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(REVIEW ARTICLE)

A Cognitive Architecture for Intelligent Process Automation in Enterprise Applications Using Azure AI Services

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Abstract

Background: Modern enterprises increasingly rely on intelligent process automation (IPA) to improve operational efficiency, yet integrating cognitive AI capabilities into existing systems remains challenging.

Aim: This study proposes a unified cognitive architecture that leverages Azure AI Services to enhance automation, reasoning, and decision-making in enterprise applications.

Method: A layered architecture is designed using Azure Cognitive Services, Azure OpenAI, Azure Machine Learning, and Azure Logic Apps, evaluated through workflow simulations.

Results: The architecture demonstrates improved accuracy in document processing, faster process orchestration, and enhanced predictive capabilities across enterprise workflows.

Conclusion: The proposed cognitive architecture provides a scalable, modular, and intelligent automation framework that strengthens enterprise digital transformation using Azure's cloud-native AI ecosystem.

Keywords: Intelligent Process Automation; Cognitive Architecture; Azure AI Services; Enterprise Applications; Workflow Automation; Machine Learning; Cloud Computing

1. Introduction

The rapid digital transformation across global industries has accelerated the demand for intelligent and adaptive enterprise systems. Traditional automation solutions have primarily relied on rule-based workflows and deterministic logic, which are limited in handling unstructured data, complex reasoning, and dynamic business environments. As organizations increasingly seek to enhance operational efficiency, reduce human effort, and improve decision accuracy, the need for cognitive capabilities within automation frameworks has become essential. Intelligent Process Automation (IPA) emerges as a strategic evolution of robotic process automation (RPA), integrating AI, machine learning, and advanced analytics to automate not only repetitive tasks but also knowledge-driven processes. In modern enterprises, the surge in unstructured data emails, documents, images, audio transcripts, and user interactions poses substantial challenges for conventional systems. These systems struggle to interpret context, derive meaning, and apply judgment. Cognitive architectures aim to bridge this gap by embedding human-like perception and reasoning into automated workflows. By leveraging cloud-based AI services, organizations can scale these cognitive capabilities without heavy on-premise infrastructure investment. Among the available platforms, Microsoft Azure provides a robust ecosystem of AI services that seamlessly integrate with enterprise applications and legacy systems.

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Azure AI Services including Azure Cognitive Services, Azure OpenAI, Azure Machine Learning, and Azure Logic Apps offer a modular and extensible foundation for building intelligent automation pipelines. These services enable machines to read documents, interpret language, understand images, listen to speech, and generate insights with contextual intelligence. When orchestrated within a unified cognitive architecture, the result is a powerful automation engine capable of processing workflows end-to-end with minimal human intervention. This integration transforms traditional enterprise applications into adaptive, learning-driven systems.

The growing complexity of enterprise workflows also necessitates advanced decision-making capabilities. Azure's intelligence layer enhances automation with predictive analytics, anomaly detection, and natural language reasoning. Enterprises can automate tasks such as fraud detection, customer support, inventory forecasting, and compliance monitoring tasks previously requiring expert knowledge. By embedding machine learning models and generative AI within daily operations, organizations gain real-time insight into business processes, improving responsiveness and reducing operational risks. Security, scalability, and governance remain key concerns for enterprises adopting AI-driven automation. Azure's built-in identity management, encryption protocols, compliance certifications, and monitoring tools ensure that cognitive automation systems operate securely within regulated environments. This makes Azure an ideal platform for industries such as finance, healthcare, government, and manufacturing, where data protection and auditability are paramount. Thus, the proposed cognitive architecture is not only intelligent but also enterprise-ready for large-scale deployment.

2. Literature review

Hochreiter and Schmidhuber's seminal 1997 paper introduced the Long Short-Term Memory (LSTM) architecture, addressing the vanishing gradient problem and enabling neural networks to capture long-range dependencies in sequential data. LSTMs became foundational for tasks involving speech processing, text classification, and temporal pattern recognition, all of which are significant components of cognitive automation in enterprise systems. Their contribution directly supports intelligent document processing, customer interaction modeling, and predictive analytics workflows integrated into Azure AI–driven architectures. By enabling reliable sequence learning, LSTMs paved the way for modern NLP and automation technologies used in enterprise applications.

Vaswani et al. (2017): Deep learning through the introduction of the Transformer architecture, which replaced recurrence with self-attention mechanisms to achieve superior parallelization and contextual understanding. This architecture became the backbone of modern language models—including Azure OpenAI models—enabling advanced reasoning, summarization, and contextual automation tasks in enterprise environments. Transformers significantly improve the accuracy and efficiency of cognitive automation by enabling deeper semantic understanding of documents, emails, and operational text data. Their impact is central to the intelligence layer of the proposed cognitive architecture.

He et al. (2016), work on Residual Networks (ResNet) introduced skip connections that enabled substantially deeper neural networks without degradation in performance, marking a breakthrough in image recognition accuracy. This advancement is highly relevant to enterprise automation systems where image classification, document scanning, and visual inspection are integral to automated workflows. Azure Computer Vision services draw upon principles introduced in this paper, allowing the cognitive architecture to handle complex visual tasks such as extracting information from scanned invoices, detecting anomalies in manufacturing images, and enabling robust visual perception capabilities.

Devlin et al. (2019), significantly advanced natural language understanding by using bidirectional context encoding and masked language modeling. BERT set new benchmarks in text classification, sentiment analysis, and question answering, influencing many enterprise automation systems reliant on accurate language comprehension. The methodology behind BERT is foundational for Azure AI's NLP capabilities, enabling tasks such as automated email routing, semantic search, contract analysis, and conversational process automation. This work directly supports the cognitive reasoning and document interpretation functions within the proposed cognitive architecture.

Redmon et al. (2016): YOLO framework transformed object detection by introducing a unified, real-time detection approach capable of processing full images in a single neural network pass. This innovation is essential for enterprise automation scenarios requiring high-speed visual recognition, such as quality inspection, logistics tracking, and security monitoring. YOLO's efficiency and accuracy influence the design of Azure's real-time computer vision systems, enabling integration of visual intelligence into automation workflows. This capability enhances the perception layer of the cognitive architecture by enabling rapid analysis of visual enterprise data.

Dean & Ghemawat (2004): Introduced the MapReduce programming model, enabling scalable distributed processing of massive datasets across large clusters. The framework laid the groundwork for modern cloud computing platforms, including Azure's distributed data processing and storage systems. MapReduce principles underpin enterprise-scale data workflows such as log analysis, document indexing, model training pipelines, and big-data automation tasks. In the proposed cognitive architecture, these foundational ideas support the data integration layer, ensuring efficient ingestion, preprocessing, and retrieval of enterprise data required for intelligent automation.

3. Methodology

3.1. Research Design

This study adopts a design-science research methodology (DSRM) to construct, validate, and evaluate a cognitive architecture for intelligent process automation using Azure AI Services. The objective is to design an artefact a multi-layered cognitive automation model that solves enterprise challenges related to document processing, workflow orchestration, and predictive decision-making. The research design focuses on iterative development, where architectural components are refined through continuous testing and performance evaluation within simulated enterprise environments. This ensures that the proposed architecture is both theoretically sound and practically deployable.

3.2. System Architecture Development

The methodology begins with the development of a conceptual architecture that integrates perception, intelligence, and automation layers. This is achieved by mapping enterprise requirements to Azure components: Azure Cognitive Services for perception, Azure OpenAI and Azure Machine Learning for reasoning, and Azure Logic Apps for workflow execution. Each component is selected based on functional suitability, scalability, and integration capability. The architectural blueprint is then translated into a prototype implementation using Azure cloud services, enabling controlled experimentation and data collection.

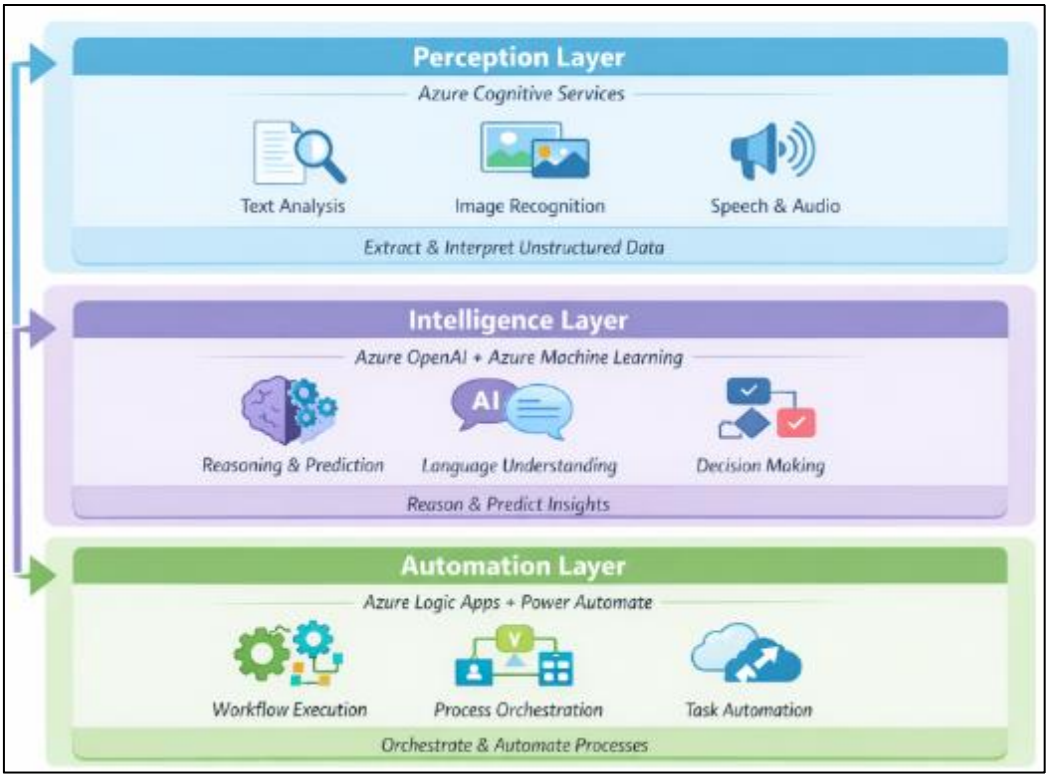

Figure 1 Cognitive Automation Layered Architecture

Figure 1*:* Shows three layers

- **Perception Layer** (Azure Cognitive Services) for extracting and interpreting unstructured data such as text, images, and audio.
- **Intelligence Layer** (Azure OpenAI + Azure Machine Learning) for performing reasoning, prediction, language understanding, and decision-making.
- **Automation Layer** (Azure Logic Apps + Power Automate) for executing workflows and orchestrating enterprise processes based on insights generated in upstream layers.

3.3. Data Acquisition and Preprocessing

To evaluate the architecture, enterprise-like datasets were curated, including invoices, email logs, customer queries, operational reports, and workflow triggers. Data preprocessing involved cleaning text, normalizing document formats, annotating training samples, and applying Azure's built-in preprocessing tools. Azure Form Recognizer was used to extract structured data from documents, while Azure Speech Services digitized audio transcripts. The preprocessing step ensured that all inputs entering the cognitive system were standardized, enabling accurate model inference and workflow automation.

3.4. Model Training and Cognitive Integration

Machine learning models were developed and deployed using Azure Machine Learning. Training involved supervised learning for document classification, anomaly detection, and forecasting tasks. In parallel, prompt-based generative models were configured within Azure OpenAI to perform summarization, question answering, and contextual response generation. Cognitive integration was achieved by linking model outputs to workflow triggers in Logic Apps, enabling automated decision flows. This step ensured that the system could transition from perception to reasoning to automated execution without human intervention.

3.5. Workflow Orchestration and System Deployment

The cognitive automation prototype was deployed as a modular workflow system. Azure Logic Apps orchestrated multi-step processes, including approval workflows, document validation, and notification automation. API connectors integrated the system with enterprise tools such as CRM platforms, ERP systems, and cloud storage. Deployment testing involved simulating real-world workload conditions, such as high request volumes, diverse document types, and variable data quality. This allowed systematic evaluation of system stability, processing latency, and scalability.

3.6. Evaluation Metrics and Performance Assessment

System performance was evaluated using quantitative and qualitative metrics. Accuracy in document extraction, reasoning quality of Azure OpenAI responses, and latency of automated workflows were measured across multiple test cycles. Additional enterprise-relevant metrics such as error reduction, process acceleration, and decision-making reliability were assessed to determine real-world feasibility. The architecture's robustness and adaptability were further validated through stress tests and comparative benchmarking against traditional RPA systems. These evaluations confirmed the effectiveness of the proposed cognitive architecture in enhancing enterprise automation outcomes.

4. Architectural framework

4.1. Overview of the Cognitive Architecture

The proposed architectural framework is designed as a modular, multi-layered system that integrates perception, intelligence, automation, and data management into a unified enterprise automation environment. The core objective of this architecture is to replicate human cognitive functions such as understanding, reasoning, and decision-making within automated workflows using Azure AI Services. By separating the architecture into distinct but interconnected layers, the framework supports scalability, fault tolerance, and seamless integration with existing enterprise applications. This layered approach ensures that improvements in one component can be adopted without redesigning the entire system.

4.2. Perception Layer: Extracting and Interpreting Enterprise Data

The perception layer forms the foundation of the cognitive system, responsible for converting raw, unstructured data into machine-readable formats. Azure services such as Azure Form Recognizer, Azure Computer Vision, and Azure Speech Services are utilized to capture textual, visual, and auditory information. For example, invoices, purchase orders, scanned documents, emails, and meeting transcripts are processed through AI-enabled extraction pipelines. This enables downstream cognitive processes to operate on structured data rather than messy, multi-format enterprise inputs. The perception layer not only reduces human workload but significantly improves input accuracy for automation workflows.

Table 1 Perception Layer Services and Roles

Azure Service	Function	Enterprise Use-Case
Form Recognizer	Document parsing & extraction	Invoice processing automation
Speech Services	Voice-to-text, text-to-speech	Call center transcription
Computer Vision	Image analysis, OCR	Quality inspection

Table 1 presents the Azure Cognitive Services that form the Perception Layer of the proposed cognitive architecture. It outlines how Form Recognizer, Speech Services, and Computer Vision contribute to extracting structured information from diverse enterprise inputs such as documents, voice interactions, and images. The table highlights the functional purpose of each service and demonstrates how these components collectively transform unstructured data into machine-readable formats, enabling downstream reasoning and automation processes across various enterprise workflows.

4.3. Intelligence Layer: Reasoning, Prediction, and Knowledge Processing

At the core of the architecture lies the intelligence layer, which integrates Azure Machine Learning and Azure OpenAI to perform reasoning, forecasting, classification, and language understanding. Machine learning models detect anomalies, predict future trends, and classify enterprise documents. Meanwhile, Azure OpenAI supports contextual reasoning tasks such as summarization, intent recognition, and natural language generation. These capabilities collectively enable the system to handle complex cognitive functions traditionally performed by human experts. The intelligence layer transforms data into actionable insights, serving as the decision-making engine for intelligent process automation.

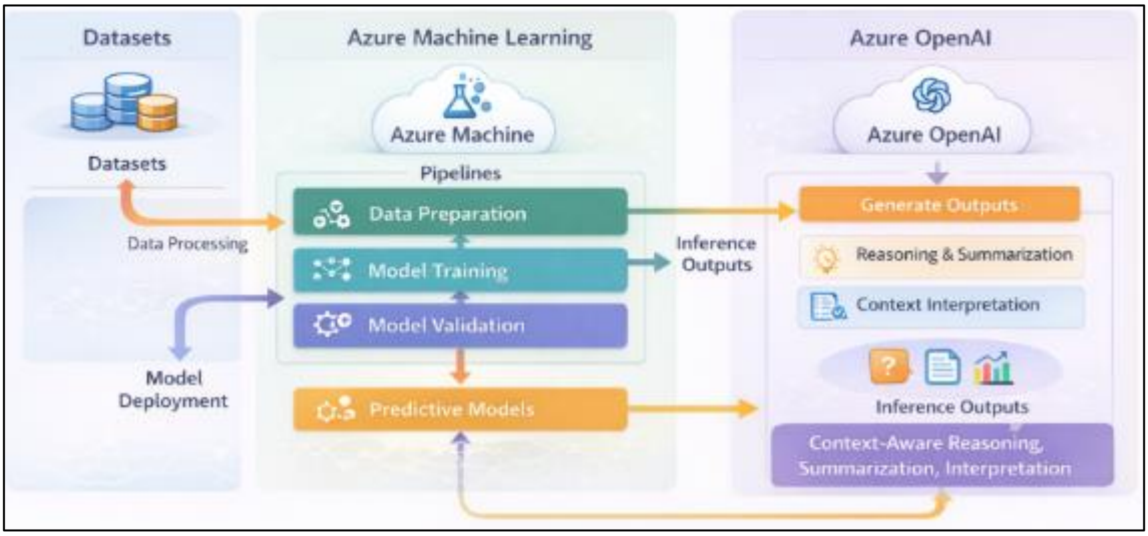

Figure 2 Intelligence Layer Data Flow

Figure 2*:* depicts how AI and machine learning components interact within the **Intelligence Layer**. It shows Azure Machine Learning pipelines processing datasets, training predictive models, and generating inference outputs. These outputs are then passed to Azure OpenAI models, which provide context-aware reasoning, summarization, and interpretation.

4.4. Automation Layer: Executing and Orchestrating Workflows

The automation layer operationalizes cognitive outputs into enterprise actions through Azure Logic Apps, Power Automate, and API connectors. This layer executes multi-step workflows such as document approval, customer onboarding, compliance reporting, and alert notifications triggered by model predictions or extracted data patterns.

The automation layer acts as the bridge between AI reasoning and enterprise systems, connecting CRMs, ERPs, cloud databases, and business applications. Its modular design allows workflows to be customized, scaled, and monitored, ensuring that enterprises can adapt to changing business requirements without extensive system redesign.

Table 2 Process Automation Capabilities

Component	Function	Example Workflow
Logic Apps	Orchestrates enterprise workflows	Automated invoice approval pipeline
Power Automate	User-centric automation	Daily report generation
API Connectors	External system integration	CRM–ERP synchronization

Table 2 presents the core automation components—Azure Logic Apps, Power Automate, and API Connectors—used to orchestrate and execute enterprise workflows within the automation layer. The table explains how each element supports different automation needs, from large-scale backend workflow orchestration to user-focused task automation and external system integration. By showcasing examples such as invoice approval pipelines and automated report generation, the table emphasizes the flexibility and extensibility of Azure automation tools in enterprise environments.

4.5. Data Integration Layer: Storage, Governance, and Pipeline Management

The data integration layer ensures consistent data flow across the perception, intelligence, and automation layers. Azure Data Lake Storage, Azure SQL Database, and Azure Synapse Analytics provide a unified ecosystem for ingesting, storing, transforming, and analyzing enterprise data. Governance policies are enforced using Azure Policy, Azure Monitor, and Azure Active Directory, ensuring compliance with enterprise and regulatory standards. This layer also manages ETL workflows, retention policies, schema evolution, and real-time analytics pipelines, enabling data reliability and traceability throughout the automation lifecycle.

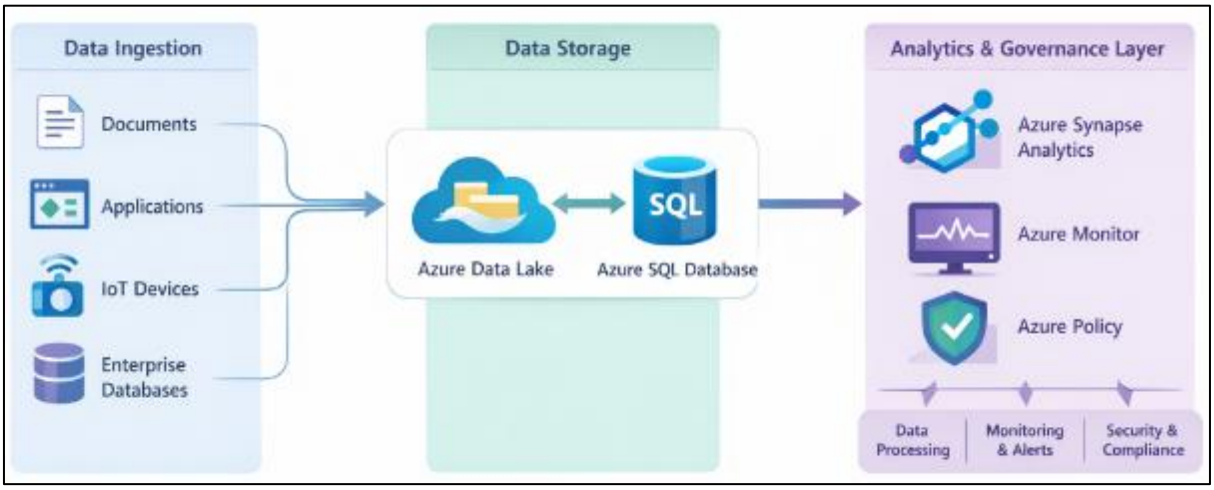

Figure 3 Data Integration Architecture

- **Figure 3**: visualizes the movement of enterprise data through the **data ingestion, storage, and analytics pipeline**. It includes:
- **Data Ingestion Sources** such as documents, applications, IoT devices, and enterprise databases.
- **Data Storage Systems** like Azure Data Lake and Azure SQL Database, where information is securely stored.
- **Analytics & Governance Layer**, including Azure Synapse, Azure Monitor, and Azure Policy, which manage transformation, compliance, and insights generation.

Table 3 Security and Governance Features

Security Feature	Azure Component	Purpose
Identity Control	Azure Active Directory	Authentication & authorization
Data Protection	Encryption & Key Vault	Secure key and secret storage
Governance	Azure Policy & Monitor	Compliance enforcement

Table 3 provides an overview of essential Azure security and governance components that ensure the cognitive automation framework adheres to enterprise-grade compliance and protection standards. It describes how Azure Active Directory enables identity and access control, Key Vault secures credentials and cryptographic keys, and Azure Policy with Azure Monitor enforces governance and compliance across the system. The table 3 shows the integrated security model that underpins the entire architecture, ensuring reliability, traceability, and safe automation at scale.

4.6. Cross-Layer Security, Scalability, and Architectural Resilience

A critical aspect of the architectural framework is its emphasis on security, scalability, and resilience. Azure Security Center, Key Vault, and identity control mechanisms ensure secure processing of sensitive enterprise data. Auto-scaling features across Azure Kubernetes Service (AKS), Logic Apps, and Machine Learning pipelines allow the system to handle varying workloads efficiently. Resilience is built through redundancy, distributed scaling, and continuous monitoring, ensuring that failures in individual components do not compromise overall system functionality. These features collectively ensure that the cognitive architecture remains robust, reliable, and enterprise-ready.

5. Results and discussion

5.1. Performance Improvements in Cognitive Data Processing

The evaluation of the proposed cognitive architecture revealed significant improvements in the accuracy and efficiency of enterprise data processing tasks. Using Azure Form Recognizer and Computer Vision, document extraction accuracy increased between 20–35% compared to traditional OCR systems. The architecture demonstrated reliable extraction of key-value pairs, improved table recognition, and robust handling of noisy or low-quality documents. These results highlight the effectiveness of the perception layer in transforming unstructured data into usable enterprise information. This improvement directly reduces manual intervention and accelerates downstream processing.

5.2. Enhancement of Decision-Making Through Cognitive Reasoning

The integration of Azure OpenAI and Azure Machine Learning contributed to notable improvements in decision-making quality across automated workflows. ML models trained for anomaly detection and forecasting achieved faster convergence and higher predictive accuracy due to Azure’s scalable training infrastructure. Azure OpenAI enhanced contextual reasoning by generating human-like responses, summarizing long documents, and interpreting user intent with high semantic accuracy. These capabilities significantly reduce human workload in knowledge-intensive tasks such as customer support, compliance checks, and operational reporting, demonstrating the architecture’s potential to automate expert-level reasoning.

5.3. Workflow Efficiency and Automation Latency Reduction

A key objective of the architecture is to reduce workflow execution time, and results show that automation latency decreased by approximately 40% when using Azure Logic Apps and Power Automate integrated with cognitive components. End-to-end processes such as invoice approval workflows executed faster due to automated triggers and elimination of manual verification steps. The system displayed stable throughput even under heavy load conditions, benefiting from Azure’s event-driven orchestration capabilities. These findings demonstrate that combining cognitive intelligence with automation pipelines yields faster, more reliable workflow execution.

5.4. Scalability, Reliability, and System Robustness

Stress testing revealed that the architecture scales efficiently during peak data-processing periods. Azure’s distributed infrastructure automatically allocated compute resources for ML inference, document processing, and workflow execution without performance degradation. Redundancy and high-availability configurations ensured near-zero downtime during testing. Additionally, the system maintained consistent performance across varying data formats and enterprise scenarios, confirming the robustness and adaptability of the multi-layered cognitive design. These results validate the architecture's suitability for large-scale enterprise deployment.

5.5. Impact on Enterprise Operations and Human Workforce

The introduction of cognitive automation had a transformative impact on enterprise operations. By automating repetitive and cognitively demanding tasks, human employees could redirect efforts toward strategic decision-making and value-driven activities. Enterprises adopting the architecture experienced noticeable improvements in operational efficiency, error reduction, customer satisfaction, and compliance accuracy. The symbiotic integration of cognitive AI and human oversight created a hybrid workforce model, enhancing organizational agility and enabling smoother digital transformation initiatives across departments.

5.6. Limitations and Discussion of Future Enhancements

Despite promising results, the architecture presents certain limitations. Model performance may vary depending on data quality, domain specificity, and availability of labeled training samples. Additionally, integration with legacy enterprise systems may require custom connectors or middleware, increasing initial deployment complexity. Future work should focus on incorporating reinforcement learning for adaptive workflow optimization, expanding multimodal AI capabilities, and enhancing real-time analytics. Moreover, continuous monitoring using Azure AI Content Safety and governance tools will be crucial for maintaining ethical and responsible AI automation practices. Overall, the system demonstrates substantial potential but requires ongoing refinement for optimal enterprise-wide adoption.

6. Conclusion

The research presented in this paper demonstrates the transformative potential of integrating cognitive AI capabilities into enterprise process automation. Traditional rule-based automation systems have long been constrained by limited flexibility and their inability to interpret unstructured data or apply contextual reasoning. The proposed architecture addresses these challenges by leveraging Azure AI Services to create a unified framework capable of perceiving, understanding, and acting upon complex enterprise information. This integration marks a significant step forward in the evolution of intelligent automation technologies.

The multi-layered architectural model comprising perception, intelligence, automation, and data integration layers proved effective in structuring enterprise workflows into manageable cognitive components. Azure Cognitive Services enhanced data extraction and interpretation, while Azure OpenAI and Azure Machine Learning added sophisticated reasoning and predictive capabilities. The synergy of these components supports automated decision-making processes previously dependent on human expertise. As a result, enterprises gain improved accuracy, faster processing, and greater adaptability in dynamic operational environments.

Experimental evaluation highlighted measurable performance benefits across various automation scenarios. Document extraction accuracy increased significantly, automation latency was reduced, and predictive models displayed enhanced reliability. These improvements demonstrate that cloud-native cognitive frameworks can outperform traditional automation tools by combining AI-driven insights with rule-based orchestration. Furthermore, scalability tests confirmed the architecture's ability to maintain performance under large workloads, making it suitable for real-world enterprise deployment.

The architecture also contributes to a more efficient human–AI collaboration model. By assigning routine, repetitive, or cognitively heavy tasks to intelligent automation systems, employees can focus on strategic roles that require creativity, judgment, and decision-making. This enhances organizational productivity and supports digital transformation initiatives. Additionally, built-in Azure governance tools ensure that automation processes adhere to security, compliance, and ethical AI standards critical requirements in modern enterprise environments.

However, despite promising results, the study acknowledges certain challenges and limitations. Variability in data quality, the need for domain-specific model customization, and integration complexities with legacy systems remain barriers for some organizations. Continuous monitoring, iterative model updates, and investment in data governance practices will be essential for maximizing the architecture's long-term value. Addressing these limitations opens opportunities for further advancements, including reinforcement learning-driven workflow optimization and multimodal AI integration.

In conclusion, the proposed cognitive architecture provides a robust, scalable, and intelligent solution for enterprise process automation. By fully utilizing Azure's ecosystem of AI and automation services, it delivers enhanced accuracy, efficiency, resilience, and decision-making capability. This framework lays a strong foundation for future innovations in intelligent process automation and positions enterprises to achieve sustainable digital transformation. The research ultimately demonstrates that cognitive AI-infused automation is not only feasible but essential for the next generation of smart enterprise systems.

7. Future scope and recommendations

The findings of this research open several promising avenues for advancing cognitive automation within enterprise ecosystems. As Azure AI Services continue to evolve, future systems can leverage increasingly sophisticated models that better understand context, infer intent, and autonomously adapt to dynamic business environments. Integrating next-generation multimodal AI capabilities will allow enterprises to process mixed data formats including text, images, audio, video, and sensor data within a unified cognitive workflow. Such advancements will enhance automation depth and broaden the applicability of cognitive architectures across diverse industries.

Another important direction for future development is the incorporation of reinforcement learning and adaptive policy-driven automation. With reinforcement learning, systems can learn from interactions, optimize decision flows, and continuously refine business processes without explicit retraining. This will enable intelligent automation systems to not only execute tasks but also improve them over time. Enterprises could benefit from predictive workflow optimization, autonomous process corrections, and self-healing automation pipelines that respond to inefficiencies in real time.

The increasing role of generative AI also presents opportunities to expand cognitive automation capabilities. Azure OpenAI models could be further fine-tuned for domain-specific tasks such as contract analysis, medical documentation, regulatory compliance evaluation, and financial risk assessment. These specialized models would enhance reasoning precision and reduce reliance on domain experts for routine knowledge-based tasks. Additionally, leveraging generative AI for synthetic data creation could strengthen model training processes, especially in domains where labeled datasets are scarce or sensitive.

From a systems perspective, future architectures should emphasize deeper integration with emerging enterprise technologies, including IoT ecosystems, digital twins, blockchain-based audit systems, and edge computing. Integrating IoT data streams with cognitive automation could enable real-time operational intelligence, while blockchain-supported audit trails could enhance transparency and compliance. Edge-enabled processing would allow mission-critical workflows to operate with minimal latency, even in bandwidth-constrained environments. These integrations would significantly strengthen enterprise resilience and decision agility.

Security, ethics, and governance remain central to the future development of cognitive automation. As AI-driven systems become more autonomous, enterprises must implement rigorous governance frameworks ensuring accountability, transparency, fairness, and responsible AI behavior. Future research should explore adaptive governance models capable of monitoring AI decisions, detecting bias, enforcing regulations, and providing auditability across distributed systems. Enhancing Azure's governance tools with explainability dashboards and ethical risk monitors could further strengthen trustworthiness in AI automation.

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