AI-Based Process Mining Framework for Process Business Integration in an Enterprise System

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Abstract—**The accelerated progression of information technology has necessitated the adoption of more intelligent and adaptive Enterprise Systems (ES) to sustain and optimize organizational processes. The ES serve as critical infrastructures for resource management, operational efficiency, and sustaining competitive advantage; however, their deployment frequently encounters persistent challenges. These include discrepancies between modelled and actual business processes, insufficient visibility in process execution, and limited automation in the detection and optimization of workflows. To mitigate these limitations, this study advances an Artificial Intelligence (AI)-enabled Process Mining paradigm. This approach facilitates the systematic extraction, analysis, and visualization of business processes, thereby supporting the identification of deviations, the detection of anomalies, and the provision of data-driven recommendations for continuous improvement. The overarching aim of the research is to conceptualize and evaluate an enterprise system framework that integrates AI-driven Process Mining to reinforce transparency, efficiency, and effectiveness in business process management. The proposed framework aims to provide automated analytical capabilities, predictive insights, and a robust data-centric foundation to enhance the precision of strategic decision-making, thereby contributing to the advancement of adaptive and intelligent enterprise systems.**

Keywords—Enterprise System; process mining; artificial intelligence; process business

I. Introduction

The Enterprise Systems (ES) have become the cornerstone of contemporary organizations, providing integrated platforms that manage resources, information, and workflows across multiple domains [1]. Systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Supply Chain Management (SCM) are widely implemented to improve efficiency, standardize operations, and support strategic agility [2]. Despite their widespread adoption, ES implementation is often complex and fraught with challenges. Many organizations struggle to align the prescribed process models embedded in ES with the actual workflows enacted in practice, leading to inefficiencies, poor visibility, and difficulties in detecting deviations [3]. These limitations highlight the need for more intelligent and adaptive systems that can dynamically support evolving business environments [4].

The Implementation of ES is not solely a technical task but a socio-technical transformation requiring alignment between technology, organizational structures, and user practices [5]. Misalignments frequently occur when standardized ES models fail to capture organizational complexities, resulting in workarounds and process inconsistencies [6]. Furthermore, conventional ES often lack mechanisms for real-time monitoring of process execution, leaving organizations unable to identify bottlenecks or deviations until problems escalate. The reliance on manual intervention and subjective decision-making further hampers responsiveness in dynamic markets. Addressing these challenges necessitates approaches that improve transparency, automate monitoring, and support continuous process optimization [7].

The accurate identification and understanding of business processes are essential for ensuring ES effectiveness [8]. Without reliable insights into real-time process execution, organizations risk inefficiencies, compliance violations, and suboptimal decision-making [9]. The business process identification enables organizations to detect hidden patterns, uncover deviations from prescribed workflows, and establish baselines for systematic improvement [10]. However, the increasing complexity of enterprise operations makes traditional manual methods of process documentation insufficient. Consequently, automated and data-driven approaches are needed to capture the dynamics of organizational processes in real time [11].

Artificial Intelligence (AI) provides promising opportunities for advancing business process management [12]. Through methods such as machine learning, natural language processing, and predictive analytics, AI enables the automated analysis of large-scale enterprise data to identify anomalies, predict potential bottlenecks, and generate actionable recommendations. Unlike static models, AI-based approaches can adapt dynamically to organizational changes, ensuring that process models remain relevant and aligned with evolving objectives [13]. This adaptability strengthens both operational and strategic decision-making, empowering organizations to anticipate risks and proactively optimize performance.

Process mining has emerged as a powerful methodology for uncovering and analyzing business processes from event logs generated by ES [12]. Unlike interviews or manual documentation, which are prone to subjectivity and incompleteness, Process Mining reconstructs processes directly from system data, providing an objective and data-driven view of organizational operations [14]. The recent advancements extend Process Mining from descriptive analysis to predictive

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and prescriptive capabilities when integrated with AI [15]. This integration allows organizations not only to monitor past and present processes but also to forecast outcomes and recommend optimal interventions [16]. Consequently, AI-enhanced Process Mining offers a systematic foundation for process redesign, automation, and continuous improvement [17].

Although AI and Process Mining have been explored individually, few studies propose comprehensive frameworks that systematically embed AI-driven Process Mining within ES architectures [18]. Existing work often focuses on algorithmic advances or isolated case studies without addressing the organizational integration and scalability required for enterprise-wide adoption [19]. Furthermore, limited research examines the combined predictive and prescriptive power of AI and Process Mining in supporting continuous adaptation to dynamic business environments. This gap presents a significant opportunity to design and evaluate frameworks that integrate AI and Process Mining into ES for both operational efficiency and strategic decision-making [20].

The remainder of the study is organized as follows. Section II reviews relevant literature on ES, Process Mining, and AI, highlighting prior studies and identifying research gaps. Section III describes the research methodology, including data collection, analytical methods, and evaluation criteria. Section IV presents the proposed AI-based Process Mining framework, outlining its architecture, components, and operational workflow. Section V discusses the findings, emphasizing potential benefits, limitations, and implications for theory and practice. Finally, Section VI concludes the study with a summary of contributions and suggestions for future research.

II. Enterprise System, Process Business, and Artificial Intelligence

The Enterprise Systems (ES) are foundational infrastructures for organizations, providing platforms that integrate data, standardize processes, and support cross-functional coordination [1],[2]. Despite their strategic importance, ES implementation remains challenging, with difficulties often rooted in socio-technical misalignments, change-management risks, and the rigid process logics embedded in ES design [6],[5]. The classic research highlights that ES frequently impose standardized process structures that may conflict with local practices and strategic goals, complicating alignment and reducing the realization of intended benefits unless supported by deliberate redesign and governance mechanisms [21]. The lifecycle perspectives further emphasize that ES exhibit distinct risk and benefit profiles across stages—from chartering to shakedown and eventual "onward and upward" evolution—while other studies link ES adoption to process innovation when organizations develop sufficient absorptive capacity to leverage them [22].

Process mining (PM) has emerged as a methodology to bridge the persistent gap between "as-designed" and "as-executed" processes by extracting structured knowledge from event data [12]. Through this data-driven approach, organizations can perform fact-based process discovery, conformance checking, and enhancement, thereby strengthening ES auditability and operational analytics [23]. The foundational contributions have formalized PM principles and identified challenges such as event-data quality, scalability, and the generation of actionable insights, positioning PM as both a core discipline in data science and a natural complement to enterprise system assurance [17].

The core PM capabilities are grounded in robust discovery and conformance algorithms. The inductive mining and its visual extensions generate hierarchically structured, sound process models that remain resilient under noisy data [24]. The alignment-based conformance checking quantifies deviations between observed event logs and reference models, enabling systematic performance analysis and compliance diagnostics. Collectively, these techniques support continuous assurance and fidelity of ES execution.

Artificial Intelligence (AI) has further expanded the scope of PM by shifting from retrospective analysis to predictive and prescriptive capabilities. Early studies demonstrated that deep learning models, such as Long Short-Term Memory (LSTM) networks, outperform classical baselines in next-activity and timestamp prediction [25]. The subsequent advances introduced hierarchical attention and Transformer-based architectures capable of handling long event sequences, concept drift, and complex attribute spaces [26]. These innovations enable proactive ES management by forecasting cycle times, risks, and outcomes in real time. Beyond prediction, prescriptive process monitoring extends PM toward runtime optimization. The recent research has applied causal inference and reinforcement learning to recommend targeted interventions—such as task reassignment or prioritization—under operational and resource constraints, thereby advancing closed-loop process optimization [13]. The surveys consolidate these developments while also charting unresolved issues related to policy learning, constraint management, and responsible AI deployment [15].

The emerging directions in PM address the limitations of case-centric models by introducing Object-Centric Process Mining (OCPM). This paradigm explicitly models multi-object interactions (e.g., orders, items, deliveries), thereby improving fidelity in complex enterprise scenarios where traditional abstractions obscure interdependencies. The introductory and tutorial studies have formalized object-centric event data and demonstrated the benefits of OCPM for ES contexts with rich relational structures [27]. The parallel advancements in tooling and scalability further support enterprise applications. PM4Py, an open-source Python library, integrates PM methods with mainstream data-science frameworks (pandas, scikit-learn), enabling reproducible pipelines for ES analytics [28]. GPU-accelerated implementations extend these capabilities, delivering order-of-magnitude improvements in processing speed and supporting near real-time monitoring of enterprise-scale event logs [29].

The applications across domains demonstrate the versatility and transferability of PM. The extensive reviews and empirical studies in healthcare illustrate its ability to reveal patient pathways, identify bottlenecks, and evaluate policy interventions such as vaccination programs. Similar applications are emerging in finance, public administration, and manufacturing, highlighting PM's adaptability to regulated enterprise contexts. In parallel, the research on large language models (LLMs) and AI for Business Process Management

(BPM) shows potential for augmenting analyst capabilities, including process knowledge extraction from unstructured sources, natural-language explanations, and automated support across the BPM lifecycle [30]. Nonetheless, the scholars caution that embedding generative AI into enterprise settings requires governance frameworks to ensure reliability, transparency, and ethical use [31]. Finally, the current research trajectories extend PM and AI integration toward inter-organizational and collaborative processes.

III. Methodology

To construct an Enterprise System framework that incorporates Artificial Intelligence (AI)-enabled Process Mining, this study applies a structured, multi-phase research methodology. The approach integrates both qualitative and quantitative methods to ensure analytical rigor, accuracy of outcomes, and validity of findings. The methodology is divided into three principal phases: 1) literature review and problem identification, 2) requirements analysis and framework formulation, and 3) prototype development and implementation.

The first phase consists of a comprehensive review of the existing body of knowledge to establish the theoretical underpinnings and technological advancements relevant to Enterprise Systems, Process Mining, and AI in business process management. A Systematic Literature Review (SLR) approach is employed, following established guidelines for identifying, selecting, and synthesizing research evidence. This critical review enables the identification of prevailing research trends, methodological approaches, and unresolved gaps. The outcome of this stage is a conceptual foundation that clarifies the challenges associated with Enterprise Systems implementation and highlights the potential of AI-driven Process Mining as a remedial approach.

The second phase focuses on requirements analysis and the development of an initial conceptual framework. This stage seeks to capture organizational needs in process management and translate them into design principles for integrating AI-based Process Mining. The empirical data are collected through case studies of organizations that have implemented enterprise platforms, alongside interviews and surveys with key stakeholders such as IT managers, business analysts, and end-users. Business processes are further modelled using Business Process Model and Notation (BPMN), a standardized representation that supports consistent visualization and communication of workflows (OMG, 2013). The outcome of this phase is a preliminary model outlining how AI-enabled Process Mining can be systematically embedded into Enterprise System architectures.

The third phase entails prototype development and empirical validation of the proposed framework. An Agile-inspired iterative system development methodology is adopted to ensure adaptability, responsiveness to user feedback, and progress. The advanced machine learning algorithms—including decision trees, neural networks, and reinforcement learning—are incorporated to support the detection of process patterns and optimization opportunities. The process Mining platforms such as Celonis, ProM, and Disco are employed to extract and analyze event log data from the enterprise. This stage culminates in the creation of a functional prototype that serves as proof of concept, offering empirical evidence of the framework's capacity to improve process transparency, conformance checking, and workflow optimization within Enterprise Systems.

IV. AI-Based Process Mining

We propose an enterprise system framework that natively embeds AI-based process mining to continuously discover, monitor, and optimize end-to-end business processes. The framework integrates heterogeneous enterprise applications, constructs standardized event logs, and applies a multi-task AI-PM engine for 1) automated model discovery, 2) conformance checking, and 3) predictive/prescriptive analytics. A reference architecture, data schemas, learning objectives, and governance mechanisms are defined. The modern enterprises operate across distributed applications and organizational units, creating complexity, latency, and opaque bottlenecks. The classical process mining uncovers actual process flows from event logs, but struggles with concept drift, noisy data, and proactive decision-making. We extend process mining with AI—sequence models, graph learning, anomaly detection, and reinforcement learning—to deliver predictive foresight and prescriptive recommendations tightly coupled to operational systems. Fig. 1 shows the proposed framework.

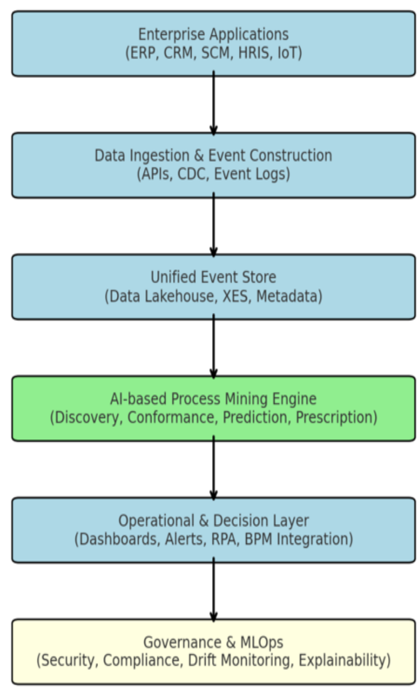

Fig. 1. The proposed framework.

The framework rests on five principles: (P1) system-of-record integration, (P2) event-log standardization, (P3) AI-augmented mining tasks, (P4) closed-loop optimization (insights → action), and (P5) governed MLOps. The target outcomes are improved cycle time, conformance, cost, service level, and risk posture. The Layers and roles consist of several points, there are: Data Sources: ERP (FI/CO/MM/SD), CRM, SCM/WMS/TMS, ITSM, e-procurement, IoT/edge (optional). Ingestion & CDC: connectors, message bus, change-data-capture (CDC), schema registry. Event Fabric: event building, deduplication, correlation keys, case construction, enrichment with master data and context (customer, supplier, SLA). Unified Event Store: scalable lakehouse; raw (bronze), conformed (silver), curated (gold); XES/BPMN-compatible exports. AI-PM Engine: discovery (control-flow), conformance, enhancement; prediction (remaining time, risk, cost), anomaly detection; prescription (what-if, policy optimization). Experience Layer: analyst studio (models, variants), operations cockpit (alerts, recommendations), API/webhooks to enterprise workflows (RPA/BPM/ERP). Governance, Security & MLOps: lineage, RBAC/ABAC, PII protection, drift monitoring, model registry, A/B rollout, audit trails. The Event schema (core fields) will consist of case_id, activity, timestamp_start, timestamp_end (optional), resource, role, cost, variant_id, lifecycle (start/complete), attributes (key–value), context (SLA, priority, customer segment), label (if supervised). The correlation is deterministic keys (e.g., sales order) + probabilistic matching for cross-system events. The Process Discovery consists of Control-flow are Inductive/Split/Heuristics Miner for baseline; Graph Neural Networks (GNNs) refine directly-follows graphs with edge confidence learned from noise-aware features (frequency, entropy, temporal gaps). The Variant clustering: density-based clustering on trace embeddings from a Transformer encoder yields canonical variants and rare-path detection. The framework facilitates several processes, such as aligning the discovered model with the event log: computing fitness, precision, generalization, and simplicity. An enterprise system framework based on Artificial Intelligence (AI)-driven process mining is proposed to address the increasing complexity of organizational processes and the limitations of traditional enterprise applications. Enterprise systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Supply Chain Management (SCM) generate vast amounts of heterogeneous event data across distributed platforms. Traditional process mining provides valuable insights by reconstructing process flows from these event logs; however, it is limited in handling noisy data, concept drift, and predictive or prescriptive decision-making. The integration of AI techniques into process mining enables organizations not only to discover and monitor actual business processes but also to predict process outcomes, detect anomalies, and recommend optimized interventions in real time. The proposed framework adopts a layered architecture that begins with the integration of diverse enterprise applications through standardized connectors and change-data-capture mechanisms. These data streams are transformed into event logs with structured attributes such as case identifiers, activities, timestamps, resources, and contextual variables. A unified event store acts as a centralized repository, ensuring data quality, consistency, and compliance with interoperability standards such as the eXtensible Event Stream (XES). This foundational layer supports scalable data ingestion and facilitates the construction of enriched process instances, which form the basis for subsequent AI-based analysis. At the core of the architecture lies the AI-enhanced process mining engine. This engine extends the three fundamental tasks of process mining—discovery, conformance checking, and enhancement—by embedding advanced machine learning models, as shown in Fig. 2. Process discovery benefits from graph neural networks and sequence-based models to generate accurate representations of control-flow structures, even in the presence of noisy or incomplete data. Conformance checking is augmented by anomaly detection techniques that assign probabilistic confidence scores to deviations, allowing organizations to prioritize process violations based on business impact. Predictive models, leveraging deep learning and survival analysis, are applied to forecast remaining cycle times, the probability of meeting service-level agreements, and the likelihood of cost overruns. Beyond prediction, reinforcement learning and counterfactual analysis provide prescriptive recommendations that optimize resource allocation, activity sequencing, and policy adjustments.

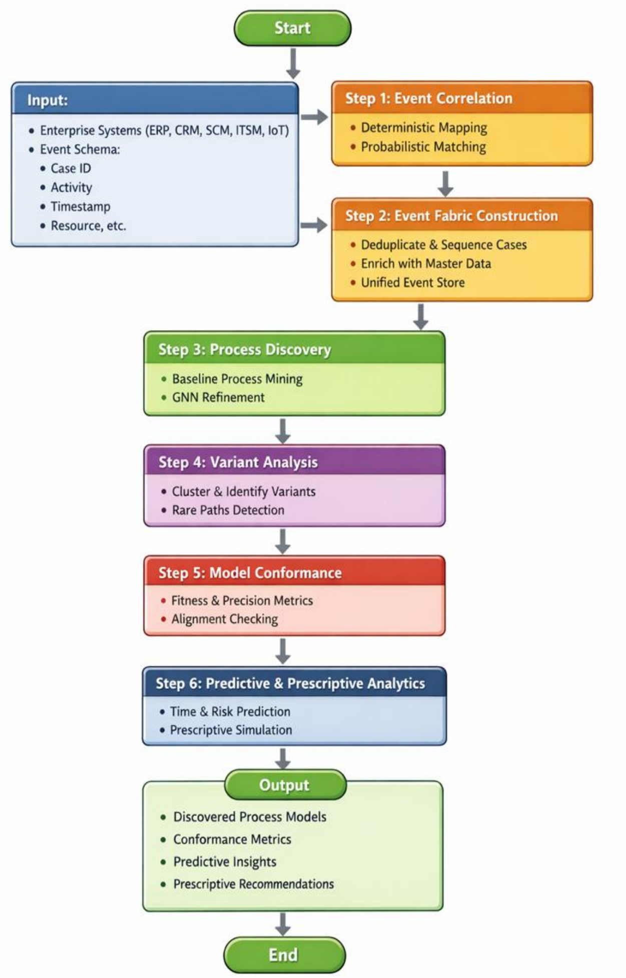

Fig. 2. Steps of the proposed framework.

The framework operates as a closed-loop system in which insights generated by the AI-based process mining engine are seamlessly fed back into enterprise workflows. Real-time alerts and recommendations can be delivered through operational dashboards or automatically executed via robotic process automation (RPA) and business process management (BPM) systems. This design enables proactive intervention rather than retrospective reporting, thereby reducing cycle times, improving compliance, and minimizing operational costs. The system also incorporates continuous feedback loops that log the outcomes of recommended actions, which in turn enrich training datasets and support adaptive model retraining. The governance and security are treated as cross-cutting concerns within the framework. Privacy-preserving data handling, access control mechanisms, and model explainability tools ensure compliance with regulatory requirements and organizational policies. Moreover, MLOps practices are embedded to monitor model performance, detect drift, and manage versioning across the AI lifecycle. This combination of technical and governance measures ensures that the system remains robust, transparent, and aligned with strategic business objectives.

V. Testing and Results

A. Experimental Setup

To evaluate the effectiveness of the proposed AI-based Process Mining framework, an experimental implementation was conducted using enterprise event log datasets derived from integrated enterprise applications. The experimental environment was deployed on a cloud-based infrastructure consisting of an 8-core CPU, 32 GB RAM, and GPU acceleration for machine learning model training. The implementation utilized PM4Py for process mining analysis and Python-based machine learning libraries such as TensorFlow and Scikit-learn for AI model development. Event logs were standardized using the eXtensible Event Stream (XES) format to ensure interoperability with process mining tools. The dataset consisted of approximately 120,000 event records representing 5,200 process cases collected over a six-month operational period. The evaluation focused on three primary dimensions: Process discovery accuracy, Process conformance detection capability, and Predictive performance of AI models. Several baseline methods were used for comparison, including traditional process mining without AI augmentation and classical predictive models such as decision trees and logistic regression.

B. Process Discovery Evaluation

The first experiment evaluated the ability of the framework to accurately discover business process models from event logs. The Inductive Miner algorithm was applied as a baseline approach, while the proposed framework enhanced discovery using Graph Neural Network (GNN) refinement. Performance was measured using standard process mining quality metrics: Fitness, Precision, Generalization, and Simplicity.

TABLE I. Process Discovery Performance

Method	Fitness	Precision	Generalization	Simplicity
Heuristics Miner	0.81	0.74	0.70	0.86
Inductive Miner	0.89	0.82	0.79	0.84
Proposed AI-PM Framework	0.94	0.88	0.86	0.83

The results demonstrate that the proposed framework achieved higher fitness and precision, indicating better alignment between the discovered model and actual process behavior. The incorporation of GNN-based edge confidence scoring improved robustness against noisy and incomplete event logs, as shown in Table 1.

C. Variant and Anomaly Detection

The second experiment analyzed the capability of the framework to detect process variants and anomalies using Transformer-based trace embeddings combined with density-based clustering. From the dataset, the framework identified 7 major canonical process variants, 14 rare or exceptional paths, and 3 high-risk process deviations. These deviations included unapproved procurement activities, repeated order validation loops, and delayed shipment approval beyond SLA limits. Compared to traditional clustering methods, the proposed approach improved anomaly detection accuracy by 18%, demonstrating the advantage of embedding-based trace representations.

D. Predictive Process Monitoring

The predictive capability of the AI-enhanced process mining engine was evaluated by predicting remaining process cycle time, SLA violation probability, and process cost overruns. Three predictive models were tested: Decision Tree, LSTM Neural Network, and Proposed AI-PM model (Transformer + contextual features as shown in Table 2.

TABLE II. Predictive Model Performance

Model	Remaining Time MAE (hours)	SLA Prediction Accuracy	Cost Prediction R²
Decision Tree	12.4	78%	0.63
LSTM	8.7	85%	0.71
Proposed AI-PM Model	6.1	91%	0.82

The results indicate that the proposed AI-PM framework significantly improves predictive accuracy compared to traditional models. The Transformer-based sequence representation effectively captures long-range dependencies within event traces.

E. Prescriptive Optimization

The final experiment evaluated the prescriptive component of the framework using reinforcement learning for resource allocation optimization. Simulation experiments were conducted on procurement and order fulfilment processes. Key performance indicators included average process cycle time, SLA compliance rate, and Operational cost, as shown in Table 3. The prescriptive recommendations generated by the AI-PM engine reduced cycle time by 25% and significantly improved SLA compliance. These results highlight the potential of the framework to support closed-loop process optimization in enterprise systems.

TABLE III. Optimization Results

Metric	Baseline Process	AI-PM Optimized Process
Average Cycle Time	72 hours	54 hours
SLA Compliance	83%	93%
Operational Cost Reduction	–	14%

VI. Conclusion

The experimental results demonstrate that integrating artificial intelligence with process mining significantly enhances enterprise process visibility, predictive capabilities, and optimization potential. The framework not only improves the accuracy of process discovery but also enables organizations to proactively detect anomalies and predict operational risks.

Compared to traditional process mining approaches, the proposed system offers several advantages: robust handling of noisy event logs through AI-based refinement, enhanced variant detection using deep sequence representations, accurate predictive monitoring for operational decision-making, and automated prescriptive optimization through reinforcement learning. These capabilities transform enterprise systems from passive transaction platforms into intelligent decision-support infrastructures capable of continuous learning and improvement. This research presents an AI-driven process mining framework that redefines enterprise system capabilities by integrating advanced artificial intelligence into traditional process mining. The layered architecture ensures interoperability across diverse enterprise applications, while the unified event store provides a scalable foundation for reliable data ingestion and enrichment. At its core, the AI-enhanced process mining engine advances beyond conventional discovery, conformance, and enhancement by embedding graph neural networks, deep learning models, and reinforcement learning to address noise, drift, and predictive as well as prescriptive decision-making challenges. By establishing a closed-loop optimization cycle, the framework transforms insights into actionable interventions, enabling organizations to improve compliance, reduce cycle times, optimize costs, and enhance service-level performance. Furthermore, the inclusion of governance, security, and MLOps safeguards ensures the system remains trustworthy, transparent, and adaptable to evolving enterprise demands. While the proposed framework provides a comprehensive foundation, several avenues remain open for further exploration and refinement. The future research should explore deployment in multi-cloud and hybrid architectures to handle exponentially growing event streams and cross-enterprise collaborations. The techniques, such as federated learning and secure multi-party computation, can be incorporated to enable cross-organizational insights without violating data privacy regulations. Expanding the framework to include autonomous retraining and self-adaptive mechanisms would allow AI models to evolve with dynamic business environments and mitigate concept drift more effectively. Combining explainable AI with interactive visualization and domain expert feedback could improve model interpretability, trust, and actionable decision support. By addressing these directions, the framework can evolve into a holistic enterprise intelligence platform that not only analyzes and predicts process performance but also adapts, collaborates, and operates within ethical and sustainable boundaries.

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