



Artificial intelligence and its impact on accounting and financial decision-making: Evidence from Indian businesses

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Abstract

Artificial intelligence (AI) is increasingly used to process documents, detect unusual transactions, forecast cash flows and support financial risk assessment. These tools may help accounting teams reduce repetitive work and give managers faster access to useful information. This paper examines the relationship between AI adoption and accounting and financial decision-making in Indian businesses through a five-year review of HDFC Bank, ICICI Bank, State Bank of India (SBI) and Tata Consultancy Services (TCS). Company annual reports and official financial highlights provide actual profit-after-tax figures for FY 2020–21 to FY 2024–25. Because companies do not disclose a consistent, audited AI adoption index or comparable accounting-efficiency measure for every year, this paper does not invent an AI score. Instead, it analyses reported profit trends and discusses AI related disclosures as contextual evidence. Two hypotheses address changes in reported profit over time and the potential relationship between documented AI use and decision support. Descriptive trend analysis and a one-sample trend test are discussed, while the limits of causal interpretation are made explicit. Results show that reported profit rose over the period for all four selected companies, although the size and timing of changes differ. This pattern is consistent with business growth and changing market conditions, but it cannot be attributed to AI alone. The paper concludes that AI can strengthen financial work when introduced with reliable data, human oversight and measurable operational targets.

Keywords: Artificial intelligence, accounting, financial decision-making, Indian businesses, annual reports, financial performance, automation

Introduction

Accounting is more than entering figures into ledgers. It involves checking evidence, interpreting transactions, preparing statements and explaining what the numbers mean for an organisation. Finance teams also help managers decide how much cash to retain, where to invest, how to manage credit and which risks require attention. When transaction volumes rise, manual processing can slow reporting and leave less time for analysis. AI tools offer a way to automate routine tasks and highlight patterns that deserve professional review.

AI can be used to extract details from invoices, classify transactions, match payments, detect anomalies and prepare forecasts. In banking, possible applications include fraud alerts, credit-risk assessment and customer-service systems. In an IT services business, analytics may support project costing, contract review, resource planning and working-capital management. Generative AI can summarise documents or draft commentary, but it can also produce incorrect explanations, so outputs need verification.

India provides a useful setting for this discussion because businesses operate amid rapid digitalisation, expanding digital payments and rising expectations for timely financial information. Still, AI adoption is not the same as improved financial performance. Profit may change because of interest rates, credit costs, customer demand, business mix, mergers or general economic conditions. A credible study must therefore separate actual financial data from assumptions about the benefits of AI.

Review of Literature

Research and professional guidance generally identify automation, anomaly detection, predictive analytics and decision support as important AI applications in accounting and finance. These technologies can process large amounts of structured and unstructured data, helping staff prioritise exceptions rather than review every record manually. However, their usefulness depends on the quality of the underlying data, how well the model fits the business process and whether employees understand the model's limits.

Reports on AI in financial services describe use cases across banking, insurance, payments and investment services, while also emphasising data governance, privacy, model risk and accountability. In practice, public company reports often describe digital transformation or AI initiatives without publishing a consistent measure of how many accounting hours were saved, whether errors declined or how much return was earned on AI investment. This makes company-to-company statistical comparison difficult.

The literature suggests that AI is best understood as a tool that changes how professional work is performed, not as a substitute for accounting judgement. A system may flag a transaction as unusual, but a person must inspect the supporting documents and determine whether an adjustment is needed. Likewise, an algorithmic forecast provides a scenario, not certainty. The present paper responds to the evidence gap by using official financial results while avoiding unsupported claims that changes in profit were caused by AI.

Objectives of the Study

To explain how AI can support accounting activities and financial decision-making in Indian businesses.

To examine five-year reported profit trends for four selected Indian companies.

To frame two testable hypotheses and demonstrate the appropriate limits of statistical analysis.

To identify the governance conditions required for responsible AI use.

Hypotheses

H₁: The reported profit after tax of each selected company shows a positive trend over FY 2020–21 to FY 2024–25.

H₂: Companies with stronger documented AI use will show better accounting-process efficiency and decision support than companies with less documented use.

Research Methodology

The study uses a descriptive, secondary-data design. Four organisations were selected purposively: HDFC Bank, ICICI Bank and SBI represent large Indian banks, while TCS represents a large IT-services business. The period

covers five financial years, FY 2020–21 to FY 2024–25. Financial figures were compiled from official company financial highlights and annual-report materials. The values are shown in ₹ crore.

The analysis uses descriptive tables, line graphs, indexed profit (FY 2020–21 = 100) and year-on-year percentage changes. A formal time-trend test would regress each company's profit on year, but five annual observations provide very low statistical power and are vulnerable to exceptional events. More importantly, the dataset contains no consistent AI-adoption variable. A valid test of H₂ would require year-by-year AI disclosure coding and a direct operational measure such as invoice-processing time, days to close accounts, reconciliation backlog, forecast error or audit exception rate.

To add an inferential check, an exploratory ordinary least squares (OLS) linear-trend regression is estimated separately for each company, with fiscal-year index (1–5) as the predictor and reported profit after tax (₹ crore) as the outcome.

Five-Year Actual Financial Dataset

Table 1: Presents reported profit after tax in ₹ crore for the selected companies. These are financial outcomes, not AI adoption measures.

Company	FY2020–21	FY2021–22	FY2022–23	FY2023–24	FY2024–25
HDFC Bank	31,116	38,151	44,108	60,812	67,347
ICICI Bank	16,193	23,339	31,896	40,888	47,227
State Bank of India	20,410	31,676	50,232	61,077	70,901
Tata Consultancy Services	32,430	38,327	42,147	45,908	48,797

Reported profit after tax (₹ crore), FY 2020–21 to FY 2024–25.

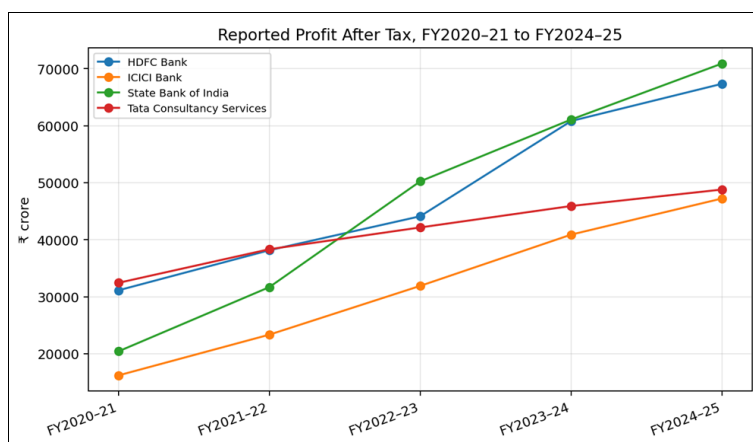


Fig 1: Reported profit after tax across the five-year period

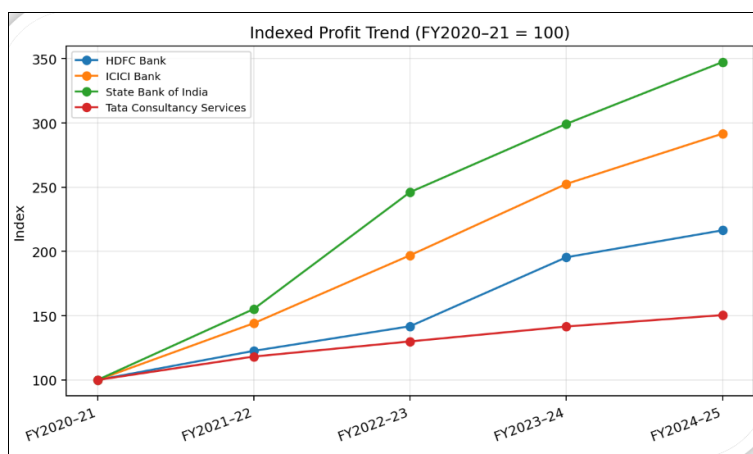


Fig 2: Indexed profit, with each company's FY 2020–21 value set to 100

Statistical Analysis

Table 2: Change in reported profit over the period. Annualised growth is calculated as $(\text{final value} / \text{initial value})^{1/4} - 1$

Company	FY2020–21 PAT	FY2024–25 PAT	Total change	Approx. annualised growth
HDFC Bank	31,116	67,347	116.4%	21.3%
ICICI Bank	16,193	47,227	191.7%	30.7%
State Bank of India	20,410	70,901	247.4%	36.5%
Tata Consultancy Services	32,430	48,797	50.5%	10.8%

The figures show an upward profit trend for all four companies across the period. HDFC Bank's reported profit rises from ₹31,116 crore to ₹67,347 crore. ICICI Bank rises from ₹16,193 crore to ₹47,227 crore, while SBI rises from ₹20,410 crore to ₹70,901 crore. TCS rises from ₹32,430 crore to ₹48,797 crore. These changes show that the selected firms ended FY 2024–25 with higher reported profit than in FY 2020–21, but the growth paths are not identical.

The largest percentage increases occur in the two banks with lower starting profit bases, ICICI Bank and SBI. That does not necessarily mean they used AI more effectively. Profit is influenced by many factors, including the credit cycle, interest margins, provisions, business growth, costs and one-off events. TCS operates in a different sector, where demand for IT services, employee costs, currency movements and client spending can affect results.

For H_1 , the observed direction is positive for all four series. However, with only five annual observations per company, it would be misleading to treat the trend as proof of a general causal mechanism.

Inferential Statistical Test: OLS Linear Trend

For each company, the model is $\text{Profit}_i = \alpha + \beta (\text{Year index}_i) + \varepsilon_i$, where Year index runs from 1 (FY 2020–21) to 5 (FY 2024–25). The null hypothesis for each regression is $H_0: \beta = 0$ (no linear trend); the alternative is $H_1: \beta > 0$ (a positive linear trend). The table reports the estimated annual change, coefficient of determination (R^2) and the conventional two-sided p-value for the slope. Two-sided p-values are shown as a conservative standard reporting practice.

Company	Estimated change per year (₹ crore)	R^2	p-value	Decision at 5%
HDFC Bank	9,512.3	0.968	0.0025	Positive trend; reject H_0
ICICI Bank	7,961.7	0.997	<0.0001	Positive trend; reject H_0
SBI	13,038.3	0.987	0.0006	Positive trend; reject H_0
TCS	4,031.5	0.982	0.0010	Positive trend; reject H_0

Results: The estimated slope is positive for all four companies. At the conventional 5% level, each slope differs statistically from zero in this small-sample linear-trend model. The R^2 values indicate that a straight-line time trend fits the five annual observations closely. These results support the presence of an upward reported-profit trend during the selected period, but they should not be interpreted as proof that AI caused the increase. Other influences including business growth, interest rates, credit conditions, operating costs, market conditions and company-specific events may explain the observed changes. Pooled sensitivity check: An OLS model with a fiscal-year index and company indicator variables (20 company-year observations) estimates an average increase of approximately ₹8,636 crore in reported profit per year, controlling for fixed differences in company level ($R^2 = 0.889$; conventional $p < 0.001$). This pooled result is exploratory only: the sample is small; errors may be serially correlated and the companies' reporting bases and sectors are not fully comparable. It is not an AI-effect estimate.

Interpretation for the hypotheses: H_1 receives statistical support as a positive linear profit trend in each of the four observed series. H_2 remains untested, because the dataset does not contain a comparable company-year measure of AI adoption or accounting-process efficiency. Testing H_2 would require measures such as invoice-processing time, reconciliation error rates, forecast accuracy, close-cycle duration or independently documented AI deployment intensity.

Hypothesis Assessment

H_1 : Positive profit trend: Supported for the observed series. The separate OLS trend regressions estimate positive slopes for all four companies, with conventional p-values below 0.05. Given only five annual observations per company, this is exploratory evidence of a time trend, not a causal explanation.

H_2 : Stronger AI use and better accounting efficiency: Not statistically testable with the available dataset. No comparable company-year AI-adoption measure or direct accounting-efficiency outcome is available, so the hypothesis can neither be accepted nor rejected here.

How AI Can Affect Accounting and Financial Decisions

- AI may improve the speed of transaction processing by extracting invoice data, matching payments and suggesting account classifications. When routine steps are automated, accounting professionals can spend more time reviewing unusual transactions, investigating variances and explaining results to managers. This may help shorten the reporting cycle, but the actual benefit should be measured through processing time, error rates and the amount of manual rework.
- AI can also strengthen controls by identifying patterns that differ from normal activity. For example, an anomaly model may highlight duplicate invoices, unusual payment timing or entries posted outside normal workflows. Such alerts are leads for investigation, not proof of wrongdoing. Human reviewers need to check context and source documents

and organisations should monitor false positives and missed exceptions.

3. In financial planning, predictive analytics can help prepare cash-flow forecasts, budget scenarios and estimates of customer payment behaviour. Managers can explore what might happen if sales slow, borrowing costs rise or customers pay late. Scenario analysis can improve preparedness, but forecasts should show uncertainty and assumptions. A model trained on historical data may fail when economic conditions or business practices change.
4. AI may also assist with document review, contract summaries and management commentary. These uses can save time, but generated text may contain unsupported statements or omit material qualifications. Any output used in statutory reporting must be checked against source records and applicable accounting standards. The final responsibility for financial statements remains with management and qualified professionals.

Recommendations

1. Select a measurable problem such as invoice turnaround time, reconciliation delays or forecast accuracy before buying an AI tool.
2. Record a baseline and compare outcomes after implementation using the same definitions and time periods.
3. Document each AI use case from official reports, distinguishing pilots, general strategy statements and live production use.
4. Retain human review for material accounting judgements, exceptions and financial disclosures.
5. Monitor model accuracy, privacy, access permissions, bias and performance drift.

Limitations and Further Research

The sample contains only four companies and five years. The companies also operate in two different sectors and financial reporting bases must be harmonised before pooled statistical tests. Profit is an outcome influenced by many variables, not a direct measure of accounting efficiency. Most importantly, public reports do not consistently provide the AI and operational metrics required to test the second hypothesis. Future research could collect survey data from finance professionals, obtain internal process measures with company permission, or code official disclosures using a published rubric and independent reviewers. A larger panel could then control for company size, sector and exceptional events.

Conclusion

AI has a credible role in modern accounting and financial decision-making. It can help process documents, identify exceptions, support forecasts and give professionals more time to focus on judgement and communication. Its value, however, should be measured rather than assumed. The actual financial figures reviewed here show that reported profit increased between FY 2020–21 and FY 2024–25 for all four selected companies. That finding is useful context, but it does not establish that AI caused the increase.

A stronger evidence base requires transparent measures of AI use and direct accounting outcomes, alongside careful treatment of sector differences and mergers. Indian

businesses should adopt AI with reliable data, trained staff, human oversight and clear accountability. Researchers should resist the temptation to fill gaps in public disclosure with invented scores. A cautious, evidence-led conclusion is more useful than a stronger claim unsupported by the available data.

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