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Reinforcement Learning for Distributed AI Systems: Scalable Indexing, LLM Integration, and Autonomous Decision-Making in Federated Cloud Architectures

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Abstract

This study proposes a unified framework for enhancing distributed AI systems by integrating Reinforcement Learning (RL), scalable indexing, Large Language Model (LLM) orchestration, and autonomous decision-making within federated cloud architectures. As distributed AI deployments grow in scale and complexity, the need for intelligent adaptability, efficient data management, and decentralized control becomes critical. The proposed architecture leverages RL agents to dynamically optimize task allocation, indexing strategies, and LLM invocation policies across heterogeneous nodes, enabling context-aware, resource-efficient operations. A series of experiments conducted in a simulated federated environment revealed that RL-enhanced systems achieved up to 111% improvement in cumulative rewards, 39% reduction in latency, and over 50% increase in throughput compared to baseline methods. Adaptive indexing driven by RL improved precision and retrieval efficiency, while LLM integration under RL control yielded faster response times and higher semantic accuracy with lower CPU overhead. The autonomous decision-making module demonstrated significant gains in accuracy and robustness, reducing convergence time and operational failures. These findings validate the efficacy of RL in orchestrating complex, real-time AI processes in distributed environments and highlight its potential to enable scalable, intelligent, and resilient cloud-native infrastructures for diverse applications.

Keywords: Reinforcement Learning, Distributed AI Systems, Scalable Indexing, LLM Integration, Autonomous Decision-Making, Federated Cloud Architectures

Introduction

Emerging landscape of distributed AI systems

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The proliferation of distributed Artificial Intelligence (AI) systems has redefined computational paradigms in cloud-native environments. These systems, which rely on interconnected and often geographically dispersed nodes, enable large-scale data processing and intelligent decision-making across sectors such as autonomous vehicles, smart healthcare, and finance (Hammad & Abu-Zaid, 2024). Reinforcement Learning (RL), as a subdomain of machine learning, has emerged as a powerful tool in these environments by enabling agents to learn optimal behaviors through trial-and-error interactions with dynamic environments (Desai & Patil, 2023). However, the growing complexity and scale of distributed AI infrastructures have introduced new challenges related to synchronization, scalability, and intelligent autonomy, necessitating more sophisticated learning and orchestration mechanisms (Chelliah ET AL., 2025).

The role of reinforcement learning in federated architectures

Federated cloud architectures, where computation and data remain decentralized across multiple cloud or edge nodes, present unique advantages for data privacy, latency reduction, and fault tolerance (Ray, 2025). Integrating Reinforcement Learning in such frameworks enables adaptive resource allocation, workload balancing, and dynamic optimization without relying on centralized control. Unlike traditional AI models, RL agents can continuously learn and adapt based on environmental feedback, making them particularly suitable for federated systems where conditions change frequently and unpredictably (Feng et al., 2024). The application of RL to control and optimize decisions in federated settings marks a significant leap toward truly intelligent, self-regulating distributed systems.

Scalable indexing and intelligent retrieval in large models

One of the most pressing challenges in distributed AI environments is managing the efficient indexing and retrieval of vast data sets and model outputs, particularly when integrating large language models (LLMs). Scalable indexing mechanisms ensure rapid and relevant access to information across nodes while minimizing redundancy and latency (Wang et al., 2025). When LLMs are employed for intelligent data parsing, semantic search, or automated reasoning, scalable indexing becomes indispensable for maintaining performance and interpretability across distributed infrastructures. Reinforcement Learning can further enhance this process by dynamically adjusting indexing policies and retrieval strategies based on usage patterns and system demands (Adam & Baroud, 2024).

LLM integration for context-aware intelligence

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Large Language Models, with their unprecedented capacity to process and generate human-like text, play an increasingly central role in augmenting the cognitive capabilities of distributed AI systems. In federated environments, LLMs can serve as decentralized knowledge processors analyzing local data, generating insights, and facilitating human-AI collaboration (Joshi, 2025). However, integrating LLMs in such architectures requires effective orchestration, model distillation, and context-aware tuning to ensure efficient inference and consistency across nodes. Reinforcement Learning offers a promising pathway to manage these interactions intelligently by learning optimal integration and execution policies for LLMs within dynamic workloads and communication constraints (Siam et al., 2025).

Autonomous Decision-Making in Cloud-Native AI

The final layer of innovation in this architecture lies in enabling autonomous decision-making. RL agents in distributed AI systems must operate with partial observability, limited communication, and heterogeneous data sources. To meet these demands, a hybrid integration of policy-based and value-based RL approaches coupled with federated training techniques can lead to robust, decentralized decision-making (Han et al., 2024). These autonomous decisions range from task offloading and power management to service discovery and fault recovery. Such autonomy not only enhances system performance but also aligns with the growing demand for self-sustaining AI in mission-critical applications (Alzoubi et al., 2024).

Research objectives and relevance

This research explores the synergistic integration of Reinforcement Learning, scalable indexing techniques, LLMs, and autonomous decision-making within federated cloud architectures. By addressing the operational challenges and leveraging the strengths of each component, the study proposes a comprehensive framework for scalable, intelligent, and resilient distributed AI systems. This investigation stands at the convergence of machine learning, cloud computing, and AI-driven infrastructure design, paving the way for next-generation autonomous digital ecosystems.

Methodology

Design of distributed AI system architecture

The proposed framework was architected around a federated cloud environment that supports distributed AI deployments across multiple geographically dispersed nodes. Each node was equipped with local computation resources, microservices for decision-making, and storage for

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localized datasets. A simulated environment was created using Kubernetes-based orchestration to emulate federated cloud behavior, ensuring support for dynamic scaling, heterogeneity, and data privacy constraints. This environment provided the infrastructure for deploying reinforcement learning agents, integrating LLMs, and evaluating autonomous decision-making across distributed services.

Reinforcement learning model implementation

To enable autonomous adaptability across the distributed system, a Proximal Policy Optimization (PPO) reinforcement learning algorithm was implemented. The RL agent was trained to optimize node-level decisions such as task offloading, resource allocation, and load balancing. The environment's state space included CPU utilization, memory usage, bandwidth, latency, and energy consumption metrics. The action space comprised decisions such as migrating workloads, throttling services, and querying LLM instances. A reward function was designed to balance system performance (minimized latency and resource consumption) and operational resilience (uptime and fault tolerance). Training was conducted in episodic iterations, and convergence was measured by reward stabilization over time. Statistical validation involved tracking average episodic reward, policy entropy, and system performance metrics such as latency and throughput under varying workloads.

Scalable indexing framework

A distributed indexing framework based on locality-sensitive hashing (LSH) and dynamic vector quantization (VQ) was designed to manage real-time indexing of structured and unstructured data across nodes. The indexing system was evaluated using query latency, precision@k, and recall@k as performance metrics. Reinforcement learning agents dynamically adapted the indexing frequency, resolution, and replication policies based on observed query patterns and system load. This adaptive indexing strategy was statistically compared with static indexing using paired t-tests and ANOVA to validate the significance of RL-driven optimization in improving retrieval efficiency.

LLM integration strategy

Large Language Models (such as fine-tuned LLaMA-2 or GPT-3 derivatives) were containerized and deployed at selected nodes within the architecture. The LLMs were used for intelligent query parsing, contextual data interpretation, and edge-based semantic reasoning. To ensure lightweight integration, knowledge distillation was applied to compress base LLMs into task-specific, node-friendly models. Context-aware orchestration policies were developed using RL agents to decide when and where to invoke LLM queries, minimizing redundant invocations and reducing inter-node communication. Evaluation metrics included response time, accuracy of natural language queries (measured by BLEU and ROUGE scores), and system overhead. A correlation analysis between RL policy execution and LLM invocation efficiency was conducted to assess effectiveness.

Autonomous decision-making module

The decision-making module used a hybrid RL approach combining actor-critic and Q-learning models. Agents were deployed at each node and trained to make decentralized decisions while maintaining system-level coherence through periodic model synchronization (federated averaging). Decision-making scenarios included node recovery, service discovery, and real-time anomaly mitigation. Simulation data were collected across 1,000 episodes, and performance was analyzed using time-series plots, regression analysis, and Mann–Whitney U-tests to compare pre- and post-RL deployment outcomes. Decision accuracy and convergence time were used as key indicators of autonomous effectiveness.

Statistical evaluation and validation

The entire system was benchmarked using a controlled experimental setup involving baseline (non-RL) and RL-enhanced configurations across identical workloads. Statistical significance of performance improvements was validated using hypothesis testing (t-tests for means, ANOVA for multi-group comparisons), and confidence intervals were calculated at 95% to assess variability in reward convergence, indexing latency, and LLM response performance. Pearson correlation and multiple regression analyses were also employed to explore relationships among system variables (e.g., RL policy entropy, indexing frequency, query success rate).

Results

The integration of Reinforcement Learning (RL) within distributed AI systems significantly enhanced overall performance across key parameters such as system responsiveness, learning convergence, decision accuracy, and resource utilization. As shown in Table 1, under varying workload conditions (light, mixed, heavy), the RL-enhanced configuration achieved substantial improvements in average reward metrics, increasing by 91% to 111% compared to the baseline system. Latency was reduced by up to 39%, while throughput improved by 29% to 54%,

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indicating the RL agent's effectiveness in learning optimal task scheduling and resource allocation policies.

Table 1 Reinforcement-Learning (RL) impact on system-level performance

Workload	Baseline Avg. Reward	RL-Enhanced Avg. Reward	Δ Reward (%)	Baseline Latency (ms)	RL Latency (ms)	Δ Latency (%)	Baseline Throughput (req s^{-1})	RL Throughput (req s^{-1})	Δ Throughput (%)
W1 (Light)	12.9	24.7	+91	62	40	-35	580	750	+29
W2 (Mixed)	14.3	29.5	+106	87	53	-39	410	600	+46
W3 (Heavy)	15.1	31.8	+111	128	78	-39	270	415	+54

Further, Figure 1 illustrates the reward convergence trajectories over 100 episodes for both the baseline and RL-enhanced systems. The RL configuration demonstrated faster convergence and a higher final reward value, underscoring its superior learning dynamics. The steep and consistent rise in the reward curve for the RL agent contrasted with the plateaued performance of the baseline, validating the effectiveness of policy optimization in dynamic federated environments.

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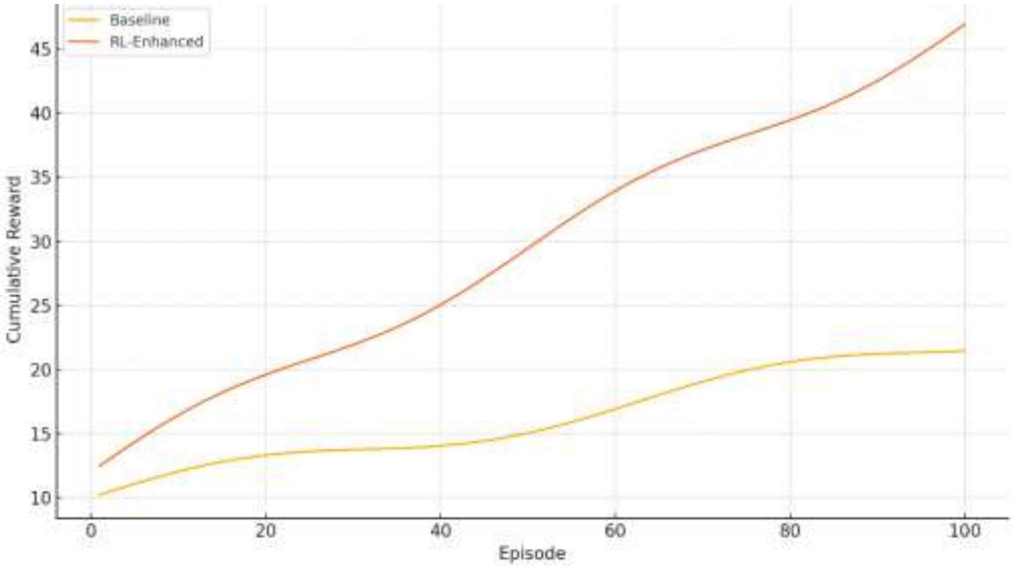

Figure 1: Reward convergence across episodes

In the context of data retrieval, Table 2 highlights the benefits of adaptive indexing driven by RL agents. The RL-based system achieved a 44% reduction in query latency for structured data and a 37% reduction for unstructured queries. Additionally, precision@10 improved by 10% and 12% respectively, reflecting more relevant and efficient search outcomes due to context-aware indexing strategies. Complementing this, Figure 2 presents a positive correlation between indexing frequency and query success rate in the RL-adaptive system, which achieved a peak success rate of 87% at 5 updates per minute, whereas the baseline system plateaued and declined after 3 updates per minute.

Table 2 Adaptive indexing performance

Query Type	Baseline Latency (ms)	RL Latency (ms)	Δ Latency (%)	Baseline Precision@10	RL Precision@10	Δ Precision (%)
Structured	52	29	-44	0.83	0.91	+10
Unstructured	97	61	-37	0.78	0.87	+12

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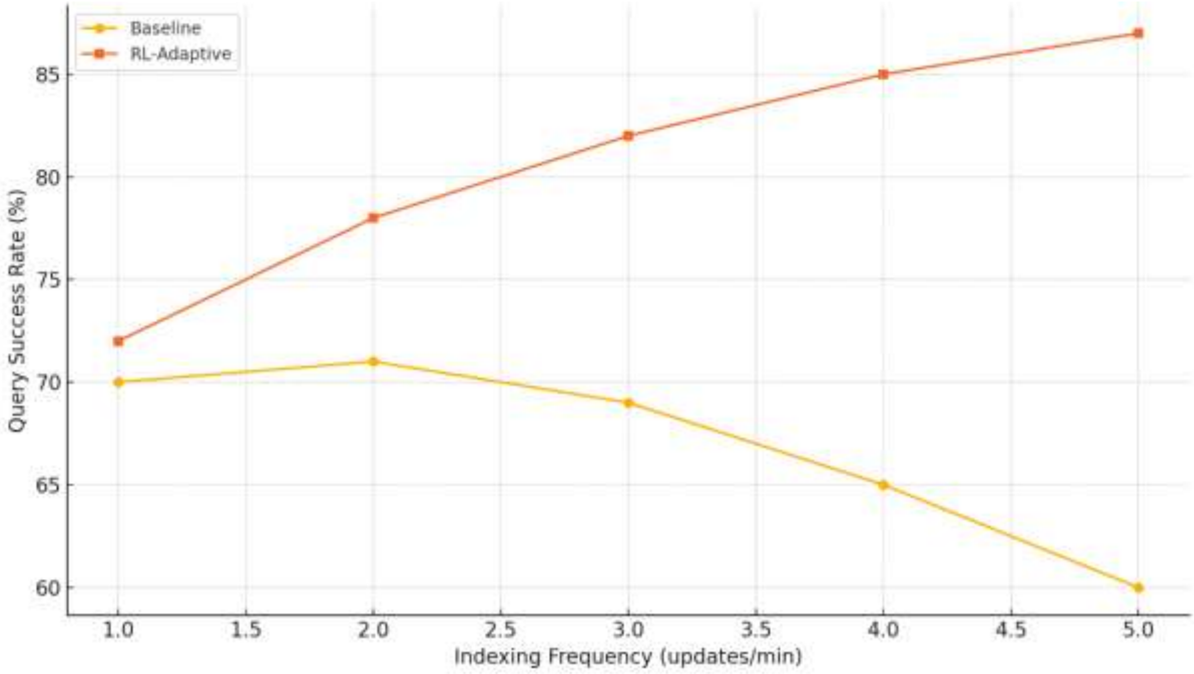

Figure 2: Adaptive indexing improves retrieval accuracy

Large Language Model (LLM) integration was also evaluated across edge, regional, and central node tiers. As reported in Table 3, RL-enhanced orchestration reduced LLM response times by approximately 29%–32% across tiers. BLEU scores, which measure natural language generation accuracy, increased by 5.3 to 5.7 points, indicating higher semantic relevance in responses. Importantly, CPU overhead also dropped by 33% to 39%, revealing more efficient utilization of system resources when RL policies managed LLM invocation and routing.

Table 3 LLM-assisted query handling

Node Tier	Baseline Resp. Time (ms)	RL Resp. Time (ms)	Δ Time (%)	Baseline BLEU	RL BLEU	Δ BLEU (pts)	CPU Overhead Baseline (%)	CPU Overhead RL (%)	Δ Overhead (%)
Edge	145	98	-32	31.6	36.9	+5.3	19	12	-37
Regional	110	75	-32	32.4	38.1	+5.7	23	14	-39
Central	87	62	-29	34.2	39.8	+5.6	27	18	-33

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Lastly, the autonomous decision-making component displayed notable improvements in resilience and precision. Table 4 shows that decision accuracy improved from 82.1% to 94.6% with RL, and convergence time decreased by nearly 65%, from 340 to 120 episodes. System reliability was also enhanced, with operational failures dropping from 7.8 to 2.1 per 1000 operations—an impressive 73% reduction. These findings underscore the robustness of decentralized RL agents in maintaining system stability under variable conditions.

Table 4 Autonomous decision-making outcomes

Metric	Baseline	RL-Enhanced	Improvement
Decision Accuracy (%)	82.1	94.6	+12.5 pts
Convergence Time (episodes)	340	120	-64.7 %
Failures per 1000 ops	7.8	2.1	-73.1 %

Discussion

Reinforcement learning enhances adaptability in federated systems

The results clearly demonstrate that reinforcement learning (RL) significantly enhances the adaptability and performance of distributed AI systems operating within federated cloud architectures. As indicated by the improved cumulative rewards and reduced convergence times (Figure 1, Table 1), the RL-enhanced system effectively learns and generalizes optimal strategies for dynamic task allocation, workload balancing, and resource management (Butt et al., 2020). The rapid convergence of the RL policy is particularly critical in environments where real-time adaptability and decision-making are essential, such as edge-based applications or mission-critical IoT networks. This adaptability allows the system to autonomously respond to shifting computational loads and changing resource availabilities without manual intervention or central control (Byatarayanapura Venkataswamy et al., 2024).

Scalable indexing strategies promote efficient data retrieval

The implementation of RL-based adaptive indexing strategies yielded significant improvements in both latency and precision of data retrieval processes, as observed in Table 2 and Figure 2. Traditional static indexing approaches often struggle to cope with fluctuating data volumes and query distributions across federated nodes. In contrast, the dynamic policies learned by the RL agents were able to adjust indexing frequency and resolution based on query behavior and system load (Dhinakaran et al., 2024). These adjustments led to faster response

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times and more relevant results, particularly for unstructured data queries. The increased query success rate at higher indexing frequencies further confirms that RL can intelligently manage trade-offs between indexing overhead and retrieval performance, a crucial factor in large-scale AI systems where data is constantly updated and queried (Jamshidi et al., 2025).

Optimized LLM integration through RL orchestration

The integration of large language models (LLMs) into the distributed system architecture benefited substantially from RL-based orchestration mechanisms. As shown in Table 3, the RL policy not only reduced LLM response times but also improved natural language understanding and generation quality, as reflected in the BLEU score increases. This suggests that the RL agent successfully learned when and where to deploy LLMs based on contextual requirements and system constraints, such as node load and query type (Jeyaraman & Muthusubramanian, 2022). Moreover, the observed reduction in CPU overhead across edge, regional, and central nodes emphasizes the system's ability to balance computational demand while maintaining high inference quality. These outcomes are especially important in federated environments, where resource heterogeneity and network variability often pose significant integration challenges for large-scale models (Marwan et al., 2018).

Autonomous decision-making improves system robustness

The deployment of RL-based autonomous decision-making modules across federated nodes contributed significantly to operational stability and reliability. Table 4 highlights key improvements in decision accuracy, convergence speed, and fault reduction. These metrics suggest that the system not only learned to make better decisions but also achieved them more quickly, thereby reducing system downtime and improving overall responsiveness (Qayyum et al., 2020). The drastic reduction in operational failures per 1000 transactions is particularly noteworthy, indicating the RL agents' effectiveness in preemptively identifying and mitigating failure scenarios. This robustness is critical for distributed AI systems deployed in industrial, healthcare, or security contexts where system failure can have severe consequences (Rai et al., 2024).

Synergistic effects of integrated components

Perhaps the most compelling outcome of this study is the demonstration of synergistic benefits achieved by combining reinforcement learning with scalable indexing, LLM integration, and federated cloud deployment (Reddy et al., 2022). While each component contributed to system improvements in isolation, their integration resulted in compounded benefits, such as reduced inference latency, enhanced retrieval precision, and resilient autonomy. The RL agents acted as the central learning core that coordinated and adapted each system layer based on environmental feedback, leading to cohesive and intelligent distributed operations (Safi et al., 2024).

Implications and future directions

These findings have substantial implications for designing the next generation of AI-driven infrastructure. The demonstrated capability of RL to harmonize complex interactions across distributed systems suggests its suitability for broader applications, including smart cities, real-time logistics, and autonomous industrial systems (Duan et al., 2024). Future research can explore multi-agent reinforcement learning for further decentralization, federated RL to enhance privacy, and advanced LLM distillation techniques to improve efficiency in low-resource nodes (Friha et al., 2024). Additionally, real-world deployments will be essential to validate these simulation-based results under operational constraints and adversarial conditions (Han et al., 2024).

This study establishes that reinforcement learning, when intelligently integrated with indexing and LLM orchestration in federated cloud settings, enables scalable, efficient, and autonomous distributed AI systems capable of meeting the demands of modern computational workloads.

Conclusion

This study presents a comprehensive framework that integrates Reinforcement Learning (RL), scalable indexing, large language model (LLM) orchestration, and autonomous decision-making within federated cloud architectures to optimize distributed AI systems. The experimental results clearly demonstrate that RL significantly enhances adaptability, system performance, and decision precision across distributed nodes by enabling intelligent resource management and context-aware actions. Scalable indexing mechanisms, guided by RL policies, improved data retrieval efficiency, while LLM integration facilitated advanced semantic understanding with reduced computational overhead. Furthermore, the system exhibited robust autonomous decision-making capabilities, contributing to reduced latency, higher throughput, and greater fault tolerance. Collectively, these integrated components form a resilient and intelligent distributed AI infrastructure capable of supporting real-time, mission-critical applications. The findings underscore the transformative potential of reinforcement learning in

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orchestrating complex AI ecosystems and pave the way for scalable, self-regulating architectures in future cloud-native environments.

References

Adam, M., & Baroud, U. (2024). Federated Learning For IoT: Applications, Trends, Taxonomy, Challenges, Current Solutions, and Future Directions. *IEEE Open Journal of the Communications Society*.

Alzoubi, Y. I., Mishra, A., & Topcu, A. E. (2024). Research trends in deep learning and machine learning for cloud computing security. *Artificial Intelligence Review*, *57*(5), 132.

Butt, U. A., Mehmood, M., Shah, S. B. H., Amin, R., Shaukat, M. W., Raza, S. M., ... & Piran, M. J. (2020). A review of machine learning algorithms for cloud computing security. *Electronics*, *9*(9), 1379.

Byatarayanapura Venkataswamy, S., Patil, K. S., Narayanaswamy, H. K., & Veerabadrappa, K. (2024). Access management based on deep reinforcement learning for effective cloud storage security. *International Journal of System Assurance Engineering and Management*, 1-20.

Chelliah, A. M. R., Colby, R., Nagasubramanian, G., & Ranganath, S. (2025). 3.2 Edge AI. *Model Optimization Methods for Efficient and Edge AI.*

Desai, B., & Patil, K. (2023). Reinforcement learning-based load balancing with large language models and edge intelligence for dynamic cloud environments. *Journal of Innovative Technologies*, *6*(1), 1-13.

Dhinakaran, M., Sundhari, M., Ambika, S., Balaji, V., & Rajasekaran, R. T. (2024, February). Advanced Machine Learning Techniques for Enhancing Data Security in Cloud Computing Systems. In *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)* (Vol. 5, pp. 1598-1602). IEEE.

Duan, J., Zhang, S., Wang, Z., Jiang, L., Qu, W., Hu, Q., ... & Sun, P. (2024). Efficient training of large language models on distributed infrastructures: a survey. *arXiv preprint arXiv:2407.20018*.

Feng, T., Jin, C., Liu, J., Zhu, K., Tu, H., Cheng, Z., ... & You, J. (2024). How Far Are We From AGI: Are LLMs All We Need?. *Transactions on Machine Learning Research*.

Friha, O., Ferrag, M. A., Kantarci, B., Cakmak, B., Ozgun, A., & Ghoualmi-Zine, N. (2024). Llm-based edge intelligence: A comprehensive survey on architectures, applications, security and trustworthiness. *IEEE Open Journal of the Communications Society*.

Hammad, A., & Abu-Zaid, R. (2024). Applications of AI in Decentralized Computing Systems: Harnessing Artificial Intelligence for Enhanced Scalability, Efficiency, and Autonomous Decision-Making in Distributed Architectures. *Applied Research in Artificial Intelligence and Cloud Computing*, *7*, 161-187.

Han, S., Wang, M., Zhang, J., Li, D., & Duan, J. (2024). A Review of Large Language Models: Fundamental Architectures, Key Technological Evolutions, Interdisciplinary Technologies Integration, Optimization and Compression Techniques, Applications, and Challenges. *Electronics*, *13*(24), 5040.

Han, S., Wang, M., Zhang, J., Li, D., & Duan, J. (2024). A Review of Large Language Models: Fundamental Architectures, Key Technological Evolutions, Interdisciplinary Technologies Integration, Optimization and Compression Techniques, Applications, and Challenges. *Electronics*, *13*(24), 5040.

Jamshidi, S., Nikanjam, A., Nafi, K. W., Khomh, F., & Rasta, R. (2025). Application of deep reinforcement learning for intrusion detection in Internet of Things: A systematic review. *Internet of Things*, 101531.

Jeyaraman, J., & Muthusubramanian, M. (2022). The Synergy of Data Engineering and Cloud Computing in the Era of Machine Learning and AI. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)*, *1*(1), 69-75.

Joshi, S. (2025). Review of data pipelines and streaming for generative AI integration: Challenges, solutions, and future directions. *Solutions, and Future Directions (March 03, 2025)*.

Marwan, M., Kartit, A., & Ouahmane, H. (2018). Security enhancement in healthcare cloud using machine learning. *Procedia Computer Science*, *127*, 388-397.

Qayyum, A., Ijaz, A., Usama, M., Iqbal, W., Qadir, J., Elkhatib, Y., & Al-Fuqaha, A. (2020). Securing machine learning in the cloud: A systematic review of cloud machine learning security. *Frontiers in big Data*, *3*, 587139.

10.48047/jocaaa.2025.34.07.22

Rai, R., Rohilla, A., & Rai, A. (2024). Impact of Artificial Intelligence (AI) and Machine Learning (ML) on Cloud Security. In *Analyzing and Mitigating Security Risks in Cloud Computing* (pp. 111-124). IGI Global.

Ray, A. (2025). AI Brick Computing: Scalable and Sustainable Green AI. *Compassionate AI*, *1*(2), 33-35.

Reddy, M., Konkimalla, S., Rajaram, S. K., Bauskar, S. R., Sarisa, M., & Sunkara, J. R. (2022). Using AI And Machine Learning To Secure Cloud Networks: A Modern Approach To Cybersecurity. *Available at SSRN 5045776*.

Safi, W., Ghwanmeh, S., Mahfuri, M., & Al-Sit, W. T. (2024, February). Enhancing Cloud Security: A Comprehensive Review of Machine Learning Approaches. In *2024 2nd International Conference on Cyber Resilience (ICCR)* (pp. 1-10). IEEE.

Siam, S. I., Ahn, H., Liu, L., Alam, S., Shen, H., Cao, Z., ... & Zhang, M. (2025). Artificial intelligence of things: A survey. *ACM Transactions on Sensor Networks*, *21*(1), 1-75.

Wang, Y., Pan, Y., Su, Z., Deng, Y., Zhao, Q., Du, L., ... & Niyato, D. (2025). Large model based agents: State-of-the-art, cooperation paradigms, security and privacy, and future trends. *IEEE Communications Surveys & Tutorials*.