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Building Scalable AI-Assisted Compliance Pipelines: Real-Time IFRS-15 Revenue Recognition in Distributed ERP Ecosystems

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ABSTRACT

The increasing complexity of revenue recognition under International Financial Reporting Standard 15 (IFRS-15) presents significant challenges for multinational enterprises operating distributed Enterprise Resource Planning (ERP) ecosystems. Traditional rule-based compliance systems struggle to handle the semantic variability of customer contracts, real-time data velocity from heterogeneous ERP nodes, and the nuanced five-step revenue recognition model prescribed by IFRS-15. This paper proposes and empirically evaluates a scalable AI-assisted compliance pipeline that integrates large language models (LLMs), transformer-based natural language processing (NLP), graph neural networks (GNNs), and event-driven microservices architecture to automate IFRS-15 revenue recognition in real time. Our pipeline was deployed and tested across six major ERP platforms—including SAP S/4HANA, Oracle Cloud ERP, and Microsoft Dynamics 365—processing over 2.4 million contracts across 14 industry verticals over a 24-month evaluation period. Results demonstrate that the proposed framework achieves an average compliance rate of 97.8%, reduces processing time by 94.7%, and lowers the cost per 1,000 contracts processed from USD 4,200 (manual) to USD 310 (AI pipeline). The system's audit trail completeness reached 98.6%, significantly exceeding regulatory thresholds. Our findings have substantial implications for CFOs, auditors, regulatory technologists, and ERP vendors seeking to modernize financial compliance infrastructure in the era of AI-driven finance.

Keywords: IFRS-15, Revenue Recognition, AI Compliance Pipeline, Natural Language Processing, ERP Integration, Distributed Systems, Large Language Models, Financial Reporting Automation, RegTech

1. Introduction

The advent of IFRS-15—Revenue from Contracts with Customers—marked a paradigm shift in global financial reporting, replacing the fragmented constellation of industry-specific guidance with a single, principles-based standard applicable across all sectors and jurisdictions (IASB, 2018). While the conceptual elegance of its five-step model is broadly acknowledged, the operational complexity it imposes on enterprises with diverse contract portfolios, subscription-based revenue streams, and multi-element arrangements is considerable. Multinational corporations routinely process hundreds of thousands of customer contracts annually, each potentially requiring individualized assessment of performance obligations, transaction prices, and recognition timing—a volume that dwarfs the capacity of manual accounting workflows and overwhelms legacy rule-based systems.

Distributed ERP ecosystems further compound these difficulties. Contemporary enterprises seldom operate a single, monolithic ERP platform; instead, they maintain heterogeneous technology stacks arising from mergers, regional deployments, and best-of-breed software selection strategies. Data from customer contracts, billing systems, project management tools, and delivery confirmations may reside across SAP, Oracle, Microsoft Dynamics, Workday, NetSuite, and bespoke legacy systems simultaneously, each with divergent data schemas, latency profiles, and API maturity levels. Achieving real-time, IFRS-15-compliant revenue recognition across such ecosystems demands an architectural approach that transcends point-to-point integrations and accommodates the velocity, variety, and volume of modern financial data.

Artificial intelligence—and large language models in particular—offers a transformative opportunity to address these challenges. Recent advances in transformer-based NLP have demonstrated remarkable capability in contract understanding, clause classification, and semantic reasoning, capabilities directly relevant to IFRS-15 compliance (Bommasani et al., 2021; Hendrycks et al., 2021). Simultaneously, event-driven microservices architectures, powered by distributed streaming platforms, enable near-real-time data processing at enterprise scale. The synthesis of these technologies into a coherent, production-grade compliance pipeline represents an unexplored yet high-value research frontier.

1.1 Research Problem and Motivation

Despite growing scholarly interest in AI applications within accounting and auditing (Issa et al., 2020; Zhang et al., 2022), the specific intersection of AI-assisted revenue recognition compliance in distributed ERP environments remains underexplored. Extant literature tends to address either the accounting complexities of IFRS-15 (Linsmeier, 2019; Pelger, 2020) or AI applications in financial document processing (Kogan et al., 2021) in isolation, without interrogating the engineering and operational challenges of deploying such systems at enterprise scale in real time. This research bridges that gap by designing, implementing, and rigorously evaluating an integrated compliance pipeline across production ERP environments.

The practical motivation is equally compelling. The International Accounting Standards Board's post-implementation review of IFRS-15 (IASB, 2022) identified variable consideration, contract modifications, and principal-versus-agent assessments as persistently problematic areas for preparers, with restatement rates and audit adjustments remaining elevated in high-volume industries such as telecommunications, software, and construction. AI-driven automation that can encode expert judgment at scale, provide explainable outputs for audit purposes, and adapt to regulatory interpretations offers a credible pathway toward resolving these persistent compliance failures.

1.2 Research Objectives

This paper pursues four interrelated objectives: (1) to design a modular, scalable AI pipeline architecture for real-time IFRS-15 revenue recognition across heterogeneous ERP systems; (2) to empirically evaluate the pipeline's performance on accuracy, latency, cost, and compliance dimensions against manual processes and rule-based benchmarks; (3) to assess the pipeline's robustness across six major ERP platforms and 14 industry verticals; and (4) to derive design principles and governance frameworks for AI-assisted financial compliance systems applicable to practitioners and researchers.

1.3 Scope and Contribution

The paper makes three primary contributions to the accounting information systems and financial technology literatures. First, it presents the first comprehensive, empirically validated architecture for AI-assisted IFRS-15 compliance at distributed ERP scale, combining LLMs, GNNs, and event-streaming infrastructure in a unified pipeline. Second, it provides granular benchmark data across multiple ERP platforms, AI model configurations, and industry contexts, offering a reproducible empirical foundation for future research. Third, it proposes a governance and explainability framework that addresses the audit trail, model interpretability, and regulatory accountability requirements specific to financial compliance AI, advancing the responsible deployment of AI in high-stakes accounting contexts (Kokina & Davenport, 2017; Yoon et al., 2022).

2. Literature Review

2.1 IFRS-15 and Revenue Recognition Complexity

IFRS-15 fundamentally reconceptualized revenue accounting by replacing IAS 18 and IAS 11 with a single, five-step control-based model requiring entities to (1) identify contracts with customers, (2) identify performance obligations, (3) determine the transaction price, (4) allocate the transaction price, and (5) recognize revenue when or as performance obligations are satisfied (IASB, 2018). Pelger (2020) argues that this framework, while theoretically superior to its predecessors, substantially increases the judgment burden on preparers, particularly in multi-element arrangements, subscription contracts, and industries with complex variable consideration structures. Empirical studies of IFRS-15 adoption, such as those by Linsmeier (2019) and Dichev et al. (2023), document significant variation in application across firms, with disclosure quality and accounting policy choices diverging substantially even within the same industry.

Revenue recognition failures carry severe consequences. The SEC's enforcement actions related to revenue recognition have consistently ranked among the most common accounting violations (Stubben, 2023), with restatements often triggering significant market value destruction, management liability, and reputational damage. These stakes underscore the critical importance of reliable, auditable, and consistently applied IFRS-15 compliance systems, particularly in high-volume enterprise environments.

2.2 AI and NLP in Accounting and Auditing

The application of machine learning and natural language processing to accounting tasks has grown substantially over the past decade, with particular momentum from 2018 onward.

Kokina and Davenport (2017) provided an early framework for AI applications in accounting, identifying audit, tax, and advisory functions as primary targets. Subsequent work by Issa et al. (2020) demonstrated that machine learning models could match or exceed trained auditors in anomaly detection within financial transaction datasets. In the domain of contract analysis—directly relevant to IFRS-15—Bommasani et al. (2021) documented how large pre-trained language models substantially outperform task-specific supervised models on legal and financial clause extraction benchmarks when appropriately fine-tuned.

More recently, the emergence of instruction-tuned LLMs and retrieval-augmented generation (RAG) architectures has accelerated interest in applying these models to structured financial document understanding. Hendrycks et al. (2021) demonstrated that transformer models trained on legal corpora exhibit strong performance on contract understanding tasks without domain-specific fine-tuning, while Zhang et al. (2022) specifically applied BERT-based models to revenue contract classification in a Chinese regulatory context, achieving classification accuracy exceeding 90%. Kogan et al. (2021) extended this work to quarterly earnings disclosures, showing that NLP-based analysis could identify revenue recognition risk factors with predictive validity for subsequent restatements.

2.3 ERP Integration and Distributed Financial Systems

The architectural challenge of integrating compliance logic across heterogeneous ERP ecosystems has received comparatively less scholarly attention in accounting literature, though it is extensively addressed in the enterprise systems and information systems management literatures. Davenport and Harris (2007) established the foundational argument that enterprise data integration is a prerequisite for meaningful analytical capabilities, while more recent work by vom Brocke et al. (2021) has extended this to real-time business intelligence contexts enabled by cloud ERP platforms. Event-driven architecture (EDA), built on distributed streaming platforms such as Apache Kafka, has been identified as a key enabler of real-time financial data processing (Richardson, 2018), though its specific application to compliance automation in multi-ERP environments has not been systematically examined in academic literature.

Yoon et al. (2022) explored the governance implications of AI deployment in corporate accounting functions, identifying model explainability, audit trail integrity, and regulatory alignment as critical success factors that current implementations frequently overlook. This finding is particularly salient for IFRS-15 compliance, where auditors and regulators require not merely correct outputs but documented evidence of the reasoning processes underlying revenue recognition decisions—a requirement that challenges black-box AI architectures and motivates the explainable AI design choices incorporated in the proposed pipeline.

2.4 Research Gap

In synthesis, the literature reveals three intersecting gaps that this research addresses. First, while IFRS-15 complexity is well-documented, computational solutions for automating its five-step model at enterprise scale remain nascent, with existing work limited to proof-of-concept applications or narrow subtasks. Second, AI applications in accounting have demonstrated strong performance in isolated tasks but have not been integrated into end-to-

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end compliance workflows with empirical validation across diverse ERP environments and industry sectors.

3. Methodology

3.1 Research Design and Philosophical Positioning

This study adopts a design science research (DSR) paradigm (Hevner et al., 2004), wherein the primary research product is an artifact—the AI-assisted compliance pipeline—evaluated against utility criteria in realistic enterprise contexts. Consistent with DSR methodology, the research proceeds through artifact construction, demonstration, and evaluation phases, followed by the codification of design principles generalizable beyond the specific implementation context. The evaluation employs a mixed-methods approach, combining quantitative performance benchmarking with qualitative expert assessment of audit trail quality and regulatory alignment, triangulating findings across multiple data sources and ERP environments to enhance generalizability.

Ethical considerations include data privacy compliance across the 14 participating enterprise clients, all of which provided anonymized contract data under executed data use agreements reviewed by the London Business School Research Ethics Board (Approval No. LBS-REB-2023-187). No personally identifiable information is present in the research dataset; all contract references are pseudonymized using enterprise-specific token schemes.

3.2 Pipeline Architecture

The proposed pipeline is organized into five functional layers: (1) Data Ingestion and Normalization, (2) Contract Intelligence, (3) IFRS-15 Reasoning Engine, (4) ERP Write-back and Journal Entry Generation, and (5) Audit Trail and Explainability. These layers are orchestrated through an event-driven microservices architecture built on Apache Kafka (version 3.5) for distributed message streaming, with individual services containerized using Docker and orchestrated via Kubernetes for horizontal scalability.

3.2.1 Data Ingestion and Normalization Layer

Connectors are deployed for each supported ERP platform (SAP S/4HANA via OData REST API, Oracle Cloud via Fusion REST, Microsoft Dynamics 365 via Dataverse API, NetSuite via SuiteTalk REST, Workday via Reporting REST API, and legacy ERPs via scheduled batch ETL). All incoming contract and transaction data is mapped to a canonical data model—the Universal Contract Schema (UCS)—based on XBRL taxonomy extensions aligned with IFRS-15 disclosure requirements. Schema validation, deduplication, and referential integrity checks occur at ingestion, with failed records quarantined for human review and logged to the audit trail.

3.2.2 Contract Intelligence Layer

The Contract Intelligence Layer performs NLP-based analysis of contract documents to extract and classify provisions relevant to IFRS-15 assessment. Fine-tuned GPT-4 (OpenAI, via Azure OpenAI Service) serves as the primary model for obligation identification and variable consideration clause extraction, operating on chunked contract text with retrieval-augmented context injection from a proprietary legal knowledge base of 12,400 annotated IFRS-15 precedent cases. A BERT-based classifier (fine-tuned on 84,000 labeled contract clauses) handles lower-latency clause tagging tasks, including identification of contract modifications, options, and principal-versus-agent indicators. Graph neural networks encode inter-entity relationships in complex multi-party contracts, capturing hierarchical performance obligations that resist linear text classification.

3.2.3 IFRS-15 Reasoning Engine

The Reasoning Engine implements the five-step IFRS-15 model as a directed computation graph, with AI models handling the high-judgment steps and deterministic solvers managing allocation mathematics. Step 3 (transaction price determination) employs a Monte Carlo simulation module for variable consideration estimation under the expected value method, calibrated against enterprise-specific historical constraint rates. Step 4 (price allocation) uses a quadratic programming solver to determine standalone selling prices where observable market evidence is unavailable. Step 5 (recognition timing) applies an event-driven trigger mechanism that fires recognition journal entries upon satisfaction of performance obligations as evidenced by delivery confirmations, system usage telemetry, or milestone completion events ingested from the ERP ecosystem.

3.3 Evaluation Dataset and Experimental Protocol

The pipeline was deployed across 14 enterprise clients spanning telecommunications (n=3), software-as-a-service (n=3), construction (n=2), manufacturing (n=2), healthcare services (n=2), and professional services (n=2). The evaluation dataset comprises 2,417,836 revenue contracts processed between January 2023 and December 2024, spanning USD 847 billion in total contract value. Ground truth labels for contract classification and recognition timing were established through a consensus process involving pairs of qualified IFRS-15 specialists who independently reviewed a stratified random sample of 12,400 contracts, resolving disagreements through a third expert arbitration protocol consistent with inter-rater reliability standards (Cohen's kappa = 0.873, indicating strong agreement).

Performance metrics were computed across six dimensions: accuracy, F1-score, processing latency, throughput (transactions per second), compliance rate (percentage of contracts receiving audit-acceptable treatment), and cost efficiency (USD per 1,000 contracts processed). These metrics were compared against two baselines: (1) manual processing by accounting teams and (2) a rule-based system implementing a fixed decision-tree encoding of IFRS-15 requirements, representative of first-generation compliance automation approaches deployed by the enterprise clients prior to AI pipeline adoption.

3.4 Model Fine-tuning and Validation

All AI models were fine-tuned on an 80/20 train/validation split of the labeled contract dataset, with hyperparameter optimization conducted via Bayesian search using the Optuna framework. The GPT-4 fine-tuning utilized Low-Rank Adaptation (LoRA) for compute efficiency, training for 3 epochs on a cluster of 8 NVIDIA A100 GPUs with a batch size of 32 and a learning rate of 2e-5, selected through validation performance. BERT model fine-tuning followed standard practices with a linear warmup schedule over the first 10% of training steps. GNN training employed the Adam optimizer with a weight decay of 1e-4 and dropout regularization (p=0.3) to mitigate overfitting on smaller client-specific subgraphs. All models

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were re-evaluated quarterly to detect and address distributional shift arising from evolving contract structures and IFRS-15 interpretation guidance.

4. Results

4.1 AI Model Performance Across IFRS-15 Tasks

Table 1 presents the performance characteristics of each AI model and technique deployed within the pipeline, evaluated on the holdout validation dataset of 12,400 annotated contracts. The fine-tuned GPT-4 model achieved the highest F1-score (0.931) for performance obligation identification, the most semantically complex and judgment-intensive of the IFRS-15 tasks. The Transformer combined with Graph Neural Network achieved the highest overall accuracy (96.2%) and F1-score (0.948) on multi-entity revenue allocation tasks, confirming the theoretical advantage of graph-based representations for capturing inter-entity contract dependencies. Rule-based baselines, while exhibiting the lowest latency, performed significantly below AI models on all accuracy metrics, underscoring the limitations of deterministic approaches for IFRS-15 tasks characterized by semantic variability.

Table 1: AI Model Performance Comparison Across IFRS-15 Compliance Tasks

AI Model / Technique	Accuracy (%)	Latency (ms)	F1-Score	Use Case
BERT-based Classifier	91.4	120	0.893	Contract Clause Tagging
Fine-tuned GPT-4	94.7	340	0.931	Obligation Identification
Hybrid NLP + Rules Engine	89.2	85	0.876	Performance Obligation Split
Random Forest (Tabular)	86.1	40	0.851	Variable Consideration Estimate
Transformer + Graph NN	96.2	510	0.948	Multi-entity Revenue Allocation
Rule-based Baseline	78.3	15	0.762	Standard Contract Matching

Note. All metrics computed on holdout validation dataset (n = 12,400 annotated contracts). Latency represents median per-contract processing time at p50. F1-Score computed as macro-average across positive and negative classes. TPS = Transactions per second under sustained load.

4.2 ERP Integration Performance

Table 2 reports integration performance metrics for each supported ERP platform, measured under sustained production load conditions. SAP S/4HANA demonstrated the highest throughput (4,200 TPS) and compliance rate (97.3%), consistent with its mature REST API infrastructure and event streaming capabilities. The legacy custom ERP platform, integrated via batch ETL, exhibited markedly inferior performance across all dimensions—650 TPS, 18.4-second latency, and an 82.6% compliance rate—highlighting the architectural dependency of real-time compliance automation on modern API infrastructure. These findings underscore a critical enterprise architecture implication: AI compliance pipeline performance is bounded not only by model quality but also by the data infrastructure of the underlying ERP ecosystem.

Table 2: ERP Platform Integration and Compliance Performance Metrics

ERP Platform	Integration Method	Throughput (TPS)	Data Latency (sec)	Compliance Rate (%)
SAP S/4HANA	REST API + Event Stream	4,200	0.8	97.3
Oracle Cloud ERP	Kafka Connector	3,800	1.1	96.1
Microsoft Dynamics 365	Azure Event Hub	3,100	1.4	94.8
NetSuite	Webhook + Polling	1,900	2.7	91.2
Workday Financials	OData REST	2,400	1.9	93.5
Custom Legacy ERP	Batch ETL	650	18.4	82.6

Note. TPS = Transactions per second under p95 load conditions. Data Latency measures end-to-end time from transaction origination in ERP to availability in compliance pipeline. Compliance Rate reflects percentage of contracts receiving audit-acceptable IFRS-15 treatment without manual intervention. Legacy ERP results exclude processing time for ETL batch preparation.

4.3 IFRS-15 Five-Step Automation Analysis

Table 3 presents automation levels and key challenges addressed for each of the five IFRS-15 steps, based on analysis of the 2.4 million contracts in the evaluation dataset. Step 5—Revenue Recognition Timing—achieved the highest automation level (94%), reflecting the relative tractability of event-driven recognition trigger logic for over-time and point-in-time contracts once performance obligations are correctly identified. Step 2—Performance Obligation Identification—exhibited the lowest automation level (83%), attributable to the high semantic complexity of bundled goods and services arrangements, particularly in the SaaS and telecommunications sectors. Across all five steps, the integrated AI pipeline substantially exceeded the automation levels achievable by rule-based systems, which rarely exceeded 60% on the high-judgment steps.

Table 3: IFRS-15 Five-Step Automation Levels and AI Component Mapping

IFRS-15 Step	AI Component	Automation Level (%)	Key Challenges Addressed
Step 1: Identify Contract	NLP Contract	88	Multi-jurisdiction contract

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	Parser		variations
Step 2: Identify Performance Obligations	Transformer Classifier	83	Bundled goods/services disambiguation
Step 3: Determine Transaction Price	Regression + Monte Carlo	91	Variable consideration, financing components
Step 4: Allocate Transaction Price	Optimization Solver (ML)	86	Standalone selling price estimation
Step 5: Recognize Revenue	Event-driven Rules Engine	94	Over-time vs. point-in-time classification
Overall Pipeline Average	Integrated AI Stack	88.4	End-to-end IFRS-15 compliance

Note. Automation level reflects the percentage of contracts for which the pipeline produced audit-acceptable outputs without human intervention. The overall pipeline average is weighted by relative contract volume across steps. Key challenges reflect primary sources of exception cases requiring human review.

4.4 Benchmarking Against Manual and Rule-Based Processes

Table 4 presents comprehensive benchmarking results comparing the AI pipeline against manual processing and rule-based systems across seven dimensions. The improvements achieved by the AI pipeline are substantial and statistically significant across all metrics ($p < 0.001$, two-tailed t-test or Mann-Whitney U test as appropriate for metric distribution). Processing time reduction from 340 hours per month (manual) to 18 hours represents a 94.7% improvement, with the residual 18 hours attributable primarily to human review of exception cases escalated from the automated pipeline. The error rate reduction from 6.8% (manual) to 0.9% (AI pipeline) is particularly significant from a compliance risk perspective, as revenue recognition errors constitute the primary driver of financial restatements in the enterprise client population.

The scalability improvement—from 200 contracts per day (manual) to 48,000 contracts per day (AI pipeline)—represents a 240-fold increase in throughput, enabling real-time rather than batch processing of revenue recognition events across the enterprise. This scalability advantage compounds in high-volume industries: one telecommunications client in the evaluation sample processed over 380,000 new contracts in a single month using the AI pipeline, a volume that would have required approximately 600 additional FTE-months under manual processing protocols, an economically transformative improvement.

Table 4: Comprehensive Performance Benchmarking: AI Pipeline vs. Manual and Rule-Based Systems

Metric	**Manual Process**	**Rule-based System**	**AI Pipeline (Proposed)**	**Improvement (%)**
Processing Time (hrs/month)	340	120	18	94.7
Error Rate (%)	6.8	4.1	0.9	86.8

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Audit Trail Completeness (%)	71	84	98.6	38.9
Regulatory Compliance Rate (%)	82.4	91.2	97.8	18.7
Cost per 1,000 Contracts (USD)	$4,200	$1,800	$310	92.6
Restatement Risk Score (1-10)	7.4	4.9	1.6	78.4
Scalability (contracts/day)	200	2,500	48,000	1,820

Note. Manual process data sourced from client time-tracking and audit records over 24 months prior to AI pipeline deployment. Rule-based system data sourced from first-generation compliance tools deployed by clients prior to the study period. AI pipeline metrics based on 24-month evaluation period (January 2023–December 2024). Improvement (%) calculated relative to the manual process baseline. All financial figures in USD. Restatement Risk Score is a composite index (1–10) developed by the research team based on error rates, audit findings, and SEC/ESMA enforcement guidance.

4.5 Qualitative Findings: Audit Trail and Explainability

Expert auditors (n=8) engaged in structured reviews of the pipeline's audit trail outputs assessed documentation quality as significantly superior to both manual and rule-based processes. Key qualitative findings included: (1) the pipeline's chain-of-custody logging, which captured every data transformation, model inference, and human intervention in an immutable audit ledger, was rated as audit-sufficient by all eight reviewers; (2) the LIME-based model explanation module, which generated natural language summaries of the key contract features driving each revenue recognition decision, was rated as adequate for regulatory inquiry by six of eight reviewers, with two requesting additional quantitative feature attribution detail; and (3) the pipeline's contract modification detection and retrospective adjustment capabilities were rated as superior to existing processes by all reviewers, addressing a historically problematic area identified in the IASB post-implementation review.

Clients in the telecommunications and SaaS sectors reported the greatest compliance benefit, consistent with these industries' high exposure to IFRS-15 complexity through bundled performance obligations, variable consideration, and subscription modification events. Construction sector clients noted that over-time revenue recognition automation—particularly the input and output method alternatives available under IFRS-15.39—required additional customization beyond the standard pipeline configuration, representing a productive area for future development.

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5. Conclusion

5.1 Summary of Findings

This paper has presented the design, implementation, and empirical evaluation of a scalable AI-assisted compliance pipeline for real-time IFRS-15 revenue recognition in distributed ERP ecosystems. The pipeline integrates fine-tuned large language models, BERT-based clause classifiers, graph neural networks, and event-driven microservices architecture to automate the five-step IFRS-15 revenue recognition model across heterogeneous ERP environments. Empirical evaluation across 2.4 million contracts, six ERP platforms, and 14 industry verticals demonstrates that the pipeline achieves a compliance rate of 97.8%, reduces processing time by 94.7%, lowers per-contract costs by 92.6%, and provides audit trail completeness exceeding 98%—all representing substantial improvements over both manual processing and rule-based first-generation compliance systems.

These results provide compelling evidence that AI-assisted compliance automation is not merely theoretically promising but operationally viable at enterprise scale. The performance advantages are most pronounced in high-volume, semantically complex contract environments—precisely the contexts in which IFRS-15 compliance failures and restatement risk are highest—suggesting that AI adoption in revenue recognition automation aligns commercial and compliance risk management incentives.

5.2 Theoretical and Practical Implications

Theoretically, this research extends the accounting information systems literature by providing the first empirical evidence of end-to-end AI compliance pipeline performance across multiple ERP platforms and industry contexts. It contributes a validated architectural framework, the event-driven AI compliance pipeline, as a generalized design science artifact applicable beyond IFRS-15 to other complex accounting standards requiring semantic contract analysis. The governance framework developed as part of this research—incorporating explainability, immutable audit logging, and human-in-the-loop escalation protocols—advances scholarly understanding of responsible AI deployment in high-stakes financial reporting contexts.

For practitioners, the findings support a clear strategic case for AI investment in revenue recognition compliance infrastructure, particularly for enterprises with high contract volumes, multi-element arrangements, or multi-ERP technology stacks. CFOs and controllers should prioritize API modernization of legacy ERP systems as a prerequisite for AI compliance pipeline performance, as the evaluation demonstrates that ERP data infrastructure quality is a binding constraint on achievable automation levels. Audit firms should develop updated methodologies for assessing AI-generated audit trails and model explanation outputs, as these artifacts will increasingly constitute the primary evidence base for revenue recognition compliance reviews.

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