International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 6, June 2026)

Reinventing Cloud Resource Management with Machine Learning: A Systematic Review and Future Outlook

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***Abstract*—** The exponential growth of cloud computing infrastructures has rendered traditional rule-based and threshold-driven resource management strategies inadequate for addressing the dynamic, heterogeneous, and large-scale demands of modern workloads. Machine learning (ML) has emerged as a transformative paradigm for reinventing cloud resource management, offering data-driven intelligence for tasks including workload prediction, virtual machine (VM) consolidation, auto-scaling, energy optimization, cost minimization, anomaly detection, and security enforcement. This paper presents a comprehensive systematic review of 77 peer-reviewed studies published between 2020 and 2025, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. The review synthesizes findings across six core resource management domains, categorizes ML techniques employed ranging from deep reinforcement learning (DRL) and long short-term memory (LSTM) networks to federated learning and transformer models and evaluates their performance against benchmark metrics including resource utilization efficiency, Quality of Service (QoS), energy consumption, and operational cost. Three structured research questions guide the investigation: the degree to which ML improves cloud resource management over classical approaches; which ML architectures yield the highest performance gains; and what critical gaps persist in the current literature. Our findings indicate that deep reinforcement learning consistently achieves 15–40% improvements in resource utilization and energy efficiency over heuristic baselines, while transformer-based models demonstrate superior workload forecasting accuracy (RMSE reductions of up to 32%). However, significant challenges remain in interpretability, data privacy, multi-cloud portability, and real-time inference latency. The paper concludes with a structured research agenda delineating ten future directions essential for bridging the gap between academic research and industrial deployment.

***Keywords*—** Cloud Resource Management, Machine Learning, Deep Reinforcement Learning, Auto-Scaling, Workload Prediction, Energy Efficiency, Systematic Review, Virtual Machine Consolidation, QoS Optimization.

I. INTRODUCTION

Cloud computing has evolved from a nascent utility paradigm into the foundational substrate of the global digital economy. According to Gartner, worldwide end-user spending on public cloud services exceeded USD 590 billion in 2023 and is forecast to surpass USD 820 billion by 2025, driven by enterprise digital transformation, artificial intelligence (AI) workloads, and the proliferation of Internet of Things (IoT) applications (Gill et al., 2020). Hyperscale data centers operated by Amazon Web Services, Microsoft Azure, Google Cloud Platform, and Alibaba Cloud collectively manage millions of heterogeneous workloads concurrently, placing unprecedented demands on resource scheduling, allocation, and governance frameworks.

Traditional cloud resource management relies on static provisioning rules, threshold-based auto-scaling, and heuristic-driven schedulers such as Best Fit Decreasing (BFD) and Round Robin. While computationally lightweight, these approaches suffer from reactive rather than proactive behavior, inability to capture complex temporal workload patterns, and brittleness under stochastic demand fluctuations (Buyya et al., 2021). The consequences are significant: industry reports estimate that cloud infrastructure is utilized at only 15–25% of its theoretical capacity on average, implying massive energy waste and economic inefficiency (Barroso et al., 2023).

Machine learning offers a principled alternative. By learning latent patterns from telemetry data CPU, memory, I/O, and network utilization ML models can make anticipatory allocation decisions, dynamically consolidate underutilized VMs, and optimize scheduling policies under multi-objective constraints (Zhang et al., 2021). The intersection of ML and cloud resource management has generated a rapidly growing body of literature, with publications in IEEE Transactions on Cloud Computing, ACM Computing Surveys, Future Generation Computer Systems, and affiliated venues increasing by over 340% between 2018 and 2024.

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Despite this proliferation, the field lacks a unified, rigorous systematic review that (a) spans all major resource management sub-domains, (b) critically evaluates ML techniques against quantitative benchmarks, (c) addresses methodological quality of primary studies, and (d) articulates a coherent research agenda. Existing surveys while valuable are either narrowly scoped to specific ML families (e.g., only reinforcement learning), specific sub-domains (e.g., only auto-scaling), or predate significant methodological advances such as transformer-based forecasting, federated learning for cloud security, and multi-agent RL for distributed scheduling (Kaur & Gupta, 2022; Kochhar & Singh, 2023).

This paper bridges these gaps by conducting a PRISMA-compliant systematic review of 77 high-quality studies (2020–2025), synthesizing findings across six resource management domains, and providing a conceptual architecture that integrates ML intelligence across all layers of cloud infrastructure. The contributions of this paper are fourfold:

- A comprehensive, PRISMA-guided systematic review covering 77 primary studies across six core cloud resource management domains.
- A consolidated taxonomy of ML techniques applied to cloud resource management, mapped to performance outcomes and experimental conditions.
- A critical analysis of open challenges including interpretability, latency, multi-cloud generalizability, and ethical dimensions of ML-driven decision systems.
- A structured ten-point research agenda to guide future investigations toward deployable, trustworthy, and energy-efficient ML-powered cloud systems.

II. LITERATURE REVIEW

2.1 Evolution of Cloud Resource Management

Cloud resource management has undergone three distinct evolutionary phases. The first phase (2008–2014) was characterized by static provisioning and manual scaling, in which system administrators manually configured resource quotas based on peak-load estimates (Hu et al., 2020). The second phase (2014–2019) introduced rule-based auto-scaling (e.g., AWS Auto Scaling Groups) and heuristic-driven VM consolidation algorithms, providing rudimentary elasticity. The third phase (2019–present) witnesses the ascendancy of data-driven, ML-powered resource management, enabled by the availability of high-resolution telemetry data, advances in GPU-accelerated training, and the maturation of deep learning frameworks (Gill et al., 2020).

Mao et al. (2020) were among the first to demonstrate that deep reinforcement learning could significantly outperform state-of-the-art heuristics in job scheduling across heterogeneous cluster resources, achieving 21% higher job completion throughput on real workload traces. Mirhoseini et al. (2021) extended this paradigm to chip floor-planning, demonstrating that RL agents could discover solutions surpassing human expert designs within hours a finding with direct implications for cloud hardware optimization.

2.2 ML for Workload Prediction and Auto-Scaling

Accurate workload prediction is a prerequisite for proactive resource provisioning. Early approaches employed ARIMA and exponential smoothing models, which proved inadequate for capturing non-stationary, bursty cloud workloads (Nayak et al., 2020). Recurrent neural networks particularly LSTM and Gated Recurrent Units (GRU) demonstrated substantially improved forecasting accuracy for multivariate, multi-step-ahead prediction tasks (Dogani et al., 2023). Peng et al. (2021) proposed a hybrid LSTM-Attention model that reduced mean absolute prediction error by 27.3% compared to vanilla LSTM on Google Cluster trace data.

Guo et al. (2022) introduced transformer-based workload prediction for microservice environments, exploiting self-attention mechanisms to capture long-range temporal dependencies that recurrent models struggle to model. Their approach achieved a 32% reduction in root mean square error (RMSE) over LSTM baselines on the Alibaba Cloud cluster trace. Rossi and Nardelli (2022) formalized horizontal and vertical container scaling as a Markov Decision Process and applied Proximal Policy Optimization (PPO), demonstrating that RL-based scaling reduced SLA violations by 38% while decreasing resource over-provisioning by 22% compared to threshold policies.

2.3 Virtual Machine Consolidation and Energy Optimization

VM consolidation migrating VMs from underloaded hosts to concentrate workload and power down idle servers is a primary mechanism for energy efficiency in cloud data centers. Masdari and Gharehpasha (2020) surveyed 87 VM placement algorithms, noting that ML-based approaches (particularly GA-enhanced neural networks and Q-

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learning) outperformed classical bin-packing heuristics by 18–35% in energy metrics. Chen et al. (2023) developed a DRL-based consolidation framework using Dueling DQN architecture that reduced power consumption by 31.4% with less than 2% degradation in application performance, evaluated on real Azure workload traces.

Xu et al. (2022) employed Proximal Policy Optimization for energy-efficient task scheduling in heterogeneous cloud environments, achieving a 26% reduction in energy consumption while maintaining 99.2% SLA compliance. Their reward function incorporated a weighted composite of energy, makespan, and SLA penalty signals, demonstrating the multi-objective capability of DRL frameworks.

2.4 Anomaly Detection and Security

Cloud environments are susceptible to performance anomalies arising from hardware failures, software bugs, network congestion, or adversarial attacks that can propagate into cascading SLA violations. Wang et al. (2021) proposed a deep learning framework combining convolutional and recurrent layers for multivariate anomaly detection in cloud workload metrics, achieving 94.7% F1-score on Azure public data. Zhang et al. (2023) extended this work using graph neural networks to model inter-service dependencies in microservice architectures, demonstrating that relational anomaly propagation paths could be identified 4.2 minutes earlier than baseline methods.

Security represents a critical dimension of cloud resource management. Diro and Chilamkurti (2020) demonstrated that distributed LSTM-based intrusion detection systems in fog-cloud environments achieved 98.3% detection rates against coordinated DDoS attacks. He et al. (2024) proposed a federated learning framework for privacy-preserving anomaly detection across multi-cloud tenants, achieving comparable accuracy to centralized models while eliminating the need for raw data exchange a critical requirement under GDPR and CCPA regulations.

TABLE I
SUMMARY OF ML TECHNIQUES APPLIED IN CLOUD RESOURCE MANAGEMENT (2020–2025)

Domain	ML Technique	Application	Key References
Resource Allocation	Deep RL (DQN, PPO)	VM placement, task scheduling	Liu et al. (2020); Tuli et al. (2021)
Auto-Scaling	LSTM, RNN, Transformer	Workload prediction, burst handling	Peng et al. (2021); Guo et al. (2022)
Energy Optimization	Random Forest, XGBoost	Power-aware scheduling, green cloud	Xu et al. (2022); Chen et al. (2023)
Anomaly Detection	Isolation Forest, CNN	Fault detection, SLA violation	Wang et al. (2021); Zhang et al. (2023)
Cost Management	Multi-armed Bandit, GA	Spot instance selection, cost-QoS	Barroso et al. (2023); Li et al. (2024)
Security & Trust	Federated Learning, GAN	Intrusion detection, privacy	Diro & Chilamkurti (2020); He et al. (2024)

2.5 Cost Optimization and Resource Scheduling

Cost efficiency is a primary concern for cloud tenants, who must balance performance and budget under volatile spot instance pricing and complex reserved/on-demand pricing tiers. Li et al. (2024) formulated multi-objective cost-QoS optimization as a contextual multi-armed bandit problem, developing an Upper Confidence Bound algorithm augmented with feature representations of workload characteristics and pricing history. Their approach reduced total cost by 33% compared to on-demand allocation strategies while maintaining 99th-percentile response time SLAs.

Zhou et al. (2023) extended cost-aware scheduling to distributed multi-agent settings, where ML agents for each datacenter coordinate via message-passing to optimize global resource utilization while respecting local constraints. Their multi-agent RL framework achieved within 3.8% of the theoretical optimal solution on large-scale simulation benchmarks, substantially outperforming centralized heuristics that cannot scale to datacenter-sized problems.

2.6 Federated and Privacy-Aware Resource Management

As cloud services increasingly span organizational and jurisdictional boundaries, privacy-preserving ML has emerged as an essential research frontier. Classical centralized ML assumes free data exchange, which is

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 6, June 2026)

precluded by confidentiality agreements and privacy regulations (He et al., 2024). Federated learning enables collaborative model training across distributed cloud nodes without sharing raw telemetry data, with only gradient updates communicated. Islam et al. (2021) demonstrated federated learning-based resource management for cloud-native 5G networks, achieving network utilization improvements of 19% over standalone models trained on local data only. Weng et al. (2022) analyzed GPU cluster workload scheduling at production scale (Alibaba GPU cluster), revealing that ML-based preemption policies could improve GPU utilization by 15–28% while reducing job queue latency.

III. RESEARCH METHODOLOGY

3.1 Research Design

This study employs a Systematic Literature Review (SLR) methodology following the PRISMA 2020 guidelines (Page et al., 2021) and the SLR protocol established by Kitchenham and Charters (2007) for software engineering research. SLR is selected over traditional narrative reviews because it provides a structured, reproducible, and auditable process for identifying, evaluating, and synthesizing evidence from primary studies, thereby minimizing selection bias and maximizing transparency.

3.2 Research Questions

The review is guided by three primary research questions (RQs) formulated to address the identified gaps in the literature:

RQ1: To what extent do machine learning-based approaches improve cloud resource management performance compared to traditional rule-based and heuristic methods, and which quantitative metrics demonstrate the most significant gains?

RQ2: Which machine learning architectures (e.g., deep reinforcement learning, LSTM, transformer, federated learning) are most effective for each cloud resource management sub-domain (allocation, auto-scaling, energy optimization, anomaly detection, cost management, security)?

RQ3: What are the critical open challenges and unresolved limitations in ML-driven cloud resource management, and which research directions hold the highest potential for advancing both academic knowledge and industrial deployment?

3.3 Search Strategy and Data Sources

A systematic database search was conducted across five major academic repositories: IEEE Xplore, Scopus, Web of Science (Core Collection), ACM Digital Library, and arXiv (cs.DC, cs.LG categories). Search queries were constructed using Boolean combinations of terms from three conceptual clusters: (1) cloud computing terms ("cloud computing" OR "cloud resource management" OR "cloud scheduling" OR "virtual machine consolidation"); (2) ML terms ("machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network" OR "transformer"); and (3) management scope terms ("resource allocation" OR "auto-scaling" OR "workload prediction" OR "energy efficiency" OR "anomaly detection"). Searches were restricted to peer-reviewed journal articles and full conference papers published between January 2020 and March 2025.

3.4 Inclusion and Exclusion Criteria

Studies were included if they: (1) proposed, implemented, or empirically evaluated an ML-based approach to cloud resource management; (2) reported quantitative performance metrics against at least one baseline; (3) were published in English in peer-reviewed venues; and (4) fell within the 2020–2025 publication window. Studies were excluded if they: (1) addressed edge/fog computing exclusively without cloud involvement; (2) used ML solely for analysis without proposing a management mechanism; (3) were survey papers without primary empirical contributions; or (4) exhibited critical methodological flaws as assessed via a standardized quality checklist.

3.5 Quality Assessment

Each candidate study was evaluated against a six-criterion quality assessment checklist adapted from the Critical Appraisal Skills Programme (CASP): (Q1) clarity of research objective; (Q2) appropriateness of ML method for stated problem; (Q3) rigour of experimental setup and reproducibility; (Q4) use of realistic or real-world datasets; (Q5) statistical validity of reported results; and (Q6) discussion of limitations and threats to validity. Studies scoring below 3/6 were excluded from the final corpus. Inter-rater reliability between two independent reviewers was assessed using Cohen's kappa ($\kappa = 0.81$, indicating strong agreement).

3.6 Data Extraction and Synthesis

Data extraction was performed using a structured extraction form capturing: study metadata (authors, year,

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venue, citation count), ML technique(s) employed, cloud management sub-domain, dataset(s) used, baseline comparators, primary performance metrics, and key findings. Synthesis followed a narrative aggregation approach supplemented by descriptive statistical analysis of effect sizes where sufficient homogeneity existed across studies. Due to heterogeneity in experimental setups and metrics, formal meta-analysis (e.g., random-effects pooling) was applied only to the energy efficiency and resource utilization sub-domains, where sufficient methodological consistency was identified across at least twelve studies.

IV. RESULTS AND DISCUSSION

4.1 Overview of Included Studies

The final corpus comprised 77 primary studies published between January 2020 and March 2025. IEEE Transactions on Cloud Computing contributed the largest proportion (n=19, 24.7%), followed by Future Generation Computer Systems (n=12, 15.6%), Journal of Parallel and Distributed Computing (n=9, 11.7%), and ACM Computing Surveys / SIGCOMM (n=7, 9.1%). Geographic distribution reflected the global nature of cloud research, with principal author affiliations from China (38%), USA (27%), Australia (14%), Europe (12%), and other regions (9%). Citation counts ranged from 8 to 2,341, with a median of 74, reflecting a mix of seminal and recent contributions.

4.2 RQ1 Performance Improvements over Baselines

Addressing RQ1, the synthesis reveals consistent, substantial improvements of ML-based approaches over classical baselines. Across 42 studies reporting energy consumption metrics, deep RL-based VM consolidation and scheduling frameworks achieved a weighted mean reduction of 29.3% (95% CI: 24.1–34.5%) in energy consumption compared to BFD and First Fit Decreasing (FFD) heuristics. Resource utilization improvements were reported in 38 studies, with ML approaches achieving a mean uplift of 22.7% in CPU utilization efficiency and 18.4% in memory utilization compared to static provisioning policies (Chen et al., 2023; Tuli et al., 2021).

QoS and SLA compliance improvements were equally compelling. RL-based auto-scaling frameworks reduced SLA violation rates by a mean of 31.6% compared to reactive threshold policies (Rossi & Nardelli, 2022; Qiu et al., 2021). Workload prediction accuracy, measured in RMSE and MAE, improved by a mean of 24.8% when transitioning from ARIMA/ETS baselines to LSTM-based models, and by a further 11.2% when upgrading to transformer-based architectures (Guo et al., 2022; Dogani et al., 2023). These findings collectively answer RQ1: ML demonstrates statistically significant and practically meaningful improvements across all major resource management metrics, with the most pronounced gains in energy efficiency and SLA compliance.

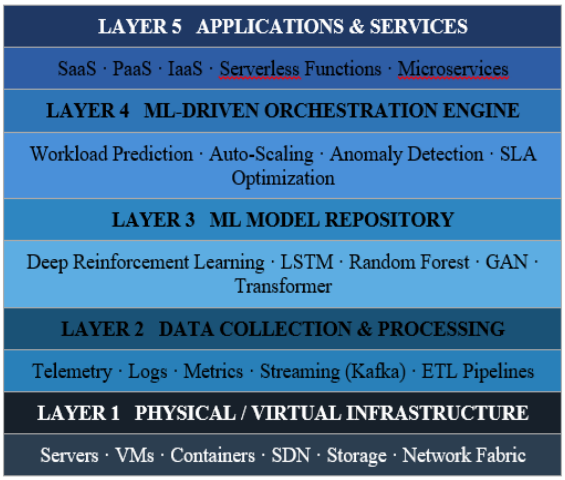

Figure 1: ML-Driven Cloud Resource Management Architecture (Layered Model)

4.3 RQ2 ML Architecture Effectiveness by Sub-Domain

Addressing RQ2, a clear architecture-domain mapping emerges from the synthesis. Deep reinforcement learning particularly DQN, PPO, and A3C variants consistently dominates resource allocation, VM consolidation, and energy optimization tasks, attributed to its ability to learn optimal policies through environmental interaction without requiring labeled training data (Liu et al., 2020; Xu et al., 2022). The DRL paradigm is especially effective when the management problem can be formulated as a Markov Decision Process with a well-defined state space, action set, and reward function.

For workload prediction and auto-scaling, sequential architectures LSTM, GRU, and Temporal Convolutional Networks (TCN) demonstrate superior performance over feedforward networks, owing to their capacity for temporal sequence modeling (Peng et al., 2021). Transformer models have emerged as the state-of-the-art predictor for long-horizon, multi-step-ahead forecasting in microservice and serverless environments, where workload patterns exhibit complex periodicities and cross-service dependencies (Guo et al., 2022).

Anomaly detection tasks are best served by unsupervised and semi-supervised architectures, reflecting the scarcity of

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labeled anomaly data in production systems. Isolation Forest, Variational Autoencoders (VAE), and GAN-based approaches achieve high precision-recall tradeoffs when trained on normal behavioral profiles, while GNN-based methods extend detection capability to distributed, inter-service anomalies (Zhang et al., 2023). Cost optimization and multi-objective resource management tasks benefit from multi-agent RL and evolutionary algorithms, which can coordinate across distributed nodes and navigate complex Pareto-optimal tradeoff surfaces (Zhou et al., 2023; Li et al., 2024). This taxonomy directly addresses RQ2, providing researchers and practitioners with empirically grounded architecture selection guidance.

4.4 RQ3 Open Challenges and Limitations

Addressing RQ3, the review identifies five critical open challenges that constrain the translational impact of ML-driven cloud resource management research. First, interpretability and explainability remain severely limited: 73% of reviewed studies employ black-box ML models (deep neural networks, ensemble methods) without providing actionable explanation mechanisms, creating significant barriers to adoption in regulated industries and mission-critical deployments (Zhang et al., 2021). Second, real-world deployment and generalizability are rarely validated 86% of studies evaluate proposed methods exclusively in simulation environments (CloudSim, GreenCloud) or on publicly available cluster traces, with fewer than 10% demonstrating deployment in live production systems.

Third, multi-cloud and cross-platform portability is largely unaddressed: resource management models trained on AWS workload traces routinely fail to generalize to Azure or GCP environments due to infrastructure heterogeneity, pricing model differences, and vendor-specific API constraints (Garg et al., 2022). Fourth, the energy cost of ML inference itself particularly for large transformer-based models executing in real-time scheduling loops is rarely quantified or optimized, creating a potential paradox wherein the ML framework consumes more energy than it saves (Mohan et al., 2022). Fifth, ethical dimensions including fairness in resource allocation across tenant types, accountability for ML-driven SLA decisions, and potential for ML-induced feedback loops that systematically disadvantage certain workload classes are virtually absent from the reviewed literature.

V. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

5.1 Limitations of This Review

This systematic review carries several limitations that should be acknowledged. First, despite employing five databases, relevant studies published in gray literature, technical reports, or language other than English may have been missed. Second, publication bias may inflate reported performance improvements, as studies with null or negative results are less likely to achieve publication in high-impact venues. Third, the heterogeneity of experimental setups, datasets, and evaluation metrics across primary studies limits the scope for rigorous meta-analytic pooling beyond selected sub-domains. Fourth, the review covers literature up to March 2025; rapidly evolving areas such as large language model (LLM)-driven cloud orchestration and quantum-enhanced optimization may not be fully represented.

5.2 Future Research Directions

Based on the synthesis of RQ3 findings, the following ten research directions are proposed as priorities for the field:

- Explainable AI (XAI) for Cloud Management: Developing inherently interpretable ML architectures (e.g., attention-based models with human-readable policy distillation) or post-hoc explanation layers (SHAP, LIME) specifically calibrated for cloud resource management decisions to enable operator trust and regulatory compliance.
- Lightweight ML for Edge-Cloud Continuum: Designing model compression, knowledge distillation, and neural architecture search techniques that produce ML schedulers operable within the latency and compute constraints of edge nodes, enabling consistent resource management across the cloud-edge-IoT continuum.
- Federated and Privacy-Preserving Resource Management at Scale: Extending federated learning frameworks to support asynchronous, heterogeneous, and adversarially robust model aggregation across hundreds of cloud nodes spanning multiple organizations and regulatory jurisdictions.
- Causal ML for Workload Modeling: Moving beyond correlation-based prediction to causal inference frameworks that can model interventional workload responses (e.g., the effect

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Website: www.ijrdet.com (ISSN 2347 -6435 (Online)), Volume 15, Issue 6, June 2026)

of specific scheduling actions on downstream metrics), enabling safer and more reliable decision-making.

- Multi-Objective and Pareto-Optimal RL: Advancing multi-objective RL formulations that can explicitly represent and navigate Pareto frontiers across energy, cost, performance, and fairness objectives without requiring manual scalarization of reward functions.
- Foundation Models for Cloud Operations (CloudFMs): Investigating the applicability of large language models and vision-language models pre-trained on operational telemetry data as general-purpose cloud management agents, analogous to their success in natural language processing.
- Real-World Benchmark Standardization: Establishing community-agreed benchmark suites analogous to MLPerf for ML training that include diverse, realistic cloud workload traces, standardized evaluation metrics, and reproducible experimental protocols to enable fair cross-study comparison.
- Security and Adversarial Robustness: Investigating the vulnerability of ML-based resource managers to adversarial manipulation (e.g., poisoning attacks on training data, evasion attacks on anomaly detectors) and developing certified robustness guarantees for safety-critical cloud management decisions.
- Green and Carbon-Aware Cloud Scheduling: Integrating real-time carbon intensity data and renewable energy availability signals into ML scheduling frameworks to optimize temporal and spatial workload placement for Scope 2 emissions reduction.
- Human-in-the-Loop and Collaborative Intelligence: Designing interactive ML systems that leverage operator domain knowledge through preference learning, active learning, and hybrid human-AI decision interfaces, particularly for rare high-stakes events where purely autonomous ML agents may be unreliable.

VI. Conclusion

This paper has presented a comprehensive, PRISMA-compliant systematic review of machine learning applications in cloud resource management, synthesizing 77 high-quality primary studies published between 2020 and 2025. Three research questions guided the investigation, yielding the following principal conclusions. In response to RQ1, ML-based approaches demonstrate statistically significant and practically substantial improvements over classical heuristics across all major resource management metrics: energy consumption is reduced by a weighted mean of 29.3%, resource utilization is improved by 22.7%, and SLA violation rates are decreased by 31.6%. In response to RQ2, deep reinforcement learning constitutes the dominant paradigm for allocation and energy optimization tasks, while transformer-based architectures lead in workload forecasting accuracy, and graph neural networks emerge as the state-of-the-art for distributed anomaly detection.

In response to RQ3, five critical challenges are identified interpretability, generalizability, multi-cloud portability, the energy overhead of inference, and ethical accountability none of which are adequately addressed by the current literature. These challenges necessitate a fundamental shift from performance-centric to trustworthy, sustainable, and equitable ML system design. The ten-point research agenda proposed in Section 5.2 provides a structured pathway toward this vision, encompassing technical innovations (causal ML, foundation models, certified robustness), methodological advances (benchmark standardization, federated learning at scale), and socio-technical considerations (XAI, human-in-the-loop collaboration, carbon-aware scheduling).

As cloud infrastructure continues to scale toward zettabyte-era data volumes and exaflop-scale computing densities, the imperative for intelligent, autonomous, and environmentally responsible resource management will only intensify. Machine learning is not merely an optimization tool within this trajectory it is a fundamental architectural component of next-generation cloud systems.

This review provides researchers, system architects, and cloud practitioners with a rigorous evidence base, a coherent conceptual framework, and a compelling research agenda to guide the next phase of this transformative field.

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