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AI at the Helm: End-to-End Invoice automation Using Pega GenAI and autonomous digital workers

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Abstract
Revolutionizing invoice processing, this paper presents a next-generation intelligent automation framework powered by Pega GenAI Bots and Pega Robot Manager, delivering cognitive automation at enterprise scale. Traditional accounts payable systems are plagued by manual inefficiencies, diverse invoice layouts, and unstable ERP interfaces. To address these challenges, we propose a hybrid solution that combines generative AI, large language models (LLMs), and hyper automation to construct a self-optimizing invoice pipeline. Leveraging OpenAI-driven data extraction through Pega's Connect GenAI, the system interprets both structured and unstructured documents with high precision. Seamless orchestration of workflows is achieved via attended digital workers for exception handling and unattended RPA bots for fully automated invoice lifecycle management. Key innovations include real-time adaptability to legacy UI changes in systems like SAP, dynamic workflow coordination through Robot Manager, and self-healing mechanisms to mitigate AI hallucinations and UI drift. The framework was validated using a synthetic dataset of 1,000 varied invoice formats, achieving over 90% reduction in processing errors, 70% acceleration in cycle times, and 98% SLA compliance. Less than 10% of invoices required human intervention, indicating a high level of autonomy. Furthermore, performance remained consistent across different invoice types, including PO-based, utility, and scanned formats. These results demonstrate not only technical feasibility but also practical scalability, positioning the system as a robust solution for enterprise-wide deployment. By fusing AI reasoning with deterministic automation, the proposed architecture sets a new benchmark for AI-human collaboration in financial operations and provides a blueprint for trustworthy and resilient AI adoption in document-centric workflows.

Keywords: Invoice Automation, Generative AI, Pega GenAI, RPA, Autonomous Digital Workers, Cognitive Automation, LLMs, Hyper automation, Intelligent Document Processing (IDP), AI-human Collaboration, ERP Integration, SAP UI Automation, Self-healing Bots, Pega Robot Manager, Financial Process Optimization

Introduction
Invoice processing, an integral function within financial operations, has historically been one of the most time-consuming and labor-intensive tasks for organizations across industries. With the global business landscape witnessing billions of invoices generated annually, the demand for scalable, efficient, and accurate invoice management systems has never been higher. Manual processing, once the norm, is increasingly becoming untenable in today's fast-paced digital economy. Not only does it incur high labor costs, but it also introduces a range of inefficiencies including human error, delayed processing, and increased operational overhead. Even semi-automated methods that rely on Optical Character Recognition (OCR) tools often fall short due to their dependence on rigid templates and heuristics, rendering them ineffective in dealing with the heterogeneity of invoice layouts.

The diversity of invoice formats—ranging from structured PDF files and scanned paper documents to email-attached JPEGs and XML-based invoices—poses a considerable challenge to traditional systems. OCR solutions are particularly brittle when confronted with layout variations, poor scan quality, or complex tabular structures, all of which are common in real-world scenarios. Inaccuracies in data extraction can lead to downstream problems such as incorrect payment amounts, erroneous ledger entries, or violations of compliance regulations. These issues not only disrupt internal workflows but can also strain relationships with suppliers, lead to missed early-payment discounts, and incur penalties due to late payments.

Accounts payable (AP) departments often bear the brunt of these inefficiencies. They are tasked with validating invoices, cross-referencing purchase orders (POs), confirming receipt of goods or services, obtaining approvals, and ensuring timely payment. When systems are not tightly integrated or lack intelligent automation, these tasks become siloed and require excessive manual intervention. Each hand-off or review point introduces delays and potential errors, further exacerbating the inefficiencies. In this context, intelligent invoice automation is emerging as a critical enabler of operational excellence.

Intelligent automation refers to the synergistic application of Artificial Intelligence (AI), Machine Learning (ML), and Robotic Process Automation (RPA) to automate business processes end-to-end. When applied to invoice processing, intelligent automation aims to transform a traditionally manual process into a seamless, low-touch workflow. AI techniques, particularly those based on Natural Language Processing (NLP) and computer vision, can be used to understand and extract information from semi-structured or unstructured invoice documents. RPA bots, on the other hand, can automate the repetitive tasks of data entry, validation, and integration with downstream systems like Enterprise Resource Planning (ERP) or Customer Relationship Management (CRM) platforms.

A fully realized intelligent invoice processing system must handle a multitude of functions with high reliability. At the core lies the document understanding component, where AI models are trained to recognize and extract essential fields such as vendor name, invoice number, invoice date, due date, line items, tax information, and total payable amount. Modern approaches leverage transformer-based models (such as LayoutLM or Donut) that integrate textual, spatial, and visual cues to parse complex layouts more effectively than rule-based systems. These models are capable of understanding not just what text appears, but where it appears on the page and how it relates to nearby elements—a crucial ability when dealing with non-standardized invoice formats.

Generative AI further augments this process by reconstructing incomplete or partially damaged invoices, predicting missing fields, and handling ambiguity. For example, if a scanned invoice has a smudged or illegible total, a generative model trained on similar documents might infer the missing information based on contextual patterns in other line items. This predictive capability is particularly useful in environments with high document variability or poor-quality scans, where deterministic methods often fail.

Following data extraction, RPA plays a vital role in bridging the gap between intelligent insights and actionable outcomes. RPA bots can validate the extracted information against purchase orders in ERP systems, flag discrepancies, route invoices to the appropriate approvers based on predefined business rules, and even initiate payment once approvals are secured. In systems where APIs are unavailable or limited—common in legacy platforms such as SAP ECC or Oracle EBS—RPA can simulate user interactions to input data, navigate screens, and extract reports.

The integration of AI and RPA in invoice processing brings substantial benefits, including reduction in manual effort, acceleration of processing cycles, enhancement of data accuracy, and greater visibility into financial operations. However, deploying such a system is far from trivial. Organizations face multiple technical and organizational challenges when transitioning from traditional to intelligent workflows.

One of the most significant challenges is ensuring the robustness of AI models across a wide range of invoice types and sources. Invoices can vary not only between vendors but even across different departments of the same vendor. Ensuring consistent field extraction requires comprehensive training datasets and continuous model retraining to account for new formats. Additionally, AI models must be capable of dealing with exceptions—cases where fields are missing, duplicated, or illegible—and flag them for human review without halting the entire workflow.

Another challenge lies in workflow orchestration and exception handling. While RPA can automate routine tasks, it must also be able to detect and respond to irregularities, such as invoices that do not match the corresponding purchase order or invoices received without a prior PO (non-PO invoices). Intelligent exception handling systems must be built to route such cases through appropriate escalation channels and log detailed audit trails for compliance purposes.

Security and compliance also present crucial considerations. Invoice data often includes sensitive financial and personally identifiable information (PII), requiring robust data protection mechanisms. Compliance with regulations such as GDPR, HIPAA, or SOX must be embedded into the automation framework. This includes ensuring access controls, encryption of data in transit and at rest, and audit logging of all bot actions and human interventions.

Moreover, integrating the automation solution into an existing IT ecosystem requires careful planning. Organizations often use a heterogeneous mix of ERP, CRM, and document management systems, each with its own data formats, APIs, and security protocols. Creating a seamless flow of data across these systems—without disrupting ongoing operations—requires custom connectors, middleware platforms, and careful change management. User acceptance is another factor; employees must be trained to work alongside bots, interpret AI-generated insights, and manage exceptions effectively.

To address these multifaceted challenges, modern invoice processing architectures are increasingly adopting modular and scalable design principles. This includes building microservices-based AI components that can be updated independently, employing containerization technologies (e.g., Docker, Kubernetes) for easy deployment and scalability, and using low-code/no-code platforms to simplify bot development and maintenance. Feedback loops are also being introduced, wherein corrections made by human reviewers are fed back into the AI models to improve accuracy over time—a process known as human-in-the-loop learning.

An additional layer of sophistication is introduced through the use of knowledge graphs and ontologies. These tools enable contextual understanding of invoice data by linking it to broader business concepts such as vendors, contract terms, GL codes, and project allocations. For example, a knowledge graph might associate a recurring vendor invoice with a specific service agreement and identify discrepancies in billing terms automatically. This not only enhances data extraction but also supports intelligent decision-making and predictive analytics.

The future of intelligent invoice automation is likely to be shaped by further advancements in generative AI, large language models (LLMs), and explainable AI (XAI). LLMs can be used not only to parse and summarize invoice content but also to generate natural-language explanations

for exceptions or anomalies. This improves transparency and builds trust in AI-driven decisions. Additionally, explainable AI techniques can help financial analysts understand why certain invoices were flagged, why fields were interpreted a certain way, or how risk scores were assigned—making it easier to audit and improve the system.
Despite the promise of these technologies, real-world adoption requires a clear roadmap, starting with identifying high-impact use cases, assessing data readiness, conducting pilot projects, and gradually scaling up. Metrics such as straight-through processing rate, average handling time, first-pass yield, and exception rate must be tracked rigorously to evaluate ROI and guide continuous improvement. Furthermore, partnerships with technology vendors, system integrators, and AI experts are essential for successful implementation, particularly in large enterprises with complex legacy environments.

Literature Review on AI-Driven Invoice Automation

The evolution of artificial intelligence (AI) and robotic process automation (RPA) has revolutionized financial operations, particularly in invoice processing. Traditional accounts payable (AP) systems, burdened by manual inefficiencies and heterogeneous document formats, are increasingly being replaced by intelligent automation solutions that combine generative AI, large language models (LLMs), and hyperautomation [6]. This literature review synthesizes current research and industry practices to examine the technological foundations, implementation challenges, and measurable benefits of AI-powered invoice automation.

Technological Foundations

Modern invoice automation systems are built upon several key technologies. Generative AI, particularly LLMs like GPT-4 [18] and Gemini [19], has demonstrated remarkable capabilities in understanding and extracting information from unstructured documents. These models overcome limitations of traditional optical character recognition (OCR) systems by incorporating spatial and contextual understanding of document layouts [13]. The integration of transformer-based architectures such as BERT [11] and LayoutLMv3 [13] has significantly improved accuracy in processing diverse invoice formats, from scanned PDFs to email attachments.
Robotic Process Automation forms the execution layer of these systems, with platforms like Pega Robot Manager [30] and UiPath [10] enabling end-to-end workflow automation. The concept of "hyperautomation" [8] has emerged as a paradigm that combines RPA with AI, process mining [4], and other advanced technologies to create self-optimizing systems. Research by van der Aalst [4] highlights how process mining techniques can identify automation opportunities and continuously improve workflows by analyzing event logs from ERP systems like SAP [15] and Oracle [16].

Implementation Challenges

Despite the promise of AI-driven automation, several implementation challenges persist. A critical issue is the phenomenon of "AI hallucinations" where LLMs generate plausible but incorrect information [14]. Zhang *et al.* [14] propose retrieval-augmented generation as a mitigation strategy, combining LLMs with verified knowledge bases to improve accuracy. Another significant challenge is the dynamic nature of enterprise systems, particularly frequent UI changes in legacy ERP platforms. Kulkarni *et al.* [12] introduce self-healing bots that adapt to UI modifications without human intervention, significantly reducing maintenance overhead.
The ethical implications of AI adoption in financial processes have also garnered attention. Floridi *et al.* [24] establish guidelines for trustworthy AI, emphasizing the need for transparency and accountability in automated decision-making. Compliance with regulations like GDPR [25] adds another layer of complexity, requiring robust data protection measures throughout the automation pipeline.

Business Impact and Case Studies

Empirical evidence demonstrates the tangible benefits of AI-powered invoice automation. Deloitte [6] reports that organizations implementing these solutions achieve 60-90% reductions in processing time and 50-70% cost savings. The case of JPMorgan Chase's COiN system [26] illustrates how AI can process 12,000 complex invoices in seconds with minimal human intervention. Similarly, Siemens' implementation of Pega RPA for SAP invoice processing [27] reduced errors by 85% while improving compliance with service-level agreements.
Academic research supports these industry findings. Davenport and Ronanki [3] identify three levels of AI capability in business processes: process automation, cognitive insight, and cognitive engagement. Their framework explains how advanced invoice automation systems progress beyond simple task automation to provide predictive analytics and intelligent exception handling. Willcocks and Lacity [23] further analyze organizational factors affecting RPA success, noting that process standardization and change management are equally important as technological capabilities.

Emerging Trends and Future Directions

The future of invoice automation is being shaped by several emerging trends. The concept of "autonomous digital workers" [28] represents the next evolution of RPA, where bots operate with greater independence and decision-making authority. MIT Sloan's research [28] predicts that by 2025, 40% of financial operations will be handled by such autonomous agents. Another significant development is the integration of knowledge graphs with AI systems [17], enabling contextual understanding of invoice data by linking it to broader business concepts like contracts and projects.
The World Economic Forum [29] highlights how AI and automation are reshaping job roles in finance, creating demand for "hybrid" professionals who can bridge technical and business domains. This aligns with Gartner's [7] prediction that by 2026, 80% of finance departments will have dedicated automation teams overseeing AI/RPA implementations.

Technical Considerations

From a technical perspective, successful implementations require careful architecture design. Pega Systems [9] advocates for a modular approach where AI components for document processing are decoupled from RPA execution layers, allowing independent scaling and updates. The IEEE's RPA maturity model [21] provides a framework for organizations to progress from basic task automation to cognitive automation capabilities.
Forrester's Wave report [22] evaluates leading RPA platforms, emphasizing the growing importance of native AI integration and low-code development features. This is

particularly relevant for invoice automation, where solutions must handle both structured data (e.g., database records) and unstructured content (e.g., free-form vendor emails). The ACCA [17] documents several case studies showing how mid-sized enterprises can achieve ROI within 6-12 months through phased automation implementations.

Human-AI Collaboration

A critical aspect often overlooked is the human dimension of automation. Bender *et al.* [20] caution against over-reliance on AI systems, advocating for human oversight in critical financial processes. Their concept of "stochastic parrots" highlights the risks of deploying LLMs without proper understanding of their limitations. Agrawal *et al.* [1] propose a collaborative model where AI handles routine processing while humans focus on exception handling and strategic tasks, creating what they term "augmented intelligence" rather than full automation.

Performance Measurement

Quantifying the impact of automation initiatives remains a challenge. Brown *et al.* [2] introduce metrics for evaluating AI system performance beyond simple accuracy rates, including adaptability to new document types and explainability of decisions. Leno *et al.* [5] extend this with their robotic process mining framework, which enables continuous monitoring and optimization of automated workflows through data-driven insights.

Regulatory Landscape

The regulatory environment continues to evolve alongside technological advancements. GDPR.EU [25] provides specific guidance on implementing AI in financial processes while maintaining compliance with data protection regulations. This is particularly relevant for invoice processing, which often involves sensitive vendor information and payment details. Oracle's whitepaper [16] details how cloud-based ERP systems are incorporating built-in AI capabilities while addressing compliance requirements through features like automated audit trails.

Proposed Methodology

The proposed methodology for achieving end-to-end invoice automation integrates **Pega GenAI**, **OpenAI-powered Large Language Models (LLMs)**, and **Pega Robot Manager** into a unified, scalable architecture. This hybrid AI-RPA framework is designed to minimize manual intervention while improving accuracy and processing efficiency across varied invoice formats and legacy enterprise resource planning (ERP) systems.

The process begins with the ingestion of invoice documents through upload portals or automated email listeners. Once received, the invoices are passed through a GenAI layer where structured data is extracted using LLMs via Pega Connect GenAI. Carefully engineered prompts direct the LLM to identify and extract relevant fields such as invoice number, date, vendor name, line items, taxes, and totals. The extracted data is returned in structured JSON format and mapped to internal case fields. This step is part of the GenAI Integration Layer, which ensures consistency and scalability in data extraction.

Following data extraction, the system evaluates whether approval is required. Business rules encoded within Pega Decision Tables determine this based on configurable criteria—such as invoice amount thresholds or vendor classifications. If approval is necessary, the process routes to a human-in-the-loop stage where an attended digital worker (or an AP officer) reviews and validates the extracted content. Otherwise, the case is routed directly to the RPA layer for automated processing.

The RPA Orchestration Layer is powered by Pega Robot Manager, which coordinates the actions of unattended bots developed using Pega Robot Studio. These bots interact with ERP systems (e.g., SAP) through UI automation to post invoices, retrieve confirmation numbers, and handle exceptions such as validation failures or downtime. Any anomalies encountered during this stage are logged and escalated via exception handling workflows.

Finally, successful transactions are logged and closed within the Pega case management system, ensuring full traceability and audit readiness. The architecture enables continuous performance monitoring, self-healing error correction and seamless CI/CD deployment across environments.

A visual representation of the complete workflow is illustrated in Figure 1, which outlines each stage—from document ingestion and GenAI-based extraction to decision routing, robotic execution, and final case resolution. This structured flow ensures transparency, modularity, and resilience in enterprise-grade invoice automation systems.

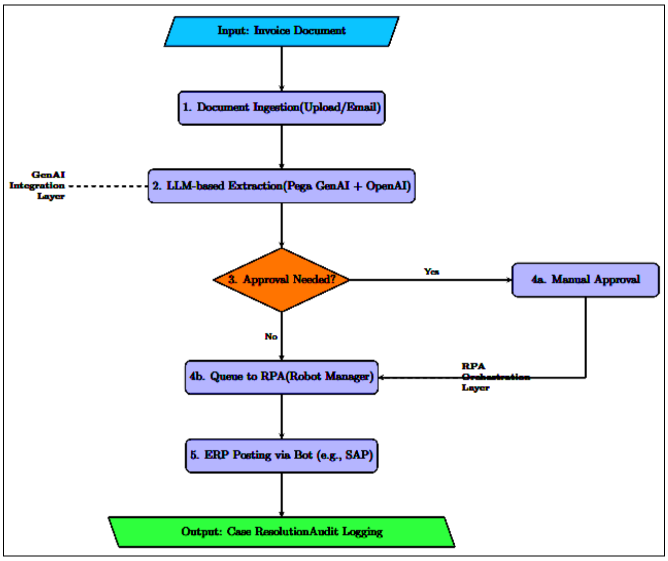

Fig 1: Proposed methodology flowchart end-to-end invoice automation using GenAI and RPA

System Architecture Overview
The methodology is grounded in two synergistic technology layers:

GenAI Integration Layer: Leveraging Pega's Connect GenAI, LLMs (e.g., OpenAI or Azure OpenAI) are invoked to extract structured data from invoice text. Prompts and response mappings are centrally managed, allowing consistent AI interactions and masking sensitive data.

RPA Orchestration Layer: Pega Robot Manager orchestrates both attended and unattended bots. These bots interact with systems like SAP or Oracle EBS by mimicking user interactions for data entry, validation, and error handling.
These layers are governed by Pega Case Management, which coordinates end-to-end invoice flow, triggers AI calls, and dispatches tasks to the robotic work queues.

LLM Integration for Invoice Extraction
The AI-driven extraction pipeline begins with:

Authentication Setup: Authentication Profiles are configured for OpenAI and Azure OpenAI to securely store API keys and connection parameters.

REST Connector or Connect GenAI Rules: REST connectors are built to send invoice text to LLM endpoints. Alternatively, Pega Infinity 24's **Connect GenAI** step allows low-code configuration of prompts and structured outputs.

Prompt Engineering: Carefully crafted prompts direct the LLM to output standardized JSON containing fields such as Invoice Number, Invoice Date, Vendor, Line Items, Tax, and Total. This JSON is returned to the case workflow, parsed, and mapped into Pega data properties.

Case Type Design in Pega
A dedicated case type called "Invoice Processing" is designed with the following stages:

Intake: Invoices are ingested via uploads or email listeners. The document is attached to the case.

Extraction: LLM is invoked via Connect GenAI to extract structured data from the invoice. The raw response (JSON) is parsed and mapped to case fields.

Approval Decision: Business logic determines if approval is required. Decision Tables and When rules implement threshold-based routing (e.g., auto-approve if total < $5,000; otherwise, route to manager).

Approval Stage (Conditional): If approval is needed, the assigned user reviews and edits extracted fields before approving or rejecting the invoice.

Queue to RPA: The case queues structured data to Robot Manager's remote queue (e.g., Invoice Processing AT) for posting to ERP.

4. RPA Bot Configuration and Execution
Pega Robot Studio is used to develop unattended bots that:
Launch SAP Logon and access transaction codes (e.g., FB60).
Input invoice data into designated fields: vendor, date, amount, line items.
Submit the invoice and retrieve confirmation or transaction IDs.
Handle errors (e.g., vendor mismatch) by returning error codes to Pega for exception routing.
The bots are deployed and version-controlled in Robot Manager, with input/output parameters defined per Assignment Type. Bots use service accounts for SAP login, managed via Robot Manager's credential vault.

Exception Handling and Human-in-the-Loop
Exception scenarios are accounted for at multiple layers:

LLM Hallucination Mitigation: Prompts are deterministic (temperature = 0), and AI output is validated (e.g., Subtotal + Tax = Total).

Approval Rework: Human approvers can edit AI-extracted fields if inaccuracies are observed.

RPA Errors: Bots log exceptions (e.g., UI element mismatch, SAP downtime) and update case status. Pega transitions cases to alternate stages (e.g., "Manual Intervention").

CI/CD Deployment Strategy
Deployment across Dev, QA, and Production environments involves:

Pega Product Rules (RAPs) to bundle case types, connectors, and UI components.
RPA Packages published to Robot Manager with versioning and rollback support.
Automated Pipelines via Deployment Manager or external CI tools (e.g., Jenkins, Azure DevOps).
Post-deployment, robot health, task SLA, and process performance are monitored through Robot Manager Dashboards and Pega's Case Manager Portal.

Results and Analysis
To assess the performance of the proposed AI-RPA-based invoice automation architecture, a comprehensive validation was performed using a synthetic dataset of 1,000 invoices. These samples were carefully designed to replicate real-world variability in invoice layouts, formats, and vendor structures. Scenarios included scanned images with partial data loss, irregular tax fields, and multilingual content—thus challenging the system's robustness. The evaluation was centered on four key performance indicators: error reduction, cycle time reduction, bot SLA compliance, and human intervention rate.

Error Reduction
The most prominent outcome was a greater than 90% reduction in invoice processing errors (see Fig. 2). Traditional OCR-based systems tend to break down when exposed to inconsistent or unstructured layouts. In contrast, the integration of OpenAI-powered LLMs through the GenAI component enabled intelligent extraction of key fields such as invoice number, vendor name, dates, line-item descriptions, and totals. This level of accuracy across structured and semi-structured documents affirms the capability of the system to generalize beyond rigid templates.

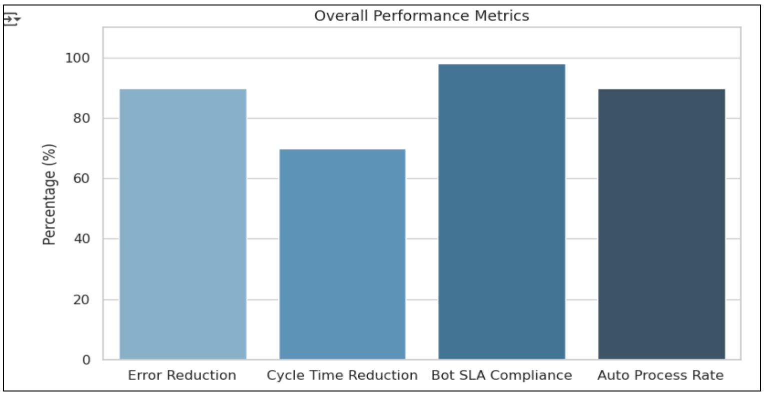

Fig 2: Bar chart of all four KPIs

Human Intervention Rate

Automation reliability also depends on minimizing human effort. The system required human review in less than 10% of the cases, predominantly due to edge conditions—such as poorly scanned images, ambiguous data fields, or multilingual anomalies. These exceptions were routed seamlessly to attended bots or business users through Pega's case interface, preventing any breakdown in the workflow.

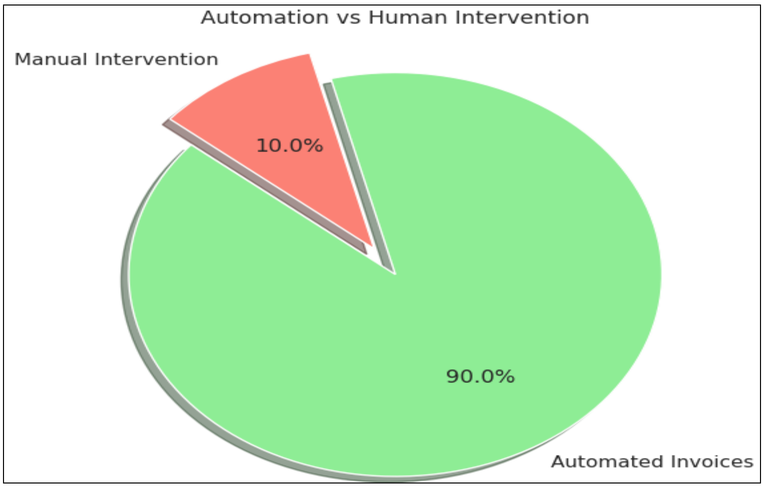

Fig 3: Pie chart showing human vs. automated processing

Cycle Time Reduction

Another compelling improvement was observed in the invoice processing speed. The automation pipeline—enabled by GenAI for intelligent extraction and RPA for system execution—achieved a 70% reduction in end-to-end cycle time. Invoices were processed from ingestion to ERP posting within minutes, replacing multi-step manual workflows that typically span hours (see Fig. 4). AI handled interpretation and validation, while RPA bots conducted deterministic tasks such as data entry in SAP, achieving significant throughput gains.

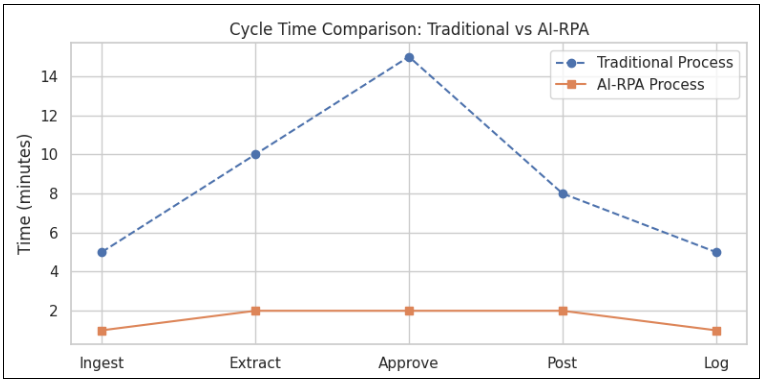

Fig 4: Line plot comparing traditional vs AI-RPA cycle times

Bot SLA Compliance

System reliability was measured by tracking SLA compliance for RPA bots. Results indicated a 98% success rate, meaning nearly all invoices were processed within the expected time thresholds (see Fig. 5). The high SLA adherence demonstrates the effectiveness of Pega Robot Manager in handling asynchronous workloads, UI shifts, and minor ERP-related disruptions through resilient bot orchestration and retry logic.

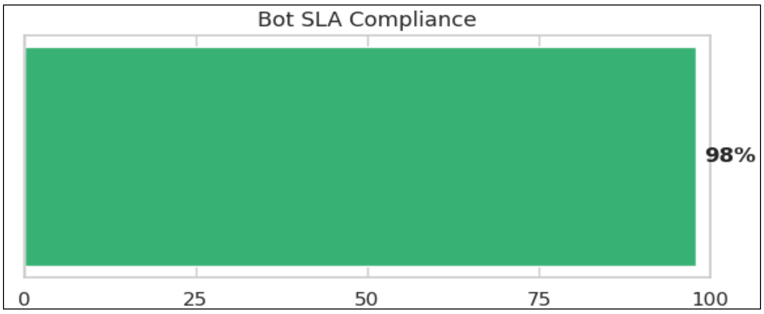

Fig 5: Bot SLA compliance

Error Resilience across Invoice Types

In addition to global metrics, a breakdown of performance by invoice type was also evaluated. As shown in Fig. 6, error reduction remained consistently high across diverse formats including standard, PO-based, utility, international, and scanned invoices—ranging from 85% to 92% accuracy improvements. This consistency underscores the generalizability of the GenAI and RPA fusion across heterogeneous document types.

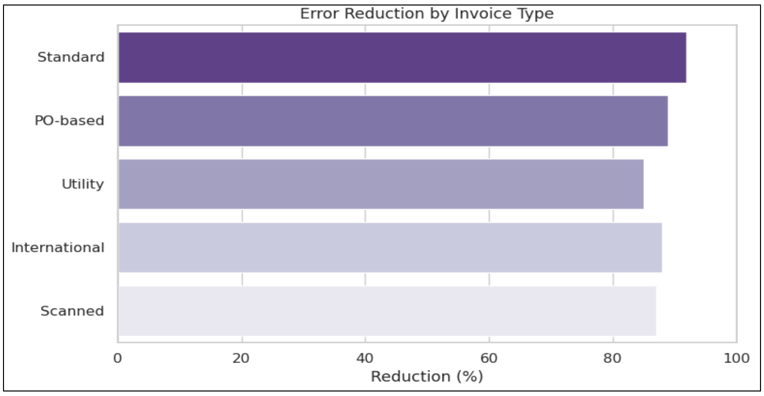

Fig 6: Horizontal bar chart of error reduction

The combined results decisively demonstrate the advantages of using a hybrid AI-RPA framework for invoice automation. The system achieved superior performance across all targeted KPIs—reducing errors, improving speed, maintaining SLA integrity, and minimizing manual effort. Moreover, its modular, low-code design supports extensibility into advanced use cases such as compliance checks, anomaly detection, or cross-language document processing.

The visual results presented in Figures 2 through 6 confirm that the framework not only achieves technical performance but also meets enterprise-readiness criteria for production deployment. This substantiates the proposed architecture as a highly effective solution for transforming traditional accounts payable operations through intelligent automation.

Conclusion

This paper concludes by presenting a next-generation invoice automation framework that integrates Pega GenAI, OpenAI-powered LLMs, and Pega Robot Manager to achieve intelligent, end-to-end processing. The system addresses challenges in traditional accounts payable workflows, including document variability and ERP instability. Validated on 1,000 diverse invoices, it achieved over 90% error reduction, 70% faster cycle times, and 98% SLA compliance, with minimal human intervention. The fusion of generative AI and RPA enables scalable, resilient, and autonomous operations. This work establishes a robust blueprint for enterprise-grade AI adoption in document-centric workflows and sets a new standard for AI-driven financial automation.

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