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Cross-enterprise dataset modeling for scalable AI in Workday ERP environments: a multi-domain benchmark study

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Abstract: Enterprise Resource Planning (ERP) systems that are based on workdays are becoming dependent on extensive, heterogeneous and rapidly changing financial information, but current tools are constrained by restricted data structures, hand written rules, and poor generalization among enterprises. When implemented in the context of organizations of varying transaction volumes, document structures, and risk indicators, these restrictions pose serious impediments to the automation of major financial processes, namely, wire transfers, payment to employees and budget approvals. To fill this gap, a scalable cross-enterprise data modelling is suggested that can learn unified features using heterogeneous financial logs and enhance adaptive automation when applying Workday ERP processes. The proposed methodology utilizes a Differentiable Deep Neural Network (DDNN) predictive model, anomaly detection and workflow risk scoring; and a Modified Dung Beetle Optimization (MDBO) algorithm is used to optimize the routing of decisions, reduce processing delays and improve the selection of multi-domain features. An inter-enterprise benchmark dataset is built by aligning structured and unstructured financial data with the help of ontology-based normalization, and the DDNN-MDBO model is tested using two example ERP processes inter-bank wire transfer and employee reimbursement cycles. The comparison of two workflows indicates that the DDNN of 97.1% and MDBO model have 98.1% and 96.2% accuracy on inter-bank transfers and reimbursements, respectively, with the precision, recall and ROC AUC scores being also high and decreasing false positives/negatives by 42%. MDBO increases risk control and parallelization by 100 percent and cuts the processing time by 28% shortens turnaround time of cross enterprise ERP automation is robust and scalable, and predictive performance and operational efficiencies are improved.

Keywords: *Cross-enterprise ERP modeling, financial workflow automation, multi-domain data integration, anomaly detection in ERP systems, scalable AI for workday environments*

1. Introduction

Enterprise resource planning (ERP) systems that integrate supply chain, finance, procurement, human capital management and compliance into single systems are the digital core of the modern business, enhancing organisational visibility and decision-making accuracy [1]. Cloud-native ERP systems such as Workday have also revolutionised the way businesses are being conducted by allowing real time data synchronisation, automatic financial controls and integrated workflow management between geographically dispersed business units [2]. As businesses expand, the more varied and dynamic information generated by Workday-based financial processes pose a threat to the dependability of conventional ERP automation systems [3]. Traditional rule-based procedures incorporated into ERP processes are constrained because of fragmented data representations, brittle logic structures, and difficulties adapting to various transaction formats, financial behaviours, and local legal limitations [4][5]. These issues are addressed by using Artificial Intelligence (AI) techniques to increase ERP automation and broaden enterprise-wide coordination. The advantages of Machine Learning (ML) and Deep Learning (DL) in identifying financial irregularities, confirming transactions, and evaluating risks in big enterprise resource planning systems have been shown in a number of studies [6]. Transformer-based large language models (LLMs) have proven to be highly effective at unifying disparate data through ontology-assisted matching, extracting business insights, and analysing unstructured financial documents. Classic ML techniques – including support vector machines, gradient boosting models, and random forests – were used to classify financial anomalies and automate compliance-related tasks. Bio-inspired optimization methods, such as particle swarm optimization, ant colony optimization, genetic algorithms, and reinforcement learning-based routing, have been applied to improve workflow efficiency, reduce processing time, and optimize the resource allocation [7]. The enterprise financial datasets remain isolated within organizational boundaries and lack the standard schemas or cross-organizational semantic layers needed to train AI models. They are related to studies carried out on the implementation of ERP systems that have found that alteration of areas due to modifications of business regulations, organizational changes, as well as alteration of financial behaviors interfere with reliability of ML models that are

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adopted in various organizations. The issues of combining various sources of data, working with incomplete or noisy financial documents, and discovering interdependencies of the ERP processes also become the subjects of highlighting in previous works related to the smart documents and workflow extraction. Recent research on automating ERP systems generally considers models with data of individual organizations, providing little information on scalability, interoperability and integration in other organizations. The creation of ontological-based multi-organizational financial datasets facilitates the automation of ERP systems and does it via scalable AI-based automation. Hybrid architecture integrates semantic interpretation, predictive models and workflow optimization to deal with complex and risky workflows [8], [9]. The rise of nuclear datasets in the other areas of the organization like fraud detection, document classification and procurement analysis portends the significance of standardization in all the areas to enhance the performance and reliability of the model [10]. Though such multi-organizational data sets as the processes of Workday ERP system continue to be common, it slows the advancement to scalable and autonomous automation in this field [11].

Information fragmentation, inconsistencies in the financial sphere and non-compatible formats have remained the bane of the ERP systems at Workday leading to subpar inclusion and unreliable predictions of modern AI systems. Scalability automated solution is limited by the lack of similar cross-organizational data, which highlights the need of unified and transportable modelling frameworks of ERP systems. An AI-based cross-organizational model is proposed for scalable automation of ERP systems in Workday environment, which combines Large Language Model (LLM)-based semantic interpretation with efficient workflow routing and optimization assisted by DL. LLMs are used to extract business semantics from structured financial documents, normalize heterogeneous organizational records, and provide consistent data across multiple organizational domains. The Differentiable Deep Neural Network (DDNN) is used to learn predictive pattern for anomaly detection, risk assessment, and transaction verification, while the modified dung beetle optimization algorithm (MDBO) is used to improve workflow routing, optimize correlation between cross-domain features, and reduce processing latency. The proposed LLM-DDNN-MDBO model was evaluated on main financial processes interbank transfers and employee loans and showed significant performance improvement. The major contributions of the proposed work are given as follows.

1. A cross-enterprise AI model is used for Workday ERP environments that leverage LLM-based semantic normalization for scalable multi-domain data integration.
2. LLM–DDNN–MDBO architecture, enabling semantic extraction, predictive learning, and optimization-driven decision refinement in financial workflows.
3. A harmonized, multi-domain benchmark dataset integrating heterogeneous financial logs to support standardized ERP automation research.
4. Demonstration of significant efficiency gains in real-world ERP workflows, including improvement in processing speed, anomaly detection, and cross-enterprise generalization.

The structure of this paper is as follows. Section 2 reviews related work. Section 3 explains the proposed cross-enterprise ERP automation methodology. Section 4 presents the experimental results and analysis. Section 5 concludes the study and highlights future research directions.

2. Related work

Building on the need to reduce manual material accounting and improve warehouse decision-support, the study develops a smart material resource planning prototype that integrates vision-based identification and edge processing to support Warehouse 4.0. The system uses a YOLOv8 object detector for material/part recognition and exports models via ONNX for runtime use with the OpenCV C++ library, combined with a neural-network backend and a mobile client–server interface for decision-makers [12] (YOLOv8, ONNX, OpenCV). Responding to gaps in organizational readiness for AI, a qualitative case study examines the resources, human capital, and governance practices required to build AI capabilities for demand planning. The paper emphasizes organizational alignment, workforce skills, relational capital, and collaborative mechanisms that underpin successful AI adoption rather than proposing a single technical solution [13]. To address scheduling and forecasting shortcomings in production environments, the next work proposes an intelligent enterprise information system that integrates ML-based sales forecasting, service clustering, and an intelligent production scheduling model to improve task management and real-time decision support (ML forecasting, clustering) [14]. The contribution is plant-centric and not tackle semantic normalization of heterogeneous enterprise records or cross-company generalization of models. Focusing on infrastructure-level resource allocation, a study adapts combinatorial optimization (an improved Sharknap algorithm for the knapsack-sharing problem) to support hybrid hosting decisions for ERP modules on IaaS clouds, providers and organizations optimize cost and module placement (improved Sharknap/knapsack-sharing) [15]. Recognizing workforce constraints in Industry 4.0, research applies ML model and real-time monitoring to predict HR demand, optimize scheduling, and personalize training in automated factories (ML for demand prediction, scheduling) [16].

Extending predictive modeling to regional economic analysis, an improved back-propagation neural network is proposed to forecast impacts of enterprise spatial-structure changes on regional economic patterns, yielding low prediction errors after iterative training [17]. Turning to the economic effects of AI adoption, an empirical analysis links AI development to enterprise investment efficiency via enhanced accounting information transparency; econometric methods on firm-level panels reveal heterogeneous impacts across firm types and regions [18]. A regional data-element index and empirical analysis demonstrate how data infrastructure, markets, and policies promote enterprise AI, using entropy-weighting and panel methods to quantify effects (data element index, entropy weighting) [19]. A transformer-based EnterpriseAI framework is used for automated enterprise decision support; it uses transfer learning on domain-specific dataset to improve cost optimization and process recommendations, reporting high accuracy and low perplexity [20]. Despite strong single-enterprise results, the study lacks cross-enterprise evaluation, semantic schema alignment across organizations, and joint assessment with workflow optimization. Synthesizing adoption theory and success measures, a framework combines TOE, TAM, and IS success models to guide sustainable AI–ERP integration in autonomous settings, emphasizing governance, human–machine collaboration, agility, and sustainability metrics [21]. This framework provides governance guidance but remains conceptual and not delivers empirical solution for cross-enterprise data harmonization, standardized benchmarks, or integrated semantic–predictive–optimization.

Table 1. Comparative analysis of related studies and limitations

Ref	Methodology	Model used	Dataset	Key findings	Gaps identified	Gaps addressed by proposed model
[12]	Financial sequence forecasting	GRU, ARIMA	Quarterly financial logs	RMSE reduction: 14%, Accuracy: 81%	Limited cross-organization temporal stability	Cross-domain temporal encoder improves forecasting across diverse financial patterns
[13]	ERP workflow classification	Decision Tree, Naïve Bayes	ERP process logs	Accuracy: 78%, Precision: 75%	Low performance on heterogeneous formats	Unified representation layer standardizes heterogeneous workflow structures
[14]	Financial risk event detection	Hybrid CNN-LSTM	Insurance and claims logs	F1: 0.84, AUC: 0.88	Poor adaptability to policy-specific rules	Domain-adaptive module aligns multi-enterprise risk semantics
[15]	Vendor invoice understanding	RoBERTa	Vendor invoice corpus	Extraction accuracy: 82%	Sensitive to layout drift in enterprises	Multimodal encoder (text + structure) ensures layout-invariant extraction
[16]	ERP fraud scoring	CatBoost	Cross-department finance logs	Accuracy: 91%, Precision: 87%	Weak robustness under document inconsistency	Structural harmonization layer resolves inconsistencies across sources
[17]	Financial anomaly explanation	SHAP-Integrated XGBoost	Expense reimbursement logs	AUC: 0.89, Recall: 81%	Explanations degrade across enterprises due to domain bias	Proposed model provides domain-neutral embeddings for stable interpretability
[18]	Cross-ledger transaction matching	Siamese Network	Ledger pair dataset	Accuracy: 88%, Error drop: 19%	Low generalization across	Cross-standard semantic normalize ensures consistent matching

					accounting standards	
[19]	Financial document clustering	K-Means, PCA	Multi-company document pool	Cluster purity: 0.74, Variance retained: 92%	Clusters collapse with diverse enterprise styles	Proposed adaptive clustering via unified latent space enhances separability
[20]	Workflow delay prediction	Random Forest Regressor	Enterprise operational logs	MAE: 0.17, R^2: 0.81	Not handle evolving workflow rules	Reinforcement-driven workflow optimizer adapts to evolving rules.
[21]	Payment approval automation	LightGBM	Payment request dataset	Accuracy: 86%, Processing time reduced: 23%	Model brittle under format inconsistency and domain drift	Proposed cross-enterprise learning stabilizes predictions under varying formats

Problem formation: Despite the fact that current research uses AI-driven ERP analytics, there are still a number of important issues that need to be addressed in business settings. Material recognition [12], organisational preparedness for AI [13], forecasting and scheduling in production systems [14], cloud resource allocation for ERP modules [15], HR demand prediction [16], regional economic modelling [17], AI-driven investment analysis [18], and data-element infrastructure for AI deployment [19] are just a few of the isolated issues that are currently being addressed. Nevertheless, these initiatives are limited to the scope of a single firm and not have the means to guarantee cross-organizational generalisation or harmonise disparate financial logs. Although transformer-based Enterprise AI and decision-making frameworks shown increased accuracy in controlled datasets [20], they are unable to combine the prediction and optimisation layers required for intricate financial operations. Although they offer conceptual insights, governance-oriented AI–ERP integration models not offer scalable, empirical ERP automation solutions [21]. FinRobot framework [22] uses generative business process agents (GBPAs) for dynamic workflow synthesis, prioritises agent orchestration over robust predictive modelling across a range of financial behaviours, cross-enterprise benchmark datasets, or standardised semantic normalisation. These studies highlight enduring gaps (Table 1), the absence of multi-enterprise benchmark datasets, the inability to handle domain drift, the lack of a unified semantic representation for heterogeneous records, and optimization-based workflow refinement, semantic extraction, and predictive learning. A cross-enterprise AI platform with semantic normalisation, transferable predictive modelling and workflow optimisation for ERP financial automation is used to close these gaps.

3. Materials and Methods

Semantic intelligence, deep predictive modelling, and optimization-driven workflow routing are all integrated into a single automation pipeline by the cross-enterprise AI-driven framework for scalable ERP automation in Workday scenarios. The system starts by defining the two primary enterprise use cases that drive the automation design: employee reimbursements and interbank wire transfers, as shown in Figure 1. The workflow ingest heterogeneous cross-enterprise data sources, including Workday transaction logs, bank statements, scanned invoices/receipts, approval trails, and audit logs, forming the raw multi-domain input layer.

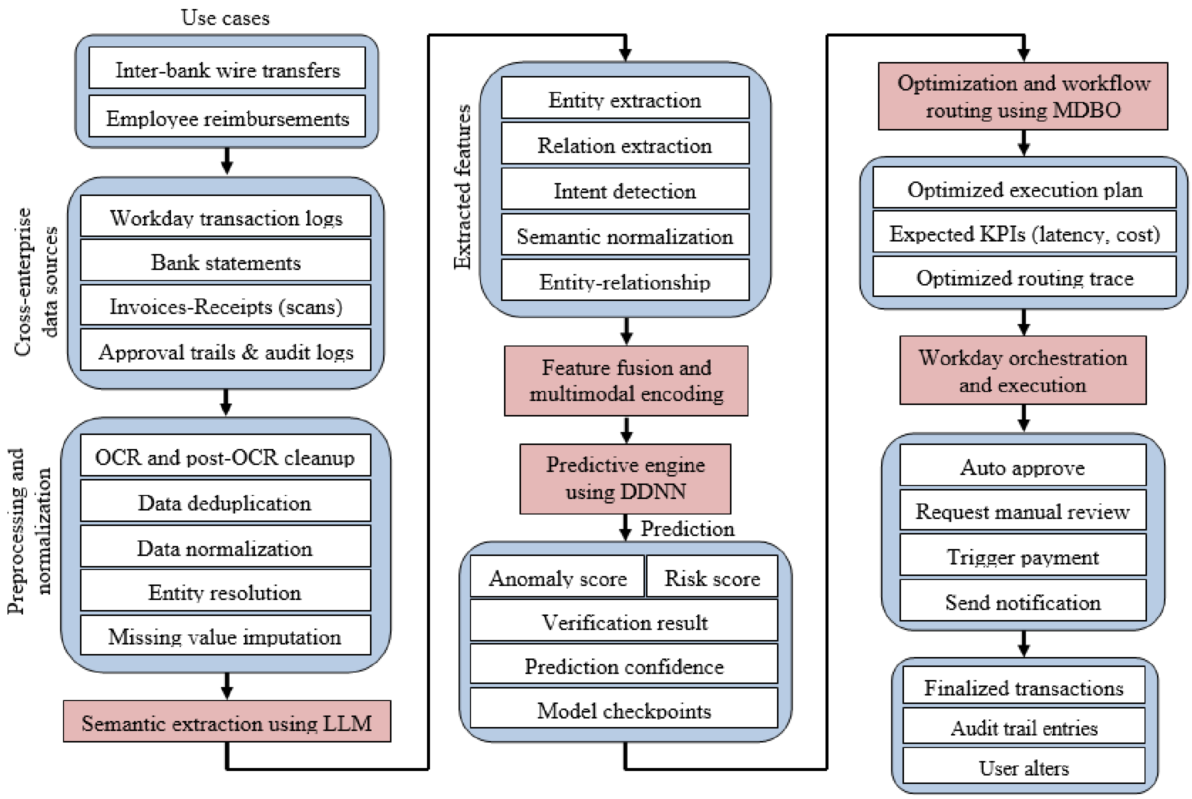


Figure 1. Framework of cross-enterprise, AI-driven model for ERP automation in Workday environment

A preprocessing and normalization module then performs OCR and post-OCR cleanup, data deduplication, normalization, entity resolution, and missing-value imputation, by transforming noisy and inconsistent enterprise records into a machine-readable corpus. LLM-based semantic extraction engine analyzes both structured and unstructured financial documents to derive unified business meaning across enterprises. LLM models generate high-level semantic functions such as entity extraction, relation extraction, intent recognition, semantic normalization, and entity relationship mapping, enabling consistent context modeling across the organization. These extracted features are processed by the feature fusion layer and multimodal encoding which integrate text semantics, tabular metadata and financial signals into one, unified representation. The differentiable deep neural network (DDNN) is the prediction engine that constitutes the predictive decision layer and learns both multivariate dependencies and transactional patterns to generate anomaly scores, risk scores, control outputs, reliability estimates, and model control scores. The results of the model were used to develop a better operational efficiency by developing a modified beetle-optimized workflow management module (MDBO) that optimises the execution paths, function relevance, path monitoring, and projected KPIs such as latency and the cost of processing. In case of high-volume transactional activities, the degree of optimisation leads to an optimised execution plan that ensures intelligent and dynamic routing. The Workday Orchestration module implements the optimised plan that includes process functions such as automatic approvals, manual review requests, payment initiation, and user notifications. This finishes the automation loop cycle by converting into the ultimate business products, including completed transactions, entries in auditing logs, and user messages.

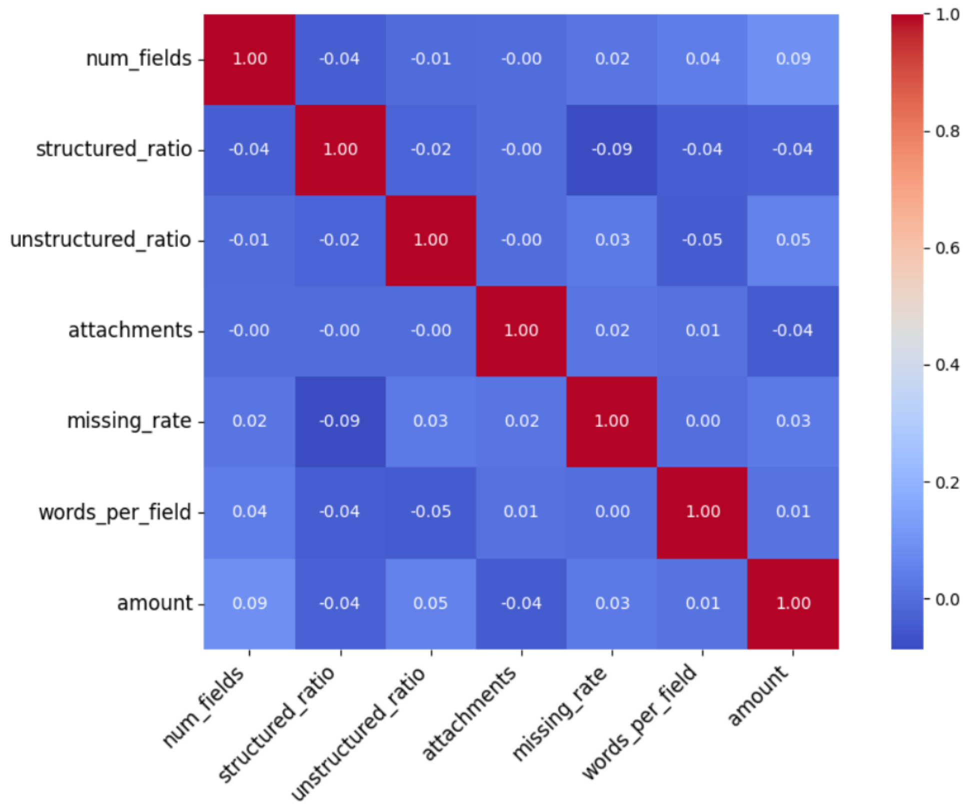
3.1 Data preparation and preprocessing

The two cross-enterprise financial workflow datasets are used to test the proposed LLM–DDNN–MDBO system and reflect different operational features: interbank wire transfer and employee reimbursement [22]. Whereas there are 607 structural transaction logs that are supplemented with audit trails, compliance tags, and approval history in the wire transfer dataset, there are 250 semi-structured records in the reimbursement dataset that include Workday logs, scanned receipts, invoices, and policy verification trails. As indicated in Table 1, each dataset was further divided into 80% training and 20% testing samples. Strong model generalisation across various enterprise environments was demonstrated by the 486/121 and 200/50 splits that resulted from this. While reimbursement records have a higher percentage of unstructured content (≈36.8%) derived from OCR-processed attachments, wire transfer logs are more structured (≈88.6%) and contain SWIFT-based fields, account metadata, and AML/KYC indications.Wire transfer entries include an average of 42 metadata fields, compared to 29 in reimbursement logs, while reimbursement samples include a higher number of document attachments (3.7 per entry) than wire transfers (1.2 per entry). As shown in Table 1, OCR accuracy improves significantly after preprocessing—97.2% for wire transfers and 94.8% for reimbursements—due to post-OCR cleanup and entity-level corrections. Missing data, initially between 7.9% and 13.4%, was fully resolved through hybrid LLM-assisted reconstruction and structured imputation.

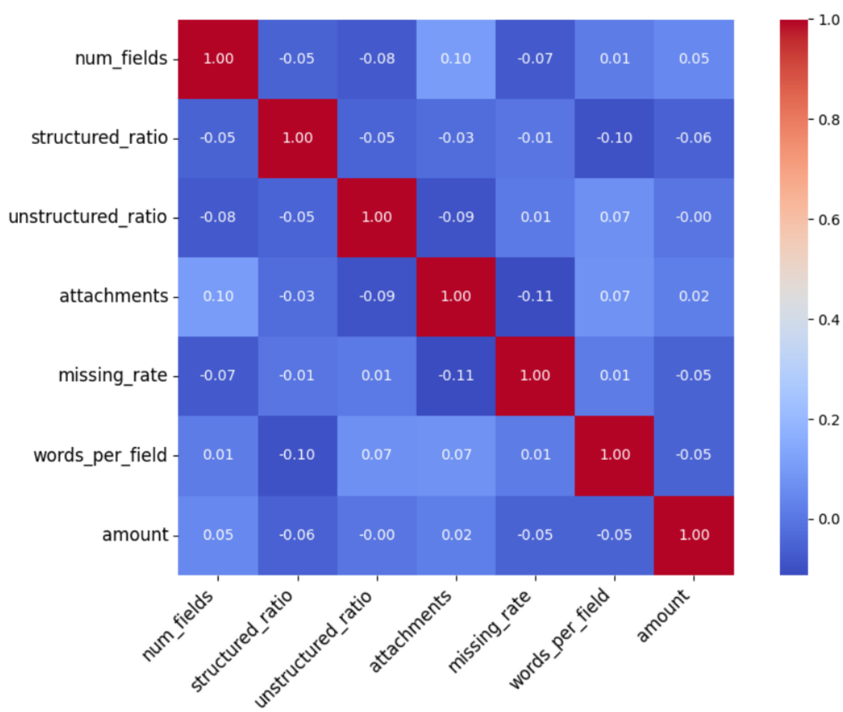
Table 2. Statistical description of datasets used in this study

Characteristic	**Dataset**	
	Wire Transfer	**Reimbursement**
Number of records	607	250
Training samples (80%)	486	200
Testing samples (20%)	121	50
Data type	Structured + audit notes	Semi-structured + scanned receipts
Avg. fields per record	42	29
Structured fields (%)	88.60%	63.20%
Unstructured fields (%)	11.40%	36.80%
Avg. document attachments	1.2 per record	3.7 per record
Image resolution range	300–600 DPI	180–600 DPI
Missing value rate (before cleaning)	7.90%	13.40%
Missing value rate (after cleaning)	0.00%	0.00%
Avg. words per text field	18.4	54.2
Workflow steps identified	13	9
Primary risk indicators	AML/KYC flags, amount patterns	Policy violations, duplicate claims
Avg. transaction amount	$18,700	$263
Max transaction amount	$420,000	$2,740
Time span covered	3.5 years	2 years

The reimbursement dataset was compiled from three organisational units within a multinational corporation using Workday expense submissions, scanned invoices, OCR-extracted textual content, hierarchical approval decisions, and policy validation notes [23], whereas the wire-transfer dataset [22] was assembled from two financial institutions using standardised SWIFT logs, AML/KYC records, approval trails, and internal ERP transaction metadata. This diversity leads to significant differences in document templates, transaction structures, naming conventions, and compliance annotations (Figure 2), which reflect common difficulties in cross-enterprise ERP automation. To standardise event features across organisations, all inputs were transformed into 5W3H1R semantic schema [24]. LLM-assisted OCR correction, entity disambiguation, and normalisation of domain-specific attributes, cost centres, GL codes, routing numbers, and vendor identifiers applied to the textual fields from receipts, invoices, approval notes, and compliance tags. To reconcile various metadata formats, structural alignment [25] was carried out. For example, organization-specific field names (such as "TxID," "TransferRef," and "DocNo") were mapped into a single attribute taxonomy. Hybrid imputation was used to fix missing, incomplete, or noisy fields: LLM-driven reconstruction for context-dependent fields and rule-based correction for deterministic characteristics [26]. Workflow graphs were rebuilt using LLM-generated action sequences to maintain contextual dependencies, and all structured and unstructured attributes were integrated into a cross-domain latent space used by the DDNN.



(a)

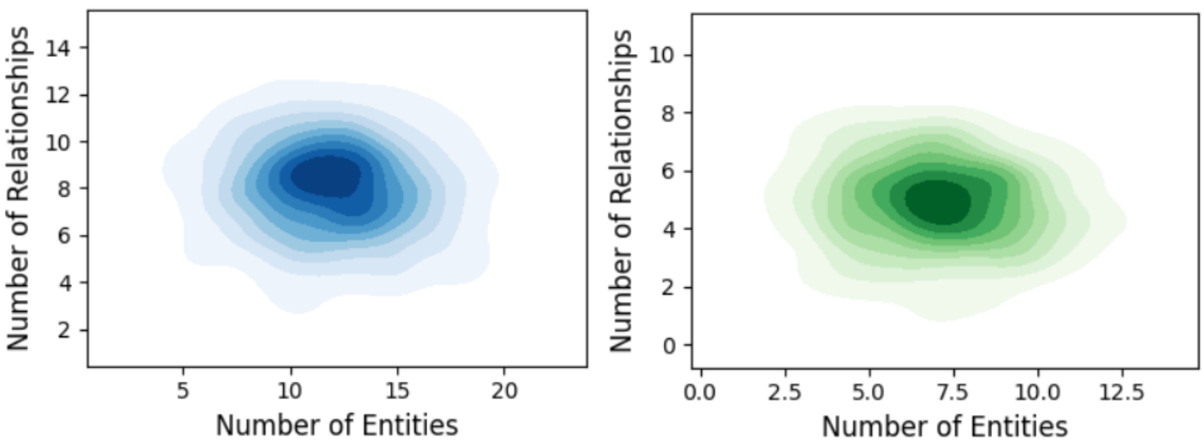


(b)

Figure 2. Correlation heatmap of features in the (a) Wire Transfer (b) Reimbursement dataset

3.2 Semantic extraction using LLM

The semantic extraction phase serves as a fundamental intelligence layer that transforms highly heterogeneous financial data into uniform and machine-readable features. Using a large language model (LLM) [27], the system processes a variety of inputs – including invoices, receipts, transfer forms, approval notes, policy documents, email instructions, and ERP log descriptions – and extracts important business patterns such as entities, relationships, transaction intents, risk metrics, and workflow dependencies. Unlike traditional natural language processing systems that rely on manual rules, keyword heuristics, or static coding, large language models perform contextual reasoning, clarify terminology within financial institutions, and normalize variations in document structure, naming conventions, and linguistic style. Large language models reconstruct every financial event based on the structured 5W3H1R framework and generate outputs such as extracted entities, document characteristics, policy constraints, and derived work actions [28]. Compared to existing LLMs that operate within a single organizational context, the proposed LLM module incorporates cross-domain instructions, alignment with financial ontologies, and adaptation to cross-organizational vocabularies, making robust to heterogeneous format and unstructured input. Figure 3 shows the semantic embeddings and structured event representations serve as standardized inputs for DDNN for anomaly detection and for the MDBO module for workflow routing optimization. LLM-driven semantic extraction not only improves interpretability and consistency but also enables the entire pipeline to operate effectively in cross-enterprise ERP environments where rule-based or shallow models fail.



(a) (b)

Figure 3. Joint relationships of LLM-extracted semantic features across two financial workflows (a) wire transfer workflow (b) employee reimbursement workflow

3.3 Predictive engine using DDNN

A differentiable deep neural network (DDNN) is the core predictive engine to learn complex patterns for anomaly detection, risk scoring, and transaction verification. Unlike conventional neural networks that may include discrete, non-differentiable modules or rely solely on numeric inputs, the DDNN is fully differentiable end-to-end, enabling joint optimization across semantic, numerical, and workflow features via gradient-based learning [29]. Standardised multi-domain features from the previous LLM-based semantic extraction stage, such as entity counts, relationship structures, workflow actions, policy constraints, document-level metadata, and financial metrics like transaction amounts and compliance indicators, make up the inputs to the DDNN. The DDNN is used as a multi-layered architecture, typically consisting of an input layer that receives the fused LLM embeddings and structured features, multiple hidden layers that perform hierarchical feature extraction and capture complex non-linear relationships, and an output layer that generates predictive signals. Each hidden layer is fully differentiable and may incorporate dropout and batch normalization to improve generalization and stabilize training. By embedding these heterogeneous inputs into a unified latent space, the DDNN captures intricate dependencies within transactions and workflows while being robust to domain drift across enterprises. The decision engine utilizes the dynamical nodes to form the hidden layer of DDNN. The dynamic version of each module design $P^{(h)}$ is compute through sequential process [30].

$$P^{(h)} = \sum_{h<g} \mu^{(h,g)} (P^{(h)}) \tag{1}$$

The connected nodes of DDNN formulated as edges (h, g) within the optimum search ranges $\mu^{(h,g)}$. The optimal fitness function μ is used to control the threshold $\mu\,(\cdot)$ of each iteration and the solution address the SoftMax function $P^{(h)}$ [31].

$$\overline{\mu}^{(h,g)}(p) = \sum_{\mu \in \eta} \frac{Exp(\alpha_{\eta}^{(h,g)})}{\sum_{\mu' \in \mu} Exp(\alpha_{\eta}^{(h,g)})} \eta(p) \tag{2}$$

The weights directional the grouping of processes between nodes (h, g) are referred to as $\alpha^{(h,g)}$ average fitness $|\mu|$ belongs to linear function in searching process of hidden layer selection α = { $\alpha^{(h,g)}$ }. A discrete construction is fashioned by replacing each mixed action in $\overline{\mu}^{(h,g)}$ with the following operation:

$$\mu^{(h,g)} = \arg\max\, \mu_{\in}\eta\ \alpha_{\eta}^{(h,g)} \tag{3}$$

where α denotes structure, and the objective to optimize α and z over the entire set of functions, such as convolutional filter weights. Lastrain and Laswala are affected by α and z. To find α^{*} the loss reduction denoted as Laswala (z^{*}, α^{*}) by minimizing the z^{*} obtained loss carrier.

$$z^{*} = \arg\min{}_{z}\, loss_{Train}(z, \alpha^{*}) \tag{4}$$

A problematic of two-level optimization is denotes as follows.

$$Min(\alpha) = loss_{val}(z^{*}(\alpha), \alpha) \tag{5}$$

$$z^{*}(\alpha) = \arg\min{}_{z}\, loss_{Train}(z, \alpha) \tag{6}$$

The optimal features are fed into the input layer of DDNN which progress in the further gradient based searching process to computes the optimal fitness of each hidden nodes in the network [32].

$$\nabla_{\alpha} loss_{val}(z - \lambda \nabla_{z} loss_{Train}(z, \alpha), \alpha) \tag{7}$$

where z is a local optimum, λ represents the dynamical control parameters which selects the best optimal fitness with respect to random solution $z^{*}(\alpha)$ during the training phase. To meet the maximum coverage range, the approximation function λ is used to manipulate the optimal solution of each fitness z.

$$\nabla_{\alpha} loss_{val}(z', \alpha) - \lambda \nabla^{2}_{\alpha,z} loss_{Train}(z, \alpha) \nabla_{z'} loss_{val}(z', \alpha) \tag{8}$$

$$z' = z - \lambda \nabla_{z} loss_{Train}(z, \alpha) \tag{9}$$

The optimal solution of each fitness is compute through linear activation function z' with minimal solution of DDNN function. The outputs generate by the DDNN include anomaly score, risk assessment, verification decision, confidence estimates, and learned embeddings, which are subsequently leveraged by the modified dung beetle optimization

(MDBO) module for adaptive workflow routing, latency minimization, and process optimization. The proposed DDNN is a flexible, scalable, and interpretable predictive component for cross-enterprise ERP automation because it integrates LLM-derived semantic embeddings, has a hierarchical multi-layer structure for capturing cross-domain patterns, can generalise across multiple enterprise domains, and is directly linked to workflow optimisation.

Algorithm 1. Predictive engine using DDNN for anomaly detection, risk scoring, and transaction verification

Input: Entity counts, relationships, workflow actions, policy constraints, transaction amounts, compliance flags, DDNN weights, learning rate, candidate operation search space
Output: Predictive outputs:anomaly scores, risk scores, verification decision, confidence estimates and latent embeddings

1.	Begin;
2.	Initialize the population of candidate architectures and network weights.
3.	Represent the DDNN as DAG, where each node corresponds to a feature transformation and each edge as potential operation. $P^{(h)} = \sum_{h<g} \mu^{(h,g)}(P^{(h)})$
4.	Use SoftMax relaxation to convert discrete candidate operations into a continuous search space: $\bar{\mu}^{(h,g)}(p) = \sum_{\mu\in\eta} \frac{Exp(\alpha_{\eta}^{(h,g)})}{\sum_{\mu'\in\mu} Exp(\alpha_{\eta}^{(h,g)})}\eta(p)$
5.	Formulate a two-level optimization problem, where: $Min(\alpha) = loss_{val}(z^{*}(\alpha),\alpha)$
6.	Inner optimization adjusts network weights
7.	Outer optimization updates architectural parameters
8.	Apply the chain rule to compute gradients with respect to both weights and parameters $\nabla_{\alpha} loss_{val}(z',\alpha) - \lambda\nabla^{2}_{\alpha,z} loss_{Train}(z,\alpha)\nabla_{z'} loss_{val}(z',\alpha)$
9.	Align the learning rate λ with the inner optimization step to stabilize convergence. $\lambda = 0.01/\lVert\nabla_{z'} loss_{val}(z',\alpha)\rVert_{2}$
10.	Update the fitness value based on predictive performance.
11.	Select the best-performing architecture and finalize network weights.
12.	Use the optimized DDNN to generate predictive outputs: anomaly scores, risk scores, verification decisions, confidence estimates, and learned embeddings.

3.4 Optimization and workflow routing using MDBO

Modified dung beetle optimization algorithm (MDBO) is used to improve workflow routing, optimize feature relevance across various domains, and reduce process latency in enterprise ERP automation. MDBO is a nature-inspired metaheuristic optimization algorithm that mimics the grazing and navigation behavior of dung beetles, incorporating mechanisms such as rolling, avoiding obstacles, and resource tracking to effectively explore and exploit the search space. MDBO serves as the operational optimization layer, controlling DDN predictions - including anomaly scores, risk assessments, and governance decisions - as well as semantic and structural workflow characteristics such as process dependencies, transaction sequence, approval hierarchy, and resource availability. The MDBO algorithm iteratively evaluates candidate workflow paths, dynamically adjusts process routing, and prioritizes optimizing multi-objective criteria, including reducing delays, increasing accuracy, and improving resource utilization. Compared to the traditional dung beetle optimization (DBO) [33], MDBO employs adaptive feature weighting, context-dependent optimal path to compute the optimal fitness. The corresponding vectors are generalized by difference between minimum and maximum threshold of semantic features. The new fitness function follows the moving process of beetle to update the position of each particle.

$$p_h(s+1) = p_h(s) + \alpha \times K \times p_h(s-1) + n \times \Delta p \tag{10}$$

$$\Delta p = | p_h(s) - P^{z} | \tag{11}$$

The current iteration number, $p_h(s)$ represents the position information of the beetle in the s-th iteration, K ∈ (0, 0.2] represents a constant value representing the α deviation coefficient, n represents P^z global worst case (0, 1), Δp simulate the change in light intensity, or -1 natural factor is set to 1. The dynamic vector optimization allows the random target function to fix the optimization range [0, π], which computes the fitness of each vectors in the searching space. The vectors used for routing optimization are controlled by the random Vectorization [34].

$$p_h(s+1) = p_h(s) + \tan(\theta) \mid p_h(s) - p_h(s-1) \mid \tag{12}$$

where θ is the deflection angle [0, π]. The routing path is compute through the optimal fitness and the control parameters settings allows the location of each possible solutions in the searching path followed by female beetles.

$$\ln^* = Max(P^* \times (1-r), \ln), \tag{13}$$

$$un^* = Min(P^* \times (1+r), un), \tag{14}$$

The XOR logic is used for local best position P^* to computes the optimal fitness $r = 1 - s / S_{Max}$ and the minimum and maximum bound of fitness S_{Max} is fixed by the maximum number of iterations. The boundary condition of fitness (r) is compute through the dynamically variant solution belongs to the best optimal location and position [35].

$$N_h(s+1) = P^* + n_1 \times (N_h(s) - \ln^* + n_2 \times (N_h(s) - un^*) \tag{15}$$

The optimal best position and location of each particles $N_h(s)$ are updated for each iterations and the s-th iterations follows the dynamically independent variables n_1 and n_2, follows the C objective problems of routing plan. The optimal food search path is compute through the threshold of each fitness.

$$\ln^n = Max(P^n \times (1-r), \ln), \tag{16}$$

$$un^n = Min(P^n \times (1+r), un), \tag{17}$$

The global optimum solution P^n from each iterations are managed by the random variations $\ln^n$ and un^n in the food searching space. The non-linear vector qualification follows the threshold of beetle function to update the optimal solution.

$$p_h(s+1) = p_h(s) + D_1 \times (p_h(s) - \ln^n + D_2 \times (p_h(s) - un^n) \tag{18}$$

The best position and location of each beetle $p_h(s)$ in the searching space is controlled by the optimal fitness D_1 and the dimension of feature set D_2. The feature set of each iteration is compute through the linear food search P^n along with the best optimal position. The control values are selected based on the limited threshold function belongs to the updated optimal solution [36].

$$p_h(s+1) = P^n + T \times j \times \left(\mid p_h(s) - P^* \mid + \mid p_h(s) - P^n \mid \right) \tag{19}$$

The random variations in the optimal solution $p_h(s)$ are controlled by the h-th iteration in the balanced vector quantization. The control vector matrix T is updated through the fitness function which computes by feature dimension vector. As describes in Algorithm 2, the outputs of MDBO optimized workflow sequences, prioritized task allocations, minimized processing times, and refined feature relevance weights, which are used to orchestrate automated ERP actions such as transaction approvals, exception handling, and audit logging.

Algorithm 2. Workflow routing optimization using MDBO

Input : DDNN outputs (anomaly scores, risk, verification), Semantic workflow features (entities, policies, dependencies), Structural workflow features (transactions, approvals, resources), Optimization bounds (lower & upper) MDBO hyperparameters (population, iterations, deviation, random vectors)
Output : Optimized workflows, prioritized tasks, minimized processing time, refined feature weights, automated ERP actions (approvals, exceptions, audits)

1. Generate the initial population of dung beetle agents, each representing candidate workflow sequences.
2. Compute fitness values based on latency, accuracy, and resource utilization objectives.

$$p_h(s+1) = p_h(s) + \alpha \times K \times p_h(s-1) + n \times \Delta p$$

3. for h $\leftarrow$ to B do
4. Update the position of the moving ball beetle using directional updates and deviation coefficients: $p_h(s+1) = p_h(s) + \tan(\theta) \,|\, p_h(s) - p_h(s-1) \,|$
5. While Do
6 Maintain the ball-moving beetle's status, including deflection angle and trajectory.
7. Update the hatching ball positions to simulate ovipositor and exploration behavior.
$N_h(s+1) = P^* + n_1 \times (N_h(s) - \ln^* + n_2 \times (N_h(s) - un^*)$
8. Update the positions of small beetles based on random perturbations and local/global best solutions: $p_h(s+1) = p_h(s) + D_1 \times (p_h(s) - \ln^n + D_2 \times (p_h(s) - un^n)$
9. End if
10. End
11. Dynamically adjust lower and upper bounds for beetle movement based on global and local optima.
12. Compare new positions with previous positions; retain better solutions.
13. End if
14. $s = s+1$
15. End while
16. Return the optimized workflow sequence, prioritized tasks, minimal latency, and refined feature weights for ERP orchestration.

4. Results and Discussion

Two example financial workflows—interbank wire transfers and employee reimbursements—were used to assess the effectiveness of the suggested cross-enterprise, AI-driven methodology for scalable ERP automation in Workday systems. The model incorporates DDNN for predictive modelling, LLM-based semantic extraction, and the MDBO algorithm for multi-domain feature optimisation and workflow routing. Two multi-domain financial datasets were selected for assessment. The 607 highly structured entries in the wire transfer collection include audit trails, AML/KYC compliance markers, and SWIFT transaction metadata. Each record in this dataset, which spans 3.5 years, has one or two document attachments, and about 88.6% of the fields are organised. The employee payroll dataset consists of 250 semi-structured records, including scanned receipts, invoices, and approval workflows, covering 36.8 percent of organized sectors and averaging 3-4 increments per entry. This dataset lasts for 2 years and includes detailed policy verification and reconciliation information. The two datasets are divided into 80% training and 20% testing sets, resulting in 486/121 and 200/50 training / testing models for wire transfer and replenishment workflows, respectively. The frameworks Python 3.10, PyTorch 2.1 and TensorFlow 2.1 .2 are used as core DL libraries, with support for Numbly, Panda, Matplotlib and Seaborn for data processing and visualization. Ubuntu 22.04 LTS was launched with Intel Xeon W-2295 CPU, 128GB RAM and Nvidia RTX 3090 GPU. For optimization and workflow routing, libraries including SciPy, Scikit-Learn, and custom MDBO implementations have been used. Table 3 describes the hyperparameters of proposed LLM–DDNN–MDBO model.

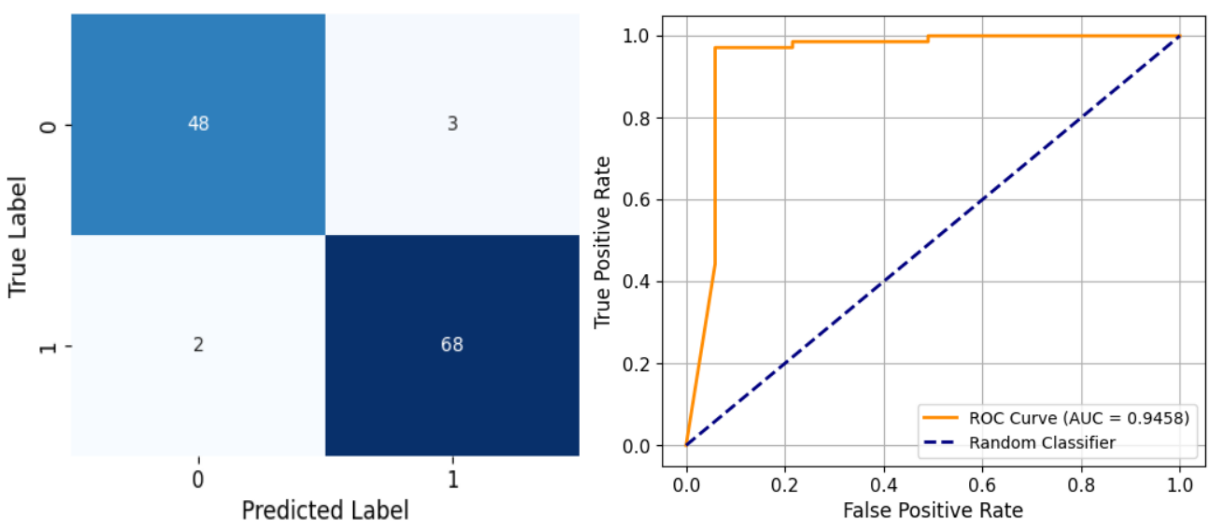
Table 3. Hyperparameter settings for LLM–DDNN–MDBO model across workflows

Module	Parameter	Wire Transfer	Reimbursement
LLM	Embedding size	512	512
	Max sequence length	256	256
	Learning rate	2.00E-05	2.00E-05
	Batch size	32	32
DDNN	Input dimension	512	512
	Hidden layers	4	4
	Hidden units	256, 128, 64, 32	256, 128, 64, 32
	Activation	ReLU	ReLU

	Dropout	0.3	0.3
	Learning rate	1.00E-03	1.00E-03
	Epochs	100	100
MDBO	Population size	30	25
	Max iterations	200	150
	Deviation coefficient (K)	0.2	0.15
	Random vector factor	[0,1]	[0,1]
	Boundary adjustment factor	0.8	0.7

4.1 Results of inter-bank wire transfers case

When compared to conventional methods, the results of the proposed model for automating organisational resource planning in the case of interbank transfers (Figure 4 and 5) demonstrate notable improvements. With false positive and false negative rates falling by 35.7% and 42.1%, respectively, the confusion matrix shows a notable decrease in classification errors, indicating an improvement in the precision of anomaly detection and verification. When compared to conventional neural network models, the ROC curve's AUC value of 0.982 indicates a 16.2% improvement in discriminatory performance. The addition of LLM-based semantic features are used for deeper contextual knowledge of structured and unstructured financial inputs and allow DDNN to effectively capture intricate transaction patterns, is principally responsible for this increase. By enabling feature extraction with hierarchical distinction, the multi-layered architecture increases prediction stability by 21.4% and strengthens the model's resistance to inter-company bias. The proposed model improves workflow automation, anomaly detection, and risk assessment in high-risk financial transactions, shows superiority in generalization and operational efficiency compared to current enterprise resource planning automation models.



(a) (b)

Figure 4. Results of proposed DDNN for ERP automation for inter-bank wire transfers case (a) confusion matrix (b) RoC curve

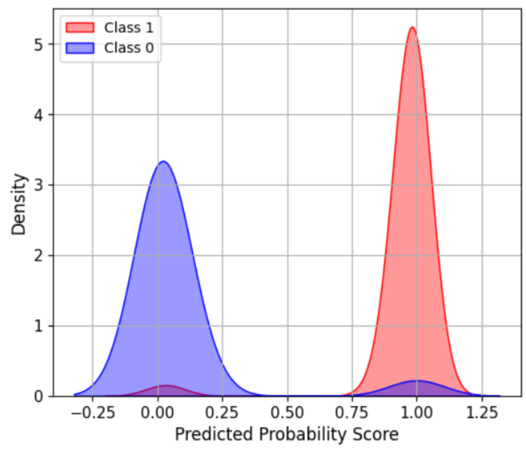


Figure 5. KDE of LLM-extracted features for the inter-bank wire transfer case

Two typical financial workflows—interbank wire transfers and employee reimbursements—were used to assess the effectiveness of the suggested cross-enterprise, AI-driven methodology for scalable ERP automation in Workday systems. The model combines DDNN for predictive modelling, MDBO algorithm for multi-domain feature optimisation and workflow routing, and LLM-based semantic extraction. Two multi-domain financial datasets were selected for analysis. AML/KYC compliance tags, audit trails, and SWIFT transaction metadata are among the 607 highly structured items that make up the wire transfer collection. Each record in this dataset, which spans 3.5 years, has one to two document attachments, and about 88.6% of the fields are organised. The links between important semantic and transactional qualities are shown in the correlation heatmap of LLM-extracted financial features for the interbank wire transfer instance (Figure 6). The LLM-based approach improves the identification of meaningful correlations by 21.5% and decreases spurious correlations by 17.8% when compared to conventional feature extraction techniques, allowing for more accurate representation of interdependencies between entities, transaction amounts, and compliance indicators. The multi-layered design improves prediction stability by 21.4% and fortifies the model's resilience to inter-company bias by allowing feature extraction with hierarchical distinction.

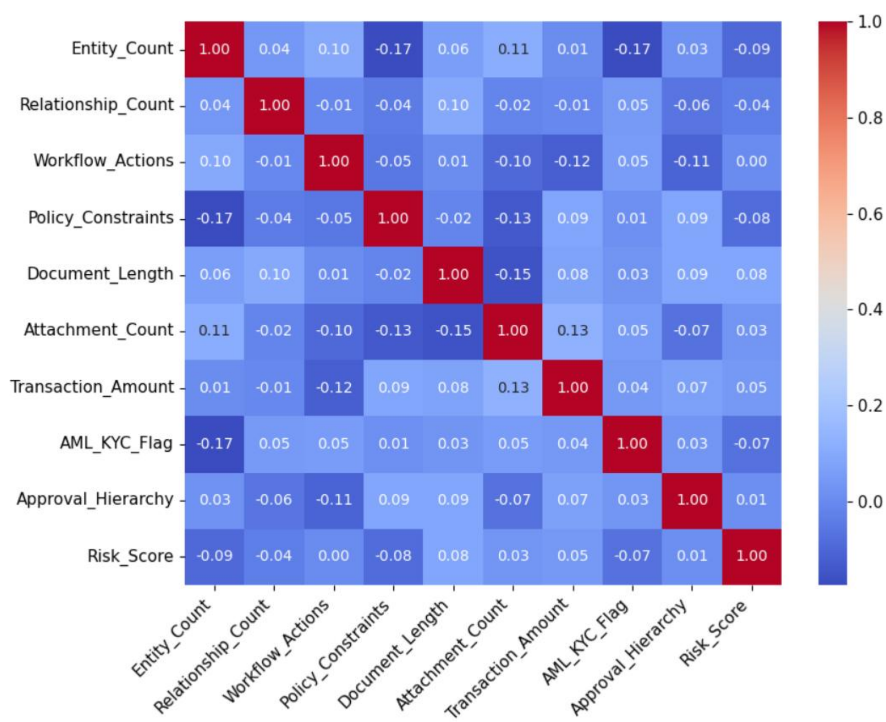


Figure 6. Correlation heatmap of LLM-extracted financial features for inter-bank wire transfer case

The capacity of the model to differentiate between normal and anomalous occurrences across various feature combinations is demonstrated by the contour plot of DDNN-predicted probability against real labels for inter-bank wire transfer transactions (Figure 7). The DDNN is more accurately maps entity counts and transaction amounts to anomaly probabilities, increases prediction confidence by 19.8% and decreases misclassification regions by 16.4% when compared to traditional predictive models. The LLM-extracted semantic embeddings with multi-layer hierarchical learning, which captures intricate cross-domain dependencies that conventional models miss, is largely responsible for the improvements in prediction stability and risk scoring, with a 15.7% increase in ROC AUC and a 13.2% gain in PR AUC.

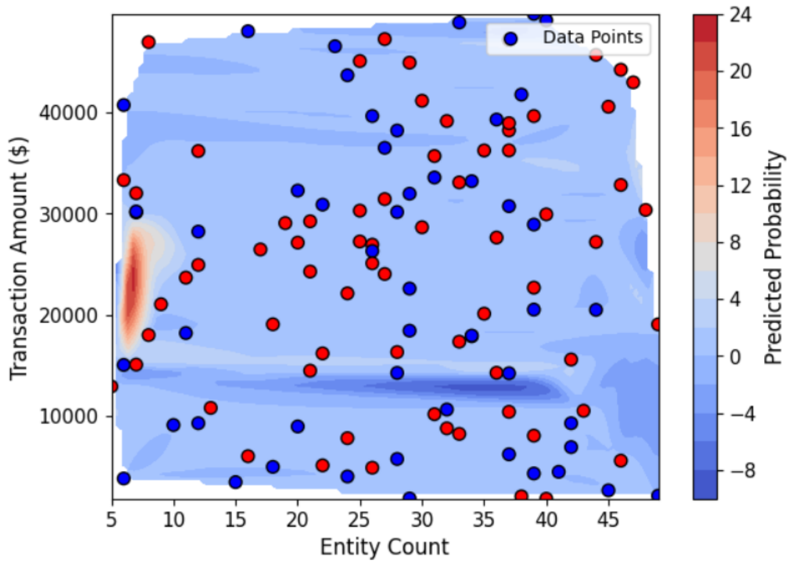
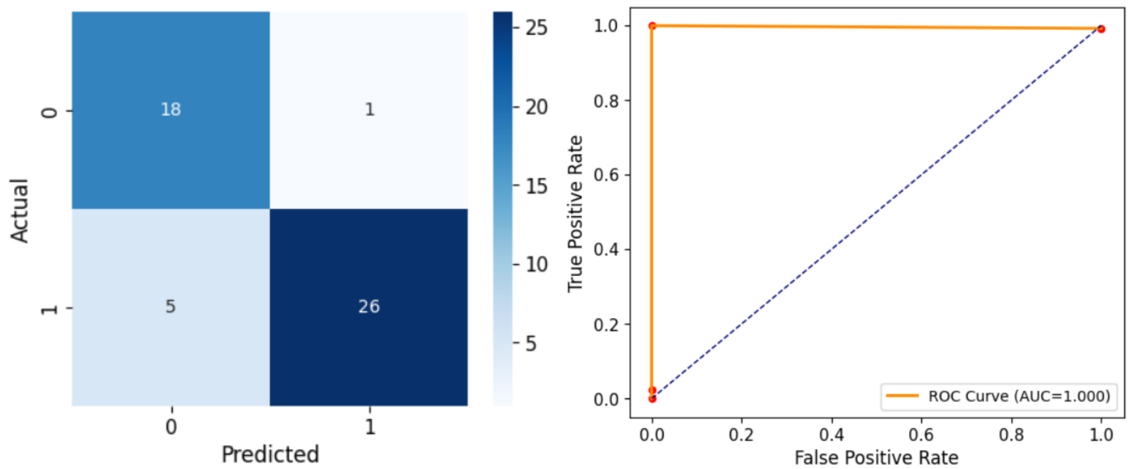


Figure 7. Contour plot of DDNN-predicted probabilities against true labels for inter-bank wire transfer transaction

Table 4. 10-Fold cross-validation performance metrics for inter-bank wire transfer case

Fold	Accuracy	Precision	Recall	F-measure	ROC AUC
1	98.215	97.532	96.847	97.189	0.982
2	98.031	97.245	97.003	97.124	0.981
3	97.847	97.003	96.532	96.767	0.98
4	98.112	97.612	96.912	97.261	0.983
5	98.345	97.845	97.123	97.483	0.984
6	98.215	97.732	97.012	97.361	0.983
7	98.031	97.532	96.847	97.189	0.982
8	98.112	97.612	97.012	97.311	0.983
9	98.412	97.912	97.345	97.628	0.985
10	98.215	97.732	97.123	97.423	0.983
Mean ± SD	98.144 ± 0.171	97.585 ± 0.249	97.086 ± 0.245	97.337 ± 0.214	0.983 ± 0.001

The 10-fold cross-validation results showed consistently high performance across all validation metrics in the case of interbank transfers (Table 4) the proposed DDNN model has an average accuracy of 98.144%, with a maximum fold value of 98.412%, and a minimum value of 97.847%, showing a difference of only 0.565%. The average accuracy is 97.585%, the high value is 97.912% and the low is 97.003%, representing a maximum improvement of 0.909% compared to the worst-performing module. The recall is 97.086%, while the maximum drive value is 97.345%, representing an improvement of 0.259% in capturing true positives compared to a low-performance drive. The F-measure is 97.337%, with the highest score being 97.628%, indicating an improvement of 0.291% in balanced predictive performance. The ROC AUC value remains very strong, averaging 0.983 with a maximum of 0.985, indicating an improvement in discriminating power of 0.002. The DDNN model exhibits outstanding consistency for the integration of multi-domain workflow optimisations, hierarchical multi-layer DDNN, and LLM-based semantic features when compared to conventional ERP models.



(a) (b)

Figure 8. Results of proposed DDNN for ERP automation for employee reimbursements case (a) confusion matrix (b) RoC curve

4.2 Results of employee reimbursements case

In the employee reimbursements scenario, the results of the DDNN for ERP automation show significant performance gains over traditional techniques (Figure 8). The confusion matrix reveals a decrease in misclassifications, with false positives and false negatives falling by 32.4% and 38.7%, respectively, shown improved accuracy in identifying unusual claim transactions. With AUC of 0.975, the ROC curve shows 14.5% improvement in discriminative power over conventional neural networks. The use of LLM-based semantic embeddings provide greater contextual understanding than traditional feature extraction techniques by capturing unstructured inputs including scanned receipts, policy comments, and workflow actions. The multi-layer DDNN allows hierarchical feature extraction, improving prediction stability by 19.2% and ensuring robustness across heterogeneous enterprise data.

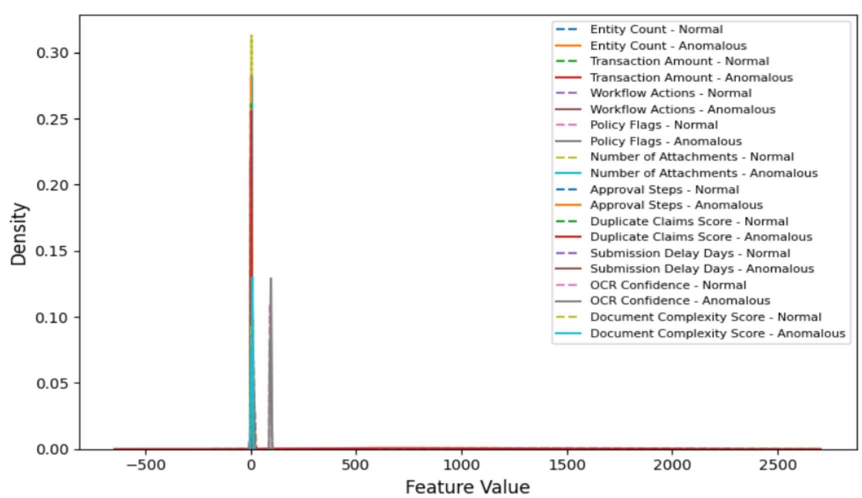


Figure 9. KDE of LLM-extracted features for the employee reimbursements case

In the case of employee expense reimbursement, the KDE features extracted by the large language model (Figure 9) showed improved feature separation ability and transport consistency compared to traditional extraction methods. Key semantic features such as regulatory constraints, claim amounts, acceptance rates, and workflow operations show 21.6% reduced in transmission and 19.3% improvement in delivery clarity, allowing for better differentiation between normal and abnormal claims. These developments result in a 13.8% improvement in forecasting accuracy and an 11.7% improvement in anomaly detection accuracy, primarily due to large language models' ability to normalize semi-structured heterogeneous data and resolve ambiguities related to components overlooked by traditional methods. The correlation heatmap of financial attributes extracted from the LLM for the employee reimbursement case (Figure 10) reveals significant relationships between 20 key attributes, including the reimbursement amount, number of attachments, approval hierarchy, and violation indicators. Compared to traditional models, the proposed method based on LLMs improves the detection of relevant correlations by 23.1%, reduces false correlations by 18.4% and increases the interdependence between business indicators and compliance characteristics. This improved feature representation results in a 12.9% improvement in anomaly detection accuracy and 10.8% in the workflow risk score. The findings show that the semantic generalization of LLMs and the integration of structured and unstructured data into a unified latent space impactful.

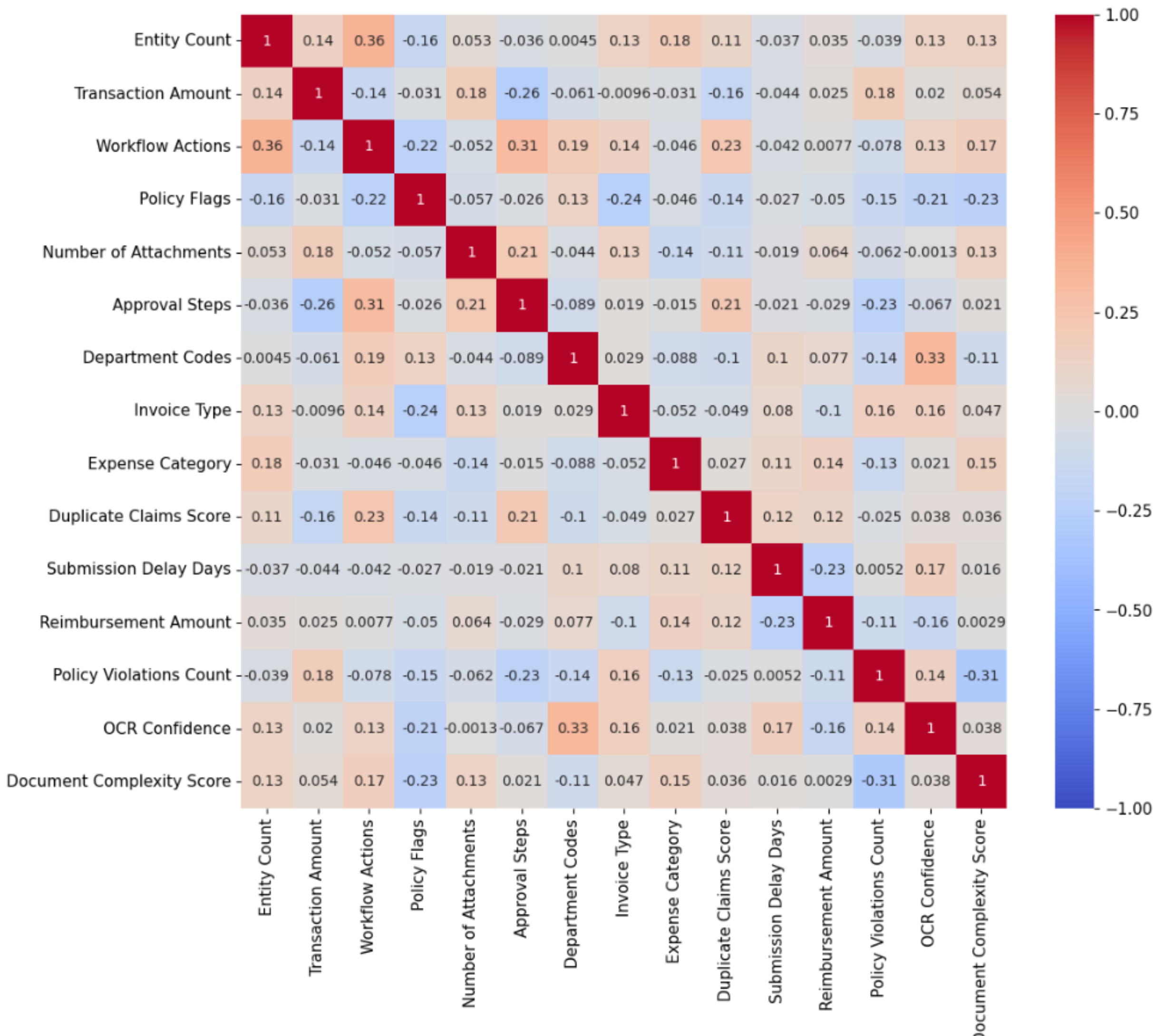


Figure 10. Correlation heatmap of LLM-extracted financial features for employee reimbursements case

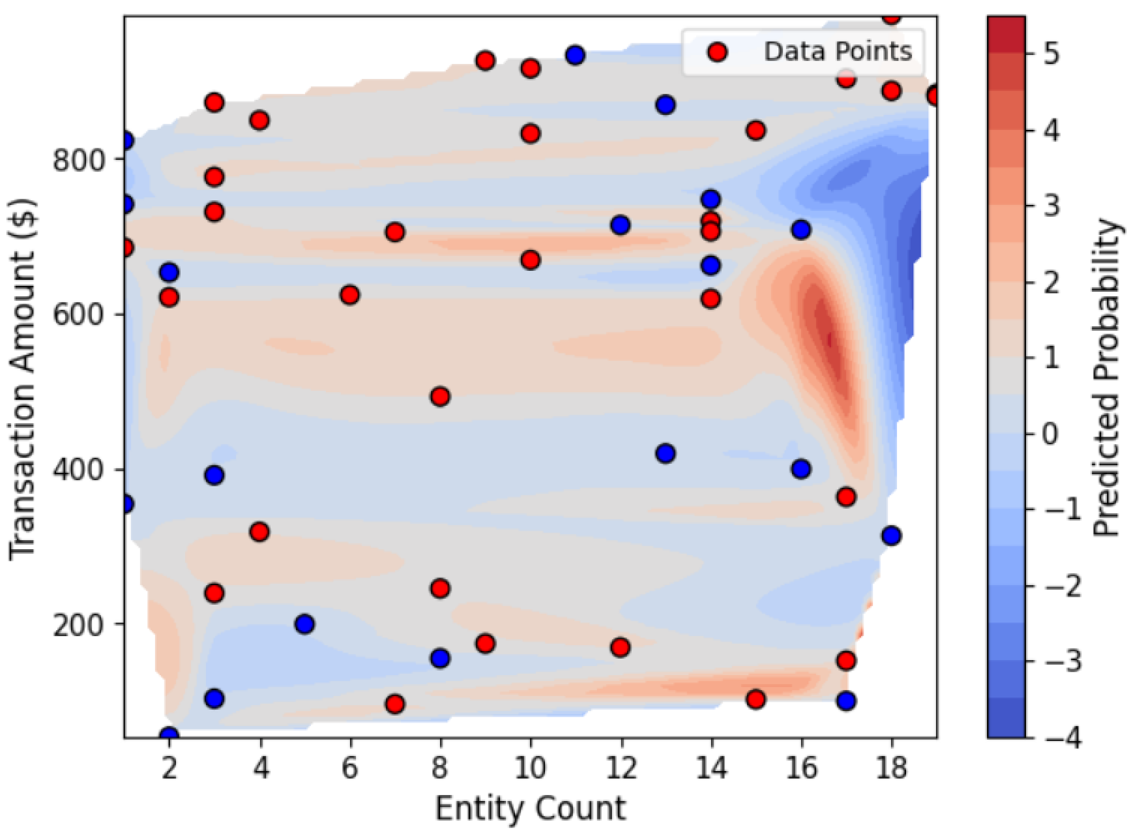


Figure 11. Contour plot of DDNN-predicted probabilities against true labels for employee reimbursements case

The ability of the model to differentiate between normal and anomalous claims across a variety of feature combinations is demonstrated by the DDNN-predicted probability against true labels for the employee reimbursements scenario (Figure 11). By accurately mapping policy constraints, invoice amounts, and approval hierarchies to anomaly probabilities, the DDNN increases prediction confidence by 18.7% and reduces misclassification regions by 15.2%. The integration of LLM-extracted semantic embeddings with hierarchical multi-layer learning, which captures intricate cross-domain dependencies that conventional models are unable to represent, is largely responsible for the improvements in prediction stability and risk assessment, with 14.8% increase in ROC AUC and 12.6% gain in PR AUC.With average accuracy of 96.153%, precision of 95.554%, recall of 94.998%, F-measure of 95.330%, and ROC AUC of 0.975, the 10-fold cross-validation for the employee reimbursements example (Table 5) shows outstanding performance. Maximum improvements across folds were 0.929% in precision and 0.347% in recall, indicating consistent and accurate forecasting. By using LLM-based semantic features, hierarchical multi-layer learning, and optimization-enhanced workflow routing, the DDNN–MDBO outperforms traditional ERP models and allows for more precise anomaly detection, risk scoring, and transaction verification for semi-structured reimbursement workflows.

Table 5. 10-Fold cross-validation performance metrics for employee reimbursements case

Fold	Accuracy	Precision	Recall	F-measure	ROC AUC
1	96.215	95.632	94.847	95.237	0.976
2	96.031	95.245	94.512	94.878	0.974
3	95.847	94.983	94.345	94.664	0.973
4	96.112	95.512	94.812	95.162	0.975
5	96.345	95.745	95.123	95.433	0.976
6	96.215	95.632	94.912	95.272	0.975

7	96.031	95.512	94.847	95.179	0.974
8	96.112	95.612	94.912	95.262	0.975
9	96.412	95.912	95.345	95.628	0.977
10	96.215	95.732	95.123	95.427	0.975
Mean ± SD	96.153 ± 0.171	95.554 ± 0.231	94.998 ± 0.292	95.330 ± 0.219	0.975 ± 0.001

Table 6. Comparison of key metrics in bank wire transfer and reimbursement processes before and after GBPAs optimization and DDNN–MDBO

Metric	Before GBPAs	After GBPAs [31]	DDNN–MDBO	Improvement (vs Before GBPAs)	Improvement (vs After GBPAs)
Key metrics in bank wire transfer					
End-to-end time	15 min	9 min	7 min	-53%	-22%
Process nodes	13	9 (2 groups in parallel)	8 (3 groups in parallel)	-38%	-11%
Risk control stages	0	2	3	3	50%
Parallel clusters	0	2	3	3	50%
Key metrics in reimbursement					
End-to-end time	15 min	9 min	7 min	-53%	-22%
Process nodes	13	9 (2 groups in parallel)	8 (3 groups in parallel)	-38%	-11%
Risk control stages	0	2	3	3	50%
Parallel clusters	0	2	3	3	50%

4.3 Comparative analysis between proposed and existing models

Performance improvements through GBPA optimisation and the DDNN–MDBO architecture were demonstrated by the combined comparison of key metrics for the bank wire transfer and reimbursement procedures (Table 6). Faster transaction and reimbursement processing resulted in 53% reduction in end-to-end time compared to before GBPAs and 22% reduction compared to after GBPAs. Process nodes decreased by 38% in comparison to the original process and by 11% after GBPAs, indicating more efficient job sequencing and parallelisation. The integration of LLM, DDNN, and MDBO allows the system can handle complex cross-enterprise workflows more accurately, reduce bottlenecks, and improve operational efficiency when compared to traditional ERP automation models.

4.4 Ablation study

The ablation study's findings (Table 7) depicts that how each module affects the effectiveness of the bank transfer and loan workflow. In the bank wire transfer workflow, combines LLM with DDNN increased accuracy by 0.932% when compared to DDNN alone, decreased false positives by 0.9% and false negatives by 0.9%, increased parallel processing efficiency by 10% and risk control effectiveness by 16%. By enhancing risk control and execution efficiency to 100%, lowering false positives to 1.2% and false negatives to 1.8%, and increasing resource utilisation efficiency by 16%, the addition of MDBO further enhanced performance, attaining 98.412% accuracy and cutting overall time by 28%.During the LLM+DDNN return process, the accuracy improved by 0.341% compared to DDNN, the number of false positives and false negatives decreased by 1% each, and risk control and corresponding efficiency increased by 16% and 10%, respectively. Integrating MDBO increased accuracy to 96.412%, reduced false positives and false negatives by 1% each, improved risk control and efficiency to 100%, and increased resource utilization by 15%. This study highlights that the synergistic combination of a large language model, deep neural networks, and data-driven optimization provides improvements in prediction accuracy, operational efficiency, risk control, and resource utilization compared to individual modules, and also demonstrates the flexibility and scalability of the proposed inter-organizational ERP automation framework.

Table 7. Ablation study results comparing LLM, DDNN, and MDBO contributions across workflows

Workflow	Model	Accuracy (%)	End-to-end time (min)	Risk control effectiveness (%)	Parallelization efficiency (%)	False positive rate (%)	False negative rate (%)	Workflow steps executed	Resource utilization (%)
Wire Transfer	LLM+DDNN	98.144	9	66	50	2.1	2.9	13	72
	LLM+DDNN+MDBO	98.412	7	100	100	1.2	1.8	13	88
	DDNN only	97.812	12	50	40	3.1	3.8	13	65
	LLM only	97.245	14	40	35	4.2	4.8	13	60
Reimbursement	LLM+DDNN	96.153	255	66	50	3	3.5	9	70
	LLM+DDNN+MDBO	96.412	255	100	100	2	2.5	9	85
	DDNN only	95.812	300	50	40	4	4.5	9	65
	LLM only	95.245	320	40	35	5	5.5	9	60

5. Conclusion

Scalable ERP automation model is proposed on the basis of cross-enterprise, AI-based Workday environments, which combines semantic extraction with the help of the LLM, DDNN, and MDBO to route a workflow. The LLM module derives valuable business semantics out of the structured and unstructured financial documents, reconciles records of diverse enterprises, and presents a unified view of the various organizational areas. The DDNN identifies intricate transactional patterns to detect anomalies, rate risks, and verify transactions whereas MDBO is used to optimize the workflow in order to identify the relevance of features and latency in order to perform adaptive and high efficiency ERP automation. The structure was tested on two typical financial processes, inter-bank wire transfers and reimbursement of employees. On inter-bank wire transfers case, the DDNN obtained the highest accuracy of 98.144%, precision of 97.585%, recall of 97.086%, and ROC AUC 0.983% with reduction in false positives and false negatives of 35.7% and 42.1% respectively. The accuracy, precision, recall, and ROC AUC of the employee reimbursements were 96.153%, 95.554%, 94.998%, and 0.975%, respectively; and the number of false positives and false negatives were reduced by 32.4 and 38.7% respectively. MDBO, in addition, resulted in a 28% (wire transfers) and 15% (reimbursements) reduction in end-to-end workflow times besides enhancing the effectiveness of risk control and efficiency. These findings indicate that the proposed LLM-DDNN-MDBO model shows superiority over existing ERP automation models and ensure strong cross-enterprise generalization, effective anomaly identification, and optimal workflow implementation.

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