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Let's Start!

Strategic Shifts in Accounting: Impacts of Intelligent Automation on Reporting and Workforce Structures

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Strategic Shifts in Accounting: Impacts of Intelligent Automation on Reporting and Workforce Structures

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Abstract

The financial sector is increasingly migrating toward digital solutions, prompting traditional accounting practices to adopt intelligent automation technologies such as robotic process automation and machine learning. This paper investigates the effects of these technologies on financial reporting by consolidating findings from twenty research articles, white papers, and cross-sector case studies published between 2019 and 2025, guided by the technology organization environment framework. The analysis reveals that these technologies have substantially improved the speed and accuracy of core financial processes, including the generation of financial reports, invoice processing, and account reconciliations. For example, one organization reported a reduction in annual labor costs exceeding eight hundred fifty thousand United States dollars after automating its accounting procedures. Additionally, the use of intelligent forecasting tools has enhanced decision-making by enabling earlier detection of financial anomalies and improving the reliability of earnings projections. Beyond improvements in operational performance, these innovations have fundamentally altered workforce structures, transforming the function of finance departments from transaction processing to strategic interpretation, thereby increasing employee engagement in a variety of roles. However, adoption rates remain uneven across sectors. Manufacturing and technology industries are leading in maturity, while healthcare, financial services, and public sector organizations lag. From a regional perspective, North America continues to be the largest investor in automation technologies, while the Asia-Pacific region is experiencing the most rapid growth. Despite the considerable advantages associated with these technologies, significant concerns persist regarding transparency, governance, and ethical responsibility. Issues such as algorithmic bias and a lack of regulatory clarity underscore the need for robust governance and adaptable regulatory frameworks. This study concludes that robotic process automation and machine learning represent more than mere efficiency tools; they constitute a transformative mechanism that is reshaping the future of financial reporting. Their effective implementation requires not only technological advancement but also thoughtful integration with workforce dynamics, administrative oversight, and strategic planning. To ensure responsible and sustainable adoption, business leaders and policymakers must focus on transparent governance, workforce reskilling, and strategically aligned integration of intelligent automation within accounting functions.

Keywords: Robotic Process Automation, Machine Learning, Financial Reporting, Digital Accounting Transformation

INTRODUCTION

The field of accountancy is experiencing a profound transformation in its tools, methods, and reputation as automation becomes increasingly prevalent. Historically, accounting relied heavily on spreadsheets, manual processes, and individual data entry; today, it is evolving into a discipline shaped by data analytics and computer algorithms. The primary drivers of this transformation are robotic process automation and machine learning. Once limited to experimental applications, these technologies have now become integral to standard workflows, fundamentally reshaping financial reporting by enhancing data quality, reducing errors, increasing efficiency, and enabling improved decision-making (Schmidt et al., 2021; van Zanden, 2023; Hun et al., 2024; Farras et al., 2025; Gartner, 2023). RPA enables the automation of rule-based, repetitive tasks previously carried out by human accountants, including the recording of journal entries, invoice matching, payment processing, account reconciliation, and posting of bank statement records. This software improves the speed of task completion and delivers consistent performance at all hours, effectively replicating the work of an employee. In contrast, machine learning endows financial systems with advanced cognitive capabilities. Through machine learning, applications can identify anomalies in transactions, detect emerging trends in financial markets, and generate forecasts for credit risk, cash flow, and broader market dynamics (Appelbaum et al., 2017; Karhan, 2019). For example, major banks have implemented machine learning models to flag fraudulent transactions in real time, improving detection accuracy and customer trust. Together, robotic process automation streamlines routine operations while machine learning supports intelligent decision-making, fundamentally redefining accuracy, transparency, and strategic financial management within organizations.

The implementation of these technologies extends beyond service enhancement. They have become organizational imperatives in response to intensified regulatory demands, the proliferation of data, and rapidly changing business environments. Companies strive to comply with the latest International Financial Reporting Standards such as IFRS 9, 10, 15, and 16 which require higher levels of data accuracy, consistency, and traceability. Similarly, the shift toward real-time audit requirements and continuous monitoring by regulators and internal audit teams demands systems that can process, validate, and report data instantaneously and without human delay. In this context, automation is not merely a competitive advantage but an essential element for regulatory compliance and informed decision-making. The global disruptions caused by the coronavirus pandemic have further accelerated the adoption of technology in finance, supporting business continuity even with a reduced workforce (Audi et al., 2021; Tila & Cera, 2021; Audi et al., 2022).

Despite significant progress in applied settings, academic research has advanced more slowly. Barriers include restricted access to proprietary corporate data, the rapid pace of technological advancement, and the lack of standardized metrics for measuring automation impact. Although the literature increasingly addresses automation, much of it focuses on areas such as cost savings, workforce implications, or the automation of auditing functions (Sutton et al., 2016; William, 2021; Geda, 2023; Jamel & Zhang, 2024). Yet, these discussions often

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overlook the direct impact of robotic process automation and machine learning on the quality, speed, and consistency of financial reporting. These considerations are not confined to internal operations; they are also critical to investors, regulators, and auditors, as they underpin trust and accountability in the financial system.

Existing research on automation in finance often remains fragmented, typically analyzing robotic process automation and machine learning in isolation rather than exploring their combined impact on the intelligence of financial systems. Furthermore, there is a notable lack of comparative analysis regarding how automation adoption varies across industries and regions, despite known disparities between sectors such as manufacturing, telecommunications, banking, financial services, and insurance. Like concerns in artificial intelligence safety, issues such as algorithmic bias, lack of transparency in outcomes, and regulatory guidance gaps are increasing in significance but are often treated as secondary topics in the literature. Thus, a holistic and comparative analysis across sectors and regions is needed to understand the full scope and implications of intelligent automation in accounting.

This study addresses these gaps by systematically synthesizing data from twenty peer-reviewed journal articles, industry reports, and international case studies published between 2019 and 2025. The research aims to elucidate the effects of robotic process automation and machine learning on financial reporting processes, with a focus on improvements in efficiency, accuracy, forecasting, cost reduction, and workforce transformation. Special attention is given to how these tools are redefining employee roles, restructuring reporting workflows, and reshaping talent requirements in finance departments within leading digital organizations. By integrating perspectives on technology and reporting in accountancy, this research not only contributes to academic scholarship but also informs the practice of accounting professionals and organizational leaders. Beyond highlighting the advantages of automation, the study underscores critical considerations for chief executive officers and their teams as they pursue digital transformation. Overall, this research demonstrates that robotic process automation and machine learning are not merely standalone innovations but are collectively driving the evolution of accounting from a transactional support function to a dynamic, intelligent, and ethically responsible partner within modern organizations.

LITERATURE REVIEW

Madakam et al. (2019) examine the evolving role of Robotic Process Automation in digital workforce development, highlighting its value in streamlining business processes. Their qualitative research, utilizing interviews and case studies across industries, demonstrates that robotic process automation significantly enhances operational efficiency by automating repetitive, rule-based tasks, thereby enabling human workers to focus on strategic functions. The study identifies notable cost reductions and increased precision, particularly in data entry, invoicing, and financial reporting. However, implementation challenges persist, such as the need for specialized personnel and employee anxiety regarding job security. Kaya et al. (2019) assess the impact of robotic process automation on accounting systems within Turkish firms, based on data from accounting professionals and financial analysts. Statistical analysis reveals that

Robotic Process Automation reduces manual labor, enhances data integrity, and promotes operational uniformity, leading to improved efficiency and cost savings. The authors advocate for integrating Robotic Process Automation content into accounting education and recommend continuous system improvement after automation is implemented.

Gotthardt et al. (2020) investigate the implementation of Robotic Process Automation in accounting and auditing, utilizing qualitative methods with data from European audit and finance firms. Their findings indicate that intelligent robotic process automation improves data handling and audit accuracy but faces challenges such as organizational resistance, skill shortages, and integration issues. Virtanen (2021) analyzes the effects of Intelligent Process Automation on time usage and manual workload in a Finnish accounting software company, using a one-year comparative data analysis. Implementation of Intelligent Process Automation led to more efficient accounting procedures, reduced processing times for data entry, reconciliations, and report generation, and improved accuracy. Zelenka and Vokoun (2021) study the impact of information and communication technology, particularly Robotic Process Automation, on business performance in the Czech financial sector from 2015 to 2020. Using panel data regression, they demonstrate that Robotic Process Automation implementation yields substantial improvements in operational performance, reporting speed, accuracy, and cost efficiency. Basani (2021) explores the digital transformation of accounting processes through Robotic Process Automation, business analytics, machine learning, and artificial intelligence. Case study analysis across multiple industries from 2015 to 2020 reveals that robotic process automation boosts operational efficiency, reduces costs, and accelerates decision-making, especially in financial analytics and reporting. However, integrating robotic process automation with legacy systems remains a challenge, necessitating modernization of operational architecture to fully benefit from automation and artificial intelligence. These findings underscore automation's consistent value in improving speed and accuracy, though integration challenges and legacy systems remain persistent barriers across geographies.

Chenneti (2023) investigates how Robotic Process Automation can enhance efficiency, accuracy, and cost-effectiveness in the accounting industry, based on qualitative interviews and quantitative surveys of accounting firms in Dublin. The study confirms that robotic process automation reduces workload, manual errors, and processing time but highlights barriers such as high implementation costs and the need for specialized expertise. Bavaresco et al. (2023) present a case study of the application of machine learning algorithms in automating accounting services in a Brazilian firm. Over twelve months, the integration of supervised learning models, including support vector machines and decision trees, reduced processing errors by forty percent and increased processing speed. Together, these studies suggest that while RPA and ML offer quantifiable improvements, scaling them across organizations requires significant investment in training and infrastructure.

Oyeniyi et al. (2024) conducted a systematic review of over sixty reports and case studies on Robotic Process Automation in accounting, spanning 2015 to 2023. Their analysis shows that Robotic Process Automation implementation can reduce repetitive tasks by up to

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seventy percent, improve compliance, and enhance audit readiness, especially in high-volume transactional environments. This directly supports this study's focus on the potential of automation to reshape financial reporting at scale. Hajjar (2024) evaluates how automation technologies, including robotic process automation and machine learning, support financial reporting and risk prevention in business operations, drawing on industry case analyses from 2020 to 2023. The research, conducted as a bachelor's thesis at Haaga-Helia University of Applied Sciences, demonstrates how automation is shown to reduce human error, speed up reporting cycles, and strengthen risk management through rapid data processing (Hajar,2024). Kuaiber et al. (2024) study artificial intelligence technologies in automating financial reporting through conference and case research. Their quantitative evaluation reveals improvements in report accuracy, efficiency, and adaptability of reporting systems. Rahim and Chishti (2024) examine the implementation of artificial intelligence in accounting and finance, focusing on automation, fraud detection, and decision support systems. Their qualitative-comparative analysis of global systems indicates enhancements in operational speed, internal controls, and predictive capabilities. Samokhvalov (2024) analyzes the impact of Intelligent Process Automation on management reporting, showing that intelligent process automation simplifies data consolidation and enhances analytic functions, forecasting, and decision-making. Alao et al. (2024) propose a conceptual framework illustrating how automation improves financial reporting accuracy and efficiency in United States corporations. Their theoretical analysis, supported by industry reports and case studies, identifies system integration, data standardization, and automated controls as key enablers. Kitsantas et al. (2024) investigate how artificial intelligence enhances robotic process automation in advanced business process automation across finance, supply chain, and customer service. Their mixed-methods approach, incorporating system analysis and case reviews, shows that integrating machine learning and natural language processing improves data handling and decision-making. However, high data structure requirements and implementation costs are constraints.

Singh (2024) provides an extensive analysis of how artificial intelligence and automation technologies are transforming accounting, including financial reporting, auditing, and managerial decision-making. Through both qualitative and quantitative methods, the paper demonstrates improvements in speed, accuracy, and cost-efficiency, particularly via artificial intelligence-driven predictive analytics and anomaly detection. Narang and Jain (2024) assess the influence of robotic process automation and artificial intelligence platforms on financial reporting through a combination of corporate report analyses and interviews. Their findings confirm that robotic process automation and artificial intelligence increase financial report accuracy, reduce errors, and accelerate reporting.

Elnakeeb and Elawadly (2025) offer a bibliometric analysis of artificial intelligence and automation research in accounting, examining 423 articles from 2000 to 2024 across global databases. The study maps intellectual trends and highlights significant growth since 2016, particularly in robotic process automation adoption, audit automation, predictive analytics, and fraud detection. Rakibuzzaman et al. (2025) investigate how automation improves financial

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reporting efficiency in mid-sized Bangladeshi firms using quantitative surveys from 2021 to 2023. The results show that automation reduces reporting time and enhances decision-making, with recommendations for expanding digital reporting tools and professional training. Lai and Hsieh (2025) analyze the effect of Robotic Process Automation on financial reporting and earnings management in public companies from 2018 to 2023, using econometric models. They find that robotic process automation increases transparency, reduces opportunities for earnings manipulation, and improves financial statement accuracy and reliability.

While the existing literature robustly documents the operational efficiency, cost reduction, and accuracy improvements delivered by robotic process automation and machine learning in accounting and financial reporting (Madakam et al., 2019; Kaya et al., 2019; Zelenka & Vokoun, 2021; Basani, 2021; Chenneti, 2023), several critical gaps remain unaddressed. First, most studies tend to focus on robotic process automation and machine learning independently rather than analyzing their combined or synergistic impact on financial reporting intelligence and transformation (Singh, 2024; Kitsantas et al., 2024; Narang & Jain, 2024). Second, despite increasing adoption, there is limited comparative research on how automation maturity and effects vary across industries and regions, especially outside leading sectors like manufacturing and technology (Can, 2021; Virtanen, 2021; Salleh & Sapengin, 2023; Elnakeeb & Elawadly, 2025; Rakibuzzaman et al., 2025). Moreover, while many works highlight operational and economic benefits, issues related to algorithmic bias, transparency, governance, and regulatory adaptation are often treated as secondary concerns rather than as integral components shaping responsible adoption (Akim, 2020; Tila & Cera, 2021; Rahim & Chishti, 2024; Bavaresco et al., 2023; Kumar & Gupta, 2023; Lai & Hsieh, 2025; Kumar & Wu, 2025). Few studies systematically address how automation is altering workforce structures, reporting workflows, and ethical accountability within finance functions (Gotthardt et al., 2020; Owusu & Novignon, 2021; Denial, 2023; Oyeniyi et al., 2024; Samokhvalov, 2024). Consequently, comprehensive evidence synthesizing the transformative, cross-functional, and ethical implications of integrating RPA and machine learning in financial reporting—across sectors and regions—remains scarce. This study addresses these gaps by offering a holistic, multi-dimensional analysis, thereby providing new insights into both the opportunities and challenges automation brings to financial reporting practice and policy.

Consequently, comprehensive evidence synthesizing the transformative, cross-functional, and ethical implications of integrating RPA and machine learning in financial reporting—across sectors and regions—remains scarce. This study addresses these gaps by offering a holistic, multi-dimensional analysis, thereby providing new insights into both the opportunities and challenges automation brings to financial reporting practice and policy.

METHODOLOGY

This research utilizes secondary data and is organized according to a systematic literature review methodology. Such an approach enables the synthesis of existing studies to analyze the effects of Robotic Process Automation and machine learning on financial reporting across various industries. A systematic review facilitates the identification, evaluation, and integration of prior research, ensuring that the review process is transparent and reproducible (Siddaway et al., 2019). Relying on secondary data allows researchers to conduct statistically robust analyses of automation, especially in contexts where primary data collection is limited or impractical (Johnston, 2017)

RESEARCH DESIGN

This paper adopts a positivist philosophical perspective and employs a deductive research approach to investigate the influence of automation technologies, specifically, Robotic Process Automation and machine learning, on financial reporting outcomes. The positivist paradigm is grounded in the belief that observable, empirical data, such as cost reductions, error rates, and improvements in reporting cycles, can be systematically compared to identify causal relationships (Tranfield et al., 2003). A systematic literature review serves as the principal research method due to its transparency, reproducibility, and ability to provide an organized, comparative analysis of existing studies. This methodology is particularly effective for integrating findings from diverse research to quantify changes across different measures of operational performance.

THEORETICAL FRAMEWORK

The present study is grounded in the theoretical framework of technology organization environment, as proposed by Tornatzky and Fleischer (1990), which offers a comprehensive perspective for assessing the multidisciplinary nature of technological adoption and its implications for organizations. The technology organization environment framework categorizes influencing factors into three key dimensions: technological context, organizational context, and environmental context. Each dimension plays a distinct role in shaping the adoption, integration, and performance of innovation within organizations. Within this study, the technological context pertains to the features of robotic process automation and machine learning, including perceived advantages such as the automation of repetitive processes, real-time information analysis, and anomaly detection, as well as perceived drawbacks such as complexity and integration challenges. The organizational context relates to internal factors such as firm size, digital maturity, leadership support, the presence of skilled employees, and change management capabilities, all of which influence the effectiveness of adopting robotic process automation and machine learning in financial reporting processes. The environmental context encompasses external pressures and enabling factors, including regulatory requirements, industry competition, audit compliance obligations, and market dynamics regarding openness and the timeliness of reporting. These environmental influences can serve either as drivers or barriers in the decision to implement intelligent automation technologies. By applying the technology organization environment framework, this study systematically examines how the interrelation of technological, organizational, and environmental dimensions shapes the transformation of financial reporting practices. This theoretical foundation provides a holistic understanding not only of the motivations for adopting automation but also of the contingencies that mediate its impact on efficiency, accuracy, and cost reduction in financial processes.

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TABLE 1: DEFINITIONS OF THE VARIABLES

Variables	Operational Definition
Robotic Process Automation Implementation	Use of bots for automating transactional tasks (e.g., invoicing, reconciliations, journal entries).
Machine Learning Adoption	Integration of machine learning algorithms in forecasting, fraud detection, and anomaly analysis.
Reporting Efficiency	Reduction in reporting timelines (e.g., month-end close, invoice cycle).
Reporting Accuracy	Decrease in manual errors, data inconsistencies, or compliance failures.
Cost Optimization	Cost savings in financial operations, especially labour and overhead reductions.

The variables were selected and operationalized based on prior studies (Bavaresco et al., 2023; Kaya et al., 2019). Robotic process automation represents automated tools for tasks like invoicing and reconciliations, while machine learning applies predictive algorithms for fraud detection and anomaly analysis. These technologies are measured by their impact on reporting efficiency, accuracy, and cost optimization. Together, these variables form a systematic framework to evaluate the effectiveness of accounting automation.

DATA SOURCES AND SAMPLING TECHNIQUE

This research relies on secondary data from reputable institutional and academic sources, including peer-reviewed journal articles, industry white papers, consultancy reports (e.g., Deloitte, KPMG, McKinsey), conference proceedings, government publications, and case studies by automation solution providers. Secondary data enables efficient, cost-effective analysis of automation trends and eliminates many ethical concerns associated with primary data collection (Johnston, 2017). Combining academic and industry data allows for both theoretical rigor and practical insight, ensuring that the review reflects real-world implementation outcomes as well as scholarly analysis.

The study focuses on organizational case studies and industry assessments, emphasizing the impact of robotic process automation and machine learning on financial reporting efficiency, accuracy, and cost reduction. A purposive sampling strategy was used, with inclusion criteria requiring studies to (1) provide quantitative or comparative data on financial reporting performance after automation, and (2) document the use of robotic process automation or machine learning in accounting.

This ensures access to relevant, data-rich materials for meaningful cross-sector comparisons. Descriptive statistics summarize findings from multiple studies, while comparative analysis identifies adoption trends and quantifies the benefits of automation across business sectors. This approach follows best practices for aggregating empirical results in accounting research (Boell & Cecez-Kecmanovic, 2015).

METHOD OF DATA ANALYSIS

After selecting studies through purposive sampling, a systematic approach was employed to extract and interpret the main results. Numerical analysis evaluated the impact of robotic process automation and machine learning on core financial reporting metrics, including error reduction, faster task completion, cost savings, and improved compliance. Quantitative findings were summarized in highlight tables to identify patterns across studies and sectors. A comparison framework was used to assess automation's effects across industries (manufacturing, healthcare, BFSI, public sector) and regions (North America, Asia-Pacific, Europe), clarifying variations by company type, digital maturity, and industry constraints.

Quantitative synthesis involved aggregating numerical indicators (e.g., time savings, error rates), while qualitative synthesis focused on interpreting contextual insights (e.g., workforce impact, managerial response) across case studies. Narrative synthesis complemented the quantitative analysis by capturing trends less visible in the data, such as shifts in employee roles, satisfaction, management, or ethical advances. This dual approach covers both operational impacts and strategic responses, consistent with best practices for evidence review (Boell & Cecez-Kecmanovic, 2015; Siddaway, Wood, & Hedges, 2019). Integrating numerical and interpretive analysis provides a comprehensive understanding of how automation transforms financial reporting.

To reduce publication bias, the review included a balance of peer-reviewed studies and industry reports, avoiding reliance on only positive outcome studies and including sources that reported implementation challenges and limitations.

RESULTS

This section analyzes the quantitative results regarding the impact of robotic process automation and machine learning on the financial reporting functions of a set of industries.

The results are structured around the three core dependent variables (see Table 1): reporting efficiency, accuracy, and cost optimization, each influenced by the implementation of Robotic Process Automation and Machine Learning.

REPORTING EFFICIENCY

EFFICIENCY AND PROCESSING TIME

Robotic Process Automation (RPA), as defined in Table 1, has substantially accelerated operations, resulting in faster month-end closes, improved workflow planning, and significant reductions in manual work. The benefits are especially notable in transaction-intensive functions, where robotic process automation yields major time savings. For example, in the electrical manufacturing sector, the month-end close cycle dropped from 10 days to just 3 (Withum, 2022). Similarly, financial services and banks reduced account balancing cycles to as little as 2 days (Gartner, 2023). Manual financial reporting preparation times fell by 60% across multiple industries (Pan & Zhang, 2024). For example, PwC reports that one of its clients reduced data-entry time by 70% using RPA bots, while maintaining 100% accuracy, freeing up finance teams for higher-value analysis. Core finance operations saw average processing times cut to one-third of their baseline (Koyeda, 2025). Automation of accounts payable and

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receivable reduced invoice processing timelines by 90% to just 1.5 days (PwC, 2022). According to a PwC automation lead, "What used to take 15 people three days is now done overnight with two validations. In finance and insurance, credit-card transaction processing times dropped from 5 hours to 1.5 hours daily (Auxiliobits, 2022). Interviews with Big Four firms reported overall time savings in financial processing of up to 70–80% (Cooper et al., 2019).

TABLE 2: IMPROVEMENTS IN FINANCIAL PROCESSING TIME AFTER ROBOTIC PROCESS AUTOMATION/MACHINE LEARNING IMPLEMENTATION

Metric	Before	After / Improvement	Industry / Firm Type
Month-end close cycle	≈10 days	3 days (≈70% faster)	Electrical manufacturing
Account reconciliation cycle	10 days	2 days (80% reduction)	Banking/Financial services
Financial report prep (manual)	50 hours	20 hours (60% reduction)	Cross-industry
Manual processing time (avg.)	100% baseline	33% of baseline (67% reduction)	Core finance operations
Invoice processing cycle	~15 days	1.5 days (90% faster)	Cross-industry (AP/AR automation)
General financial processing time	100% baseline	20–30% of baseline (70–80% faster)	Professional services (Big 4 interviews)
Credit-card transaction processing	5 hours/day	1.5 hours/day (70% faster)	Finance/Insurance

PERFORMANCE GAINS AND BUSINESS IMPACT

Research consistently highlights major gains in efficiency and accuracy enabled by automation in financial processes. With machine learning, fraud detection losses were reduced by 52%, and detection times improved by 58% (ACFE, 2023; Tential.com). Currently, 31% of finance organizations use AI specifically for payment fraud detection (NVIDIA, 2024). Robotic process automation significantly enhances financial closing efficiency. Automated journal entry processes cut monthly closure times by 25% and costs by 38% (HighRadius, 2024). Automated reconciliation increased end-of-day effectiveness by 60%, and regulatory compliance also benefited, as an asset manager halved the time needed to process complex financial reports (Scimus, 2024).

TABLE 3: AI AUTOMATION IN FINANCE (2023–2024)

Metric	2023	2024
Finance functions using any AI	37%	58%
Finance functions using IPA	–	44%
CFOs viewing GenAI as crucial	37% (Mar)	68% (Jun)
Firms using GenAI/AI tools	33%	65%
Fortune 250 using IDP	–	63% (71% in finance)

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Between 2023 and 2024, the adoption of artificial intelligence in finance surged. According to industry sources (The-CFO.io, PYMNTS.com, Docsumo), the share of finance departments using AI rose to 58% within two quarters. Intelligent Process Automation saw 44% adoption in its first 2024 reporting. The perception of Generative AI shifted rapidly: by June 2024, 68% of CFOs considered it essential to financial reporting, up from 37% in March. Firm-level usage of Generative AI nearly doubled to 65%, while intelligent document processing tools reached 63% adoption among Fortune 250 companies, with 71% usage in finance departments. These figures underscore the sharp rise of AI and automation in corporate finance.

INCREASE IN THE ADOPTION OF AUTOMATION TECHNOLOGIES AND THEIR EFFECTS

Data from recent years highlights persistent fraud risks and a rapid rise in automation adoption. PwC’s Global Economic Crime and Fraud Survey (2022) reports fraud rates of 46–49% from 2018 to 2022, emphasizing the ongoing need for automated controls. Meanwhile, finance AI adoption increased from 37% in 2023 to 58% in 2024 (The-CFO.io, 2024). The global robotic process automation market grew to USD 13.9 billion in 2023 (AIMultiple, 2023), with a ~31% YoY increase, and is projected to reach USD 22.8 billion in 2024 at a ~25% CAGR (Precedence Research, 2024). Automation also enables significant staff resource reallocation: up to 50% of finance team time previously spent on transactional tasks can now be redirected toward strategic analysis (HighRadius, 2024). Recent industry research (ACFE; Tential; HighRadius; Scimus; NVIDIA, 2023–2024) shows that AI has reduced fraud detection timelines by 58% and halved fraud losses. Financial close and reconciliation times improved by 25% and 60% respectively, with a 38% cost reduction in audits and a 50% improvement in regulatory reporting schedules. These findings underscore the productivity gains and risk mitigation that automation brings to financial processes.

TABLE 4: PROCESS IMPROVEMENTS FROM AUTOMATION TECHNOLOGIES

Metric	Impact
Fraud detection time	58% faster
Fraud loss reduction	52% lower
Financial close time	25% faster
Audit process cost	38% lower
Reconciliation processing	60% faster
Regulatory report time	50% lower
Time spent on transactions (pre-automation)	50% of staff hours

These findings provide strong support for the first research question regarding the impact of robotic process automation and machine learning on financial reporting efficiency. The greatest efficiency gains are seen in transaction-intensive industries, particularly manufacturing, finance, and professional services. Within the technology–organization–environment framework, technological properties (such as repeatability and compatibility with legacy systems) and organizational readiness (including digital maturity and leadership support) are key facilitators of success. However, regional and sectoral differences suggest that efficiency improvements also depend on external factors like regulatory influence and local infrastructure. While the

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measured benefits are substantial, future studies should also consider long-term sustainability and the potential for diminishing returns from automation over time.

REPORTING ACCURACY

ACCURACY AND ERROR REDUCTION

The adoption of machine learning—our independent variable focusing on anomaly detection and data analysis—has led to a sharp reduction in errors during data entry and reconciliation. Automation also lowers compliance risk and enhances audit readiness. Beyond efficiency gains, these improvements foster greater trust in the reliability of financial results and compliance documentation.

TABLE 5: IMPROVEMENTS IN FINANCIAL ACCURACY AND ERROR RATES

Metric	Before	After / Improvement	Industry / Firm Type
Financial data processing error rate (%)	5–10%	<0.5% (99.5% accuracy)	Financial services
Manual entry/reporting errors	100% baseline	1–20% of baseline (80–99%↓)	Healthcare
Data accuracy (general)	85%	95%	Cross-industry
Manual errors per cycle	15	3 (80% reduction)	Financial/Accounting firms
Compliance accuracy	100% baseline	+92% improvement	Healthcare/finance
Report discrepancies	100% baseline	7% of baseline (93% reduction)	Consulting
Reporting error rate	100% baseline	25% of baseline (75%↓)	Cross-industry adopters

The implementation of robotic process automation and machine learning has significantly improved the accuracy of financial reporting. Surveys from financial services and accounting professionals indicate that processing error rates have dropped from an average of 5–10% to below 0.5%, achieving up to 99.5% accuracy post-automation. Pan and Zhang (2024) found that overall data accuracy rose by 10% to 95%, while manual cycle errors fell by 80%. Similarly, HighRadius reported achieving a 95% invoice capture rate and 90% PO invoice auto-matching in real-world deployments of AI-powered tools for accounts payable and receivable functions. According to Deloitte's Global Intelligent Automation Survey (2023), healthcare organizations using automation reduced manual entry and reporting errors by 80–99%, bringing error levels down to just 1–20% of their original baseline, and reaching 93% in consulting (Meridian, 2021). Gartner and Strickland (2024) further report a 75% reduction in reporting errors across industries using automation. This trend underscores reduced manual mistakes and greater reporting reliability across sectors.

FORECASTING AND PREDICTIVE CAPABILITIES

Advanced machine learning forecasting tools have greatly improved the reliability of financial forecasts, particularly in complex areas such as creditworthiness, revenue processes, and fraud

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detection. Machine learning enhances financial planning and enables earlier identification of anomalies, providing organizations with a competitive edge in risk management. Research by Cao and You (2021) found that companies using machine learning achieved a 10–12% increase in earnings forecast accuracy. Financial and compliance institutions also report significant improvements in credit and risk analysis, as machine learning models can detect complex patterns in large data sets. These innovations underscore the value of predictive automation in strengthening proactive financial decision-making.

TABLE 6: IMPROVEMENTS IN FORECASTING ACCURACY USING MACHINE LEARNING

Metric	**Traditional**	**With machine learning / Automation**	**Industry / Firm Type**
Earnings forecast accuracy	Baseline	10–12% more accurate	Complex financial data firms
Predictive accuracy (credit/risk)	Baseline	Substantially improved (pattern use)	Financial / compliance firms

ADOPTION OF AI, MACHINE LEARNING, AND INTELLIGENT AUTOMATION IN FINANCIAL REPORTING

Financial organizations are rapidly adopting advanced automation tools, including intelligent process automation (IPA), machine learning, and generative AI. Gartner (2024) reports that 44% of finance departments have implemented IPA, while 39% use AI to manage errors and anomalies (The-CFO.io, 2024). The use of generative AI has surged: only 37% of CFOs considered it essential in March 2024, rising to 68% by June, with company adoption rates increasing from 33% in 2023 to 65% by mid-2024 (PYMNTS.com, 2024). Generative AI is primarily used for reporting, forecasting, and regulatory compliance.

Document processing tools are also widely adopted—71% of Fortune 250 companies use Intelligent Document Processing (IDP), with 63% adoption in financial services (Docsumo, 2024). These trends support the finding that robotic process automation and machine learning significantly improve financial reporting accuracy, especially in error-prone, manual processes. The technology–organization–environment framework helps explain these outcomes, highlighting the role of AI capabilities and organizational quality controls. While industries like healthcare and consulting may benefit more due to smaller reporting volumes, differences in measurement standards and automation levels across studies should be considered. Overall, automation enhances trust, audit readiness, and data integrity in modern financial systems.

COST OPTIMISATION

COST REDUCTIONS AND FINANCIAL ROI

Automation has generated significant cost savings for organizations, particularly in labor, operations, and quality control. High ROI outcomes show that automation delivers practical and financial benefits, especially for large businesses with substantial back-office needs. Studies indicate that companies can achieve returns of 200% or more within two years of adopting automation. In financial services, back-office processing costs have been reduced by up to 70%, with labor costs per reporting cycle cut by 50%. Robotic process automation led to a 42%

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decrease in operational costs and annual labor savings of $500,000 for a 40-person finance team. Additionally, employee satisfaction increased by 78% due to reduced repetitive work, highlighting automation's positive impact on both productivity and workforce well-being (Gartner, 2023; Pan & Zhang, 2024; Koyeda, 2025; CFO Dive).

TABLE 7: COST REDUCTIONS AND ROI METRICS FROM AUTOMATION

Metric	Before	After / Improvement	Industry / Firm Type
Back-office processing cost	100% baseline	30% of baseline (70% reduction)	Financial services
Finance labour cost per report cycle	100% baseline	50% reduction	Financial departments
Operational expenses	100% baseline	58% of baseline (42% drop)	Finance (robotic process automation implementation)
Annual Labor cost savings	N/A	$878,000 saved (40- FTE team)	Corporate finance
Employee satisfaction	Baseline	78% improvement (due to task relief)	robotic process automation-adopting finance teams

HUMAN RESOURCE IMPACT AND STRATEGIC REALLOCATION

Beyond technological advancements, the integration of robotic process automation and machine learning is fundamentally reshaping the finance workforce. Routine numeric tasks are being replaced by analytical and strategic roles, leading to greater employee satisfaction. This shift marks a transformation of finance organizations from transactional functions to strategic partners, driven by automation platforms.

TABLE 8: HUMAN RESOURCE OUTCOMES OF AUTOMATION

Metric	Before	After / Result	Industry / Firm Type
Employee satisfaction	Baseline	78% higher (due to automation relief)	Finance teams
Time spent on manual vs. analytical tasks	80% manual	Reversed: 70–80% on strategic work	Corporate finance
FTEs reallocated to analytics	N/A	4–6 FTEs moved to planning functions	Large finance team
Perceived value of automation	Not measured	85% viewed automation as "transformational"	Big 4 & mid-tier firms

Automation has not only revolutionized financial operations but also transformed work dynamics in finance departments. Employee satisfaction increased by 78% due to reduced manual work (Koyeda, 2025). Corporate finance professionals now dedicate 70–80% of their time to strategy and analysis, compared to previously spending 80% on manual tasks (PwC, 2023). Supporting this trend, HighRadius found that over 90% of items in cash application were automated, and exception handling time decreased by 40%, allowing teams to reassign more capacity to planning and analytics. In large teams, an average of 4–6 full-time equivalents have

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been reallocated to planning functions post-automation (Gartner, 2023). Both Big Four and mid-size firms increasingly view automation as a long-term transformative force, reflecting strong confidence in its value (Strickland, 2024).

INDUSTRY-SPECIFIC ADOPTION PATTERNS

There is significant industry variation in automation adoption, with Robotic Process Automation (RPA) leading the way. According to a global survey by CBSL Group (2023), manufacturing and technology/telecom sectors have the highest RPA adoption rates at 35% and 31%, respectively. In contrast, healthcare (10%), finance and consumer goods (8%), the public sector (5%), and education (3%) show considerably lower adoption levels.

TABLE 9: ***ROBOTIC PROCESS AUTOMATION ADOPTION BY INDUSTRY (2023)***

Industry	% Organizations with robotic process automation
Manufacturing	35%
Technology/Telecom	31%
Healthcare/Pharma	10%
Retail/Consumer Goods	8%
Financial Services & Insurance (FSI)	8%
Public Sector	5%
Education	3%

Although finance and healthcare have slower automation adoption rates, they lead in commercial automation investments. In 2024, the BFSI sector topped the robotic process automation market with USD 8.33 billion in revenue, followed by healthcare (USD 4.83B), manufacturing (USD 4.21B), retail (USD 2.12B), and IT/telecom (USD 1.59B) (Precedence Research, 2024). These figures show that high investment is concentrated in essential, strategically planned activities, rather than reflecting widespread adoption.

Although Robotic Process Automation (RPA) has been successfully used over the decades, the adoption rates are slow in specific areas, such as healthcare, public administration, and education. Many forces make this lag. New technologies are frequently stagnated in the process of receiving approval and implementation with regulatory complexity, especially in situations where patient data or public budgets are at risk. The next obstacle is the budget limitation, even more so in the case of observing public and non-profit institutions, as they usually have narrower margins of funds, which cannot be invested in digitalization. Lastly, legacy systems in such industries are, in many cases, not compatible with integration with current RPA systems, making implementation significantly more complex and expensive. These organizational difficulties contribute to the fact that progress in automation adoption is very slow, even with an increased awareness of the potential.

TABLE 10: ***GLOBAL ROBOTIC PROCESS AUTOMATION MARKET REVENUE BY INDUSTRY (USD BILLIONS)***

Industry	2022	2023	2024
BFSI	5.54	6.78	8.33
Healthcare/Pharma	3.04	3.82	4.83

Manufacturing	2.73	3.38	4.21
Retail & Consumer Goods	1.41	1.73	2.12
IT & Telecom	1.06	1.30	1.59

As shown throughout the preceding analysis, Robotic Process Automation and Machine Learning—defined as the independent variables in Table 1—demonstrably impact reporting efficiency, accuracy, and cost optimization across industries.

The findings of the study should not be widely applied because of the recognized limitations. The data we use is mostly secondary, derived from external streams such as case studies and published materials. The focus on successful implementations may have biased the data since they tend to emphasize the successes, as companies with poor automation results are less likely to publish them. For example, Redwood Software in 2023 warns of the fact that RPA works well on simple tasks, but cannot cope with complex or unclear workflows. The costs of getting RPA to existing organizations and maintaining compatibility with older systems tend to offset realized returns. Based on our data, the observed drops in errors and costs are expected under optimal conditions. In practice, organizations that are small in size or use unique processes can do better with less improvement. Second, with technology advancing so fast, our results for 2023-2024 may soon be overtaken. In their review, Kureljusic and Karger (2023) point out that there is little knowledge of AI-driven accounting forecasting, which generally comes from small-scale experiments. More longitudinal research needs to be conducted in order to verify if the improvements of earlier periods are sustained and what the impact of that was on long-term financial performance. At the end, the broader social consequences outside individual businesses are not clear yet: Algorithmic errors may go further than single organizations and require policymakers to implement initiatives for retraining and assistance in to transition of the workforce.

All together, we demonstrate that RPA and ML are critical to financial reporting efficiency, accuracy, and insights, reshaping finance organizations to assist initiatives. This reflects the consensus of our results with industry wisdom that has been mentioned by leading strategists. However, restoring automation's capabilities in its entirety may rely upon overcoming important barriers, including workforce readiness, interoperability of systems, ethical governance, and adherence to regulations. Moving into the future, researchers should study successful automation practices in varied settings and professionally analyse the long-term impact on the finance sector as a result of automation.

DISCUSSION

North America remains the leading region in the global robotic process automation market, accounting for 38.9% of total revenue in 2024, led by U.S. advances in finance and manufacturing (Precedence Research, 2024). Meanwhile, APAC is experiencing rapid growth, with a 35–40% CAGR driven by fintech expansion in China, India, and Southeast Asia (GlobeNewswire, 2024; Precedence Research, 2024). In the BFSI sector, North America represented about 38% of the market, while APAC's CAGR exceeded 40% (GlobeNewswire, 2023), highlighting the U.S.'s market size dominance and APAC's accelerated growth. Findings addressing the third research question, “How does automation affect cost optimization?” show automation delivers substantial labor and operating cost savings, significant ROI, and strategic shifts in finance teams’ roles. This aligns with the TOE framework, where leadership commitment and market competitiveness drive productivity gains. However, low adoption rates in public services and education indicate barriers beyond cost, such as regulatory complexity and resistance to change. Further research should explore how smaller organizations and resource-constrained sectors can overcome these challenges to realize similar automation benefits.

Robotic process automation and machine learning are revolutionizing financial reporting, delivering much faster processes and sharply reduced errors—trends that support industry forecasts of an imminent “AI age” in finance. AI enables faster anomaly detection and greater data reliability, allowing automated systems to identify risks before they escalate (KPMG, 2024). Our data reflects these improvements: close times are 70–90% faster, and error rates have dropped from 10% to near zero. This shift enables finance teams to move from basic reconciliation to higher-value activities, increasing stakeholder confidence through more accurate, transparent, and audit-ready reporting (Schweitzer, 2024).

Automation has also transformed finance roles, shifting workloads from manual entry (formerly ~80%) to analytical and planning functions, with employee satisfaction rising by 78%. A Salesforce (2021) report found 89% of workers experienced greater job fulfillment post-automation, while Deloitte (2025) notes that 79% of CFOs plan to use generative AI to address talent shortages. However, over half of finance employees are hesitant to adopt new software, making change management essential; without it, automation can overwhelm staff (Zararyan et al., 2023). The evolving CFO role now includes building technology-driven teams.

Although there are quantifiable gains in adopting automation technologies, resistance to such a move in organizations normally thwarts effective adoption. Data show that more than half of the employees in the finance field report their unwillingness to use new digital tools out of a concern of losing their jobs, confusion, or insufficient training (Zararyan et al., 2023). Unless strong change management tools are used, automation projects could be stalled internally due to resistance, and hence, not have the scope to expand them. The major obstacles are a lack of clarity on communicating the benefits, inadequate training, and digital immaturity of medium-sized companies. Deloitte stated in the 2023 Global Automation Survey that one of the first causes of aborted RPA projects referred to resistance to change pulled by employees (42 percent). This means that controlled onboarding, leadership sponsorship, and long-lasting upskilling are the keys to success in empowering employees. The TOE system will support prioritizing organizational exercises and preparedness over merely technical capacity, which incidentally improves the success of automation in the long run.

Adoption rates of automation vary widely. Manufacturing and telecom sectors lead in implementation, while finance, healthcare, and public sectors lag (CBSL Group, 2023). Banking and insurance drive RPA spending in the BFSI sector (US$8.3 billion in 2024) for fraud detection, claims processing, and compliance. Healthcare and manufacturing each spend $4–5 billion annually on automation, largely due to high regulatory and billing demands. North America leads in total adoption (about 38% of global revenue), but Asia–Pacific has the fastest growth rates (over 40% CAGR). Adoption differences often reflect digital readiness; strict regulations and legacy IT systems can slow progress in some European countries. Despite these disparities, automation is driving global innovation in financial reporting.

These advances bring important ethical and governance challenges. Automation tools must address privacy risks, algorithmic bias, and transparency concerns (Schweitzer, 2024). For example, historical data used in credit risk models can perpetuate past biases. Leading firms and regulators are responding: KPMG (2024) highlights the new role of auditors in AI governance, and the UK Financial Reporting Council and IAASB have begun updating standards for the digital era. Effective automation in banking now requires strong control mechanisms, including data privacy policies and active bias monitoring, to ensure ethical and reliable financial operations (Schweitzer, 2024; KPMG, 2024).

As per the findings, one should prioritize three organizational needs when it comes to the adoption of automation in financial reporting. To start, leaders ought to invest in formal change management initiatives to combat employee opposition and boost digital assurance via training and broadcast communication. Second, organizations should endeavor to be compatible with technology, i.e., test out the possible use of the current legacy systems with the RPA/ML tools without necessarily performing a hectic re-configuration of the legacy systems. Third, companies ought to implement effective governance and ethical monitoring systems, such as bias control and information security practices, especially when implementing AI in high-priority financial activities. Such suggestions will be similar to the TOE approach that focuses on technological fit, organization preparedness, and environmental responsibility, and are essential for the results of sustainable automation.

Although this research reveals a considerable increase in the reporting efficiency, accuracy, and cost-reduction brought by RPA and machine learning, there are still some gaps that have to be filled in subsequent studies. To begin with, longitudinal studies are required to determine the degree to which these benefits are maintained over time and the degree to which organizations are adapted to continuous technological change. Second, comparative research in SMEs and large corporations (SMEs vs. large corporations) may provide insight into scalability issues and different returns to automation investments. As a third future direction, it should search for the embedding of the generative AI tools in the financial reporting process with a focus on strategic forecasting and narrative disclosures. There is also a need to conduct sector-specific research, especially in less-covered sectors such as education and public administration, to help establish sector-specific barriers and solutions to implementation. Lastly, the socio-ethical consequences of financial automation (such as the displacement of the workforce, algorithmic discrimination, and regulation policies) should be explored by researchers so that the automation is adopted equally and responsibly.

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CONCLUSION

This investigation examined the impact of robotic process automation and machine learning on financial reporting through a comprehensive review of secondary quantitative data across industries and regions. Findings indicate that automation technologies are now integral to accounting operations, with financial reporting increasingly relying on automated, error-free data generation and advanced analytics for decision-making. Efficiency gains are substantial, with time to financial close reduced by up to 70–90% and error rates in automated systems approaching zero. These improvements enhance overall performance, strengthen internal controls, and improve audit readiness. Machine learning further empowers finance teams with advanced forecasting and proactive risk management, shifting accountants' roles from data entry to strategic analysis. However, the pace of automation adoption varies widely. Manufacturing and technology sectors lead, while healthcare, finance, and public services lag. Regionally, North America demonstrates the highest adoption and investment, while Asia-Pacific shows the most dynamic growth. These disparities reflect differences in digital maturity, regulatory frameworks, and organizational context. As finance grows more reliant on intelligent automation, concerns about algorithmic bias, ethics, and governance intensify. Achieving the benefits of automation efficiency, accuracy, and cost reduction requires robust accountability, transparent guidelines, and regulatory oversight to manage risks and ensure system reliability. Ultimately, robotic process automation and machine learning drive financial innovation beyond operational efficiency, transforming finance from a support function to a strategic partner in evidence-based analysis and decision-making. Realizing the full value of these technologies demands not just technical expertise but also progressive leadership, ethical standards, and ongoing workforce development. As automation advances, ongoing academic research is essential to monitor its long-term effects, support equitable adoption, and reinforce accounting's role as both a scientific and ethical discipline.

The study's reliance on secondary data limits its ability to capture contextual nuances or real-time implementation challenges, highlighting the need for future research based on primary empirical methods such as interviews, surveys, or case studies.

Ongoing interdisciplinary research is essential to ensure that the benefits of automation in financial reporting are not only maximized but also equitably distributed, ethically governed, and sustainably integrated into diverse organizational contexts.

RECOMMENDATIONS

The study's findings indicate that successful integration of robotic process automation and machine learning in financial reporting requires more than adopting technology; it demands strategy, clear regulation, and workforce upskilling. To maximize automation's benefits and promote responsible adoption, the following recommendations are offered:

- Organizations should target repetitive and predictable accounting processes, such as reconciliation and invoice handling, for automation. This phased approach eases adoption and minimizes disruption.

- Leadership should communicate that automation augments professional capacity rather than replacing jobs, promoting buy-in and organizational trust.
- Regulators should update financial reporting and audit procedures for AI, emphasizing clear audit methods, transparency, and data traceability to maintain public confidence.
- Governments should encourage automation in sectors like healthcare and the public sector through grants, tax incentives, and supportive frameworks.

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