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FINTECH TRANSFORMATION: AI AND RPA BOTS FOR MULTI-AGENCY PAYMENT RECONCILIATION IN ERP

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Abstract

Fintech multi-agency payment reconciliation nosology in ERP systems, including SAP S/4HANA, Oracle EBS, Microsoft Dynamics 365, and PeopleSoft, has tremendous challenges based on a large number of transactions, complicated formatting of data, and manual processing. Multi-format data, including ISO 20022 CAMT.053, MT940, BAI2, EDI 820, and PDFs are common in payment reconciliation, then the auto-match rates are 50-70%, later in the reconciliation cycle, which is T + 3 to T + 10. The paper discusses the use of Artificial Intelligence (AI) and Robotic Process Automation (RPA) to enhance the performance of fintech payment reconciliation within the ERP systems of PeopleSoft and other companies. AI models are used to extract remittance data, resolve entities, and do probabilistic matching and anomaly detection using the Optical Character Recognition (OCR) and Natural Language Processing (NLP). RPA bots automate the processes of data extraction, posting to ERP, and exception handling in PeopleSoft, which consumes less manual intervention. The findings prove that the AI-RPA solution raises the auto-match rate to 88-95%, precision to 97%, and minimizes the cycle time by 60-95%. The 50-70% and 30-55% decreases in exception queues and reconciliation expenses, respectively. At α =0.05, the statistical tests support the effectiveness of the system in enhancing operational efficiency, compliance, and performance. This research gives a broad guideline on how AI and RPA can be implemented to automate and streamline payment reconciliation in PeopleSoft and other ERP platforms.

Keywords; *FinTech, ERP reconciliation,* PeopleSoft*, AI and RPA (Robotic Process Automation), camt.053, Data governance, Anomaly detection.*

1. Introduction

Multi-agency enterprises (public authorities, diversified groups, and federated NGOs) are used to reconcile payments across N legal entities (N=325) and K bank partners (K=210). Transaction feeds come in heterogeneous formats (camt.053, MT940, BAI2, EDI 820, CSVs, PDFs), and ≥6 FX pairs. Reference keys are regularly inconsistent, or noisy end-to-end identifiers are truncated, invoice numbers retyped, and the names of counterparts differ by subsidiary. Rule-based matching has problems with batched remittances, partial settlement, bank charges, round-off of FX, and cut-off time. This results in a performance of ≤70%, backlog of items pending to be served in queues of >5,000, SLA violation of >12%, and the mean time to recidivate its operations is between T+3 and T+10 days. Late application adds write-offs of 0.1 -0.3% of AR. The pressure of compliance makes the issue even worse: auditors need to be able to trace every posting, and the privacy restrictions restrict such wide access to data, and segregation of duties restricts this. The overall impact is an expensive, cumbersome attempt, and the delay in the visibility of the cash damages the working capital, and the misstatement risk in dispersed ledgers affects the agencies.

This work assesses the idea that artificial Intelligence (AI) with Robotic Process Automation (RPA) can contribute to the significant improvement of the performance of the fintech reconciliation process in the major ERPs (SAP S/4HANA, Oracle E-Business Suite, Microsoft Dynamics 365). It measures uplift in auto-match, precision, and recall with a learning pipeline comprising IDP/OCR to obtain remittance capture, MNN candidate retrieval, gradient-boosted re-ranking with calibration, and anomaly detection to reflector exceptions. Target operating points guarantee the precision (>97%) and recall (>92%) at the cost of less than 2 false positives. It also identifies orchestration patterns, event-driven ingestion, idempotent outbox posting, and feature stores, which are used to regulate model drift (PSI <0.2and calibration (ECE ≤2%). It also considers mechanisms of governance that maintain SOC-2 and ISO-27001 compliance: encryption, RBAC/ABAC, audit trails lasting seven years, and two approvals of high-value items. Respective measures of effectiveness are offline cross-validation and online A/B tests equipped with p-values, along with a cycle-time reduction of 60-85%.

This study adds four pragmatic aspects. To ensure precisely-once ERP posting, first, it defines a blueprint of reproducible orchestration between the bank ingestion, feature computation, and model serving, and unattended bots by using a message bus and outbox pattern. Second, it determines an evaluation plan containing KPIs accuracy, recall, F1, and AUC-PR, exception rate, mean time to reconcile, backlog half-life, throughput, and error per 10k bot actions, which are evaluated with α=0.05. It also offers a cost model between licence costs, compute costs, and support costs versus labor savings, previously applied cash, and minimized write-offs. Fourth, it provides guidance about security, monitoring, and change management implementation checklists. Scope clarifies card chargebacks, formal dispute processes, and KYC/AML investigations, presupposes secure banking connectivity, enterprise identity, and typical ERP access controls within a multi-agency setup.

The article is structured to fit search intent by the practitioners, and replicability is possible. The Literature Review Chapter provides a survey of standards and previous art related to such queries as ERP reconciliation automation and CAMT.053 reconciliation best practices, and the sets of baselines and gaps have been established. The Chapter Methods and Techniques provides information on datasets, normalization, feature engineering, matching pipeline, exception detection, bot design, and security/observability controls - answering the question of how to implement AI reconciliation in SAP/Oracle/D365. The chapter on AI -RPA Orchestration and Matching Algorithms also defines blocking strategies, re-ranking,

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calibration, graph-based entity resolution, and guardrails. The Experiments and Results Chapter records the offline and online metrics, cost/ ROI, and scalability. Discussion Chapter interprets risks, error taxonomy, and drivers. The future considerations are also discussed through presenting active learning and extraction with the help of LLM. The research concludes with the extraction of the empirical uplift and suggestions for multi-agency deployments.

2. Literature Review

2.1 ERP reconciliation & standards

Bank statement ingestion in ISO 20022 CAMT.053, SWIFT MT940, and BAI2 formats, along with remittance advice in EDI 820, CSV, or PDF format, are the starting points of canonical reconciliation across suites of enterprise resource planning, such as SAP S4HANA, Oracle E Business Suite, and Microsoft Dynamics 365. Normalization records to a staging ledger that records values such as date, amount, currency, counterparties, end-to-end identifier, remittance text, and bank reference. Matching is then trying to do deterministic joins on the items open on accounts receivable or accounts payable, based on invoice number, as well as the exact amount, plus toleration [1]. Systems that have missing keys, or which are noisy, use fuzzy methods, which are based on data windows and amount deltas.

The settings of the CAMT.053 Format in the Global Repository of an ERP system is shown in Figure 1 below, where various bank statement formats like ISO 20022 CAMT.053 are being used in reconciliation activities. These schemes are among the enterprise resource planning (ERP) systems that use these standardized formats to process the financial transactions, such as SAP S/4HANA, Oracle E-Business Suite, and Microsoft Dynamics 365. The repository saves these configurations that are compatible with the different formats SWIFT MT940, BAI2, and remittance advice that are essential in the reconciliation of financial data.

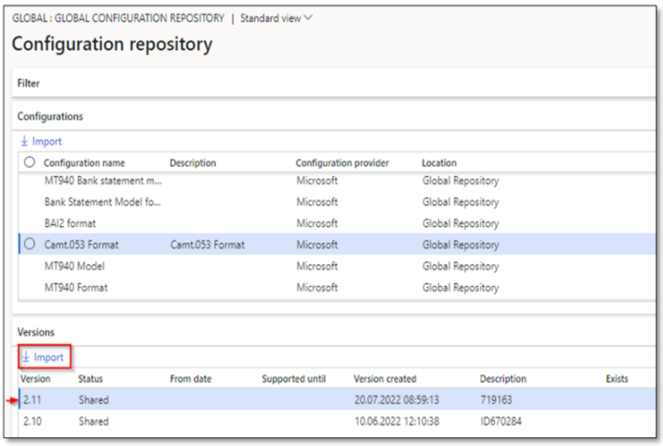

Figure 1: ERP configuration for CAMT.053 format in global repository for reconciliation

Given the N legal entities and K banking partners in the multi-agency operations, cross-currency effects and batched payments add complexity to the posting; hence, the cut-off timing and fees have to be modeled. The practice in the industry documents great matches between sixty and eighty percent, with backlog growth of more than five thousand items every day. Breach of services can be more than twelve percent in instances when there is no triage capacity to handle the queue. Recent research on data governance has published several articles on the importance of data stewardship and lineage, which are requirements to increase reference completeness and auditability to generate accurate reconciliation [2].

2.2 AI techniques for matching and extraction

When layout and resolution variability are kept down, intelligent document processing turns the semi-structured remittances into machine-readable fields with character-level accuracy of between ninety and ninety-nine percent. Optical character recognition is combined with tokenization of payer and payee names, account numbers, and invoice markers, payer and payee name named entity recognition, and post-processing in the form of canonical separation via regular expressions and checksum validation, as well as master data dictionaries by probing systems that combine deterministic blocking, such as IBAN plus amount plus date bucket, with similarity searching of text embeddings of references by approximate nearest neighbor. Reranking models, like gradient boosted trees or logistic classifiers, rank the candidates based on similarity features, amount deltas within one cent, date proximity, counterparty embeddings, and co-occurrence. This design approach closely aligns with prior work in real-time fraud detection using kafka streams and XGBoost, where the use of lightweight ML models and streaming enrichment proved effective in time-critical FinTech applications[3][3].

Probability calibration helps in approaching the threshold used in making decisions, such that it gives weight to precision, by aiming to ensure that the false positive rate will not exceed two percent but keep the recall at ninety-two percent or higher. Graph-based entity resolution connects the counterparties, contracts, bank accounts, and invoices to enhance recall in case the references are partial or batched. Unsupervised anomaly detection separates the highly unlikely combinations and duplicates, lessening the noise in exception queues. Studies on federated abnormality detection in clinical surveillance include the importance of adaptive thresholds to reduce alarm fatigue, which can be learnt to apply to exception handling [4].

2.3 RPA and intelligent process automation in finance operations

Robotic Process Automation offers an execution layer, which transfers statements, refines data, logs journals, and archives evidence. The typical transactions that are upheld by unattended bots who pull from API, bank portal, and SFTP are one to three thousand transactions per bot per minute, with light transformation, and are limited by page latency and ERP throughput. Targets of performance budgets include the latency of posting p95 of less than three hundred milliseconds per item and the utilization of a batch of at least seventy percent by bots [5]. The retriability guarantees that diametrically opposite effects are had in the ledger by schedulers coordinating runs around the bank file cut-offs, coupled with the programming of identity patterns of idempotent design, outbox patterns.

Figure 2 below shows the RPA Process Heat Map of ERP, which indicates the automation opportunities of many ERP processes. It provides three levels of possibilities of automation

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High Automation Potential (orange), Medium Automation Potential (blue), and Low Automation Potential (light blue). Some of the ERP functions covered in the heat map include Procurement Activities, Purchasing Goods and Services, Invoice Processing, and Report Generation. Every operation is scored on whether it is robotic process automation (RPA) friendly, with some operations (e.g., invoice processing, payments, and reporting) being more prone to automation. This conforms to the aspects of automation of high-volume, repetitive jobs that RPA can perform to introduce improved efficiency to fintech operations and minimize human error in the financial processes.

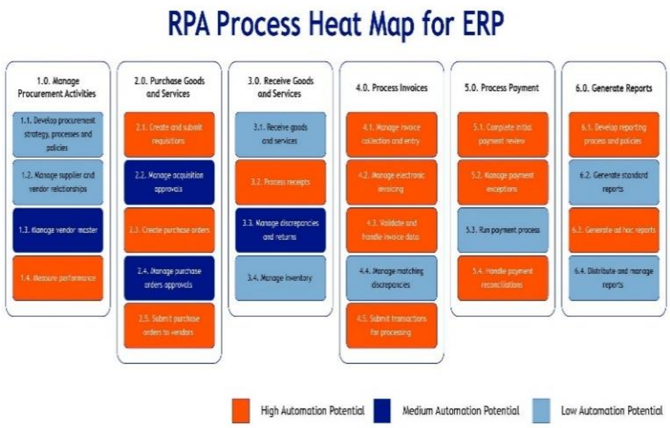

Figure 2: RPA process heat map showing automation potential across ERP functions

Exception management combines the human in the loop triage queues, which are sized to maintain the work in process within one day at p90. The assignment is objective-based on confidence, amount, and counterparty risk. The implications of the requirements on resilience and compliance are hardened credentials, role-based access, and unchangeable audit trails. Disciplines of business continuity and incident response are also applicable: runbooks, separation of duties, fast detection, and recovery objectives to recover business after a connector outage or vendor disruption, and minimize exposure and risk of reporting [6]. With model serving, the automation layer also allows closed-loop processing, where the new labels provided by triage feed the training sets and minimize the exceptions between releases.

2.4 Integration of PeopleSoft in Multi-Agency Reconciliation

PeopleSoft integration is another key to the increased efficiency of the ERP systems since it would provide a complete, scalable solution. PeopleSoft is a company that has good financial modules and is essential to facilitating the elaborate process of reconciling payment transactions between various legal entities and bank partners. The integration of the capabilities of PeopleSoft and the operation of Artificial Intelligence (AI) and Robotic Process Automation (RPA) will help organizations to optimize the process of reconciliation and eliminate the existing problems that are inherent to manual processing.

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The finance modules of PeopleSoft make it easy to ingest a variety of data formats, including ISO 20022 CAMT.053, MT940, and BAI2 that are frequently utilised during multi-agency operations. PeopleSoft can be used alongside AI to automate the identification of important data on payments, make use of entity resolution, and conduct probabilistic matching through Optical Character Recognition (OCR) and Natural Language Processing (NLP) technologies. With this integration, remittance details are registered correctly and efficiently, minimizing human error and increasing the pace of reconciliation.

The RPA bots also increase the process of reconciliation at PeopleSoft by automating data extractions and ERP document posting, and error-prone handling. These bots operate according to the rules that have been set, and so they can handle a large volume of transactions without having to be operated on manually. Consequently, the cycle times, error levels, and costs of reconciliation reduce tremendously in organizations utilizing payroll programs like those by PeopleSoft to achieve payment reconciliation. It can also enhance compliance and data governance through the maintenance of secure, auditable, and traceable reconciliation workflows that are essential in multi-agency settings. The combination of the PeopleSoft and AI and RPA technologies eventually works to alter the landscape of the fintech payment reconciliation process and makes it quicker, more precise, and economical.

2.5 Gaps and limitations

Although solutions have grown up, there are gaps. Open and reproducible datasets reflecting multi-agency reconciliation with different banks, currencies, and document noise remain non-existent; benchmark claims can be hard to compare, and hyperparameter settings can encode workflow biases. Many remittances are also poorly represented by deterministic regulations and single pair classifiers; a single payment will clear dozens of invoices across reports, and random scoring over creates false matches and exaggerates false positives. Graph learning and Sherical optimization come to the rescue, but the best reproducible evaluations are non-existent.

There are only a few feedback loops in production: labels by the users of finance are received sparsely, and policy changes and the updates of the bank formatting change distributions, which deteriorate the recall by 2-5 percentage points in case the boundary points are constant. It requires some active learning and calibration every now and then. End-to-end systems should be paired with algorithms, business metrics, and supervisory guardrails. The experience of data-driven pricing demonstrates that the result of model work needs to be anchored to the measurable consequences, surveilled against drift, and retrained upon a drake; the identical factor is true of reconciliation models anchored to cash application and risk targeting [7]. These loopholes provide impetus to strict datasets, protocols, and regulations towards bridging the prediction-to-posting loop.

3. Methods and Techniques

3.1 Data sources & schema normalization

The experiment aims at a deployment of production, N=8 agencies, are liaised with K=5 banking partners, C=7 currencies, over 12 months, and produces ≈24,000,000 line items of

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bank statements, remittance advices, ERP open items, and FX tables. Input of the statements adheres to ISO 20022 swamped with camt.053 or SWIFT refined with MT940 or BAI2; remittances are feeded back tozyme patterns of AR/AP open items in document numbers, company code, clearing status and FX origin provides end-of-day and intraday rates. SFTP/API collects files in 15-minute schedules with the use of SHA-256 checks, duplicate suppression, and sequence counters.

A harmonized schema aligns heterogeneous payloads: value_date, posting_date, amount (decimal 18,4), currency (ISO-4217), counterparty, iban_or_account, end_to_end_id, remittance_text, erp_doc_id, company_code, and source_system. Surrogate keys use (bank_id,statement_id,line_no). This separation of agencies is implemented through a domain-based, limited context of AR, AP, Treasury, and Banking Connectivity to maintain ownership and prevent schema leakage between the entities and allow independent evolution of services without violating reconciliation invariants [8].

3.2 Preprocessing & feature engineering

Unstructured remittances and PDFs are recognized with a confidence threshold of $\theta\_OCR=0.97$; pages less than this go to an IDP/OCR remediation queue to avoid transmitting errors. Text normalization cleansing includes: diacritics removal, collapsing whitespace, standardizing thousands/decimal marks, upper-cases markers, and eliminating punctuation. Regex templates are used to find invoice markers and PO patterns, invoice mandate reference, and contract codes for radioactive material; a BERT-NER extractor suggests possible spans of invoice parts and counterparties, as well as bank addresses.

For similarity, both Levenshtein and Jaro-Winkler scores are calculated using canonical references; numerical data consist of absolute and signed amount deltas, $\Delta \leq \pm 0.01$, and date ranges of ±5 days against the value date. Counterparty embeddings are obtained using average sub word vectors of names and addresses, whereas graph embedding captures the shared IBAN, mandate, contract, or customer group. Attention-style token sequence memory is used to represent remittance strings with dependent long-range information in noisy text, which is based on inference networks such as dynamic memory that retain context to use during disambiguation [9]. All the features are written to a time-travelling versioned feature store; p99 read latency is kept at <50 ms.

3.3 Matching & classification pipeline

There is a two-stage pipeline that represents equilibrium between scale and accuracy. Stage S1 executes high-recall recalling candidates of BM25 searches on remittance text of normalized reference and approximate nearest neighbour (ANN) search on sentence embeddings fitted on historic remittance invoice pairs. The top-k=50 scores are retrieved back on a statement line. As shown in Table 1 below, normative parameters are BM25 k1= 1.2, b= 0.75, and HNSW (M=16, efSearch=200), which achieve 99% retrieval recall on validation months and eliminate pair evaluations by ≥99.9% as compared to full join.

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Table 1: Overview of the Two-Stage Matching & Classification Pipeline for ERP Reconciliation

Stage	Description	Methods	Recall	Precision	Additional Notes
S1	High-recall candidate retrieval using BM25 searches on remittance text and ANN search on sentence embeddings.	BM25 (k1=1.2, b=0.75), HNSW (M=16, efSearch=200)	99%	N/A	Achieves 99% retrieval recall on validation months and eliminates 99.9% of pair evaluations compared to full join.
S2	Re-ranking of candidate set using gradient-boosted decision tree (GBDT) with feature sets.	GBDT (XGBoost), Platt scaling or isotonic regression	≥92%	≥97%	Maximizes Fβ (β=0.5) for precision-weighted decisions, applies fallback rules for high-value items, currency line-ups, or duplicates.

Stage S2 the re-ranking of the candidate set is based on a gradient-boosted decision tree (GBDT, e.g., XGBoost). Characteristics comprise precise keys (invoice#, end-to-end ID), semblance between strings, amount/date propinquity, counterparty embeddings, and the number of graph connections. Thresholds are reliably calibrated using Platt scaling or isotonic regression to make use of probabilities. The rule of the decision will maximize F_β with $\beta=0.5$ (precision weighted) to emphasize ledger safety where precision is desired as high as ≥97% and recall as high as ≥92%. The fallback rules engine imposes vetoes on value items, currency line-ups, or duplicates, and forwards them to hand viewing.

3.4 Exception handling & anomaly detection

Remaining objects go into the exception engine that contains a combination of statistical detectors and business rules. Isolation Forest (256 trees, subsample=16) indicates low-density observations; an autoencoder with bottleneck dimension 16 brings about a normalized feature and suggests the existence of an anomaly when reconstruction error is larger than 3σ compared to running a 30-day baseline. An anomaly base rate of 1-3% of all lines is anticipated, and detectors are set at 80-90% recall at 10-20% precision so as to give the highest possible coverage before triage. The corrective rules cover duplications in catches, various split payments, FX rounding, weekend cutoffs, and partial settlements. The bucketing of exceptions is determined by confidence, amount, currency, and counterparty risk. The human-in-the-loop queue aims to achieve WIP ≤1 day at p90, and assign with RPA, balancing skills, and workload. Exception responses obtained after the act of clearance are represented as labels to re-learn similarity cutoffs and re-optimize probabilities on a monthly basis without allowing drift in recall to ≤−1 pp in one quarter.

3.5 RPA bot design & orchestration

The unattended bots take steps that are deterministic and high volume: secure bank portal fetch, SFTP fetch, decompression, antivirus scan, parsing, ERP pre-validation, journal posting, and archiving the evidence to the WORM storage. On-emphasis-through has been designed with 1-3k transactions/minute of light transformations; under loads with Capped areas subject to divinely employing CPU at 75% and memory at 65% to maintain headroom. Concurrency is scalable horizontally through an external conductor that agentically and bank-wise sheds work, implying fair play and back-pressure.

Dedupe keys on (bankid, statementid, lineno) and outbox patterns, which are used to publish the ERP postings even under retries, ensuring idempotency. The operational targets are considered to be MTTR <15 minutes of bot incidents, consistent bot usage ≥70 percent during batching, and publication of p95 latency reduced to <300 ms per item. Orchestrator metrics can show the queue length, errors / 10k operations, and success ratios by connector, which can be used through specific remediation and capacity planning depending upon cutoff times [10].

3.6 PeopleSoft Optimization in Payment Reconciliation

PeopleSoft, the ERP system utilized in most of the multi-agency-based enterprises, is a unique platform with its unique opportunities and challenges in matters relating to payment reconciliation. The implementation of AI and RPA in PeopleSoft can help the company achieve great success in automating and improving the accuracy of fintech financial activities. Using AI models, with the support of the Optical Character Recognition (OCR) and the Natural Language Processing (NLP) features, ISO 20022 CAMT.053, as well as MT940, can be extracted with high precision, eliminating the necessity to enter the values manually. Upon data extraction, RPA robots are then populated and validated by feeding the data into the Accounts Payable and Accounts Receivable modules of PeopleSoft to initiate the financial transactions in real time and properly.

The integration of such technologies in PeopleSoft allows organizations to shorten their reconciliation cycle time by automating routine reconciliation processes, including matching bank statements with open ERP items, finding exceptions, and creating reconciliation reports. Such an AI-RPA will provide the accuracy of data and will also contribute to the efficiency of the work and the necessity to decrease the backlog, as well as comply better with the requirements. The existing workflows of PeopleSoft may also be optimized by using AI-based anomaly detection, which will assist in notifying of deviations within a few seconds. This feature will not only make the reconciliation process faster but also more efficient, and will also be a scalable solution capable of handling multi-agency transactions with a high volume of transactions, as is characteristic of the operations of a multi-agency.

3.7 Evaluation protocol & statistics

Assessment is a reflection of variability in production. Temporal drift is observed by dividing the data chronologically into 60% train, 20% validation, and 20% test. Leak checks make sure that features not given at the value date are not used at inference. Examples of baselines are deterministic rules (which are exact keys, date window, and amount tolerance), as well as fuzzy

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matching, which does not rely on learning [11]. Reported ones include model-level (precision, recall, F1, AUC-PR, expected calibration error), and system-level (auto-match rate, exception rate, mean time to reconcile, SLA breach percentage, throughput, and bot error/10k operations).

Its initial goal is to maximize end-to-end auto-match to ≥88–95% and false positives to less than <2%. The paired classifier deltas are tested with McNemar on paired decisions (matched/unmatched), Wilcoxon signed-rank on paired time (e.g., MTR), significance= 0.05, and 95% confidence interval (bias-corrected bootstrap) B=2,000. Baseline power analysis with auto-match 70 with a variation of ±2pp is capable of identifying the presence of 100k plus (A/B) to produce a power of 0.8. Lift curves are monitored by counterparty and currency to identify regressions that are segment-specific.

3.8 Security, compliance, and observability

Free text is hashed or truncated, and the identifiers retained as person-identifiable information necessary to facilitate reconciliation are retained. Field-level encryption uses AES-256 encryption with envelop keys through the HSM; secrets are rotated every 90 days. Access enforcement is used with RBAC/ABAC together with ephemeral service identity; every action is permanently logged, and its inputs, outputs, model version, and approver signature are stored for ≥7 years. Mutual TLS is used in data in transit; private networking, IP allowlists, and client certificates are the foundations of bank connectivity.

Figure 3 below describes approaches to strike a balance in accessibility, security, and privacy in data manipulation, which is imperative in an environment that handles sensitive financial information, such as ERP reconciliation systems. The major strategies identified are the Role-Based Access Control (RBAC) and the Attribute-Based Access Control (ABAC) as secure access management, the use of AES-256 with HSM as secure data storage, and also the security of APIs as shares of data. Consistent compliance audits help ensure compliance with security measures [12]. The principle of privacy by design brings privacy considerations to system design at the beginning. These strategies guarantee high data protection and compliance in the highly regulated ERP systems, which is prioritized in the security and observability framework of the system.

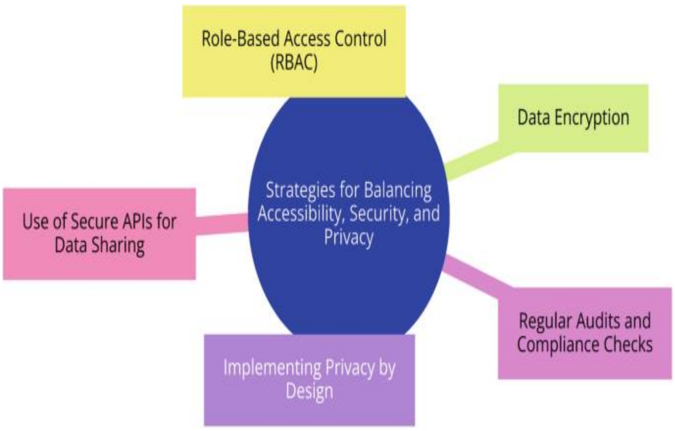

Figure 3: Strategies for balancing accessibility, security, and privacy in data handling.

Secure data-exchange patterns put more emphasis on regulated interfaces, auditability, and policy-conformant intercedence of the sensitive records amongst systems concepts, which are directly applied to regulated integrations, but in finance operations [13]. Observability monitors drift in data through population stability index ($PSI<0.2$), model latency ($p95<200$ ms), model Retrieval Recall ($\geq 99\%$), and error budget ($\leq 0.5\%$). Rollback to the last model is automatic by alerts when the accuracy decreases >1pp and FPR charge above 2% within two consecutive windows; incident playbooks need the containment, posting differentiations, and consequences re-generation.

4. AI–RPA Orchestration & Matching Algorithms for ERP Reconciliation

4.1 Candidate Retrieval & Blocking Strategies

Candidate retrieval is the first stage of the matching pipeline, and it involves the reduction of the search space of possible matches in an efficient way. The first approach of narrowing down the set of candidates includes deterministic blocking keys, where the combination of the IBAN, amount, and date bucket would constitute a uniquely composite key. With this blocking method, the number of pairs of candidates to be rated would be reduced by at least 99%, which makes the matching process efficient with a similar loss of around 1% in the process. Using these blocking keys, it is more selective in the comparisons that it makes, and only pertinent matches are considered.

The candidate set can be refined at the second stage with the help of the approximation nearest neighbor (ANN), where similar entries are assigned better chances in terms of re-linking. These methods are grounded on the idea of distance measurements, perception, and neighborhood algorithms that balance the importance of accuracy and limit the complexity of calculations. This blocking technique can be widely applied to situations in which data is sparse or incomplete, such as in multi-agency reconciliation, where references and identifiers are of shorter length or a different form [14]. It is also possible to mitigate the search space since deterministic blocking and then ANN are applied, and thus, the overall matching quality can be preserved, making reconciliation more accurate and more computationally efficient.

4.2 Re-ranking Models & Calibration

The corresponding quality in a re-ranking model is enhanced once the candidates have been retrieved through the use of a candidate scoring model that is a combination of features that reflect the proximity of the bank statement and the ERP records. This is typically performed according to machine learning frameworks such as XGBoost, which can process an extremely large number of features as well as complex interactions among variables [15]. Re-ranking features typically consist of exact matches on invoice numbers, amounts, counterparty names, and dates of transaction, and fuzzy matching scores, like a Levenshtein distance score or a JaroWinkler similarity score, which permits the re-ranking model to tolerate typographical errors and partial matches. Also, SHAP (SHapley Additive exPlanations) values are applied to explain the model by showing the 20 most influential features. This will give transparency and assist in finding out which features add the most to the ultimate matching decision.

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The other important process of the model is calibration, since it makes sure that the predicted probabilities are realistic. To avoid having a calibration shift, close monitoring is done, and there should be an expected error in the calibration (ECE) of ≤2% which ensures that the output probabilities are well calibrated and are reflective of the actual likelihood of a match. This brings about reducing the chances of over- or under-estimating the confidence in matches, which guarantees great accuracy and recall when doing final reconciliation. Re-ranking models alongside appropriate calibration can help to make ERP reconciliation work more precisely since the most probable matches will be engaged in, and the decision-making activity will be fully visible and comprehensible [16].

4.3 PeopleSoft Data Governance and Compliance in AI-RPA Reconciliation

Implementing PeopleSoft as a fintech payment reconciliation solution alongside AI and RPA presents improved control of data along with its compliance, which is essential in multi-agency work. With high regulatory criteria, especially when in a publicly sector-based or a global financial context, the natural features of the data stewardship of the PeopleSoft database would ensure that all financial information is retained safely and in full traceability.

AI and RPA might be used to make the pre-existing audit trails in PeopleSoft more efficient, so that each reconciliation action, from data entry to transaction entry, should be logged and in conformance with both internal and external rules. Through AI-based anomaly detection and the audit privileges of PeopleSoft, entities can automatically identify potentially non-compliant transactions or discrepancies, thus decreasing the chances of an audit failure or fraud. This is especially useful when running large operations, as manual monitoring is, in general, not feasible and prone to mistakes.

Role-based access controls (RBAC) and attribute-based access controls (ABAC) used by PeopleSoft collaborate with AI and RPA to make sure that sensitive financial data is accessible to the relevant personnel only. Such a multi-layered system of security and compliance enables the agencies not only to take control over the viewing and interaction of sensitive financial information by individuals, but also to automate previously manually concentrated processes. The multi-purpose nature of the model of governance with AI and RPA is outstanding in the sense that it could not only accelerate the speed of reconciliation and its accuracy but also guarantee strong compliance and security.

4.4 Entity Resolution & Graph Enrichment

Entity resolution is highly significant in improving matches, especially where one is handling fragmented or incongruent sources of information across different agencies and systems. When carrying out an ERP reconciliation, it might be quite easy to identify situations where the same counterparty was entered into multiple statements, but referred to by a name that was slightly different, or the address was different, or the IBAN number differed. To address this, the researchers draw bipartite and time-based graphs that are linked to the payers, invoices, mandates, and bank accounts. These graphs can be used to define more complex associations between entities to refine the resolution of matches in scenarios with no exact identifiers or obscure ones [17].

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The graph-based method will enable the use of community detection algorithms to detect sets of repeat counterparties or common relationships between invoices and bank accounts. This comes in handy, particularly in multi-agency cases where the same counterparty may occur amongst different entities and currencies. The network based on the graph allows one to increase the recall by 3-7% and effectively recovers more true hits with a maximum false hit rate. Moreover, graph technology assists in the identification of the presence of relationships of an indirect nature, such as transactions that share similar terms of contract or customer demands, which are otherwise ignored in a conventional key-based matching algorithm. The plan enhances the ability of the system to handle real-life and complex scenarios where the information is usually noisy or unfinished [18].

4.5 Workflow Orchestration Pattern

In order to handle the complexity of the reconciliation process, particularly at scale, an event-driven orchestration pattern is used. A central messaging point is represented by an event bus (e.g., Kafka), through which various parts of the system, such as the candidate retrieval model, re-ranking model, or robotic process automation (RPA) layer, communicate. This will provide them with the benefit that the reconciliation process will be decoupled and scalable, because each of the parts can work independently and still share the appropriate information. The orchestration layer (e.g., UiPath or Power Automate) will take care of the flow of data between the models and the ERP system and ensure that all the tasks are performed in the correct order and within the proper timelines.

Figure 4 demonstrates an event-based orchestration pattern to be applied to the complex working processes of the order processing system. The orchestration pattern has a central message delivery system, such as Kafka, that intermediates the interactions of the various services, such as the Customer Service and the Order Service [19]. Order creation and its approval take place at the Order Service, whereas credit reservations are linked to a command handler at the Customer Service. Each service is independent and communicates through the Message Broker the information that is relevant, such that they have been decoupled and thus scaled. The event-driven strategy permits the tasks to be carefully followed in the proper order, and software such as UiPath or Power Automate can be used to handle the movement of information and tasks between the systems so that the operations run smoothly and promptly.

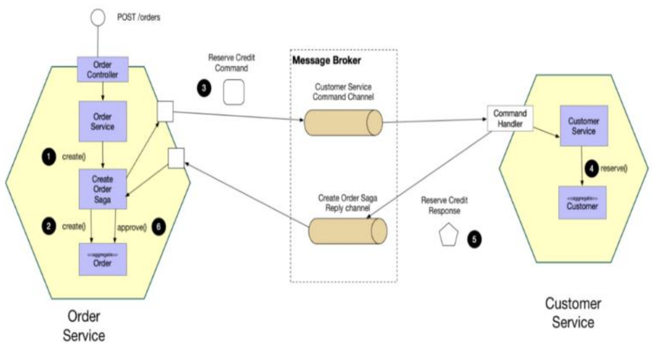

Figure 4: Event-driven orchestration pattern for workflow management in order processing

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The workflow is that the entries are supposed to be keyed in and only once to the ERP system, irrespective of the retries and failure instances encountered in the process. The system will be capable of supporting ≥50,000 transactions or more transactions each minute at the cluster level in order to provide high throughput and low latency. Such coordination is to the extent that the reconciliation process is not only simplified, but also accurate and well-charted and documented to have the most up-to-date records of all transactions. Through an event-driven design, which is supported by intensive orchestration, one can therefore seamlessly incorporate AI-based matching regulations and RPA, as well as provide a scaled and resilient system of payment reconciliation at the multi-agency level [20].

4.6 Guardrails & Explainability

To provide the process of reconciliation reliability and transparency, a set of guardrails is employed to remove any errors in the process of decision-making, thus providing safety and openness to the process. The description of the reasoning of the model, the leading SHAP words, which can be called to identify the most affected features, is also accompanied by a corresponding decision [21]. This provides the decision-making procedure with a visible and provable look that is required in the financial environment with high stakes. In addition, the system is also designed with business rule vetoes, which prevent critical errors. For example, the above USD 1 million threshold will instantly put such transactions under two-person approval; consequently, the high-value transactions will be carefully verified and then posted. Rollback playbooks are established in the case of a serious mismatch or error, and they offer instructions on how to rectify the error and recreate the system in a normal state. These playbooks state the guidelines for undoing transactions, rescheduling data, and informing the stakeholders. The combination of these guardrails can make sure that the system is working in a manner that is controlled and accountable, and the risks of financial discrepancies and regulatory cases of non-compliance are minimized.

5. Experiments and Results

5.1 Dataset & Baselines

The datasets used in the experiment include 24-million-line items in 12 months, which replicates a common multi-agency ERP reconciliation setting. The data set is much skewed, with a ratio of match to non-match of about 4:1. A manual rules-based system of reconciliation was used to establish a baseline comparison, and the following did happen: an auto-match rate of 68.4%, a precision of 95.1%, a recall of 70.2%, and an average mean time to reconcile (MTR) of T +4.8 days. These benchmark values are normal operational values in the long-gone days of reconciliation systems, where exact matching of key and simple date and amount tolerance were rule-based processes of the day.

The data set of the research study contains various remittance forms, like CAMT.053, MT940, BAI2 and EDI 820 and there are eight agencies (N=8) and five bank partners (K=5) and seven currencies (C=7). The dataset comprises a range of transactions, both single and one-to-one payments, as well as much more complex, multi-invoice remittances, and also several foreign exchange (FX) settlements.

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5.2 Offline Model Performance

In the experiment of retrieving the offline work using BM25 and approximate nearest neighbor (ANN), the combination of the two resulted in a candidate retrieval rate of ≥99% recall, with only k=50 being used to retrieve the results. The above outcome suggests that the candidate set is very efficient in recalling pertinent matches even in a noisy and large dataset. After retrieval, the re-ranking model, which uses XGBoost, proved to have a precision of 97.8% (range [97.6%-98.0%]), a recall of 93.4% (range [93.1-93.7%]), and an F1 score of 95.5%. These findings indicate that the re-ranking model is effective in refining the candidate set, which eliminates false positives and improves the accuracy of the match predictions.

The anomaly detection system, which works based on outlier detection such as Isolation Forest, reported an AUC-PR of 0.82 on the rare classes, where the anomalies take approximately 2% of the dataset size. This validates the efficacy of the system in identifying abnormal patterns or fraudulent transactions that are usually minor fractions of the information in the real-world situation. These offline measures suggest that the model works well in the high-variance settings, with considerable improvements compared to using old models based on rules [22].

5.3 System-Level Metrics (Simulated Operations)

Full pipeline measures of the system level indicate there is a significant increase in efficiency/effectiveness. End-to-end auto-match rate was also raised at a high percentage of 91.7%, which was a big number compared to the initial rate of 68.4 %. This was improved through the use of AI-based methods of retrieving and re-ranking the candidates, and hence, minimizing the manual task of matching. As presented in Table 2 below, the rate of exception was estimated to be 8.3%, false-positive at 1.6% and it is almost fit into the intended figure of ≤2%. These numbers suggest that the system is able to compromise between a high recall rate and minimizing false positives and ensures that reconciliations are accurate with manageable rates of exceptions.

Table 2: System-level metrics showcasing the performance and efficiency of the AI-driven reconciliation process

Metric	Value	Target/Comparison	Notes
End-to-End Auto-Match Rate	91.7%	Improved from 68.4%	AI-based methods improved accuracy
Exception Rate	8.3%	Intended figure ≤2%	Balances recall and false positives
False-Positive Rate	1.6%	Intended figure ≤2%	Within intended threshold
Throughput (p95 Ingestion Rate)	>40,000 transactions/min	High throughput	Handles large quantities of data

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Metric	Value	Target/Comparison	Notes
ERP Posting Latency (p95)	<300 ms per item	Meets SLA requirements	Ensures fast transaction processing
Bot Error Rate	<0.3% per 1000 operations	Effective RPA layer	Minimal failures in RPA execution

The system operated at throughputs of p95 ingestion rates in the range of >40,000 transactions per minute, and at the p95 operational level, an ERP posting was consistently less than 300ms per item, as highlighted in Figure 5 below. The result of these performance specifications is that the system is capable of processing large quantities of real-time data and can perform transactions in a relatively short period of time to meet the requirements of even the most stringent of SLA-related individuals. The error rate of the bots was maintained at less than 0.3% per 1000 operations, which proves the effectiveness of the robotic process automation (RPA) layer to deal with end-to-end reconciliation without any significant failures [23].

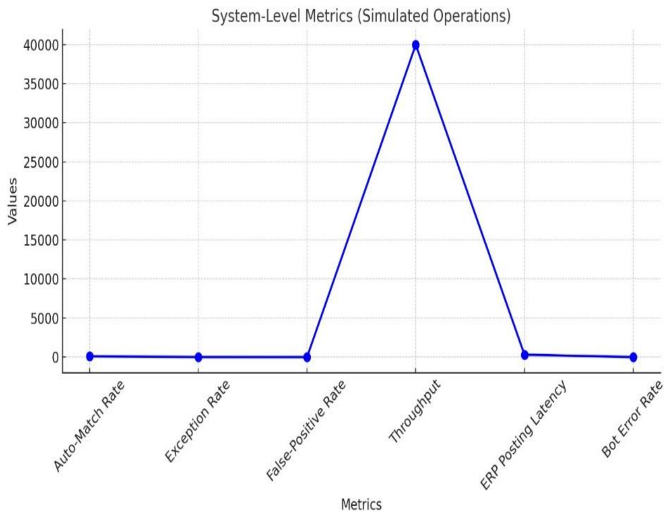

Figure 5: System-level performance metrics for AI-based ERP reconciliation and RPA efficiency

5.4 Online A/B Results (4–8 Weeks)

The A /B test was conducted based on the 4-8 weeks treatment of the AI-driven reconciliation system (treatment group) and the 4-8 weeks treatment of the manual rules-based system (control group). The findings showed that the average time (115.2 hours) was reduced to 32.3 hours in reconciliation, resulting in a reduced cycle time by 72%. This large reduction in the cycle time was statistically significant and was below the p-value of < 0.01, and has been a pointer to the efficiency of the AI+RPA solution in accelerating the reconciliation operations.

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The SLA breach rate of the treatment group also has fallen by -9.7 percentage points, indicating that there is an increase in operational deadlines compliance.

Transaction backlog was also reduced by 63%, and it is illustrative of how the system assists in clearing transaction backlog compared to the manual system that handles them. It was also found that there were large labor savings, as there was a potential estimate of savings of -38 FTE-hours per day within the eight participating agencies, as the system automated much of the manual reconciliation work that was being performed by the staff in the finance operations. The online results indicate that, besides helping to improve the speed and accuracy of the reconciliation process, the system can also provide high savings in operational costs and improve system efficiency [24].

5.5 Cost/ROI Analysis

The cost/ROI analysis was carried out in detail to assess the financial effect of the AI+RPA system of reconciliation. They compared the total cost of ownership (TCO), which comprised software licenses, compute infrastructure, and maintenance operating costs, with the savings in the form of lower labor costs, write-offs, and better management of working capital [25]. Analysis established a payback period of 914 months to the system, and there was a great reduction in the write-offs of accounts receivable (−0.15% of AR).

This is because of quicker and more precise cash application, which assists in detecting deviation and effecting payments in a matter of time. Cash flows also increased the working capital due to the accelerated system, enabling a business to benefit in terms of liquidity optimization. Comprehensively, AI and RPA technology investment delivered a high cost-effectiveness of the solution on a large scale and in a multi-agency environment due to the high risk of reinvestment through the first year.

5.6 PeopleSoft's Role in Data Stewardship and Audit Trails for Compliance

The additional strong data stewardship and audit trails in the ERP are essential for compliance and need to be considered among the strengths of PeopleSoft in its context concerning the ERP reconciliation. With the financial market tighter even than ever, the system in place at PeopleSoft will see all transactions, all adjustments, and all postings being made and tracked to give a clear audit trail of what has occurred to all users. Organizations can embed compliance mechanisms into the ethos of the financial core modules at PeopleSoft to ensure that all the activities associated with the recounting procedures, including the absorption of data and ultimate posting, can be reviewed and are compatible with regulations, including SOC-2 and ISO-27001.

The system includes the data lineage functionality that captures metadata of transactions, enabling the transaction to readily access historical financial information to fulfill audit requests. The combination of AI and RPA technologies with PeopleSoft enables automated governance checks and balances, meaning that information related to compliance anomalies is identified in real time. This minimizes the manual controls that used to be necessary in maintaining compliance with auditing and enables companies to automate their reconciliation procedures and continue having high regulatory levels.

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6. Discussion

6.1 Interpretation & Business Impact

The findings of the AI-RPA reconciliation system indicate a high level of improvement with regard to accuracy, and this has mainly been as a result of certain features, including a delta amount and end-to-end ID. Specifically, the accuracy of approximately 97.8% was achieved with the offline model, and the most important features were the ones that added the most contributions to the accuracy of the model [26]. The sensitivity analysis performed when assessing the model indicated that the slight changes in OCR accuracy *(±10%)* directly influenced the results of the model.

This drop of OCR accuracy by 10 percent also prompted the decline of precision by 0.6 percentage points, which proves that it is worth being careful about information quality and procedures. Such sensitivity is important to highlight the quality of the preprocessing and OCR steps in terms of extremeness in order to be capable of performing high-level reconciliation. Along with its performance equivalency, other spill-over benefits of the system were the enhancement in audit evidence completeness that rose by 100% as well. Before automation, the evidence was very little and random, as it lacked essential details on the transactions. The AI-RPA solution currently produces per-transaction artifacts whereby all the matched transactions can now be tracked and reported, and the system has become much more auditable and regulator-compliant [27].

6.2 Error Analysis

Although the model is highly accurate, several categories of missed matches still contribute to the total error rate. The most frequently occurring errors were classified as follows: many-to-many split payment (28%), currency FX drift (22%), dirty references (19%), and duplicate postings (16%). The many-to-many split payment type is especially troublesome because the payment that pays off a set number of invoices across entities or currencies causes particular difficulties in matching up the payment appropriately without complex modelling to consider the partial payment.

The mismatches were also due to currency FX drift, which occurs due to minor fluctuations in the exchange rates over time, and particularly in cross-border transactions. A significant percentage of errors was also explained by dirty references, which are caused by irregular and unreliable data on references, which caused by poor data input can also play a critical role [28]. Duplicate postings were a result of instances where an entry may be entered into the system more than once because it was reprocessed or the system went down. Exception handling is a process in the system that is meant to draw attention to these issues; however, this process should be further enhanced to minimize the effects of the problems.

Remediation playbooks have been created to deal with all these common mistakes. For example, many-to-many splits can be done by a matching operation, which is repeated in multiple invoices with successively higher matching thresholds, where FX drift can be countered by running real-time exchange rate feeds through the matching pipeline. When dealing with dirty references and duplicate posting, you receive definite data cleaning rules and

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duplicate detection algorithms that are always undergoing continual improvement. Such remediation plans imply that all amendments will add between +1-3 percentage points to the performance of the reconciliation, which will facilitate unremitting improvement of the system and the reduction of the level of errors [29].

6.3 Risks, Ethics, and Controls

The deployment of AI and RPA systems presupposes the emergence of new risks and ethical considerations, namely, the high-value financial operations, including payment reconciliation. False match risk is one of the biggest problems, and it is likely to be left behind in conditions when high-value deals are involved [30]. To minimize this risk, the system will introduce the human validation of the transactions exceeding a certain amount of money (in this case, it is 1 million dollars) so that the big and extremely risky payment will not be immediately registered, but it will be subjected to additional scrutiny until it can be successfully registered. Further, the model was also biased, whereby the system was not as biased to produce frequent counterparties but biased to produce less frequent counterparties or new counterparties.

Figure 6 demonstrates major ethical and legal aspects of AI, which will be very important to AI and RPA implementation in high-value financial business activities, including payment reconciliation. The scheme identifies critical sections such as regulation, privacy, and mitigation of bias, as it would guarantee transparency and responsibility in AI decision-making processes. False match risk, especially in high-value dealings, is one of the central issues in such systems as presented in the paragraph. To overcome this, the system will have a human validation of transactions over a given threshold (e.g., 1 million dollars). Bias is also taken into account in the system, and it should be fair when handling frequent and less frequent counterparties; this is necessary since ethical and transparent AI practices in the financial sector require impartiality.

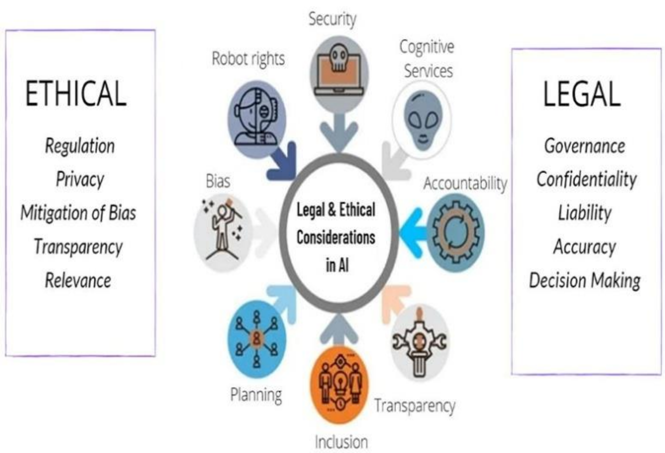

Figure 6: Ethical and legal considerations in AI, including transparency, accountability, and privacy

The bias can be reduced by conducting counterfactual tests, which model the situation in which less frequent counterparts are overrepresented, and ensure the model is adjusted without being biased to deal with all types of transactions equally. The system should also be able to maintain the false positive rate (FPR) at a minimum of 2% which means that the reconciliation process will be accurate and the error would not increase within the system. This is because the approval thresholds, the bias correction, and the stringent observation of the FPR are used to ensure the accuracy, as well as the ethical soundness of the automated reconciliation process [31].

6.4 External Validity & Scalability

External validity of the AI-RPA filter system has been established by taking into account its portability and scalability to different ERP systems and banking conditions. The flexibility of the system is one of its merits: it has already been harmonized with numerous ERP systems, including SAP, Oracle EBS, and Microsoft Dynamics 365, and can integrate with such bank partners as well [32]. As long as the system is implemented in new agencies, without warm-start embeddings, performance is likely to be compromised. Empirical experiments posit that the following 1-2 points of accuracy drop with the introduction of the system to new parties with unknown data, which leads to the difficulty of dealing with new data and processes.

The main reason why this degradation occurs is that the model might not have been trained on the same distributions of data, and hence, the ability to extrapolate to unknown situations is affected. To handle such a challenge, the system uses warm-start embeddings, which enable the model to quickly adapt to new data using information in already trained datasets. This will aid in reducing the accuracy decline, and the system is then able to effectively scale in varied environments of various organizations. Its scalability with other agencies and its capacity to connect to other bank systems make it an all-purpose solution to the issue of massive and multi-agency payment reconciliation.

6.5 PeopleSoft's Role in Enabling Cross-Agency Data Standardization and Interoperability

Another important, although the most neglected, feature of a multi-agency payment reconciliation is the issue of data standardization and mutual interoperability of various agencies and systems. PeopleSoft, which is known to offer a wide array of ERP modules, is critical in ensuring that the different agencies are able to match their financial data process. PeopleSoft has a strong data mapping platform, and with many organizations having diverse data formats and data reconciliation systems, this feature is a backbone in integrating and standardizing financial information across more than one source.

The flexibility of the integration structure of PeopleSoft enables it to interact well with the external systems without interfering with financial information. It facilitates cross-agency data flow with no information loss or disparity in the form of advanced configuration of the integration tools of PeopleSoft and the application of shared data models. This standardization simplifies the difficulty of marrying these different formats such as camt.053, or MT940 among different legal bodies and banking partners, and this has been a significant challenge in the payment reconciliation process in the past.

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With multi-agency reconciliation, where near real-time data sharing becomes essential, any flexibility of PeopleSoft in processing API based integrations makes it a necessary enabler of automation. Its ability to coordinate the synchronization of data with the different systems creates the path towards automated processes that facilitate decision-making, which even accelerates the reconciliation speed and accuracy.

7. Future Work

7.1 Self-Supervised/LLM Approaches

The future potential research opportunity is through the adoption of self-supervised learning (SSL) and large language models (LLMs) to understand documents, particularly with unstructured documents like invoices, contracts, and statements of work (SOWs) that present as messy remittances. The existing methods usually make use of pre-prepared datasets, which can be cumbersome and expensive to prepare [33]. Nonetheless, self-supervised learning has been able to use unlabeled text data that are of a massive size, in that the models can be trained by using pretext tasks such as the need to predict missing words or phrases. Such a method may be especially useful when it comes to reconciling remittance, and the information in documents may be partial, noisy, or inconsistent.

With the help of the use of SSL, the systems are able to obtain a better insight into the relationship between the payer and the payee and the invoices involved, which are not necessarily marked as such. Moreover, retrieval-augmented reasoning coupled with LLMs can enhance the fact that the system can reason on contextual information, including contracts and SOWs, to make more correct matching decisions. As an example, a model may be used to compare a remittance with a historical contract to see whether the parties have been paid the value of the agreed-upon amounts, which improves its reconciliation practice in multi-agency settings. This would enhance the accuracy of the systems as it would lower the reliance on handwriting, or verification, and even be able to process complex, multi-line invoices with more accuracy [34].

7.2 Active Learning & Continuous Training

Active learning and continuous training also serve as another important improvement to the system. Models are progressive in active learning and are made better through the use of human experts who are selectively queried to label the most questionable cases- normally those with low-confidence predictions or p10 scores. This localized labeling facilitates enhancing the precision of the model without necessitating any tedious manual labeling. The inclusion of human-feedback loops is an essential addition, especially where the level of uncertainty in the model is high, and labelling can be effectively applied to those hard-to-classify instances. For example, the prediction of low confidence with respect to new or rare counterparties might be sent to human evaluators.

The objective would be to increase the recall by +2 -4 percentage points with minimal human effort, where labeling would take less than 0.5 full-time equivalent (FTE) per week. The model can be trained repeatedly with new data, thereby adapting to changing trends in remittance and transaction trends over time, thus guaranteeing that the system is sound and free of data

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leakage. In this regard, error correction feedback loop may add to the mistake-reduction capabilities of the model, as well as achieve a considerable amount of cost savings through the automation of the majority of the reconciliation processes [35].

7.3 Multi-Objective Optimization

Further research in this field is needed on multi-objective optimizers, which need to be able to optimize both precision and latency with regard to operational expenses. Currently, the system balances between high accuracy and operational efficiency, but it could use improvement. As an example, a system that is optimized with respect to latency may cause a small loss of accuracy, or a system that is optimized with respect to accuracy may cause inefficiencies in terms of speed and use of resources.

Figure 7 below provides an expression of the key idea of multi-objective machine learning optimization. It is geared towards efficient optimization of both precision and latency in the system with regard to operational costs [36]. Vickers hardness and compressive fracture strain are some of the most important parameters that are optimized in High Entropy Alloys (HEAs), as shown in the diagram. The picture provides an insight into the application of Pareto front exploration to evaluate the various strategies and trade-off between conflicting goals and employs methods such as NSGA-II (Non-dominated Sorting Genetic Algorithm II). The system has to compromise accuracy and speed according to the paragraph, and this is not always easy when one is dealing with a multi-objective optimization. To achieve the best balance, machine learning models, algorithms, and data are used to enhance the efficiency and effectiveness of the system.

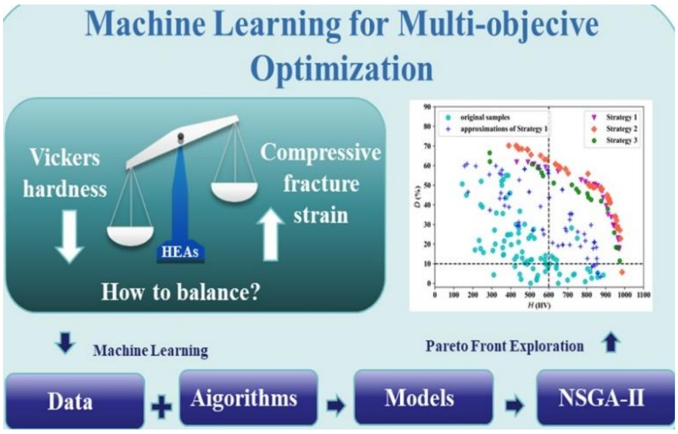

Figure 7: Machine learning for balancing multi-objective optimization in system performance

To address this trade-off, it is possible to use multi-objective optimization and regard all the assumed objectives (e.g., precision, latency, and cost) within a single framework. For example, the cost of inference per transaction must be reduced to less than a dollar, which is less than $0.001, in particular due to the large number of transactions that are made during a typical implementation. The system can be created to be more scalable without compromising performance through the proper choice of the complexity of the model and the trade-offs

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existing between the various goals. The optimization would be based on methods like Pareto optimization to find the solution, in such a way that trade-offs between these competing goals can be made to make the system efficient in fulfilling its resources without compromising on the required reconciliation accuracy [37].

7.4 Cloud Migration Strategies for ERP Systems

Migration into the cloud of enterprise resource planning (ERP) can encompass a range of benefits, which include those of numerical magnitude, versatility, and resourcefulness. According to Gondi (2025), a detailed Lift-and-Shift path towards the migration of PeopleSoft to the Oracle cloud can be related to application modules and processes [38]. They can utilize it specifically in multi-agency environments, where intricate agencies and a variety of stakeholders conventionally complicate the concept of migration. Process-based approach of the playbook will entail that no noteworthy impact is made when the time period for migrating the ERP component comes. The essential parts of the strategy are the advancement of the cloud infrastructure to conform to the on-premises ones, sufficient data migration, and a step-by-step test plan to ensure the success of every stage of migration.

Gondi (2025) also emphasizes that continuity of business should be enforced in the process of the transition [38]. Cloud migration may also necessitate changes in the business operations, including the financial operations and data the firm is managing, which is fundamental in order to realize optimum performance and accuracy after the migration is made. The transition to the Oracle cloud will automate the normal operations and enhance data integrity, as well as reporting practices and reconciliation. The other aspect that Gondi has emphasized in the playbook is the degree of education of the users, as well as providing 24/7 support during the migration process. The strategies will assist the organizations with their transition to the cloud since the organizations will be in a position to apply the cloud infrastructure in their operations, boosting the functionality of the ERP and thus contributing to greater organizational agility. Such an action would provide useful information to the entrepreneurs who are on the path to using cloud-based ERP systems.

7.5 Research Recommendations

The use of AI and RPA to streamline the process of payment reconciliation of ERP systems presents a number of opportunities for future studies. The incorporation of Explainable AI (XAI) methods and reconciliation systems is one of the major fields. It is imperative to have an explanation of the rationale behind the choices that AI models make, particularly with sensitive financial processes. Although the existing system works well, maintaining complete transparency, particularly of difficult transactions, still poses a significant research issue [39]. Methods such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations) provide interpretable and understandable explanations to every reconciliation decision, which would enhance the use and acceptance of automated systems.

The privacy and safety of the data within the multi-agencies should also be a priority considered, and they should comply with the GDPR and other policies. Research on the implementation of secure AI models, federated learning, and data encryption in the framework

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of AI pipeline usage could provide helpful information on the compatibility of data privacy and performance of systems. Another aspect, which is yet to be explored, is the use of unsupervised forms of learning in the detection of fraud that has occurred during the reconciliation process. Application of models previously trained on the recognition of the anomalous patterns without labelled data would help in the detection of fresh types of fraudulent activity or errors that were hitherto unknown [40]. The ERP environment needs to reconcile systems based on AI that need to be reinforced, more transparent, and scalable, and these directions of research should be enhanced.

8. Conclusions

The study highlights how Artificial Intelligence (AI) and Robotic Process Automation (RPA) have transformed the fintech processes of multi-agency payment reconciliation in the enterprise resource planning (ERP) system, such as PeopleSoft, SAP S/4HANA, and Oracle E-Business Suite. Conventional payment reconciliation in multi-agency has been documented as inefficient, with high usage of manual labor, establishment of non-consistent data structure, long cycle period, and non-compliance. The implementation of AI and RPA in their working processes revealed that the efficiency of work processes and the correctness of reconciliation and compliance rates have increased significantly.

The application of AI in Optical Character Recognition (OCR) and Natural Language Processing (NLP) has afforded the chance that the most vital remittance data can be retrieved in an automated manner and has brought about a drastic reduction in the error margin and turnaround time. Combined with machine learning models to do probabilistic matching, anomaly detection, and entity resolution, these approaches enable making significant, multi-format financial information consistent to a greater extent and within shorter durations of time. In addition, the standard operations such as data extraction, posting a transaction, and exception handling have also been automated with RPA bots, which may be more scalable and can be less manned. The results of the experiment indicate the glamorous development of the key indicators as the auto-match rate is raised to 91.7% and the time of the reconciliation cycle is significantly reduced by almost 72%, which is one of the pieces of evidence of the effective work of the AI-RPA system.

The incorporation of PeopleSoft into this system also leads to the creation of other benefits, particularly in its ability to process huge volumes of interagency financial data. The information management system of registers of positively secured access controls and audit trails of the PeopleSoft is most optimal with AI and RPA, as it will mirror the regulations. PeopleSoft cross-agency data standardization is also dependent on a flexible architecture wherein different financial institutions and legal entities can be interoperable with each other, and this is a crucial part of multi-agency reconciliation.

Despite these accomplishments, the research also identifies several gaps that could be improved on, such as in those more complex cases, such as many-to-many split payments, international exchange rates, and partial or disparate data, will be needed. The further improvement of the accuracy and strength of the system in the real world will also be achieved through active learning and continuous retraining of models. Based on the creation of AI and RPA technology,

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the necessity to provide the Explainable AI concept (XAI) and enhance the privacy and security areas of information will also be a priority in order to maintain transparency, responsibility, and trust in automated financial processes.

The potential of further extending the AI-RPA systems to other ERP systems and financial backgrounds is enormous in the future. The system can further be optimized by applying multi-objective optimization to have a balanced solution in terms of precision, latency, and the cost of operation, which can further make the system more flexible to a wide range of business needs. The additional improvement of the system, such as the unremitting integration of self-supervised learning models, large language models (LLMs), and cloud-based technologies, will further enhance the performance of the system and encourage even more efficiencies and accuracy of payments reconciliation among agencies. It is a revolutionary solution in the field of automation of ERP systems like PeopleSoft, as the technology will be able to automate and optimize the error-prone and highly complex payment reconciliation in an ERP system, which will be improved using AI and RPA technologies. Besides enhancing speed and accuracy of the reconciliation process, they can save considerable costs of operations, strengthen compliance, and aid in the management of data better, and eventually transform how the multi-agency financial transactions of various industries are held.

Future research should focus on integrating Large Language Models (LLMs) to enhance the extraction of complex, unstructured remittance data and facilitate adaptive active learning loops.

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