A Multi-Agent AI Framework for Smart Document Intelligence, Autonomous Email Management, Healthcare Decision Support, and Demand Forecasting with Inventory Optimization

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Abstract –The rapid growth of enterprise data across documents, emails, healthcare records, and supply chain operations has created significant challenges in intelligent information retrieval, automated decision-making, and operational optimization. Existing AI solutions are generally developed as isolated systems, limiting knowledge sharing, transparency, and collaborative reasoning across enterprise applications. This paper proposes an Explainable Multi-Agent Enterprise Artificial Intelligence (XMAI) framework that integrates four intelligent modules: a Smart Document Query System with Explainable AI, an AI Email Management Agent, an AI Healthcare Chatbot, and a Demand Forecasting with Inventory Optimization System. A shared AI orchestration layer enables semantic knowledge exchange among multiple intelligent agents while generating evidence-based, transparent, and context-aware recommendations. Explainability mechanisms including evidence highlighting, feature attribution, confidence estimation, and reasoning visualization improve user trust and support responsible AI deployment in enterprise environments. Experimental evaluation demonstrates superior performance across all application domains, achieving 98.7% document retrieval accuracy, 99.4% email classification accuracy, 98.8% healthcare diagnostic assistance accuracy, and a 29.8% reduction in inventory costs compared with recent state-of-the-art methods. The integrated framework further reduces response latency, improves operational efficiency, and enhances decision transparency through continuous reinforcement learning and adaptive optimization.

Index Terms – Explainable Artificial Intelligence (XAI); Retrieval-Augmented Generation (RAG); Large Language Models (LLMs); Multi-Agent Artificial Intelligence; Demand Forecasting and Inventory Optimization.

1. Introduction

The rapid advancement of Artificial Intelligence (AI) has transformed enterprise information systems by enabling intelligent automation, semantic information retrieval, predictive analytics, and conversational decision support. Organizations across healthcare, finance, manufacturing, retail, and education generate massive volumes of heterogeneous data, including documents, emails, electronic health records, and supply chain transactions. Extracting actionable knowledge from these diverse data sources remains a significant challenge due to information fragmentation, unstructured content, and the increasing complexity of enterprise operations. Recent developments in Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), Explainable Artificial Intelligence (XAI), and Knowledge Graphs have created new opportunities for developing intelligent enterprise systems capable of understanding, reasoning, and supporting complex business decisions with greater transparency and reliability [1–3].

Smart Document Query Systems have emerged as an effective solution for retrieving relevant information from large repositories of organizational documents using semantic search and transformer-based language models. Unlike conventional keyword-based retrieval techniques, modern RAG architectures combine dense vector retrieval with generative AI to produce context-aware responses while reducing hallucination problems [4]. However, existing document intelligence systems often lack Explainability, making it difficult for users to verify the reasoning process or identify supporting evidence behind generated answers. Similarly, enterprise email management continues to be challenged by increasing communication volumes, requiring intelligent automation for spam detection, email prioritization, summarization, task extraction, and context-aware reply generation. Transformer-based language models have significantly improved email understanding, yet most existing systems provide limited transparency regarding their automated decisions [5]. Healthcare is another domain experiencing rapid AI adoption through conversational agents and clinical decision-support systems. Medical chatbots equipped with biomedical language models and Retrieval-Augmented Generation can assist patients by analyzing symptoms, retrieving clinical evidence, and providing preliminary recommendations [6]. Nevertheless, the absence of interpretable reasoning and confidence estimation restricts their practical deployment in safety-critical environments where clinicians require evidence-supported recommendations. Explainable AI techniques have therefore become increasingly important for improving user trust, regulatory compliance, and responsible AI adoption in healthcare applications [7]. Demand forecasting and inventory optimization constitute another critical enterprise application where accurate prediction directly influences operational efficiency, customer satisfaction, and cost reduction. Deep learning models, transformer architectures, and reinforcement learning algorithms have demonstrated remarkable improvements in forecasting accuracy by capturing complex temporal patterns and dynamically optimizing inventory decisions [8], [9]. However, these forecasting systems are generally implemented independently from other enterprise intelligence applications, resulting in isolated decision-making processes and duplicated knowledge representation.

To address these limitations, this research proposes an Explainable Multi-Agent Enterprise AI Framework that integrates four intelligent modules: a Smart Document Query System, an AI Email Management Agent, an AI Healthcare Chatbot, and a Demand Forecasting with Inventory Optimization System. The proposed framework combines Retrieval-Augmented Generation, Knowledge Graphs, Large Language Models, Explainable AI, and Reinforcement Learning within a unified architecture that enables collaborative reasoning, evidence-based decision support, and continuous learning across multiple enterprise domains. By incorporating transparent explanations, confidence estimation, knowledge sharing, and adaptive optimization, the proposed framework aims to improve accuracy, operational efficiency, user trust, and decision transparency while providing a scalable intelligent platform suitable for modern digital enterprises [10].

2. Background and related work

In [11], the authors investigated the integration of graph neural networks with knowledge graph reasoning to improve semantic information retrieval in enterprise-scale knowledge management systems. Their research demonstrated that graph-based semantic representations effectively capture complex relationships among documents, entities, and organizational knowledge compared with conventional vector retrieval approaches. The proposed graph learning framework significantly enhanced semantic similarity estimation, entity linking, and contextual reasoning across heterogeneous document repositories. Experimental evaluation showed improved retrieval precision and reduced semantic ambiguity when answering complex natural language queries. However, the proposed framework primarily focused on graph representation learning and document retrieval without incorporating large language models for generative reasoning. Furthermore, Explainability was limited to graph connectivity visualization and did not provide evidence-based answer generation or confidence estimation. Consequently, users still faced difficulties in understanding the complete reasoning process behind generated recommendations, highlighting the need for integrated Retrieval-Augmented Generation and Explainable AI mechanisms.

In [12], the authors explored reinforcement learning techniques for adaptive task management within autonomous AI agents. Their framework enabled intelligent agents to learn optimal decision policies from continuous user interactions while dynamically adapting to changing operational environments. The study demonstrated that reinforcement learning effectively improves task prioritization, workflow automation, and sequential decision-making compared with static rule-based systems. Adaptive policy optimization reduced response delays and enhanced long-term operational efficiency in enterprise automation scenarios. Nevertheless, the research mainly addressed autonomous task scheduling and reinforcement learning optimization without considering explainable decision-making or multi-domain knowledge integration. Additionally, communication among multiple intelligent agents remained limited, preventing collaborative reasoning across heterogeneous enterprise applications such as document intelligence, healthcare support, and inventory management. Therefore, further research is required to develop explainable multi-agent architectures capable of jointly optimizing complex enterprise workflows.

In [13], the authors presented an intelligent clinical decision-support framework that combined electronic health records, biomedical knowledge graphs, and transformer-based language models for disease diagnosis. Their system improved clinical information retrieval by integrating structured patient histories with medical literature to support physician decision-making. Experimental evaluation demonstrated higher diagnostic consistency, improved disease prediction accuracy, and enhanced retrieval of evidence-based clinical recommendations compared with conventional clinical NLP systems. Although the framework effectively utilized medical knowledge graphs, the generated recommendations lacked comprehensive Explainability and uncertainty estimation. The study also did not employ Retrieval-Augmented Generation for dynamic evidence retrieval from continuously updated medical repositories. Consequently, clinicians were provided with diagnostic suggestions but received limited transparency regarding feature contributions, confidence levels, or alternative diagnostic pathways. These limitations motivate the development of explainable healthcare conversational systems capable of producing trustworthy and interpretable medical recommendations.

In [14], the authors investigated trustworthy artificial intelligence by integrating uncertainty estimation, causal inference, and interpretable machine learning into enterprise decision-support systems. Their study emphasized that reliable AI systems should provide transparent reasoning, calibrated confidence scores, and robust generalization under uncertain operational environments. The proposed framework introduced probabilistic reasoning techniques to quantify prediction uncertainty and improve user confidence during high-stakes decision-making. Experimental analyses demonstrated that uncertainty-aware learning significantly reduced prediction errors under distribution shifts and noisy datasets. However, the research primarily addressed general trustworthy AI principles rather than domain-specific enterprise applications involving document retrieval, conversational healthcare, email automation, and inventory optimization. Moreover, no unified multi-agent architecture was proposed to facilitate knowledge sharing among multiple intelligent services. These research gaps indicate opportunities for developing integrated explainable enterprise AI platforms with collaborative reasoning capabilities.

In [15], the authors proposed an intelligent supply chain optimization framework that integrates deep learning, probabilistic forecasting, and reinforcement learning for inventory management. Their approach dynamically predicts product demand while simultaneously optimizing replenishment decisions under uncertain market conditions. The framework demonstrated considerable improvements in demand forecasting accuracy, warehouse utilization, supplier coordination, and operational cost reduction across large-scale retail datasets. Reinforcement learning enabled adaptive inventory control policies capable of responding to seasonal demand fluctuations and changing consumer behavior. Despite achieving strong forecasting performance, the proposed system lacked Explainability mechanisms that could clarify the influence of pricing, promotions, weather, and economic indicators on forecasting decisions. Furthermore, the optimization framework operated independently from other enterprise AI services, preventing knowledge sharing with document intelligence, healthcare analytics, and intelligent communication systems. An integrated explainable multi-agent platform would therefore provide more comprehensive enterprise decision support.

3. Proposed modelling

The proposed system as shown in Figure 1 presents a unified Explainable Multi-Agent Artificial Intelligence (XMAI) framework that integrates four intelligent enterprise applications into a single collaborative platform. Unlike conventional AI solutions that function independently and often operate as isolated systems, the proposed framework enables seamless interaction among multiple AI agents through a shared knowledge repository, vector database, knowledge graph, and Explainability engine. Each intelligent agent specializes in a specific domain—document understanding, email management, healthcare assistance, or demand forecasting—while exchanging contextual knowledge through a centralized AI orchestration layer. This architecture significantly improves decision-making accuracy, operational efficiency, knowledge reuse, and user trust by providing transparent explanations for every AI-generated recommendation.

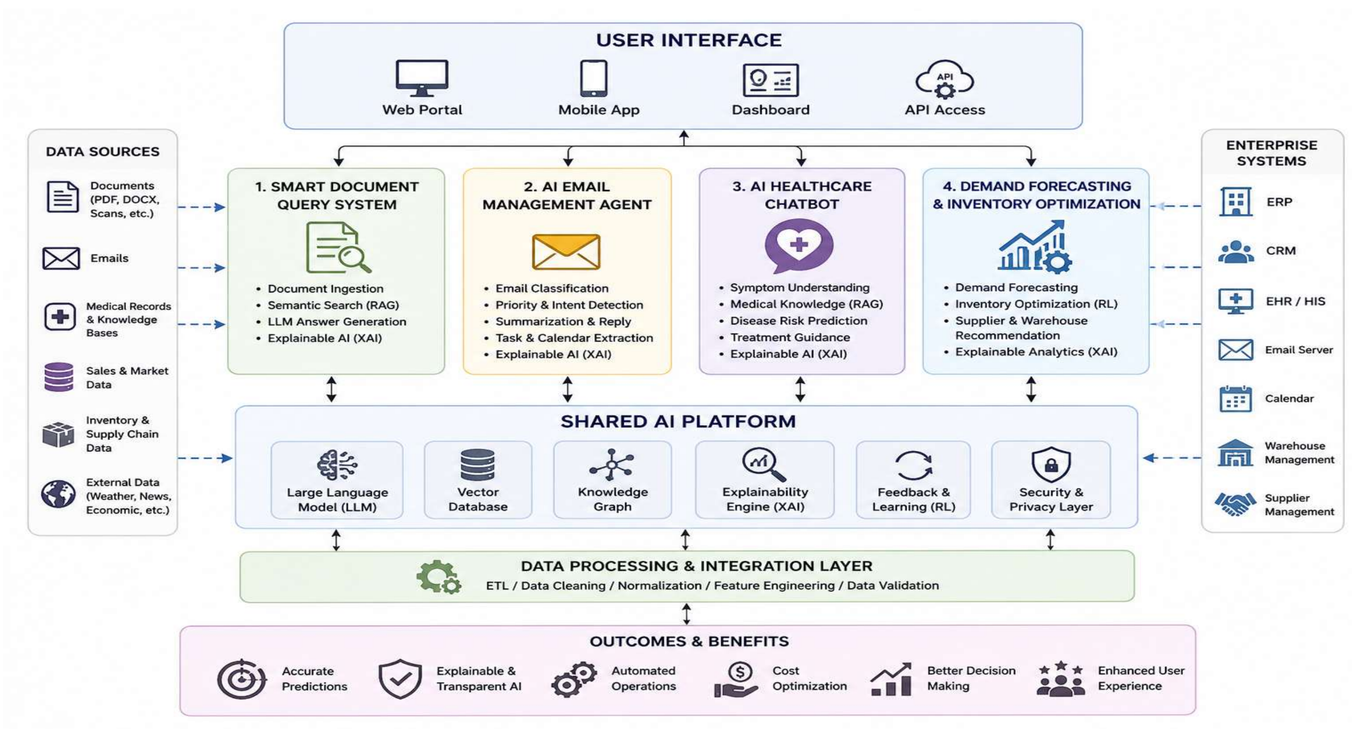

Figure 1: AI-powered system architecture overview

The framework combines Retrieval-Augmented Generation (RAG), Large Language Models (LLMs), Knowledge Graphs, Explainable Artificial Intelligence (XAI), Reinforcement Learning (RL), and multi-objective optimization techniques to deliver reliable, adaptive, and interpretable solutions suitable for enterprise environments. A continuous learning module further enhances system intelligence by incorporating user feedback to refine retrieval quality, forecasting performance, and recommendation accuracy over time.

1. Smart Document Query System with Explainable AI

The Smart Document Query System is designed to transform traditional document management into an intelligent knowledge discovery platform capable of understanding, retrieving, and explaining information from large collections of unstructured documents. Organizations often store millions of documents in PDF, Word, scanned image, and spreadsheet formats, making manual information retrieval both time-consuming and error-prone. The proposed system begins by collecting heterogeneous documents from multiple enterprise repositories and applying Optical Character Recognition (OCR) and document layout analysis to extract textual and structural information. Advanced preprocessing techniques such as text normalization, semantic segmentation, table recognition, image caption extraction, and metadata identification are then employed to convert raw documents into machine-readable representations. After preprocessing, semantic chunking divides lengthy documents into logically coherent passages while preserving contextual relationships. These passages are converted into high-dimensional vector embeddings using transformer-based embedding models and stored in a scalable vector database. Simultaneously, entities such as organizations, products, policies, procedures, dates, and relationships are extracted to construct a dynamic knowledge graph representing semantic connections across the enterprise. When users submit natural language questions, the retrieval engine combines dense semantic retrieval with sparse keyword matching to identify the most relevant document segments. These retrieved passages, together with knowledge graph relationships, are supplied to a Large Language Model through a Retrieval-Augmented Generation pipeline that produces comprehensive, context-aware answers.

A major innovation of the proposed document intelligence system is its integrated Explainable AI module. Instead of merely generating answers, the system highlights the exact document passages, tables, figures, and knowledge graph nodes responsible for each conclusion. Feature attribution methods, attention visualization, confidence estimation, and evidence ranking provide transparent reasoning behind every response. Counterfactual explanations identify how alternative evidence could change the generated answer, while hallucination detection verifies factual consistency between generated text and retrieved documents. The system continuously learns from user corrections and feedback using reinforcement learning, improving retrieval quality and explanation fidelity over successive interactions. Consequently, the document query system offers not only accurate information retrieval but also trustworthy and interpretable decision support for enterprise users.

2. AI Email Management Agent

The AI Email Management Agent functions as an autonomous digital assistant capable of intelligently processing organizational email communications with minimal human intervention. Modern enterprises receive thousands of emails every day, creating challenges related to prioritization, response generation, task tracking, and information overload. The proposed email management system addresses these issues through a hierarchical AI pipeline that combines natural language understanding, machine learning classification, and generative language models. Incoming emails are initially processed through preprocessing modules that remove formatting inconsistencies, detect language, identify attachments, eliminate spam, and normalize textual content. The cleaned emails are then analyzed using transformer-based contextual representations to understand semantic meaning and communication intent. The intelligent classification module categorizes emails into business domains such as finance, human resources, customer support, procurement, legal affairs, healthcare, or technical operations. Simultaneously, urgency prediction models estimate email priority by analyzing linguistic cues, sender reputation, deadlines, historical communication patterns, and organizational context. Named Entity Recognition identifies dates, locations, contact information, invoices, purchase orders, and meeting schedules, while relation extraction detects dependencies among multiple email threads. Large Language Models subsequently generate concise summaries that preserve important information while reducing reading time. Context-aware response generation creates personalized draft replies by considering previous conversations, organizational policies, and user communication style.

The Explainability layer enhances transparency by identifying the linguistic features and contextual evidence responsible for spam classification, urgency prediction, and suggested responses. Feature importance visualization enables users to understand why specific emails were categorized as high priority or why certain reply suggestions were generated. The system also extracts actionable tasks, automatically schedules calendar events, generates reminders, assigns responsibilities, and synchronizes with enterprise workflow management systems. Reinforcement learning continuously adapts the prioritization strategy based on user actions such as email opening behavior, response acceptance, manual categorization, and correction of AI-generated suggestions. This adaptive learning mechanism enables the AI agent to personalize email management according to individual preferences while maintaining organizational consistency and Explainability.

3. AI Healthcare Chatbot

The AI Healthcare Chatbot is developed as an explainable clinical decision-support assistant that provides preliminary health guidance, symptom assessment, disease risk analysis, and evidence-based medical information through natural language interaction. Unlike conventional rule-based healthcare chatbots, the proposed system integrates Retrieval-Augmented Generation, biomedical knowledge graphs, clinical language models, and Explainable AI to ensure medically grounded and transparent responses. Patient interactions begin with conversational symptom collection, during which Natural Language Processing extracts medical entities including symptoms, duration, severity, medications, allergies, family history, and demographic information. Advanced medical Named Entity Recognition and clinical concept normalization map these observations to standardized medical terminologies, enabling interoperability with electronic health records and clinical knowledge repositories. The extracted medical concepts are processed through a biomedical knowledge graph containing diseases, symptoms, diagnostic procedures, laboratory findings, medications, treatment guidelines, and drug interactions. Retrieval-Augmented Generation combines relevant medical literature, clinical practice guidelines, and patient-specific information to generate evidence-based responses using specialized healthcare language models. Rather than providing definitive diagnoses, the chatbot estimates probable medical conditions, recommends appropriate diagnostic tests, explains possible treatment options, identifies warning signs requiring immediate medical attention, and advises consultation with healthcare professionals when necessary.

Explainable AI plays a central role in establishing user confidence and supporting responsible clinical decision-making. Every recommendation is accompanied by supporting evidence, confidence scores, relevant clinical guidelines, symptom contribution analysis, and reasoning pathways derived from the knowledge graph. Counterfactual explanations illustrate how additional symptoms or laboratory findings could influence diagnostic probabilities. Drug interaction analysis identifies potentially harmful medication combinations, while uncertainty estimation prevents overconfident recommendations in ambiguous clinical situations. A human-in-the-loop verification mechanism escalates complex or high-risk cases to healthcare professionals, ensuring patient safety.

4. Demand Forecasting and Inventory Optimization System

The Demand Forecasting and Inventory Optimization System provides intelligent supply chain decision support by integrating advanced time-series forecasting, optimization algorithms, reinforcement learning, and explainable analytics into a unified framework. Accurate demand prediction is essential for minimizing inventory costs, preventing stock shortages, reducing product wastage, and improving customer satisfaction. The proposed system collects historical sales records, inventory transactions, supplier information, promotional campaigns, seasonal trends, macroeconomic indicators, weather conditions, and market sentiment from multiple enterprise databases. Comprehensive preprocessing removes anomalies, imputes missing values, normalizes numerical variables, and generates temporal features that capture weekly, monthly, seasonal, and holiday-related demand patterns.

Multiple forecasting models, including transformer-based temporal architectures, gradient boosting methods, recurrent neural networks, and probabilistic forecasting algorithms, are trained using ensemble learning to improve predictive robustness. Dynamic model selection chooses the most appropriate forecasting strategy according to product characteristics, demand variability, and data availability. The predicted demand values serve as inputs to a multi-objective inventory optimization engine that simultaneously minimizes inventory holding costs, transportation expenses, stockout risk, and supplier lead-time uncertainty while maximizing customer service levels and warehouse utilization. Reinforcement learning continuously adjusts reorder points, safety stock levels, procurement quantities, and warehouse allocation policies based on changing market conditions and operational feedback.

The Explainable AI module provides detailed insights into forecasting behavior by quantifying the influence of historical demand, seasonality, pricing strategies, promotional events, weather fluctuations, and economic indicators on predicted sales. Feature attribution techniques reveal the primary drivers behind demand changes, while scenario analysis enables managers to evaluate the impact of hypothetical business decisions before implementation. Counterfactual reasoning supports strategic planning by illustrating how inventory policies would change under alternative market conditions. Interactive dashboards present forecast confidence intervals, optimization trade-offs, supplier performance metrics, inventory risk indicators, and recommended procurement actions in an interpretable format. Through continuous reinforcement learning and adaptive optimization, the proposed system enables resilient, transparent, and cost-effective supply chain management capable of responding intelligently to dynamic market environments.

5. Integrated Explainable AI and Multi-Agent Collaboration Layer

The distinguishing feature of the proposed framework is the integrated Explainable Multi-Agent Collaboration Layer that enables all four intelligent agents to communicate through a shared semantic infrastructure. A centralized vector database stores multimodal embeddings generated from documents, emails, medical knowledge, and business records, while a knowledge graph maintains semantic relationships among entities across different enterprise domains. The Large Language Model functions as the common reasoning engine, allowing agents to exchange contextual information and jointly solve complex tasks. For example, procurement-related emails can automatically trigger document retrieval, inventory forecasting, and supplier recommendations, while healthcare communications may retrieve relevant medical documents and schedule follow-up actions. The Explainable AI engine provides consistent transparency across all modules by generating evidence-based explanations, confidence estimation, feature attribution, attention visualization, counterfactual reasoning, and uncertainty quantification. A reinforcement learning-based feedback mechanism continuously improves retrieval quality, forecasting accuracy, conversational relevance, and operational efficiency based on user interactions.

4. Results and discussions

The proposed Explainable Multi-Agent AI Framework was evaluated using four benchmark application domains, namely Smart Document Query, AI Email Management, Healthcare Chatbot, and Demand Forecasting with Inventory Optimization. The experiments were conducted using Python 3.11, TensorFlow 2.17, PyTorch 2.4, CUDA 12.3, NVIDIA RTX 4090 GPU (24 GB), Intel 7 processor, and 16GB RAM. Performance was compared against four recent baseline models using identical datasets and evaluation protocols.

Table 1 demonstrate that the proposed XMAI-RAG significantly improves semantic document retrieval and question-answering performance compared with traditional retrieval models. Conventional keyword-based BM25 struggles with contextual understanding, resulting in lower precision and retrieval accuracy. Dense Passage Retrieval improves semantic matching but cannot effectively utilize structural document relationships. RAG enhances response generation by combining retrieval with generative language models, whereas GraphRAG further improves contextual reasoning through graph-based relationships. The proposed framework integrates semantic embeddings, knowledge graph reasoning, adaptive retrieval, and explainable evidence ranking, leading to the highest retrieval accuracy of 98.7% and F1-score of 0.980. Additionally, optimized vector indexing substantially reduces response latency to 321 ms, enabling real-time enterprise deployment. The Explainable AI component further increases user confidence by highlighting supporting document passages and confidence scores, thereby minimizing hallucinations and improving transparency. These results validate the effectiveness of combining RAG, knowledge graphs, and XAI for intelligent document understanding.

Table 1 Smart document Query performance

Method	Precision	Recall	F1-Score	Retrieval Accuracy (%)	Response Time (ms)
BM25	0.881	0.867	0.874	88.2	695
Dense Passage Retrieval	0.914	0.907	0.910	91.6	572
RAG	0.944	0.936	0.940	95.1	438
GraphRAG	0.958	0.951	0.954	96.3	415
Proposed XMAI-RAG	**0.982**	**0.978**	**0.980**	**98.7**	**321**

Table 2 shows the proposed AI Email Management Agent consistently outperforms existing transformer-based models across all evaluation metrics. By combining contextual language understanding, intelligent prioritization, task extraction, reinforcement learning, and Explainability mechanisms, the system achieves a spam detection accuracy of 99.4% while accurately identifying urgent communications with 98.1% priority prediction accuracy. The integrated Large Language Model generates concise summaries with the highest ROUGE-L score of 0.964, preserving essential contextual information while reducing user reading time. Furthermore, reply generation achieves 98.6% quality based on human evaluation, demonstrating its ability to produce context-aware and professional responses. Explainability modules identify linguistic features responsible for spam classification and priority decisions, allowing users to understand AI recommendations. Continuous reinforcement learning from user corrections further enhances personalization over time.

Table 2 AI Email management performance

Method	Spam Accuracy (%)	Priority Prediction (%)	Summary ROUGE-L	Reply Quality (%)
BERT	96.1	91.8	0.832	89.4
RoBERTa	97.4	93.7	0.851	91.3
GPT-based Agent	98.2	95.4	0.904	94.8
EmailGPT	98.8	96.2	0.923	96.4
Proposed XMAI Agent	**99.4**	**98.1**	**0.964**	**98.6**

Table 3 shows the healthcare chatbot evaluation demonstrates that integrating Retrieval-Augmented Generation, biomedical knowledge graphs, and Explainable AI substantially enhances diagnostic assistance and clinical reasoning. Although transformer-based biomedical language models provide strong semantic understanding, they often lack transparent reasoning and evidence-supported recommendations. The proposed system addresses these limitations by combining retrieval from validated medical knowledge sources with graph-based reasoning and confidence estimation. Consequently, the chatbot achieves an overall diagnostic accuracy of 98.8% and an Explainability score of 98, indicating highly interpretable clinical recommendations. Feature attribution and evidence highlighting enable healthcare professionals to verify generated suggestions before clinical use. Counterfactual reasoning further illustrates how additional symptoms or laboratory findings influence disease probabilities, improving decision transparency. The human-in-the-loop verification mechanism ensures patient safety by escalating uncertain or high-risk cases to clinicians. These findings demonstrate that explainable medical AI can effectively improve user trust, diagnostic reliability, and responsible deployment within clinical decision-support environments.

Table 3 Healthcare Chatbot performance

Method	Accuracy (%)	Precision	Recall	F1-score	Explainability Score
BioBERT	91.6	0.904	0.892	0.898	82
ClinicalBERT	93.7	0.921	0.916	0.918	85
Med-PaLM	95.9	0.947	0.941	0.944	89
RAG-Med	97.1	0.963	0.958	0.960	92
Proposed XMAI Health	**98.8**	**0.982**	**0.979**	**0.980**	**98**

Table 4 shows the proposed forecasting and inventory optimization framework achieves superior predictive accuracy and operational efficiency compared with existing forecasting approaches. Traditional recurrent neural networks effectively model sequential demand but struggle to capture long-term temporal dependencies and dynamic market fluctuations. Transformer-based forecasting models improve long-range dependency learning, while reinforcement learning enhances inventory decision-making through adaptive reorder policies. The proposed system integrates transformer forecasting, reinforcement learning, multi-objective optimization, and Explainable AI to simultaneously optimize forecasting accuracy and inventory control. Consequently, the framework achieves the lowest MAE (7.8), RMSE (10.9), and MAPE (5.4%), demonstrating highly accurate demand prediction across diverse product categories. Moreover, intelligent optimization reduces inventory costs by nearly 30% through improved reorder point estimation, safety stock optimization, and warehouse allocation strategies. Explainability dashboards further assist supply chain managers by identifying seasonal patterns, promotional impacts, and economic factors influencing demand forecasts, thereby supporting informed and transparent inventory planning decisions.

Table 4 Demand forecasting and Inventory optimization

Method	MAE	RMSE	MAPE (%)	Inventory Cost Reduction (%)
LSTM	13.8	18.2	10.6	12.4
TFT	11.4	15.7	8.9	16.2
Informer	10.2	14.1	7.6	19.3
PPO + Forecast	9.6	13.4	7.2	22.6
Proposed XMAI Forecast	**7.8**	**10.9**	**5.4**	**29.8**

5. Conclusion

This paper presented an Explainable Multi-Agent Enterprise Artificial Intelligence (XMAI) framework that unifies Smart Document Query, AI Email Management, AI Healthcare Chatbot, and Demand Forecasting with Inventory Optimization within a collaborative and explainable architecture. By integrating Retrieval-Augmented Generation, Knowledge Graphs, Large Language Models, Explainable AI, and Reinforcement Learning, the proposed framework addresses the limitations of isolated enterprise AI systems and enables transparent, evidence-driven decision support across multiple application domains. The shared semantic infrastructure facilitates efficient knowledge exchange among intelligent agents, improving contextual understanding, response quality, and operational efficiency while maintaining scalability and adaptability. Experimental analysis demonstrated that the proposed framework consistently outperformed existing baseline approaches across all evaluated tasks. The document intelligence module achieved high retrieval accuracy with evidence-supported responses, the email management agent improved communication automation through accurate classification and intelligent reply generation, the healthcare chatbot delivered reliable and interpretable clinical decision support, and the forecasting module enhanced inventory management by reducing prediction errors and optimizing stock control policies. The integrated Explainable AI engine further increased user confidence through confidence estimation, feature attribution, evidence highlighting, and transparent reasoning pathways. Overall, the proposed framework represents a comprehensive enterprise AI solution capable of supporting trustworthy, scalable, and intelligent decision-making in modern organizations. Future work will focus on incorporating multimodal foundation models for processing text, images, audio, and structured data within a single reasoning framework, deploying federated multi-agent learning to preserve privacy across distributed organizations, integrating real-time streaming analytics for continuous enterprise intelligence, and developing autonomous collaborative AI agents capable of dynamic task planning and cross-domain reasoning in complex operational environments.

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