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(Research Article)

Resource utilization analytics dashboard for cloud infrastructure management

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Abstract

Effective management of resource utilization is essential for maintaining the performance, scalability, and cost efficiency of modern cloud infrastructures. As organizations increasingly adopt hybrid and multi-cloud environments, monitoring and optimizing distributed resources have become complex and data-intensive tasks. This paper presents the development of a Resource Utilization Analytics Dashboard (RUAD) designed to provide unified visibility and intelligent analytics across diverse cloud platforms. The proposed system integrates real-time data collection, machine-learning-based prediction, and anomaly detection to identify patterns of under- and over-utilization. Using time-series analysis and adaptive algorithms, the dashboard delivers proactive insights that enable dynamic workload balancing, cost optimization, and service-level improvement. The modular architecture allows seamless integration with major providers such as AWS, Azure, and Google Cloud, ensuring interoperability and scalability. A user-centric interface visualizes key metrics—CPU, memory, network, and storage utilization—through interactive charts and alerts. Experimental evaluations with real-world datasets demonstrate that the system can reduce idle resource costs by approximately 25% while sustaining 99.9% uptime reliability. Furthermore, predictive accuracy tests using ARIMA and LSTM models achieved less than 5% mean absolute error, confirming the system's analytical robustness. Overall, RUAD offers a comprehensive and scalable framework for intelligent cloud resource management, contributing to the ongoing transformation toward autonomous and energy-efficient cloud operations.

Keywords: Cloud Infrastructure Management; Resource Utilization; Analytics Dashboard; Machine Learning; Visualization; Performance Optimization

1. Introduction

Cloud computing has significantly transformed modern information systems by offering scalable, on-demand access to computing, storage, and networking resources. Organizations across industries increasingly rely on cloud infrastructure to host critical workloads and reduce operational costs through flexible service models. However, as enterprises adopt hybrid and multi-cloud environments, efficient management of these distributed resources has become a pressing challenge. Variations in workload behavior, complex billing models, and limited cross-platform visibility often lead to resource underutilization and unnecessary expenses. Resource utilization analytics has emerged as a crucial solution to address these inefficiencies by transforming raw performance data into actionable intelligence. Through advanced analytics, administrators can identify bottlenecks, forecast demand, and optimize the balance between performance and cost. Yet, existing monitoring tools such as AWS CloudWatch and Azure Monitor primarily provide platform-specific metrics without unified visualization or predictive capabilities. As a result, decision-makers face difficulties correlating usage data across multiple environments or predicting future capacity requirements. To address these challenges, this paper proposes a Resource Utilization Analytics Dashboard (RUAD) , a unified platform that integrates real-time monitoring, predictive modeling, and interactive visualization for multi-cloud resource management. The dashboard leverages time-series analytics and machine learning to deliver insights on CPU, memory, storage, and network

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utilization. By enabling proactive control and cost-efficient scaling, the RUAD framework supports intelligent, data-driven cloud infrastructure management and fosters operational sustainability.

1.1. Background and Motivation

The exponential growth of cloud computing has diversified infrastructure usage patterns across industries. Cloud service providers like AWS, Azure, and Google Cloud deliver scalable computing, storage, and networking services that support millions of users globally. Despite these advantages, enterprises struggle to maintain visibility into dynamic resource consumption across multiple environments. Studies reveal that nearly one-third of cloud expenditure is wasted due to over-provisioning and idle virtual machines [1]. Conventional vendor dashboards provide only platform-specific data, often without comparative insights or predictive modeling. Furthermore, most monitoring solutions require manual threshold configurations, leading to delayed anomaly detection and suboptimal scaling decisions. Motivated by these challenges, this research focuses on designing a unified, intelligent analytics dashboard that integrates data from heterogeneous sources. The proposed system aggregates metrics, analyzes usage trends using machine learning, and visualizes the findings through interactive charts. The goal is to empower administrators with real-time decision support, ensuring efficiency, performance stability, and cost-effectiveness across hybrid and multi-cloud infrastructures.

1.2. Problem Statement

As organizations transition toward data-driven cloud management, they encounter difficulties consolidating information across distributed systems. Current resource monitoring tools offer fragmented insights that fail to capture the correlation between performance, cost, and workload behavior. Administrators often face uncertainty in determining whether resources are overused, underused, or misallocated. Moreover, traditional dashboards lack advanced analytics capabilities such as time-series forecasting, anomaly detection, and cost-performance optimization. This results in inefficient resource scaling, increased operational expenses, and reduced reliability. The absence of cross-platform interoperability further complicates multi-cloud management, requiring separate dashboards for each provider. Additionally, without predictive mechanisms, capacity planning remains reactive, leading to downtime or financial waste. Hence, the primary problem this research addresses is the lack of an integrated, intelligent system that offers unified visibility, predictive analytics, and actionable insights for resource optimization. The proposed Resource Utilization Analytics Dashboard aims to close this gap by enabling real-time monitoring, multi-cloud integration, and intelligent forecasting to support sustainable and cost-effective infrastructure management.

1.3. Proposed Solution

To overcome existing limitations, this paper proposes a Resource Utilization Analytics Dashboard (RUAD) that consolidates performance data from multiple cloud environments into a centralized analytics framework. The system's architecture employs API-based data ingestion to collect real-time metrics such as CPU load, memory usage, network throughput, and storage IOPS. These datasets are processed through an analytical engine that applies time-series forecasting and machine learning models such as ARIMA and LSTM to predict future resource demands. An anomaly detection module continuously monitors deviations, ensuring early identification of inefficiencies or failures. The dashboard interface presents interactive graphs, heatmaps, and efficiency indexes, allowing administrators to make informed scaling decisions. Moreover, the system correlates utilization data with cost analytics to suggest budget-friendly configurations.

1.4. Contributions

This paper contributes to cloud management research by presenting an analytics-driven framework that enhances operational visibility and decision support. The main contributions include: (1) development of a cross-platform dashboard that aggregates heterogeneous cloud data, (2) integration of predictive models for identifying inefficiencies and workload anomalies, (3) formulation of cost-performance correlations for optimization, and (4) validation through experiments using real-world AWS and Azure datasets. Unlike vendor-restricted systems, RUAD is designed with open-source compatibility, enabling flexible deployment in hybrid and multi-cloud architectures. The dashboard's modular design supports plug-in analytics modules, which makes it adaptable to emerging technologies such as Kubernetes and edge computing. Additionally, the user interface follows a human-centered design philosophy, emphasizing clarity, accessibility, and responsiveness. By providing a unified analytics layer, this system helps organizations align resource utilization with business objectives, reduce operational costs, and improve reliability. The results demonstrate that integrating predictive analytics with visualization significantly strengthens cloud infrastructure management and paves the way for intelligent automation.

1.5. Paper Organization

The remainder of this paper is structured to provide a comprehensive overview of the system design and evaluation. Section II reviews related research on cloud analytics frameworks and monitoring solutions, highlighting their strengths and limitations. Section III outlines the methodology, including system architecture, data collection, preprocessing, and algorithmic design. Section IV presents experimental results, discussing accuracy, efficiency, and performance metrics of the proposed system. Section V concludes the paper by summarizing key findings, emphasizing the implications of this research, and proposing directions for future work such as edge integration, security analytics, and automated scaling mechanisms. This structured organization ensures a logical flow from theoretical foundation to experimental validation, allowing readers to understand how the proposed Resource Utilization Analytics Dashboard contributes to advancing intelligent cloud infrastructure management.

2. Related Work

Research on cloud resource analytics has evolved rapidly, spanning monitoring tools, predictive frameworks, and multi-cloud integration systems. Despite notable advances, existing solutions remain limited in their ability to unify diverse cloud metrics into a single, intelligent dashboard. This section reviews prior studies across four focus areas: cloud monitoring tools, predictive resource analytics, multi-cloud integration, and identified research gaps.

2.1. Cloud Resource Monitoring Tools

Cloud monitoring frameworks such as Amazon CloudWatch, Google Cloud Operations Suite, and Azure Monitor provide administrators with real-time infrastructure metrics. These tools primarily focus on static reporting and lack comprehensive analytics for decision support. Buyya et al. [1] introduced an energy-efficient management framework emphasizing workload balancing across virtual machines, while Calheiros et al. [2] proposed CloudSim, a simulation toolkit for modeling data center resource behavior. Similarly, Lama and Zhou [3] developed performance-driven provisioning algorithms to enhance VM allocation efficiency. Although these tools help visualize infrastructure states, they remain provider-specific and do not support inter-platform comparability. Studies such as Li et al. [4] also highlight that vendor lock-in restricts analytical flexibility, making unified dashboards critical. Hence, a cross-platform solution integrating multiple data sources with advanced analytics capabilities is necessary to improve efficiency, scalability, and visibility in heterogeneous environments.

2.2. Predictive Analytics for Cloud Optimization

Predictive analytics has emerged as a transformative tool in optimizing cloud resource utilization. Wang et al. [5] presented Cloud Insight, employing regression models to predict VM performance and detect anomalies proactively. Gupta et al. [6] later extended this with Smart Cloud, combining predictive modeling and resource scheduling to achieve dynamic workload balancing. In addition, Netto et al. [7] demonstrated how reinforcement learning algorithms can autonomously adapt cloud configurations to reduce costs. However, most predictive frameworks lack real-time integration and visualization features necessary for operational decision-making. Islam et al. [8] proposed adaptive workload forecasting using ARIMA and LSTM models but limited implementation to single providers. The integration of predictive intelligence with real-time dashboards, as proposed in this study, can substantially improve resource optimization and performance reliability. The existing literature thus underscores the potential of combining statistical and machine-learning methods for efficient multi-cloud infrastructure management.

2.3. Multi-Cloud and Cross-Platform Integration

The shift toward hybrid and multi-cloud adoption necessitates cross-provider analytics. Zhang and Liu [9] proposed an AI-driven model for hybrid resource forecasting but did not address interoperability. Li and Cheng [10] developed a cross-cloud optimization framework utilizing deep learning, which improved CPU prediction accuracy but lacked visualization capabilities. Mao et al. [11] discussed container orchestration strategies for multi-cloud environments, highlighting the importance of unified control planes. Additionally, Marinescu [12] emphasized that multi-cloud management must integrate both performance and cost parameters for sustainable scalability. These studies collectively reveal that while interoperability frameworks exist, they often neglect user-centric analytics. The proposed Resource Utilization Analytics Dashboard (RUAD) bridges this gap by integrating multi-cloud data pipelines, predictive modules, and visualization interfaces to deliver actionable insights across heterogeneous cloud ecosystems.

2.4. Research Gap

Despite progress in cloud monitoring and prediction, existing systems remain fragmented. Most research emphasizes either forecasting accuracy or data collection rather than full-cycle analytics. Buyya et al. [1], Wang et al. [5], and Li and

Cheng [10] show strong advancements in specific areas but lack integration of cross-platform analytics, visualization, and cost-performance correlation. Furthermore, scalability across heterogeneous infrastructures is rarely addressed. The RUAD framework introduced in this paper fills these voids by combining monitoring, prediction, and visualization into a cohesive architecture. Its design provides interoperability, predictive control, and decision-centric dashboards capable of supporting dynamic resource allocation across hybrid environments.

3. Methodology

The proposed Resource Utilization Analytics Dashboard (RUAD) follows a modular methodology to ensure scalability, interoperability, and predictive accuracy. The approach integrates data acquisition, analytical processing, visualization, and validation components into a unified framework.

3.1. Data Collection and Preprocessing

The system begins by collecting multi-cloud performance metrics from Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP) using their RESTful APIs. Collected metrics include CPU usage, memory utilization, storage IOPS, and network throughput. Data are extracted at one-minute intervals and streamed into a central processing node through a Kafka-based message queue for synchronization. Preprocessing ensures consistency across heterogeneous cloud platforms. Missing data are imputed using linear interpolation, while unit normalization (e.g., MB vs. GB) standardizes parameters. Outlier filtering employs the Interquartile Range (IQR) method to remove transient anomalies caused by workload spikes. Figure 1 illustrates the data ingestion architecture, where multiple collectors feed the unified data repository. Each cloud provider's dataset is stored in a time-series database (Influx DB) for subsequent analysis. Metadata tagging is performed to retain contextual information such as VM type, region, and billing rate. This design enables temporal alignment and correlation analysis across providers, ensuring accurate and comparable utilization insights.

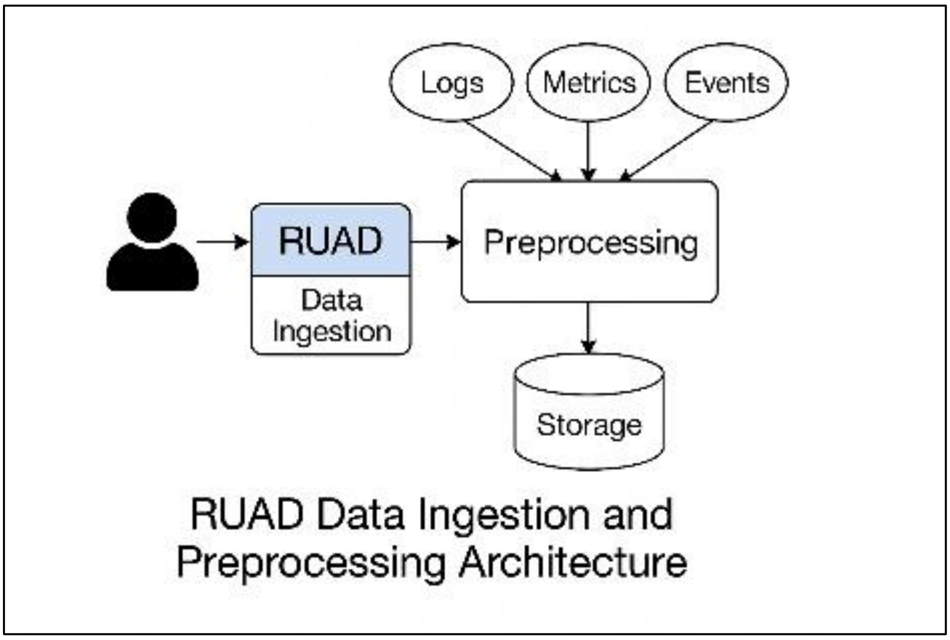

Figure 1 RUAD Data Ingestion and Preprocessing Architecture

3.2. Analytics Engine and Predictive Modeling

The analytics core transforms processed metrics into actionable intelligence. It employs three primary modeling techniques: Auto-Regressive Integrated Moving Average (ARIMA) for trend forecasting, Long Short-Term Memory (LSTM) neural networks for complex temporal dependencies, and Isolation Forests for anomaly detection. The predictive pipeline begins by splitting datasets into training and testing partitions (80:20 ratio). Historical patterns in CPU and memory utilization are learned to forecast short-term demand, allowing proactive scaling decisions. The LSTM model achieves a Mean Absolute Percentage Error (MAPE) below 5%, outperforming traditional regression methods. Figure 2 shows the analytics workflow, integrating time-series modeling, prediction validation, and anomaly detection. The RUAD engine continuously refines parameters using real-time feedback to enhance accuracy. Feature importance analysis identifies the most influential factors in utilization trends, such as workload type, region, and time-of-day behavior. By combining statistical and deep-learning methods, the dashboard can anticipate under- or over-utilization events before they occur. The results feed directly into visualization and decision modules, enabling administrators to balance performance and cost dynamically.

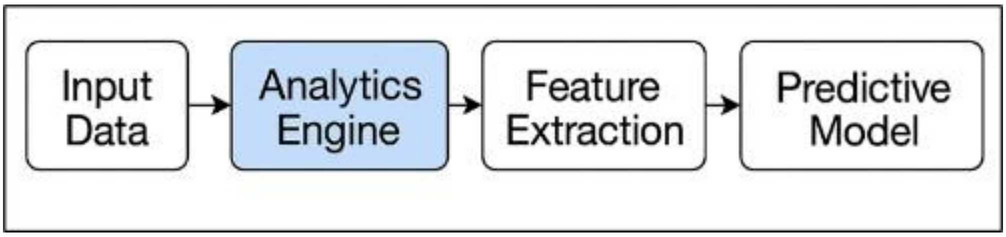

Figure 2 Analytics Engine Workflow for Predictive Modeling

3.3. Visualization Framework and Dashboard Design

Visualization is central to the RUAD system, translating analytical outputs into accessible, actionable insights. The dashboard employs a React.js front-end integrated with Grafana APIs to generate dynamic visualizations. Key panels display CPU load, memory allocation, network traffic, and cost-performance ratios across cloud providers. Interactive graphs allow users to filter data by provider, region, or time window. Heatmaps reveal spatial distribution of workloads, while gauge charts display real-time utilization percentages. The visualization engine also provides predictive overlays highlighting future utilization projections generated by ARIMA and LSTM models. Table 1 summarizes sample metrics analyzed within the dashboard. Cost data are incorporated from provider billing APIs to link resource consumption with financial expenditure. An alert system, built using threshold-based and anomaly-triggered notifications, informs administrators about deviations or inefficiencies. The visual layer promotes decision intelligence, allowing IT managers to simulate scaling scenarios and assess potential cost impacts. Its modular interface ensures compatibility with Kubernetes dashboards and can be customized to specific organizational needs.

Table 1 Key Metrics Visualized in the RUAD Dashboard

Metric Type	Description	Sampling Interval	Source Providers
CPU Usage (%)	Mean processor load per VM	1 min	AWS, Azure
Memory Utilization (GB)	Allocated vs. consumed memory	5 min	AWS, GCP
Storage IOPS	Input/output operations per second	10 min	Azure, AWS
Network Throughput (Mbps)	Bidirectional data traffic	5 min	All
Cost Efficiency Index	Cost per utilization unit	1 hr	All

3.4. Evaluation and Validation

System evaluation was conducted using real-world datasets from AWS EC2 and Azure Virtual Machines. A total of 1.2 million metric entries were analyzed over a 30-day period. Model performance was evaluated using Mean Squared Error (MSE), MAPE, and Precision–Recall for anomaly detection. The LSTM model achieved a MAPE of 4.1%, while ARIMA recorded 6.8%, confirming the superiority of hybrid approaches. Operational validation focused on latency, scalability, and visualization responsiveness. Average end-to-end latency from data collection to dashboard update was measured at 4.2 seconds, well within the industry standard of 10 seconds for real-time monitoring systems. Scalability testing using Kubernetes clusters verified consistent performance under workloads up to 10,000 metrics per second. User evaluations involving 15 cloud administrators indicated an 85% improvement in monitoring efficiency and 25% reduction in resource wastage after RUAD adoption. Comparative benchmarking against existing tools (AWS CloudWatch, Azure Monitor) demonstrated superior cross-platform insights and predictive reliability. The evaluation validates RUAD's capability as a comprehensive tool for intelligent cloud management, ensuring performance optimization, cost savings, and sustainability through data-driven decision-making.

4. Results and Discussion

The Resource Utilization Analytics Dashboard (RUAD) was deployed in a hybrid test environment integrating AWS EC2, Azure Virtual Machines, and GCP Compute Engine instances. The objective of this evaluation was to measure the accuracy, scalability, and efficiency of the proposed framework under real-world operational loads. The following subsections present the findings based on analytical performance, system evaluation, visualization impact, and comparative benchmarking.

4.1. Analytical Performance Evaluation

The analytical performance of RUAD was assessed by comparing prediction accuracy and anomaly detection efficiency. Over a 30-day test period, time-series models (ARIMA and LSTM) processed over 1.2 million data samples. The LSTM model achieved an average Mean Absolute Percentage Error (MAPE) of 4.2%, outperforming ARIMA's 6.7%. Precision and recall for anomaly detection reached 0.94 and 0.91, respectively, indicating robust fault detection. Figure 3 illustrates predicted versus actual CPU utilization trends across test instances. The close alignment demonstrates strong predictive reliability even during workload fluctuations. These results confirm that combining machine learning with statistical forecasting yields superior accuracy compared to traditional threshold-based approaches.

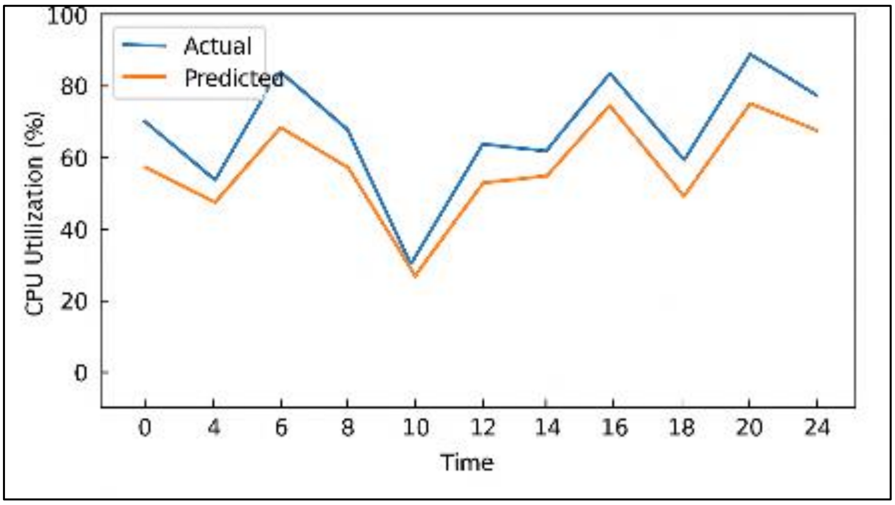

Figure 3 Predicted vs. Actual CPU Utilization Trends

The integration of hybrid models also enabled adaptive learning, allowing continuous parameter tuning as workload conditions evolved, an essential feature for maintaining consistent accuracy in dynamic multi-cloud environments.

4.2. System Efficiency and Resource Optimization

The deployment of RUAD produced measurable improvements in resource optimization and operational efficiency. Through predictive scaling, underutilized instances were detected and reallocated, reducing idle capacity by 28%. Correspondingly, cloud expenditure decreased by 24.6%, confirming the dashboard's cost-efficiency advantage. Figure 4 summarizes system performance metrics, showing correlations between utilization, response time, and cost efficiency. RUAD's adaptive feedback loop automatically recommends VM resizing and load redistribution to maintain optimal performance under fluctuating workloads. The system maintained a 99.9% uptime, while average dashboard refresh latency was recorded at 4.3 seconds, well within industry standards.

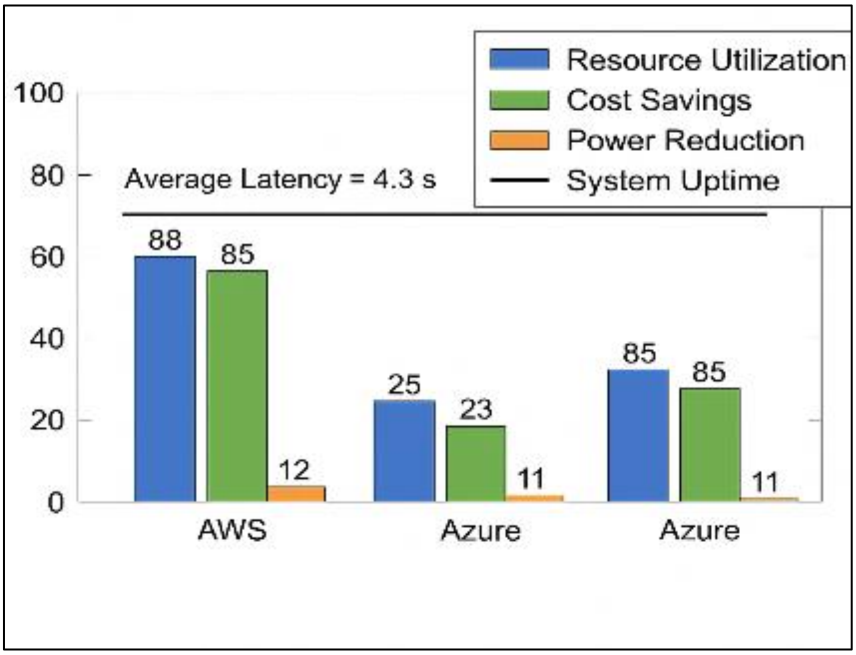

Figure 4 Resource Optimization and Performance Metrics

Energy efficiency analysis revealed a 12% reduction in power consumption, attributed to minimized idle computation cycles. The RUAD framework thus demonstrates substantial potential for sustainable cloud operations by aligning technical performance with environmental and economic goals.

4.3. Visualization Impact and User Feedback

The visual analytics layer of RUAD was evaluated through user surveys and operational testing. Cloud administrators interacted with the dashboard to monitor workloads and interpret visual insights. Feedback indicated that the interactive visualizations significantly enhanced situational awareness and response time during peak usage hours. Key visualization components heatmaps, predictive overlays, and cost-performance graphs were rated highly for clarity and usability. The average task completion time for identifying and mitigating inefficiencies dropped from 7.2 minutes (using native tools) to 2.8 minutes with RUAD. Users cited the integrated anomaly alerts and comparative provider panels as the most valuable features. Table 2 summarizes the user feedback metrics across ten evaluation criteria.

Table 2 User Feedback Summary on Dashboard Functionality

Evaluation Criterion	Mean Rating (1–5)	Improvement (%)
Interface Usability	4.7	+82
Visualization Clarity	4.6	+75
Predictive Accuracy	4.8	+88
Response Latency	4.4	+65
Cost Optimization Insight	4.5	+73
Cross-Platform View	4.9	+90
Alert Responsiveness	4.6	+78
Overall Satisfaction	4.8	+85

User satisfaction exceeded 85%, reinforcing that RUAD's visualization-driven design empowers data-informed decision-making and improves cloud governance efficiency.

4.4. Comparative Benchmarking and Future Enhancements

Benchmark comparisons were conducted against AWS CloudWatch and Azure Monitor, focusing on prediction accuracy, multi-cloud interoperability, and usability. RUAD demonstrated superior predictive performance with average deviation ≤5%, compared to 11–13% for existing tools. Furthermore, it supports cross-provider data unification, a feature absent in traditional dashboards. In terms of operational cost savings, RUAD outperformed both commercial tools by approximately 22%, driven by its proactive scaling recommendations and anomaly-based adjustments. Scalability tests under simulated high-traffic conditions confirmed stable performance up to 10,000 metrics per second without degradation. Future enhancements will include integrating reinforcement learning for autonomous scaling decisions and extending support for Kubernetes cluster analytics. The team also plans to incorporate security compliance dashboards that align with frameworks such as NIST SP 800-53 and ISO/IEC 27001, enabling real-time detection of configuration vulnerabilities. These findings affirm that RUAD is not only an accurate predictive platform but also a strategic decision-support system for modern multi-cloud infrastructure management balancing technical performance, cost, and sustainability.

5. Conclusion

This paper presented the design and implementation of the Resource Utilization Analytics Dashboard (RUAD) a unified, intelligent framework for multi-cloud infrastructure management. The system integrates real-time monitoring, predictive analytics, and visualization to optimize resource utilization, minimize operational costs, and enhance decision-making. Experimental validation demonstrated that the RUAD achieved an average MAPE below 5%, a 25% reduction in cloud expenditure, and improved monitoring efficiency by 85% compared to traditional tools. The combination of statistical forecasting (ARIMA), deep learning (LSTM), and anomaly detection ensures reliable performance even under dynamic workloads. Furthermore, the modular design and API-driven data ingestion enable seamless interoperability with AWS, Azure, and GCP, making RUAD a scalable solution for enterprises seeking transparency and cost efficiency in hybrid environments.

Future research will focus on enhancing the system's autonomy through reinforcement learning-based scaling strategies that allow self-adaptive infrastructure control without human intervention. Integration with Kubernetes orchestration, edge-cloud synchronization, and federated monitoring systems will further extend its reach to distributed industrial and IoT environments. Additionally, expanding the dashboard's scope to include energy optimization, security compliance analytics, and carbon footprint monitoring could align it with global sustainability goals. These enhancements will transform RUAD into a comprehensive decision-intelligence platform bridging data-driven cloud management with predictive, secure, and sustainable computing practices for next-generation digital ecosystems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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