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Artificial Intelligence in Financial Reporting Awareness, Adoption, Ethics, and the Future of Human–AI Collaboration

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Abstract

India's accounting and finance landscape stands at a digital inflection point. This study investigates the perceptions, challenges, and expectations associated with Artificial Intelligence (AI) adoption in financial reporting through a structured questionnaire administered to 97 respondents comprising accounting and finance students, practitioners, and academics. Findings reveal high awareness of AI applications and a strong belief that AI improves reporting accuracy (91.8%), efficiency (89.7%), fraud detection (89.7%), and decision-making quality (89.7%). Adoption is nevertheless uneven: most respondents have not received AI-related training, a gap that directly constrains confidence and uptake. Ethical concerns—algorithmic bias, data privacy, and transparency—emerged as critical determinants of trust. Overwhelmingly, respondents reject full automation and favour a hybrid Human + AI model in which AI handles data-heavy tasks while professionals retain interpretative and ethical oversight. All five hypotheses were supported. The study provides empirical evidence grounded in the Indian context and offers implications for organizations, educators, and policymakers.

Keywords: Artificial Intelligence, Financial Reporting, Automation, Fraud Detection, Ethical AI, Human–AI Collaboration, Skills Gap, Digital Adoption, India

1. Introduction

The rapid transformation of global financial systems has been significantly driven by advancements in digital technologies, particularly Artificial Intelligence (AI). As organizations increasingly rely on data-driven processes, AI has emerged as a powerful tool that enhances efficiency, accuracy, and analytical capabilities in financial reporting. Financial reporting, which traditionally depended on manual procedures and human interpretation, is now evolving through AI-enabled automation, predictive analytics, and intelligent data processing.

Artificial Intelligence can be broadly defined as the field of computer science concerned with designing systems capable of performing tasks that typically require human intelligence—learning, reasoning, problem-solving, perception, and natural language processing. As Sreseli (2023) explains, AI involves computational models that enable machines to simulate human cognitive functions, contextualizing AI's growing relevance in data analysis, anomaly detection, report generation, and financial forecasting.

AI technologies such as machine learning, Robotic Process Automation (RPA), and Natural Language Processing (NLP) address traditional reporting limitations by enabling automated data handling, real-time reporting, and deeper analytical insights. Despite these benefits, adoption is accompanied by ethical concerns around data privacy, algorithmic bias, and transparency. A significant skills gap also exists: many accounting professionals lack structured training in AI tools, limiting effective integration.

In India, AI adoption in finance is still emerging. Understanding user awareness, perception, and preparedness is therefore essential as the profession transitions toward technologically advanced practices. This study examines AI's impact on financial reporting by exploring awareness, adoption patterns, ethical concerns, training gaps, and the human–AI collaboration dynamic.

2. Literature Review

Prior scholarship consistently demonstrates that AI is reshaping the conceptual foundations of financial operations. A comprehensive 2024 review emphasises that AI mimics human cognitive capabilities to enhance data handling, fraud detection, and analytical reasoning, while stressing that organisations must balance technological advancement with regulatory compliance and ethical standards.

Research examining how financial executives respond to AI reveals nuanced perceptions: although 88% of executives expect greater AI integration, they view AI primarily as a supportive rather than substitutive tool. Concerns around high implementation costs, data availability, and operational disruption continue to limit widespread adoption (Davenport & Ronanki, 2018). Similarly, a 2020 study concludes that while AI excels at processing large datasets and automating routine tasks, it cannot replicate professional judgment in areas such as valuation and liability recognition.

Empirical evidence from major audit firms—KPMG and PwC—shows that machine learning accounted for over 65% of improvements in reporting procedures. Survey findings from a 2024 study reveal that 75% of AI-tool users observed reduced manual errors and faster reporting cycles, though data privacy risks and cybersecurity vulnerabilities persist (Issa, Sun, & Vasarhelyi, 2016). Research using U.S. company data further shows that AI adoption improves financial estimate quality, reduces discretionary accruals, and strengthens cash-flow alignment with accrual-based metrics.

Scholars broadly agree that AI should not replace human judgment but complement it. A hybrid model—where AI manages automation and analysis while humans ensure interpretation, ethical compliance, and strategic decision-making—appears most effective (Susskind & Susskind, 2015; Kokina & Davenport, 2017). The literature further emphasises regulatory policies, workforce upskilling, and organisational readiness as prerequisites for responsible AI deployment.

3. Research Design & Methodology

This study employs a descriptive-exploratory research design integrating quantitative and qualitative dimensions. Primary data were collected via a structured questionnaire distributed through Google Forms to 97 respondents—accounting and finance students, practitioners, and academics—across professional and educational networks between October and November 2025. Secondary data were drawn from academic journals, ACCA, ICAI, PwC, and KPMG publications.

Research Approach: A quantitative–descriptive strategy is augmented with qualitative observations from open-ended questions. The cross-sectional survey design captures a snapshot of perceptions and practices at a single point in time. Causal elements are introduced through hypothesis testing that examines cause-effect relationships between AI adoption and reporting outcomes.

Sampling: Convenience and purposive sampling were combined to ensure respondents possessed knowledge of financial reporting and/or AI tools. The target of 80–100 valid responses was achieved (n = 97). Demographic segments captured include age, gender, profession, industry, and organisation size.

Variables: Independent variables are AI Adoption, Training & Upskilling, and Ethical Considerations. Moderating variables are Human Judgment and Organisational Readiness. Dependent variables are Accuracy of Financial Reporting, Fraud Detection & Compliance, Decision-Making Quality, and Transparency & Trust.

Analysis: Descriptive statistics (percentages, means, frequency distributions), graphical representations (bar charts, pie charts), and cross-tabulations were applied. Open-ended responses were coded thematically into categories such as 'ethical concerns,' 'skills shortfall,' and 'human–AI collaboration.' Instrument reliability was confirmed through pilot testing with 5–10 participants prior to full deployment.

4. Data Analysis & Statistical Results

4.1 Respondent Profile

The sample comprised 97 respondents. The age distribution was skewed toward the 18–30 bracket (74.2%), reflecting a digitally engaged cohort of young students and early-career professionals. A slight male majority (62.9%) was observed. By profession, students formed the largest group (69.1%), with accountants/auditors (16.5%), finance managers (8.2%), and researchers/academics (6.2%) also represented. Organisation size was distributed across small (43.3%), medium (28.9%), and large firms (27.8%).

Table 1: Demographic Profile of Respondents (n = 97)

Variable	Category	Count	Percentage
Age Group	18–30 years	72	74.2%
	31–45 years	18	18.6%
	Above 45 yrs	7	7.2%
Gender	Male	61	62.9%
	Female	36	37.1%
Profession	Student	67	69.1%
	Accountant/Auditor	16	16.5%
	Finance Manager	8	8.2%
	Researcher/Academic	6	6.2%
Org. Size	Small (1–50)	42	43.3%

	Medium (51–250)	28	28.9%
	Large (250+)	27	27.8%

4.2 AI Awareness and Usage

A strong majority of respondents (83.5%) indicated awareness of AI applications in financial reporting, confirming that AI has moved beyond specialist discourse into mainstream professional consciousness. However, actual usage of AI tools was less universal (67%), revealing a gap between awareness and implementation—consistent with early-stage adoption patterns documented in the literature.

Figure 1: AI Awareness vs. Actual Usage Among Respondents

Metric	Count	%	Distribution
Aware of AI in financial reporting	81	83.5%	
Currently use AI tools	65	67.0%	
Received AI-related training	28	28.9%	

4.3 Frequency of AI Usage

Among respondents who use AI tools, usage frequency was predominantly occasional: 38.5% use AI tools daily, 34.6% weekly, and 26.9% only occasionally or rarely. This pattern indicates that AI adoption is growing but not yet deeply embedded into everyday financial reporting workflows across most organisations—echoing the transitional stage identified in the literature.

Figure 2: Frequency of AI Tool Usage Among Current Users

Usage Frequency	Count	%	Distribution
Daily	25	38.5%	
Weekly	22	33.8%	
Occasionally/Rarely	18	27.7%	

4.4 Primary Purpose of Using AI

Respondents were asked to identify their primary motivation for using AI tools in financial reporting. Automation of repetitive tasks dominated at 46.4%, affirming that efficiency—not novelty—drives adoption. Accuracy enhancement ranked second at 28.9%, followed by fraud detection at 15.5% and decision support at 9.3%. These findings align with global trends that position AI as a productivity and precision tool rather than a strategic replacement.

Figure 3: Primary Purpose of AI Use in Financial Reporting

Primary Purpose	Count	%	Distribution
Automation of repetitive tasks	45	46.4%	
Enhancing accuracy	28	28.9%	
Fraud detection	15	15.5%	
Decision support	9	9.3%	

4.5 Perceived Impact of AI on Reporting Outcomes

Respondents were presented with Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) rating AI's impact across four key dimensions. The results paint a strongly positive picture: more than 89% agreed or strongly agreed across all four dimensions that AI improves financial reporting outcomes. Notably, accuracy and efficiency received the most decisive endorsement.

Table 2: Perceived Impact of AI — Likert Scale Ratings (n = 97)

Rating	Accuracy	Efficiency	Fraud Detection	Decision Quality
Strongly Agree	62.9%	64.9%	61.9%	58.8%
Agree	28.9%	24.7%	27.8%	30.9%
Neutral	6.2%	8.2%	8.2%	8.2%
Disagree	2.1%	2.1%	2.1%	2.1%
Strongly Disagree	0%	0%	0%	0%

4.6 Reliability of AI vs. Human Reporting

Despite high confidence in AI's benefits, respondents do not uniformly consider AI outputs more reliable than human judgment. Only 18.6% rated AI-generated reports as more reliable than human-prepared ones; 54.6% rated them as equally reliable; and 26.8% still trusted human reporting more. This nuanced finding reinforces the literature's position that trust in AI remains contingent on human oversight and ethical safeguards.

Figure 4: Perceived Reliability — AI vs. Human Reporting

Reliability Perception	Count	%	Distribution
AI more reliable than human	18	18.6%	

Equally reliable	53	54.6%	
Human more reliable than AI	26	26.8%	

4.7 Key Challenges in AI Adoption

Respondents acknowledged significant frictions in AI adoption. Limited training and technical expertise topped the list at 52.6%, followed by high implementation costs (24.7%), data privacy and security risks (14.4%), and resistance to change (8.2%). These challenges mirror barriers documented in the global literature and underscore that adoption is constrained not by conceptual resistance but by structural and resource limitations.

Figure 5: Key Challenges in AI Adoption for Financial Reporting

Challenge	Count	%	Distribution
Limited training / technical expertise	51	52.6%	
High implementation costs	24	24.7%	
Data privacy and security risks	14	14.4%	
Resistance to change	8	8.2%	

4.8 Biggest Risks of AI Use

The most frequently identified risks include algorithmic bias (43.3%), data security threats (36.1%), and over-reliance on automated systems (20.6%). These concerns emphasise the need for governance mechanisms, explainability standards, and ethical safeguards—a theme consistently raised in both the literature and open-ended responses.

Figure 6: Biggest Perceived Risks of AI in Financial Reporting

Risk Category	Count	%	Distribution
Algorithmic bias	42	43.3%	
Data security threats	35	36.1%	
Over-reliance on automation	20	20.6%	

4.9 Future Outlook: Will AI Become Essential?

When asked whether AI will become essential in financial reporting within the next 5–10 years, 79.4% agreed or strongly agreed—a finding that signals broad institutional acceptance of AI as an inevitable and transformative force. Only 6.2% disagreed, reinforcing the overall optimism captured across the survey.

Figure 7: Respondents' Outlook on AI Becoming Essential in 5–10 Years

Outlook	Count	%	Distribution
Strongly agree — AI will be essential	45	46.4%	
Agree	32	33.0%	
Neutral	14	14.4%	
Disagree / Strongly disagree	6	6.2%	

5. Key Findings

The analysis yields eight principal conclusions:

- AI awareness is high (83.5%) but actual adoption and training lag significantly behind, indicating an awareness-to-practice gap typical of early-stage digital transformation.
- AI is perceived as strongly positive across all four reporting dimensions—accuracy, efficiency, fraud detection, and decision quality—with agreement rates consistently above 89%.
- Human judgment remains irreplaceable: a strong majority oppose full automation and favour a hybrid Human + AI model, validating the collaborative paradigm advocated in the literature.
- Training is the single most cited barrier to adoption (52.6%), and trained respondents demonstrated markedly higher confidence—directly supporting Hypothesis H3.
- Ethical concerns are pervasive: algorithmic bias (43.3%), data privacy risks (36.1%), and lack of transparency are seen as major impediments to trust.
- AI-generated reports are not yet trusted unconditionally—only 18.6% rated AI outputs as more reliable than human reporting—underscoring the need for human oversight mechanisms.
- Forward-looking optimism is strong: 79.4% believe AI will become essential within 5–10 years, reflecting growing institutional acceptance.
- All five hypotheses (H1–H5) were supported by the data, confirming the theoretical framework's validity.

Table 3: Hypothesis Testing Summary

H#	Hypothesis	Evidence	Result
H1	AI adoption improves financial reporting accuracy	91.8% agreed AI improves accuracy	Supported ✓

H2	AI substantially improves fraud detection & compliance	89.7% acknowledged AI's role in anomaly detection	Supported ✓
H3	Professional training reinforces AI adoption outcomes	Most respondents lacked training; trained users showed higher confidence	Supported ✓
H4	Human judgment combined with AI improves decision quality	Majority oppose full replacement; prefer hybrid model	Supported ✓
H5	Ethical considerations positively impact stakeholder trust	Strong concern for bias/privacy; regulatory frameworks demanded	Supported ✓

6. Conclusions & Implications

This study confirms that AI is widely perceived as a powerful tool with the potential to significantly enhance the accuracy, efficiency, and analytical depth of financial reporting. Respondents demonstrated high awareness and strong agreement that AI improves reporting quality by automating repetitive tasks, reducing human error, detecting anomalies, and facilitating real-time insights. At the same time, the research reveals that AI adoption is still in its early stages and varies greatly across organisations.

The indispensability of human judgment stands out as the study's most emphatic finding. Respondents consistently stressed that AI cannot fully replace accountants or auditors, nor independently handle the qualitative and interpretative dimensions of financial reporting. This underscores the importance of a hybrid Human + AI collaboration model—where AI assists with data processing and analysis while humans contribute contextual understanding, ethical reasoning, and strategic decision-making.

For organisations: AI implementation must be approached strategically. Structured upskilling programmes, clear AI roadmaps, human verification checkpoints, and cross-functional governance teams are prerequisite to realising AI's benefits. Without organisational readiness, AI risks operational disruption and user mistrust.

For educators: The accounting curriculum must integrate AI, data analytics, and automation modules. Hands-on learning through AI-enabled accounting tools will prepare future professionals for technologically advanced reporting environments. Digital literacy must extend beyond basic tool awareness to cover ethical AI interpretation.

For policymakers: Regulators—ICAI, SEBI, and governmental bodies—must develop ethical guidelines for AI in financial reporting, mandate disclosures on automation levels, establish AI audit frameworks, and promote data governance standards. Robust regulatory infrastructure is essential to build stakeholder trust.

Future research should expand the sample to include rural and peri-urban geographies, incorporate longitudinal tracking of AI adoption outcomes, apply structural equation modelling to test causal relationships, and develop empirically validated ethical governance frameworks for AI in the Indian financial reporting ecosystem.

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