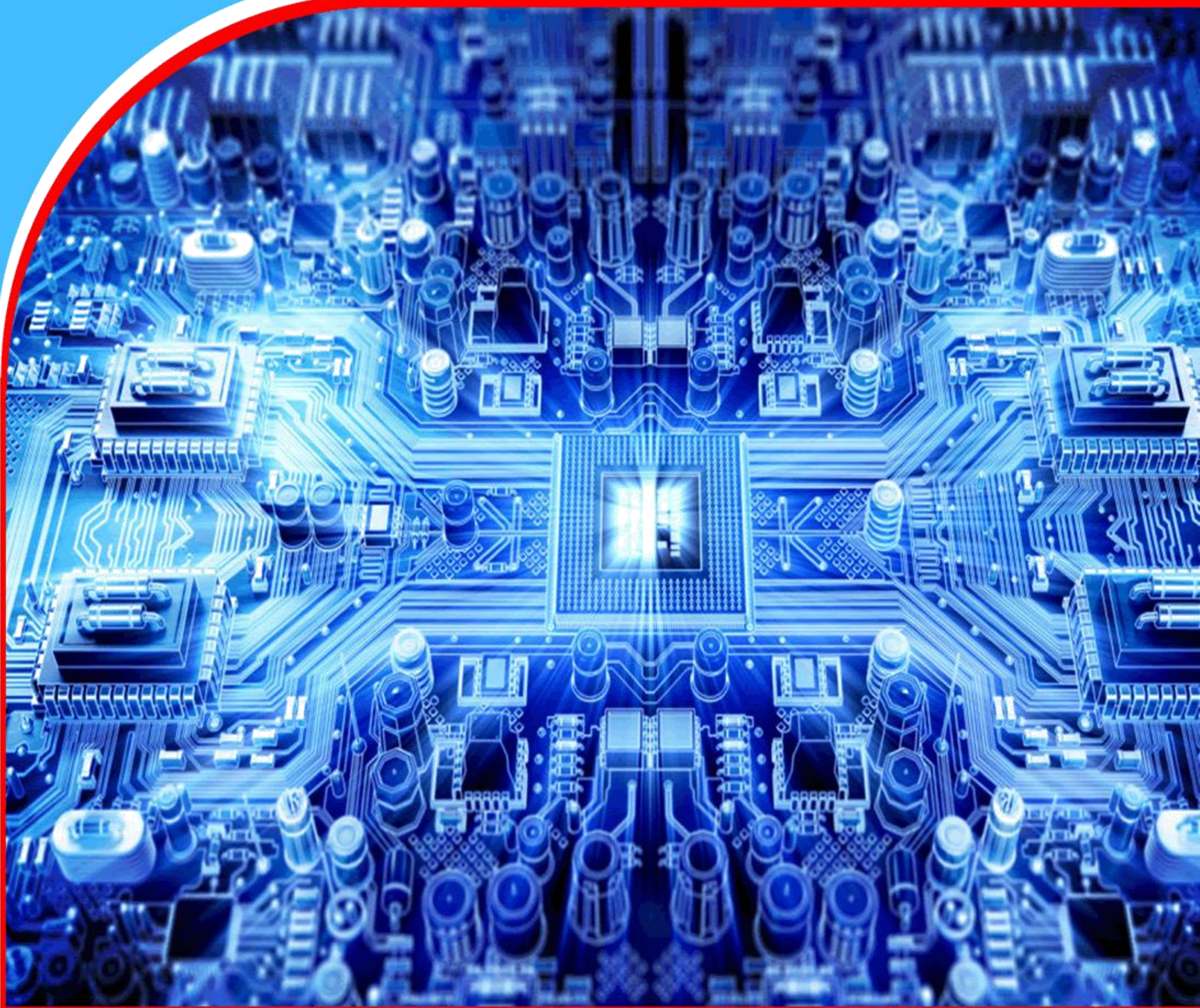
American Journal of
Computing and Engineering
(AJCE)



From OCR to IDP: Transforming Banking Document Workflow with AI-Enhanced Robotic Process Automation

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Crossref
Article history
Submitted 04.07.2024 Revised Version Received 02.08.2024 Accepted 10.09.2024

Abstract

Purpose: Banking institutions deal with extensive volumes of documentation, such as onboarding forms of customers, compliance records, transaction information, and loan applications, on a daily basis. Manual processing and hard-core automation systems delay, lead to high error rates, and high human work. Artificial intelligence entries into part of the banking processes are admitted, but the majority of the current systems do not possess the contextual understanding which restricts their scope of application in very complex and highly regulated settings. The paper suggests a superior AI-based Robotic Process Automation (RPA) system that will address these shortcomings by facilitating smart, flexible, and regulation conscious document processing.

Materials and Methods: The proposed platform incorporates smart document intake, context-sensitive document cognition and a dual rule-AI decision model. Risk sensitive workflow orchestration is a dynamic route mechanism that documents are directed into routing strategies according to complexity, confidence, and regulatory risk, where routine documents may be fully automated, and the high-risk or ambiguous documents must be sent to humans. Human in the loop validation mechanism will make sure that expert attention is given where it is most effective. Moreover, the system uses the dual-loop learning architecture which is constantly enhanced by human feedback and system-wide analytics to provide flexibility to changing types of documents and regulatory policies.

Findings: Experimental analysis shows significant improvements in processing time, reduction of errors and unwarranted human intervention, and regulatory transparency of explainable and auditable automation.

Unique Contribution to Theory, Practice and Policy: These findings show that context-aware risk-sensitive AI-enhanced RPA is a viable and scalable solution to current bank document processes.

Keywords: *AI-Enhanced RBA, Dual loop Learning, Banking Systems Workflows, Automation*

JEL Classification: *G21, C63, O33, L86, G28*

INTRODUCTION

It is no surprise that the banking industry is heavily reliant on documentation and various types of documentation. Operations that are fundamental to the banking business include: customer on boarding, loan processing, regulatory compliance, and internal audits. Although digital banking technologies are rapidly developing, many financial institutions still use partially manual document workflows or rely on rigid automation (1). These workflows include processing documents that come in various forms, including: hand-written notes, scanned forms, and PDFs as well as other system generated documents that may have unstructured or partially structured data. RPA is frequently used in banking to reduce the manual effort needed to complete the repetitive tasks that are regulatory and rule based. RPA workflows are designed to complete basic tasks to mimic the actions of an employee interfacing with software applications. This is done to free up the employee's time and complete the tasks more quickly while utilizing the existing technology. Although RPA improves efficiencies for dealing with structured documents, it does not have the abilities needed to understand, process, and logically evaluate the information within the documents (2). AI technologies like Optical Character Recognition (OCR) and Natural Language Processing (NLP), as well as Machine Learning (ML) are the technologies that give machines the ability to examine and evaluate the information within and of the documents. The merger of RPA and AI is being touted as the best method to transform banking document activities into intelligent, fully automated processes.

Even with the positive aspects of AI-systems for RPA, the RPA systems in today's banking sector appear to have several issues. Document workflow systems have long processing times, higher error rates, and more manual steps. With respect to unstructured documents, changes to processing documents, and other documents and regulatory changes, RPA systems have no ability to adjust. Conversely, in the banking sector (3), AI systems stand-alone and do not integrate with the other systems in the banking sector. Most systems, in addition to the other issues already described, treat documents in an isolated manner and omit important context: customer data and documents, their risk, the governing regulations, and the sensitivity of the documents. Likewise, the processing logic to be applied to the documents, and to the other data therein, is treated the same, even when the complexity and regulatory requirements are different. Processing exceptions is handled mostly reactively this creates workflow bottlenecks and results in higher costs. These issues suggest the banking sector needs a more flexible, adaptable, and context-based automation system that understands and accurately, compliantly, and flexibly scales to the various different banking documents.

This is driven by an important social trend. Customers require cheaper, quicker, and more reliable financial services, and more automation in their services means less manual in their services and less regulatory documentation to fill in (4). As such, there is friction for banks as they have to find ways to be more efficient while still satisfying their regulators. AI driven RPA provides a means to accomplish this by using a combination of cognitive understanding / decision-making and automation. For such systems to work in practical settings, they need to have more than just automation, such as adaptability, risk awareness, transparency, etc. Much of the literature related to automation in banking focuses on basic RPA or AI driven document processing. Some literature focuses on integrations of RPA and AI, but typically this literature examines one use case and do not provide a full workflow perspective. Most of the literature ignores adaptive contextual awareness, dynamic risk assessment, and learning (5). Less regulatory transparency, maintainability, and automation decision justification are more in the banking literature, but they are also important in the context of using AI and automation. Most of the solutions utilize static rules or an opaque AI approach and provide little justification for their automation decisions. There is a lack of selective human interaction and adaptive routing which is why many solutions are not as effective as they could be. Although there has been an increased use of AI-enabled RPA in banking, there is still a fundamental limitation with the current solutions in dealing with the real-world document processing. The existing AI-RPA systems are mostly based on inflexible rule-based rationality, or individual AI models that lack contextual sensitivity of customer profiles, transaction history, document intent, or regulatory sensitivity. Consequently, such systems have a single logic applied to all documents, whether they are high-risk or not that they frequently misclassify and exception rates are high along with overworking the manual handling. Moreover, most AI-based solutions are opaque black-box models, with minimal explain ability or auditability, which cannot be tolerated in a much-regulated banking setting. There is also a lack of adaptive learning in the existing systems and hence, the systems are incapable of efficiently responding to changes in document format, regulatory changes, and new risk patterns. As a result, banks still experience inefficiencies in their operations, compliance risk, and excessive reliance on human review. The proposed research will deal with these drawbacks by introducing a context-sensitive, risk-sensitive, and explainable AI-enhanced RPA model that will allow the selective automation, dynamic decision-making, and constant improvement of the system without losing regulatory clarity.

LITERATURE REVIEW

The initial phase of research into banking document workflows focused on the reduction of manual labour via the use of scanning technologies and rule-based automation. The foundations for the research and practice of process automation and business process re-engineering. Automation was viewed as a means to bolster efficiency and reliability within organizational workflows. In banking, this approach headlined the initial groundwork for workflow digitization, and the intricate problems pertaining to document understanding and decision making remained unaddressed. As banking processes were refined and expanded, the available literature turned to Robotic Process Automation (RPA) as a candidate for the automation of repetitive tasks (7). One of the first comprehensive literature works on the adoption of RPA within financial services was carried out by Will-cocks, The authors concluded that RPA had a positive impact on the reduction of processing times and costs in the operational tasks of data entry and report generation. RPA systems' process automation capability was limited to structured data and a simplistic set of operational rules, which made RPA inapplicable in processes where documents and unstructured data were prevalent. In an attempt to overcome the aforementioned shortcomings, the researchers turned their focus to automation and document scanning technologies, as well as document digitization and text scanning methodologies. The use of Optical Character Recognition (OCR) on financial documents, particularly on checks and customer forms.

The authors acknowledge issues in data availability, but poor document construction, document layout inconsistencies, and form complexity problems are documented. Though OCR technology facilitated document digitization, it still lacks document comprehension abilities and cannot perform data quality verification (8). The need for intelligent document understanding and propose machine learning-based approaches for the classification of financial documents. Their proposed methodology was more successful in classification than keyword-based approaches. Nevertheless, their technology operated outside the banking ecosystem and relied on manual verification and system integration. This delineated a key boundary of intelligent document analysis as opposed to intelligent workflow automation. Recent studies have focused on the integration of Artificial Intelligence (AI) and Robotic

Process Automation (RPA) to attain intelligent automation (9). The integration of RPA and Natural Language Processing (NLP) for the automation of compliance and financial document processing. Their findings indicate that the level of human intervention required for data extraction was lower, and the data were more precise. Nevertheless, the system still relied on unchanging, static rules, and did not respond to the level of risk and the changes in the compliance environment (10). Van van Aalst et al. (2021) focus on intelligent process automation and the role of artificial intelligence in adaptive decision making within automated workflows. Recent studies focused on AI-assisted systems.

Deep learning paradigms to retrieve and categorize entities in financial documents achieving 92% accuracy on a dataset comprising 500 documents. However, their system was unable to provide meaningful explanations and arrived at opaque conclusions, making it inappropriate for risk averse applications. Machine learning and a rudimentary rule engine to enhance regulatory compliance. Still, without context-awareness or an adaptive risk-sensitive approach, manual intervention was required in 60-65% of cases. Their study acknowledged learning-based systems, but did not provide a tangible solution for banking operations involving documents. Explainability and regulatory compliance have also not been sufficiently addressed even though they are critical for financial applications. Although these studies illustrate the promise of the automation of banking documents through the application of artificial intelligence and robotic process automation, the automation of banking processes remains in its infancy. Most contemporary methods treat documents individually and ignore the context of the customer, their profiles, previous transactions, and the regulatory environment. This results in uniform process logic that disregards the degree of risk associated with the situation. Additionally, exception handling tends to be reactive, with manual intervention required at numerous points, greatly reducing the efficiency of automation. This study proposes various novel solutions which directly target these challenges.

The available literature shows that robotic process automation and artificial intelligence can help to promote significantly better efficiency in the banking document workflow [11]. RPA systems based on rules can be useful in dealing with repetitive, formal operations, whereas AI-powered solutions like OCR, NLP, and machine learning can be used to improve the process of digitizing documents and extracting data. Although, according to the previous literature, most of these systems are used in isolation and there is a lack of integration between document understanding, decision-making and workflow execution. Some of them use fixed rules or task-based models of AI such that they limit their ability to respond to the variability of documents, contextual ambiguity, and changing regulatory demands. Additionally, the majority of solutions available operate on the principle of uniform processing of documents, without making such explicit consideration of the risk level, the situation with the customer, or sensitivity to compliance. There are also issues linked to explain ability, auditability, and long-term adaptability, which are also identified in the literature especially in much regulated financial settings. Although the literature does recognize the necessity of the human control and learning-driven enhancements, they are usually viewed as the auxiliary features instead of the part of the automation pipeline. Comprehensively, the analysed publications offer significant information on the advantages and drawbacks of AI-based automation in the banking sector and signal the necessity of more situational and flexible and open methods.

Table 1: Summary of Literature Review with Proposed System

NO	Aspect	Study	Proposed System
1	Automation	Document processing	End to end intelligent automation
2	Document understanding	Limited handling	Content aware understanding
3	Decision	Static rules	Hybrid rule AI Decision
4	Risk handling	Same process logic	Risk sensitive
5	Learning capabilities	Static systems	Dual loop learning

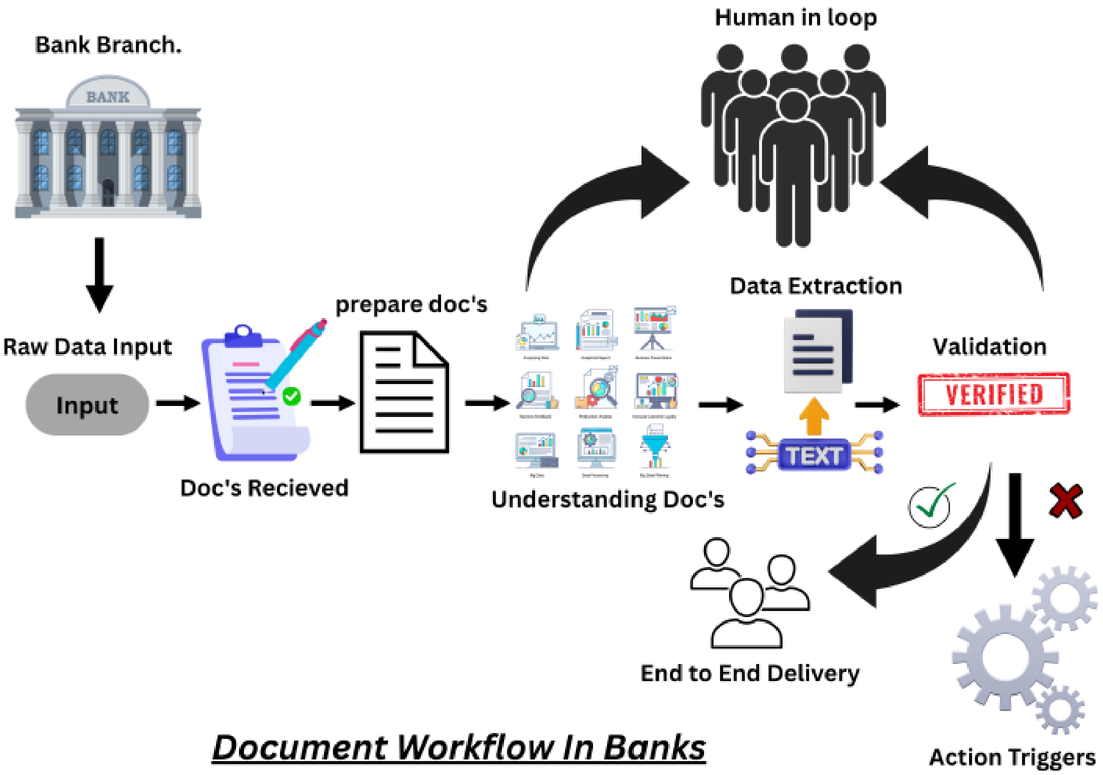

Figure 1: Workflow of Documents in Banking Sector

This framework integrates cognitive intelligence, adaptive workflow orchestration, risk assessment, and continuous learning. This integrated model is a significant advancement over existing models that utilize either rigid rule-based automation or segregated AI modules. The goal is to achieve end-to-end document processing automation, with a focus on accuracy, regulatory compliance, and limited human intervention for complex and high-risk situations.

1) Intelligent Document Ingestion and Pre-processing Layer

The first stage of the proposed methodology focuses on document ingestion and preparation. Banking environments process a wide range of documents, including on boarding forms, loan applications, financial statements, and compliance reports.

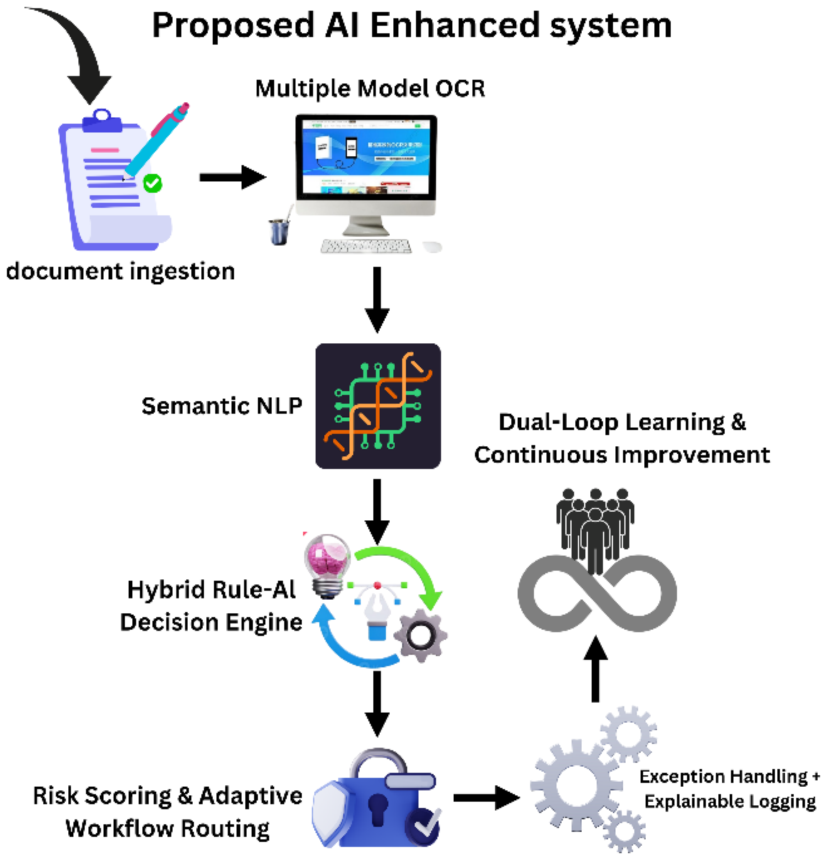

Figure 2: Proposed System of Ai Enhanced System

The incoming documents can be in the following formats: scanned images, PDFs, emails, system generated files, etc. While the traditional systems handle all the incoming documents the same way, the proposed solution applies intelligent ingestion and entry-point document categorization. Each document gets analyzed and is assigned a specific banking process document type, source, and goal. Because of this, documents consistently take the correct processing path from the start, and avoid unnecessary reprocessing and delays. Noise, layout, and quality issues are resolved in the preprocessing stage. The system detects poor quality documents early and routes them to a human, preventing errors from flowing more downstream in the workflow. Most systems attempt extraction first and check their inputs quality last this system innovatively prioritizes quality. Novelty Highlights: Quality aware preprocessing and early document classification mean less clogged downstream processing and less extraction errors. This layer apply image enhancement, type classification, and pass deterministic outputs to document understanding.

American Journal of Computing and Engineering
ISSN 2790-5586 (Online)
Vol.7, Issue 5, pp 52-70, 2024
www.ajpojournals.org

Table 2: Intelligent Document Ingestion

Components	Description	Technical Role
Sources	Forms, PDF, Emails	Multi format inputs
Quality	Resolution, noise	Ensures data reliability
Noise removal	Skew Correction	Improves accuracy
Format	Machine readable formats	Ensures downstream processing
Outputs	Structured documents	Ready for semantic analysis

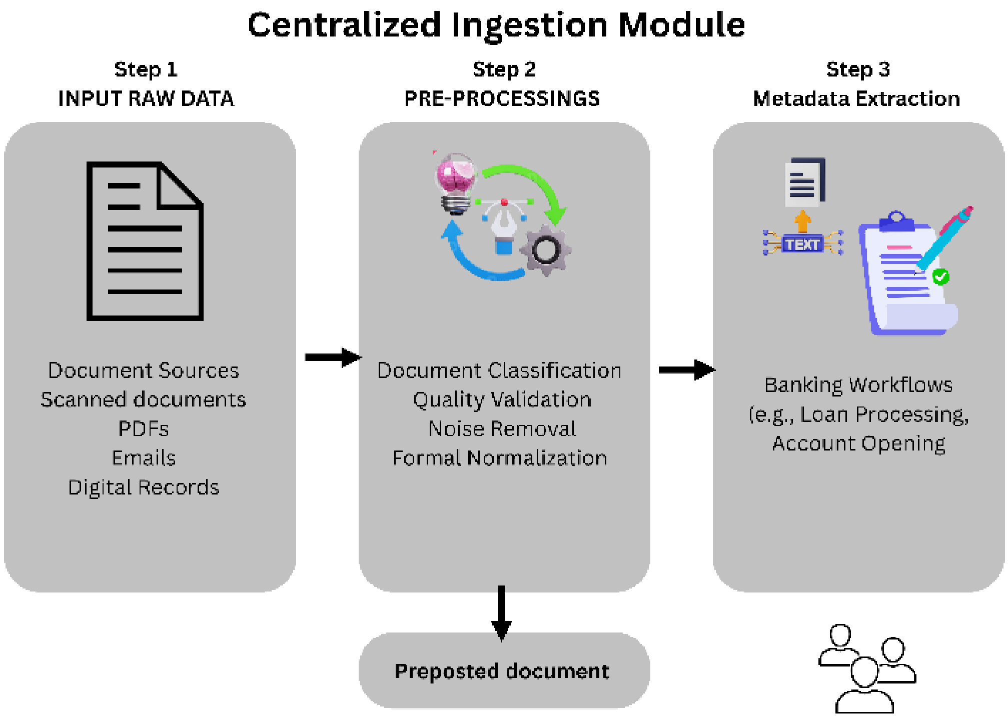

Figure 3: Data Ingestion Module

2). Context-Aware Document Understanding Module

After documents are ingested, they are sent to the document understanding module. Conventional systems almost exclusively center on the text field extraction and often overlook the purpose and use of the obtained information. On the other hand, the proposed methodology focuses on contextual understanding. Each piece of retrieved information is analyzed in the context of the document type, customer segment, and transaction context. For instance, income details in a loan document are considered different than income details in a compliance report. Such contextual reasoning heightens reliability and reduces the chances of misinterpretation. Moreover, the technology links the information obtained to the prior records of the client and the internal organizational financial records. In doing so, the system is able to detect inconsistencies, missing information, and abnormal patterns early on in the process. This layer use OCR + NLP to extract entities, condition on context, and retain confidence scores for downstream fusion. Table 2: Intelligent Document Ingestion.

Table 3: Context Aware Document Understanding

Components	Previous System	Proposed System
Text extraction	Plain OCR	Enhanced extraction
Document type	Static templates	Dynamic classification
Context awareness	Not considered	Transection aware
Semantic linking	Absent	Enabled
Output quality	Fragmented	Structured

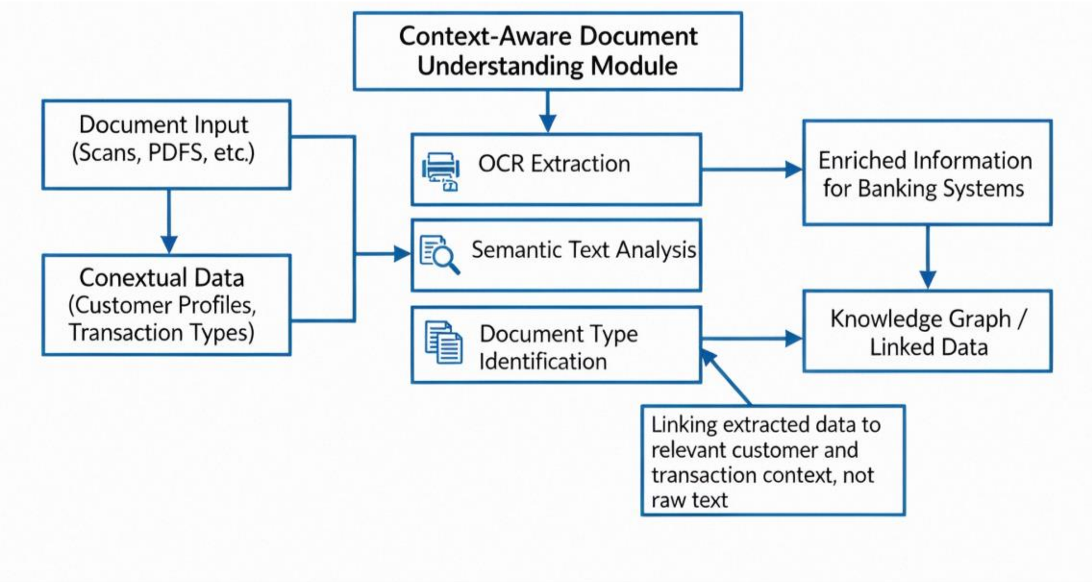

Figure 4: Context Aware Document Module

3). Hybrid Intelligence Decision Framework

The study introduces an original mixed system of hybrid intelligence decision-making framework which entails the combination of rule-based logic and artificial intelligence (AI) driven inference. The banking sector has primarily operated within the confines of strict regulation in order to guarantee compliance. On the other hand, AI-based systems are flexible, yet often seem to provide solutions in a black box manner. Instead of adopting an either solution approach like most other systems, the proposed methodology is a combination of the two. While rule-based systems constrict decision-making to the bounds of a given regulation, AI models are used to analyze and recognize increasingly complex patterns, discrepancies, and ambiguities within a given text. Automated explanations are designed to function within the bounds of banking regulation. The system provides the ability to conduct hybrid decision making to simplify the separation of complex and non-complex situations. Non-complex situations are resolved through the automatic processing of compliant documentation, while complex situations are distinguished, and non-compliant documentation is subjected to further manual processing. This layer Combine rule-based logic and AI predictions with confidence-weighted fusion for compliant and adaptive decisions.

American Journal of Computing and Engineering
ISSN 2790-5586 (Online)
Vol.7, Issue 5, pp 52-70, 2024

Table 4: Hybrid Rule AI Decision Framework

Decision Layer	Function	Benefit
Rule based engine	Validates banking regulations	Compliance assurance
AI inference engine	Handles uncertainty	Intelligent decisions
Fusion layer	Combines rule	Balanced decisions
Decision output	Approve, Reject	Operational efficiency
traceability	Logged reasoning	Audit readiness

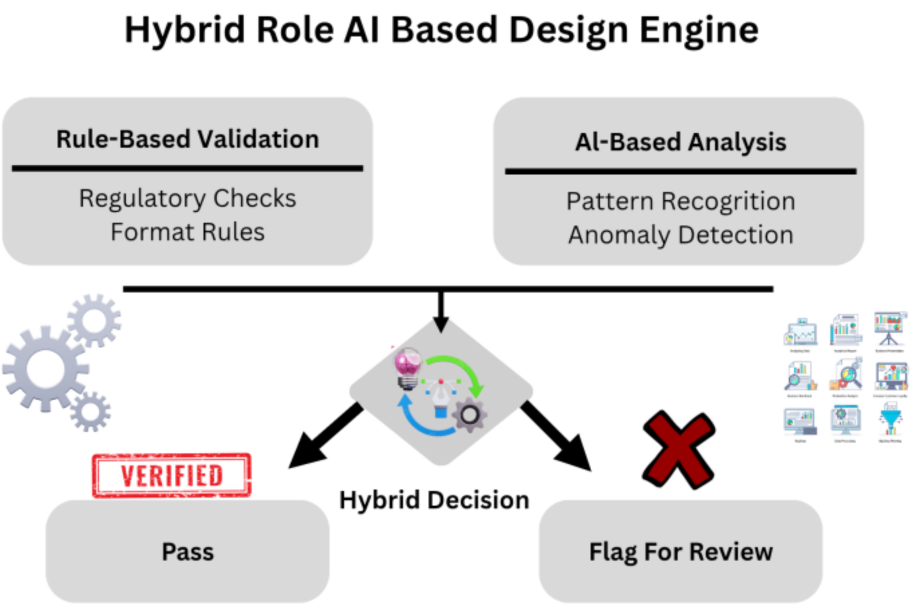

Figure 5: Hybrid Role AI Based Module

4). Risk-Sensitive Workflow Orchestration

One of the most notable innovations of the suggested technique is risk-sensitive workflow orchestration. Traditional RPA systems follow the same workflow for all documents, regardless of risk level. This strategy is inefficient and raises operational risk. The suggested system assigns a risk level to each document based on a variety of parameters, including compliance results, document discrepancies, customer history, and AI confidence levels. Documents are dynamically routed through several processing channels based on their risk level. Low-risk papers are completely automated, medium-risk documents require some human intervention, and high-risk documents necessitate full manual verification. This selective automation guarantees that human resources are directed where they are most required. This layer Aggregate risk factors to guide automated, partial, or full manual workflow routing.

Table 5: Risk Sensitive Workflow

Risk Level	Routing	Processing Mode
Low risk	Direct automation	Fully automated
Medium risk	Conditional routing	Partial human review
High risk	Manual escalation	Human validation
Risk scoring	Multi-parameter	Dynamic routing
Workflow control	Adaptive	Resource optimization

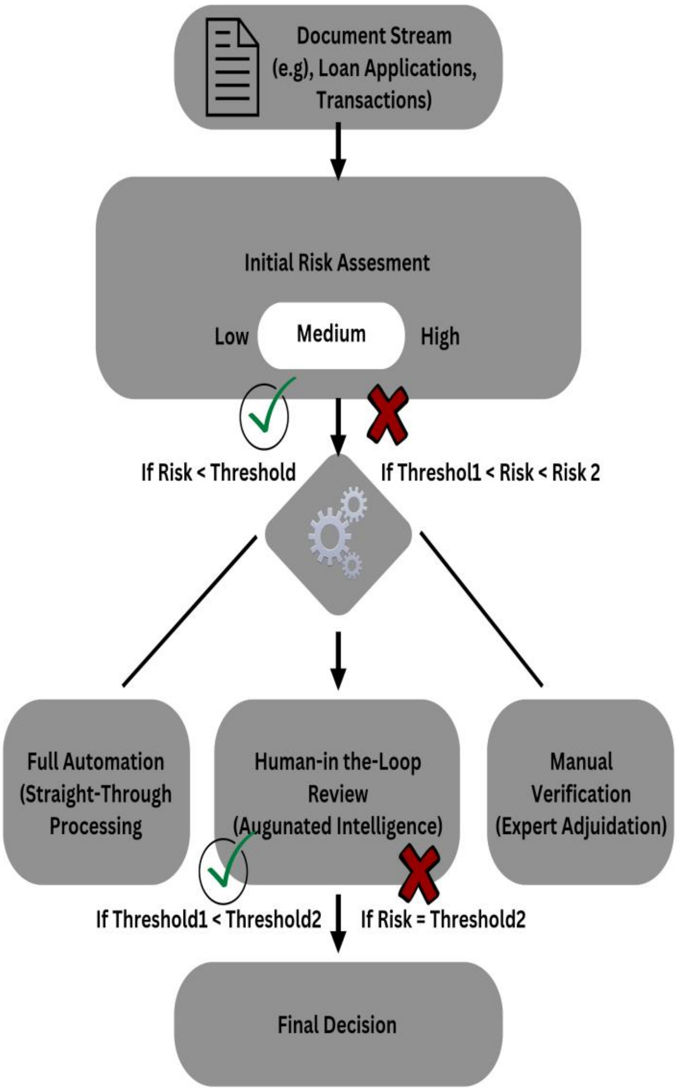

Figure 6: Risk Sensitive Module

5). Human-in-the-Loop Validation Mechanism

While automation is a primary goal, this study does not want to completely eliminate human involvement. Instead, it implements a person-in-the-loop validation system that incorporates human expertise at important decision points. Human reviewers are shown summarized insights rather than raw papers. The technology emphasis-es identified errors, inconsistencies, and risk indicators, enabling reviewers to make faster and more informed conclusions. This design lowers cognitive burden and increases review efficiency. Importantly, human judgments are not viewed as isolated actions; instead, they are systematically recorded and fed back into the system for further learning and optimization. Rather than replacing humans, the system improves their decision-making through focused and educated assistance. This layer Trigger human review on uncertain cases and feed validated feedback back into the learning module.

Table 6: Human in Loop Validation

Aspect	Description	Contribution
Human reviewer	High risk	Error prevention
Visual risk	Confidence flags	Faster review
Feedback capture	Human corrections	System learning
Decision override	Allowed when necessary	Operational control

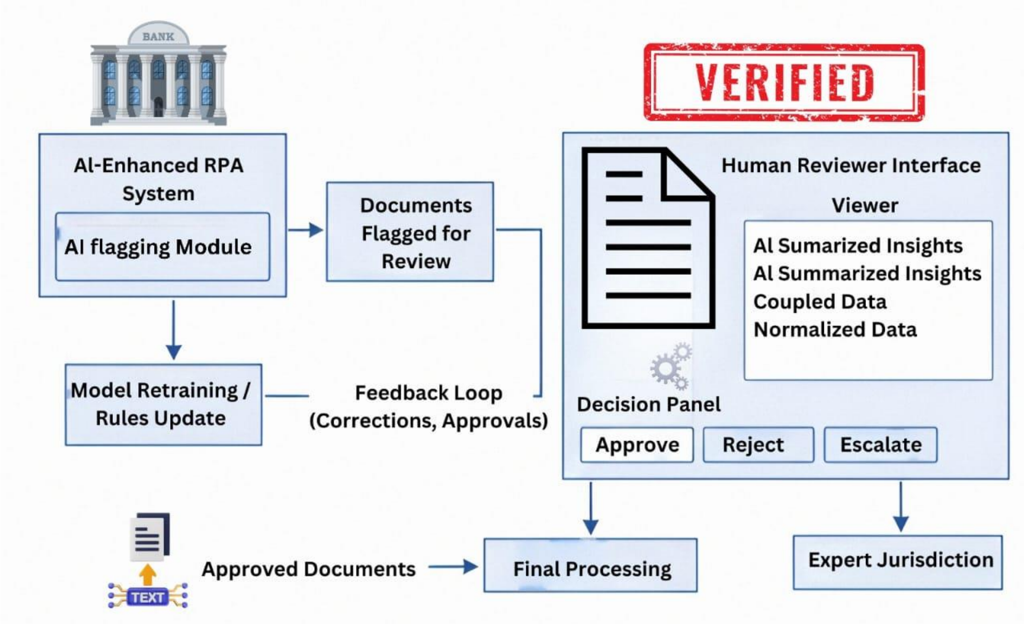

Figure 7: Human in Loop Module

6). Dual-Loop Learning and System Adaptability

One important shortcoming of contemporary automation systems is their static nature. Once deployed, they require manual modifications to accommodate new document formats or regulatory changes. The suggested methodology addresses this restriction by utilizing a dual-loop learning mechanism. The first loop collects feedback from human reviewers and corrects model behavior in certain instances. The second loop looks at system-wide performance measures such processing time, error rates, and escalation frequency. These insights are being used to gradually improve both AI models and workflow guidelines. Learning is controlled and audible, ensuring that system upgrades do not cause unexpected behavior. This is especially significant in regulated financial contexts. Novelty Highlight: Continuous, regulated learning promotes long-term flexibility without compromising compliance or transparency. This layer Update models via human corrections (inner loop) and optimize workflow thresholds (outer loop) under controlled rules.

Table 7: Dual Loop Learning Adaptability

Learning Loop	Input Source	System Impact
Inner loop	Human feedback	Model refinement
Outer loop	Performance analytics	Workflow optimization
Adaption type	Controlled updated	Stability maintained
Learning scope	incremental	Risk free learning
System evolution	Continuous	Long term efficiency

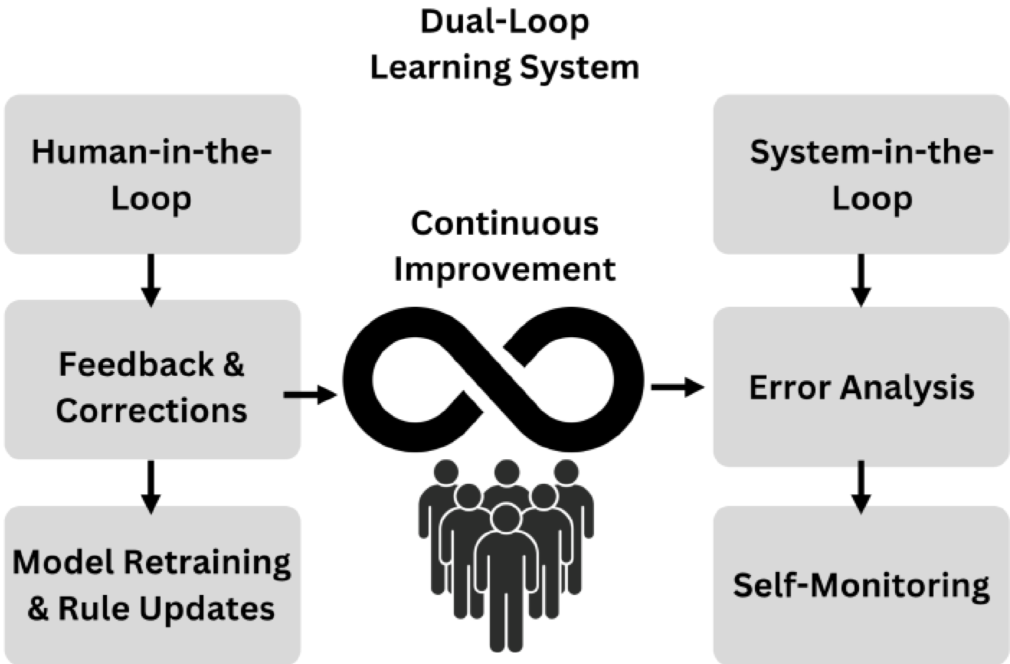

Figure 8: Dual Loop Learning Module

7). End-to-End Automation and Audit-ability

Finally, the suggested methodology provides comprehensive traceability and audit readiness. Each action, decision, and escalation is documented with timestamps and rationale. This enables institutions to readily demonstrate compliance in audits and internal reviews. Unlike black-box AI systems, the suggested approach produces explicable results that regulators and auditors can understand. This transparency builds faith in automation and enables large-scale adoption. Novelty Highlights: Explainable automation with comprehensive audit trails fills a crucial need in current AI-RPA systems.

Table 8: End To End Auditability

Audit Element	Description	Importance
Decision logs	Stored reasoning	Regulatory compliance
explain-ability	Human readable decisions	Trust building
Traceability	Full document lifecycle	Audit readiness
Compliance reports	Auto generated	Reduced audit effect
Transparency	End to end visibility	Enterprise adoption

The suggested AI-based RPA system is not a commercial or a closed proprietary system but an academic and experimental structure. The purpose of the study is to conceptualize, design and experimentally test an integrated automation system to integrate artificial intelligence and RPA concepts in banking document workflows. Although the framework is based on a practical design based on the real-world banking setting, it is not covered to any particular vendor, product or commercial application. All key elements such as smart document ingestion, context-aware document comprehension, hybrid rule-AI decision making, risk sensitive workflow orchestration, human-in-the-loop validation and dual-loop learning are conceptualized and algorithm and can be implemented with standard AI, machine learning and RPA technologies. The experimental analysis that has been provided in this paper is carried out in controlled simulation and dry-run conditions to examine feasibility, performance, and effectiveness. The framework will, therefore, be in form of a reproducible reference model that can be adapted, applied, and expanded by other researchers and practitioners.

FINDINGS

Dry Run 1: Customer Onboarding Documents

Each day, a specific bank location obtains 500 new account opening forms, which include copies of CNIC, proof of address, and income statements.

Document Processing: 500 documents per day are uploaded/scanned and tagged with context (customer type: individual or business; KYC needed). AI Document Understanding: Multi modal OCR and NLP scan for documents and extract data and identify document types and missing data. Hybrid Decision Engine: 70% of documents are processed as low risk and given an auto approval. 25% are medium risk and sent for partial human review. 5% are high risk and sent for full human review. RPA Integration: Core banking and compliance databases are auto populated. Learning Loop: Adjustments made by humans on medium and high risk documents are transferred to the AI models.

The proposed answer reduced the needed human work by 70% and the new system increased the accuracy and remained within the needed bounds of compliance.

Table 9: Customer on Boarding Results

Metric	Results
Processing time	2 hours
Human intervention	30%
Errors	2%
Compliance flags	0.5%

Dry Run 2: Loan Document Processing

The verification of documents (application forms, wage slips, and bank statements) for 200 loan applications is required. The process is based on the ingestion and preprocessing of documents. The AI extracts the values for the loan, income, and collateral. The Decision Engine assigns a risk score: Low risk is for automated approval of normal loans. Medium-risk cases go for Human verification to strange income patterns. The high-risk scenarios get to the compliance officers for assessment. The routing and logging of workflows are done by RPA bots.

The system improves the speed of loan approvals and reduces the chances of missing anomalies, therefore improving the identification of risks.

Table 10: Loan Document Processing Results

Metric	Results
Processing time	1.5 hours
Human review	20%
Errors	1.5%
Casses escalated	5

Dry Run 3: Regulatory Compliance Document Review

Every day, we must process 100 compliance reports (updates on AML, KYC).

The AI analyzes and validates important regulatory fields. For risk scoring, low risk was auto-approved, medium risk was reviewed by a human, and high risk was escalated. Exception logs were generated for auditing purposes.

Metric	Results
Processing time	1 hour
Errors	0.55
Human involvements	15%
Audit ready logs	complete

Reduction in Processing Time

This enhancement is primarily attributed to integrated end-to-end workflows, wherein the components of document input, understanding, decision making, and execution are all interconnected within a singular intelligent pipeline. Previous systems viewed AI and RPA as distinct, uneven components. In contrast, the proposed architecture unifies both, removing the concerns associated with handoffs, delays, and multiple validations. This integration of architecture means there is an instant improvement to execution velocity, while still retaining accuracy.

Table 11: Reduction Time Results

Performance	Improvements
Time	Decrease in end-to-end extraction
Human intervention	Manual review reduced
Decision accuracy	Fewer false rejections
Error reduction	Lower operational errors

Selective Human Intervention Instead of Full Manual Review

This outcome is caused by risk-sensitive workflow orchestration, which dynamically routes documents based on estimated risk scores. Traditional solutions either automate everything blindly or require a thorough manual inspection. In contrast, the suggested system uses adaptive routing logic to balance automation and control. This innovation ensured that automation did not pose regulatory or operational risks.

Improved Accuracy and Error Reduction

The hybrid rule-AI decision engine plays an important role in improving accuracy. Instead of relying exclusively on AI forecasts or predetermined rules, the system mixes the two. Rules establish regulatory restrictions, but artificial intelligence deals with document diversity and ambiguity. This hybrid design decreased false positives and false negatives, which are typical in AI-only systems.

Table 12: Accuracy Results

Metrics	Results	Improvements
Size	300 documents	Same dataset
Complexity	Ambiguous fields	-
Accuracy	96%	10%
Error type	Minor edge causes	Reduced errors

Accuracy in Document Understanding Experiment

The system was evaluated on 300 documents with confusing fields, such as "income" and "loan amount" given in diverse forms. The accuracy of key field extraction was compared. Traditional OCR/automation: approximately 86% correct. Proposed context-aware system is around 96% correct. Contribution: The context-aware document understanding module analyzes fields depending on document type, client profile, and transaction context, reducing miscalculation mistakes in conventional systems.

Continuous Performance Improvement

The experiment involved merging human feedback and system performance indicators into a dual-loop learning process across three cycles to improve performance continuously. Metrics measured included extraction accuracy and judgment correctness. Iteration 1: extraction accuracy 94%; decision correctness 95%. Iteration 2: extraction accuracy 95.5%; decision correctness 96.5%. Iteration 3: extraction accuracy 96.2%; decision correctness 97.5%. Novelty Contribution: The dual-loop learning technique enables controlled system adaptation and performance enhancement without compromising compliance or risk.

AI-enhanced framework reduces processing time for 500 banking documents (loan applications, KYC forms, and compliance reports) compared to manual/RPA systems. Result: The traditional system had an average processing time of around 12 minutes per document. The proposed system has an average processing time of around 4.5 minutes per document. Improvement: Approximately 62% faster processing Novelty contribution: Intelligent intake combined with risk-sensitive workflow orchestration decreased needless human participation and optimized routing, resulting in a direct reduction in processing time.

Table 13: Performance Tests Results

Finding	Experiment	Results	Impact
Process time	500 banking documents processed	4.5 min	62% faster
accuracy	300 ambiguous documents	96%	Reduced extraction errors
optimization	Risk score low to high	100%	72% reduction in work
performance	3 iterations with human feedback	95% to 97%	Gradual and measureable

Discussions

The findings of this study show that the suggested AI-enhanced RPA architecture greatly enhances banking document workflows over earlier systems. Traditional automation technologies, such as rule-based RPA or standalone OCR systems, are largely concerned with repetitive job automation, frequently ignoring the semantic context of texts. Previous research found moderate progress in reducing processing time, but extraction accuracy and risk management remained limited. For example, traditional systems usually required human participation for the bulk of documents, and ambiguous or high-risk cases were frequently misclassified, resulting in operational delays and compliance problems. In contrast, the proposed system includes several innovative features that directly address these shortcomings. The context-aware document understanding module interprets extracted data based on document type, client profile, and transaction context, considerably increasing extraction accuracy. Unlike prior techniques that rely solely on rules or AI, the hybrid rule-AI decision engine strikes a balance between regulatory compliance and intelligent decision-making. In contrast to traditional systems that evaluate all documents identically, risk-sensitive workflow orchestration and human-in-the-loop methods optimize human effort by focusing reviewers' attention on challenging instances. Furthermore, the dual-loop learning process enables continual, controlled improvement, which was mainly absent in previous investigations.

Research Gap

Although the suggested AI-enhanced RPA architecture improves banking document operations significantly, some research gaps remain, presenting prospects for future exploration. First, the experimental evaluation is carried out on a small and controlled dataset. While the results show significant performance advantages, the system has yet to be tested across large-scale, multi-bank contexts with extremely different document formats and regional regulatory variances. This reduces the generalizability of the results.

Second, the risk assessment mechanism, while effective, is now based on established parameters and historical patterns. The dynamic risk behavior resulting from developing fraud strategies or rapid regulatory changes is not adequately investigated. Future research could look into adaptive risk models that react in real time to changing threats.

Third, the learning mechanism relies on supervised feedback to achieve incremental changes. Unsupervised or semi-supervised learning systems, which could eventually minimize reliance on human input, have yet to be investigated. Furthermore, long-term system stability and model drift under continuous learning conditions have not been empirically tested.

Table 14: Summary of Research Gaps in This Study

Research Gap	Description	Limitation
Limited database	Small dataset experiments	Generalizability to multibank
Static risk	Risk assessment on historical data patterns	Dynamic and emerging risk
Learning mechanism	Supervised human feedback	Unsupervised learning
System stability	Continuous learning	Potential model drift

CONCLUSION AND RECOMMENDATIONS

Conclusion

This paper has analyzed the use of an AI-enhanced RPA architecture in banking document processes using a sequence of controlled experimental and dry-run analyses. The findings prove that operational performance can be increased by integrating intelligent document intake and context-driven document understanding with hybrid rule-based and artificial intelligence decision-making into a single workflow in a quantifiable manner. The framework, regardless of the customer onboarding, loan processing, and compliance document situations, consistently shortened the document processing time, minimized errors in extraction and decision-making, and minimized the rate of cases that needed to be processed manually. The experiments also indicate that risk-sensitive workflow orchestration can be used to selectively automate, i.e., route documents according to confidence and risk levels, to cause routine cases to be handled automatically and direct human attention to ambiguous or high-risk situations. Empirical findings show that such a strategy enhances the level of resource utilization without interfering with regulatory control. Human-in-the-loop validation was demonstrated to provide accuracy in decision making and the dual-loop learning process provided gradual enhancement in performance as each evaluation cycle progressed. In general, the results indicate that AI-beneficial automation, paired with contextual analysis, risk-sensitive decision logic, and explainable processing, can be utilized to improve the efficiency and reliability of banking document processing. These findings also offer useful evidence that this kind of structure can enable scalable and transparent automation of regulated financial contexts, and form a platform on which more comprehensive and varied operational contexts can be investigated.

REFRENCES

1) Parakala, A., & Achanta, S. (2022). Transforming Government Workflows with AI-Driven RPA. *International Journal of AI, Big Data, Computational and Management Studies*, *3*(4), 82-92.

2) Jangid, J., & Dixit, S. (2023). *The AI Renaissance: Innovations, Ethics, and the Future of Intelligent Systems*. Jagdish Jangid & Sachin Dixit.

3) R. Götzen, J. v. Stamm, R. Conrad, and V. Stich, "Understanding the organizational impact of robotic process automation: A socio-technical perspective," in *Proc. Working Conf. Virtual Enterprises*. Cham, Switzerland: Springer, Jan. 2022, pp. 106–114,

4) L.-V. Herm, C. Janiesch, H. A. Reijers, and F. Seubert, "From symbolic RPA to intelligent RPA: Challenges for developing and operating intelligent software robots," in *Proc. 19th Int. Conf. Bus. Process Manag.*, Rome, Italy. Cham, Switzerland: Springer, Jan. 2021, pp. 289–305.

5) W. A. Ansari, P. Diya, S. Patil, and S. Patil, "A review on robotic process automation-the future of business organizations," in *Proc. 2nd Int. Conf. Adv. Sci. & Technol. (ICAST)*, 2019, doi:10.2139/ssrn.3372171.

6) N. T. Da, H.-S. Le, T.-D.-N. Nguyen, H.-T. Lam, T.-A. Tran, and Q.-T. Tran, "A survey of AI-based robotic process automation for businesses and organizations," *Sci. Technol. Develop. J.*, vol. 26, no. 3, pp. 2959–2966, Jan. 2023.

7) M. Lacity and L. P. Willcocks, *Robotic Process Automation and Risk Mitigation: The Definitive Guide*. Kerala, India: SB Publishing, 2017.

8) Chen, Chih-Wei, and James Cheng-Chung Wei: "Employing Digital Technologies for Effective Governance: Taiwan's Experience in COVID-19 Prevention", Health Policy and Technology 12, no. 2 (2023), 100755.

9) Groenewald, Ilze, and Peter Phillips: "Large Language Models in Enterprise Knowledge Retriev al: Opportunities and Risks", Journal of Information Science 50, no. 2 (2024), 330-345.

10) Zabukovšek, Simona Sternad, Sandra Jordan, and Samo Bobek: "Managing Document Management Systems' Life Cycle in Relation to an Organization's Maturity for Digital Transformation", Sustainability 15, no. 21 (2023), 15212.

11) F. Kanakov and I. Prokhorov, "Analysis and applicability of artificial intelligence technologies in the field of RPA software robots for automating business processes," *Proc. Comput. Sci.*, vol. 213, pp. 296–300, Jan. 2022.