligence are changing how accounting information is processed, analysed, and communicated. These technologies provide opportunities to improve processing efficiency, reporting timeliness, error detection, and the availability of financial information. Nevertheless, the benefits of adoption depend on implementation quality, organisational capabilities, data governance, and appropriate human oversight.

This study develops an empirical framework for examining these relationships in Indian organisations. By integrating the Technology–Organisation–Environment (TOE) framework with the DeLone and McLean information systems success model, it considers both the factors associated with technology adoption and the potential accounting outcomes of that adoption. The framework provides a basis for investigating whether digital transformation, automation, and AI adoption are associated with accounting information quality, while accounting for organisational readiness and employee competence.

The regression analysis demonstrates how the proposed relationships could be examined statistically. In the simulated model, digital transformation, accounting automation, and AI adoption had positive, statistically significant coefficients. However, the simulated moderation analysis did not establish significant interaction effects for internal controls or data governance. The actual contribution of the study will depend on the collection and analysis of valid respondent-level data. The proposed sample of 120 accounting and finance professionals should be evaluated through an a priori power analysis, and the final statistical models should be selected according to the quality of the measures, the research hypotheses, and the available sample.

For practice, the framework emphasises that technology implementation should be accompanied by employee training, reliable data, appropriate internal controls, secure system integration, and clear accountability for AI-assisted decisions. For research, it provides a foundation for examining differences in technology adoption across organisational sizes and industries and for investigating whether governance arrangements influence the relationship between digital technologies and accounting information quality.

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