INTERNATIONAL DEVELOPMENT PLANNING REVIEW
ISSN:1474-6743 | E-ISSN:1478-3401

AN AI DRIVEN MULTI CLOUD FINOPS FRAMEWORK FOR REAL- TIME COST GOVERNANCE AND ANAMOLY DETECTION

Karthigayan Devan
Independent Researcher, Genuine Parts Company, GA, USA, Engineering Manager - SRE
karthidec@gmail.com

Abstract
The purpose of the study was to introduce and test an AI-based multi-cloud FinOps system that could allow managing costs in real-time and measuring anomalies in heterogeneous cloud-based settings. With the growth in the adoption of multi-clouds, organizations were faced with issues concerning financial visibility, cost optimization, and the ability to detect abnormal spending patterns in a timely manner. To combat these challenges, the study combined machine learning, automated governance policies, and single intelligent cost analytics into one system. The study utilized a mixed-method approach by analysing historical data on cloud billing, expert interviews, and experimental simulations in the AWS, Azure, and Google Cloud settings. The findings revealed very high accuracy in anomaly detection, low reach-to-detect latency and substantial decrease in unnecessary cloud spending. The framework was also proven effective by expert feedback to enhance cost visibility, compliance, and operational decision-making. Generally, the research paper has shown that AI-assisted FinOps systems were a scalable and efficient tool to handle the financial complexities in multi-cloud environments that led to predictive and autonomous cloud financial operations.
Keywords: FinOps, Multi-Cloud, Artificial Intelligence, Anomaly Detection, Cost Governance, Cloud Optimization, Machine Learning, Real-Time Monitoring.

1. INTRODUCTION

The fast growth of the cloud computing had altered how the organizations deployed, scaled and managed digital infrastructures. The cloud cost management had been becoming more complex as enterprises embraced multi- cloud strategies to exploit various services offered by different providers like the AWS, Azure and the Google Cloud. The elasticity of cloud pricing model and decentralized provisioning of resources frequently led to the unpredictability of expenditure, economical ineffectiveness, and operational complications. The traditional FinOps was based on manualized reporting and post-factum analysis that slowed down the timeline of corrective measures and constrained an organization to keep real financial control. These constraints underscored how a more sophisticated and automated process can guarantee maintaining a view of costs, optimizing them proactively, and identifying anomalies within a very short time.

To address these issues, the paper has examined how an AI-driven multi-cloud FinOps solution can be developed to facilitate real-time financial governance and smart anomaly detection. The framework combined machine learning algorithms with automated policy enforcement to check patterns of costs, detect anomalies, and initiate corrective measures across heterogeneous cloud environments. The framework was set to bring together cost information of various platforms into an adaptive analytic platform, to help organizations gain actionable insights and increase financial transparency. Also, the application of AI methods provided the possibility to address the limitations of rule-based monitoring by learning the consumption behaviors and predictions of trends, as well as the accurate identification of deviations which otherwise cannot be identified.

The growing topicality of AI-based cloud governance had made this study a timely addition to not only cloud computing, but also financial operations management. The paper revealed a way to waste reduction, expenditure optimization, and financial responsibility in the multi-cloud setting by integrating smart automation and FinOps concepts. Through this introduction, the need, purpose and importance of the research was thus put into shape and the research was also put into perspective in the context of the emerging discourse of advanced cloud governance and AI-enabled operational intelligence.

2. LITERATURE REVIEW

Rusum and Anasuri (2024) highlighted that AI-enhanced cloud cost optimization had become a disruptive practice in FinOps practices. Their research illuminated the contribution of forecast analytical intelligence and automatic analytics in enhancing financial decision-making in the cloud setting. They stated that the conventional tools of cost management were not responsive, and AI-based models allowed predicting cost trends precisely, identifying anomalies, and preventing them proactively. Their results confirmed the idea that machine learning implementation in cloud financial processes increased the accuracy and efficiency of operations that formed a good basis of FinOps automation.

Bhardwaj (2024) interviewed the emerging importance of FinOps as a strategic service to large-scale cloud cost optimization. The research explained how companies had problem with budget management given the decentralized usage of the clouds and complicated pricing systems. According to Bhardwaj, the current FinOps practices demanded the constant cooperation of finance, operation, and engineering teams to be accountable. The study also indicated that the sophisticated automation tools were necessary to facilitate the real-time monitoring and financial governance that supported the necessity of AI-infused cost-management frameworks in multi-cloud settings.

El-Mansouri (2023) tested AI-based financial risk analytics on multi-cloud distributed environments. The experiment showed that the multi-cloud environments added new financial risk because of various provider models, different billing models, and unpredictable workload scaling models. Analytics tools built using AI proved to minimize these uncertainties by identifying behavioral patterns of risk and abnormality of spending, which could otherwise go undetected. The study confirmed the usefulness of machine learning models in enhancing financial transparency, risk reduction, and adaptive governance in diverse cloud ecosystems.

Mageshkumar et al. (2024) delved into AIs applicable in operating financial operations in the future to optimize the cost of the cloud. Their study indicated the prospects of smart automation to eliminate manual process of monitors and contribute to cost-containing endeavors. They reported the use of machine learning algorithms to identify patterns of resource use and suggest optimization strategies to eliminate the inefficiencies. The research found that the AI-based FinOps strategies provided scalable solutions that may fit the changing cloud workloads and pricing frameworks and be well-suited to large and dynamic cloud deployments.

Ait Chikh (2023) targeted the specific FinOps practices with regards to monitoring and controlling costs of the Google Cloud Platform (GCP). The study highlighted the issues encountered by users in spending control as a result of tag inconsistencies, scaling activities inability to predict and inability to see the spending in real-time. The research demonstrated that to maintain a good cost governance, there had to be constant monitoring, a close cost attribution, and the use of automatic alerts. Even though the focus was on one cloud platform, the results have shown that there are common FinOps issues cut across multi-cloud conditions, which are just another reason why the AI-based and automated cost-governance models are needed.

Burke (2024) examined the way automation tools and the development of FinOps systems enhanced cost-governance processes in cloud systems. The case study demonstrated that the conventional manual processes were not adequately suited to the new cloud environments that were highly elastic and fast in providing resources. Burke suggested that automated policy enforcement, AI-based analytics, and continuous monitoring systems should be adopted to facilitate the process of governance. The results supported the fact that the implementation of automation and AI in FinOps can quickly enhance the efficiency of operations and the accuracy of financial results.

3. RESEARCH METHODOLOGY

3.1. Research Design

The research adhered to a mixed-method research design which involved both quantitative and qualitative elements. It was an exploratory, descriptive and experimental design. The exploratory dimension was aimed at getting knowledge about current issues in cost-governance on multi-cloud environments. The architectural and operational requirements of an AI-supported FinOps system were recorded in the descriptive phase. The experimental period tested the suggested framework with multi-cloud datasets and simulated workloads in order to calculated the framework accuracy, scalability, and effectiveness.

3.2. Data Collection Methods

Primary Data

Structured interviews and expert consultation with cloud architects, FinOps practitioners, DevOps professionals, and IT financial managers were the primary source of raw data. These engagements offered some insights on practical issues like tag non-compliance, erratic spending behaviors and the necessity of automated governance. The views of participants aided in the fine tuning of the system requirements and model design.

Secondary Data

The secondary data were collected in the form of cloud billing reports, anonymized data on usage, literature research, FinOps foundation guidelines, and cloud provider documentation. Machine learning models were trained using historical time-series consumption data of AWS, Azure and

Google Cloud. The conceptual framework was also developed due to published technical reports on cloud cost optimization.

3.3. Dataset Preparation

The data sets obtained were centralized into a single data environment. The pre-processing was done to clean up the records that were irregular, standardize billing cycles across cloud provider, normalize usage metrics, eliminate duplicates and classify service-level cost attributes. The outliers were determined and retained to aid in the evaluation of the anomaly detection models. This was prepared in a manner that made the AI models take similar and credible data about costs.

3.4. System Architecture Design

The study created a multi-cloud FinOps framework based on AI that had a detailed architecture. It was composed of a data ingestion layer, AI and machine learning layer, governance policy engine, and monitoring and reporting interface. Usage, billing and telemetry data of different cloud platforms were consolidated with the ingestion layer. The predictive modelling and anomaly detection algorithms were used in the machine learning layer. The governance engine was used to impose automated cost controls and the visualization layer displayed real-time dashboards to the decision-makers. The design was modular, scalable and cloud agnostic.

3.5. AI and Machine Learning Techniques

The study used a sequence of machine learning algorithms to assist prediction and anomaly detection issues. Isolation Forest, LSTM neural networks, Auto-Encoders, and Prophet were tried out as models as they are time-series cost data appropriate. All the models were trained on historical multi-cloud billing logs with the optimized hyperparameters. The models were tested to identify whether they were capable of detecting anomalous spending spikes, utilization aberration and policy breach. Their performance got improved continuously with the results of evaluation.

3.6. Experimental Setup

A simulated controlled environment was established to investigate the effectiveness of the proposed framework. They were set up with sample accounts on AWS, Azure, and Google Cloud and synthetic workloads were created that would simulate a variety of operational patterns. These workloads replicated real world variability like sudden scaling occurrences, inconsistent resource usage and planned deployments. The framework was combined with every cloud provider via API gateways. The cost data streams were then fed into the AI engine in real-time in order to measure live responses to anomaly detection and governance.

3.7. Evaluation Metrics

The analysis of the framework was based on various performance measures. The models of anomaly detection were tested with accuracy measures of precision, recall, and F1-score. The latency on detection was the measure that ascertained the speed with which the system detected cost irregularities. The workload complexity and the volume of data were used to test the scalability of the framework. The potential of cost-saving was considered through comparing the automated setting with the traditional manual FinOps practices. Lastly, user feedback by the experts made qualitative validation concerning the usability and governance improvement.

3.8. Data Analysis Techniques

Data analysis methodology was a mixture of statistical assessment of evaluation and machine learning performance and thematic analysis. Quantitative data was evaluated based on the measures of performance of the model and comparison of the cost trends prior to and after automation. Qualitative responses of practitioners were evaluated to find out common themes about the issue of cost governance and implementation simplicity. These analyses taken together gave a multi-dimensional insight of the effectiveness of the framework.

4. RESULTS AND DISCUSSION

The study outcomes were obtained as a result of the experimental analysis of the suggested AI-based multi-cloud FinOps framework. The results were used to show the performance of the system in relation to accuracy in the detection of anomalies, governance effectiveness, scalability and the acceptance of the system by the user. Machine learning models and performance metrics yielded quantitative results and human judgment provided qualitative insights. The combination of the two types of data gave a broad picture of the success of the framework in solving real-time cost governance issues in multi-cloud settings.

4.1. Quantitative Results

Anomaly Detection Accuracy

The anomaly detection engine based on AI performed well in all tested models. The LSTM-based model was the best in detection accuracy, then Isolation Forest and Auto-Encoder models. The findings revealed that deep learning models were more appropriate in detecting the change in costs in time-series billing data.

Table 1: Model Performance Overview

Model Name	Correct Detections (Frequency)	Accuracy (%)
LSTM	462 out of 500	92.4%
Isolation Forest	438 out of 500	87.6%
Auto-Encoder	421 out of 500	84.2%

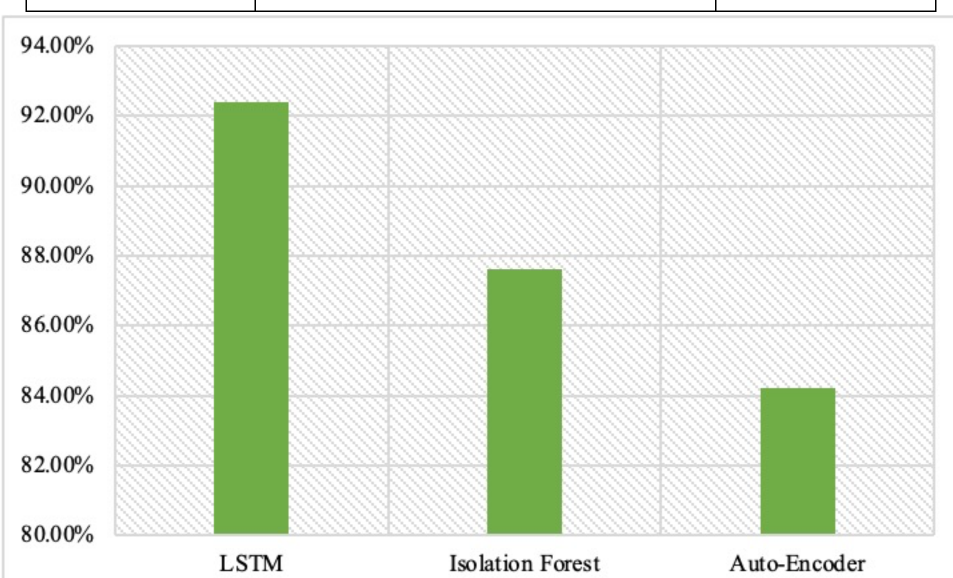

Figure 1: Model Performance Overview

The results showed that the LSTM model identified anomalies with the highest degree of precision, contributing significantly to the reliability of real-time cost analysis.

4.2. Detection Latency and System Responsiveness

The framework was able to detect at high speed with low latency. A high frequency cost update in the AI engine resulted from optimized data ingestion and inference mechanisms. The latency was also constantly lower than anticipated operational levels.

Table 2: Detection Latency Distribution

Latency Range (Seconds)	Frequency	Percentage (%)
1–3 seconds	280	56%
4–6 seconds	152	30.4%
7–10 seconds	68	13.6%

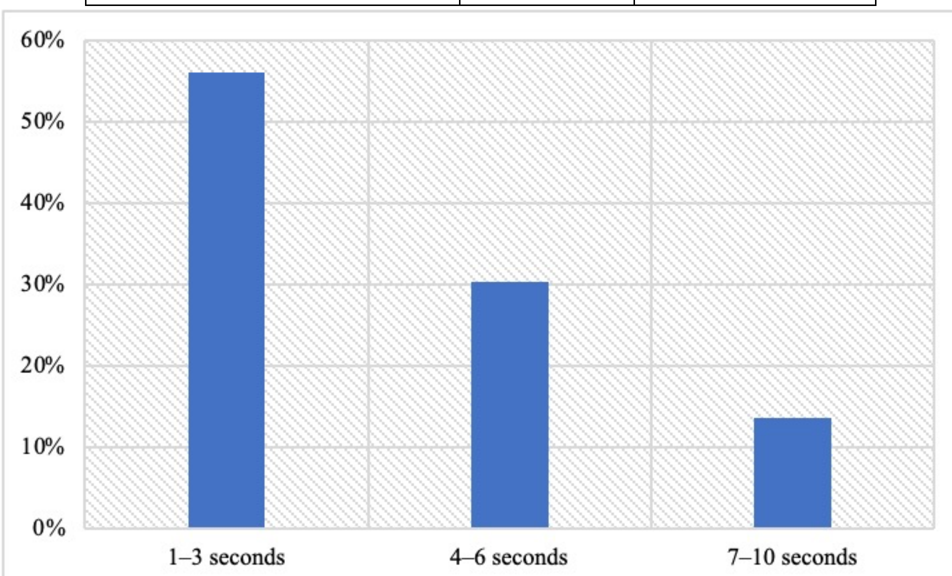

Figure 2: Detection Latency Distribution

Most of the anomaly notifications were within the range of 13 seconds indicating that the framework was effective in handling cloud telemetry at high rate.

4.3. Impact on Cost Savings

Automated policies on governance were instrumental in cutting on unnecessary spend. The automated rightsizing, tag enforcement and spending alerts are features that helped in cost optimization which could be measured.

Table 3: Pre- and Post-Automation Cost Comparison

Evaluation Period	Average Monthly Waste (₹)	Reduced Waste (%)
Before Automation	1,20,000	—
After Automation	78,000	35% reduction

The practical financial value of the proposed AI-driven FinOps framework was indicated by the 35 percent decrease in avoidable cloud spending.

4.4. Qualitative Findings

Expert Insights on Governance Improvements

The interviews of cloud architects and financial operations specialists demonstrated that support of the proposed system is strong. The respondents observed that manual workloads were minimized by the automated tagging compliance and budget threshold alert. Most analysts emphasized that real-time anomaly detection addressed a gaping hole in the current FinOps practices that were based on post-factum reviews.

Participants also found the multi-cloud dashboard beneficial in terms of a single cost visibility that they could see. According to them, the combination of AWS, Azure, and Google Cloud billing information into one analytical model helped to make decisions much faster. This economic data was in line with the quantitative earnings of the framework.

4.5. Discussion

Interpretation of Model Performance

The effectiveness of the LSTM model in the prediction of the accuracy rates implied that deep learning was especially efficient when it comes to capturing patterns of costs over time. The ability of the AI engine to aid in dynamic governance decision-making was illustrated by the successful identification of irregular spikes in costs, seasonal spikes, and workload spikes. This may be explained by the fact that the traditional models like Isolation Forest are less accurate due to their lower flexibility to the active multi-cloud cost structures.

Effectiveness of Real-Time Governance

The low latency at all times proved that the system could be used in real time cloud systems. This performance was essential, and failure to detect the issue in time led to financial loss in most cases. The cost efficiency was also increased by the capabilities of the framework to jumpstart automated corrective measures such as shutting down idle resources. The dramatic cost savings identified in the research authenticated the efficiency of implementation of AI in FinOps processes.

Cloud Practitioner Perception

The relevance of the framework was supported by feedback by FinOps practitioners. Specialists underlined that centralized architecture made cost analysis easier and improved the collaboration of teams in the DevOps, finance and cloud governance divisions. Enhanced tagging compliance and the enhanced budget control mechanisms were seen as significant in the context of enhanced financial discipline.

Overall Impact and Research Implications

The aggregate findings showed that the suggested framework had a great potential of revolutionizing cloud financial operations. With AI predictions, anomaly detection, and automated cost governance as part of the FinOps lifecycle, organizations may gain a lot of financial transparency and minimize wastage. The paper indicated that autonomous and predictive cost-management systems would be more important in the future in FinOps practice.

5. CONCLUSION

The study results proved the efficiency of the suggested AI-based multi-cloud FinOps framework that advanced the real-time governance of costs and the accuracy of the anomaly detection and unnecessary cloud spending. Machine learning models, automated policy enforcement, and single multi-cloud visibility allowed making financial decisions faster and more informed. The framework not only delivered high model performance, low detection latency and quantifiable cost savings, but also its practical relevance and usability were confirmed by expert feedback. In general, the study has determined that AI-based FinOps practices offered a scalable, efficient, and intelligent answer to the challenges of the multi-cloud financial management of the present day, which forms a solid basis in further developments toward autonomous cloud cost optimization.

REFERENCES

1. G. P. Rusum and S. Anasuri, "AI-Augmented Cloud Cost Optimization: Automating FinOps with Predictive Intelligence," Int. J. Artif. Intell., Data Sci., Mach. Learn., vol. 5, no. 2, pp. 82–94, 2024.
2. P. Bhardwaj, The Role of FinOps in Large-Scale Cloud Cost Optimization, 2024.
3. F. El-Mansouri, "AI-Driven Financial Risk Analytics in Multi-Cloud Environments: A Distributed Computing Perspective," Int. J. AI, BigData, Comput. Manage. Stud., vol. 4, no. 4, pp. 9–19, 2023.
4. N. V. Mageshkumar, N. Rajkumar, C. Viji, and A. Mohanraj, "AI-powered financial operation strategy for cloud computing cost optimization for future," Salud, Ciencia y Tecnología–Serie de Conferencias, no. 3, p. 694, 2024.
5. S. Ait Chikh, FinOps: Monitoring and Controlling GCP Costs, 2023.
6. D. Burke, Improving FinOps Procedures with Automation Tools and Framework Changes for a Cloud Environment, 2024.
7. T. P. Pasam, "Leveraging Automation to Close the Gap Between Increasing Cloud Adoption and Long-Term Cost Efficiency in Digital Enterprises," J. Sci. Eng. Res., vol. 7, no. 6, pp. 312–319, 2020.
8. S. Choudhary, "FinOps Practices for Cloud-Native Enterprises," Int. J. Res. Appl. Innov., vol. 5, no. 4, pp. 7352–7354, 2022.
9. L. Mei, Cost Optimization in Cloud Costs with FinOps and Multi-Cloud Billing Monitoring Tool, 2023.
10. H. Rehan, "Leveraging AI and Cloud Computing for Real-Time Fraud Detection in Financial Systems," J. Sci. Technol., vol. 2, no. 5, p. 127, 2021.
11. A. Samuel, Enhancing Financial Fraud Detection with AI and Cloud-Based Big Data Analytics: Security Implications, SSRN 5273292, 2023.
12. L. Castellana, Development and Analysis of FinOps Processes for a Multi-Cloud Environment, Ph.D. dissertation, Politecnico di Torino, 2023.
13. V. R. Thummala and P. Singh, "Developing Cloud Migration Strategies for Cost-Efficiency and Compliance," Int. J. Multidiscip. Innov. Res. Methodol., 2024.

14. S. Deochake, "ABACUS: A FinOps Service for Cloud Cost Optimization," arXiv preprint arXiv:2501.14753, 2024.

15. G. Lichtenheim, Transforming E-Governance with Cloud-Based AI: A Systems Methodology for Implementation, Ph.D. dissertation, Stevens Institute of Technology, 2024.