Evaluating CSPs Through Enterprise Mobility: A Hybrid TOPSIS–ML Framework

Abhishek Singh, B. B. Sagar
Department of Computer Science and Engineering
Harcourt Butler Technical University
Kanpur–208002, Uttar Pradesh, India

DOI:10.37648/ijiest.v12i01.003

[1]Date of Receiving: 24 December 2025;
Date of Acceptance: 17 January 2026;
Date of Publication: 29 January 2026

Abstract

Cloud computing has become a foundational technology for modern enterprises by enabling scalable, flexible, and cost-effective computing services. Selecting an appropriate cloud service provider (CSP) is a complex multi-criteria decision-making problem due to conflicting criteria such as performance, security, cost, and global reach. With the rapid adoption of mobile-first strategies, Mobile Device Management (MDM) and Mobile Backend as a Service (MBaaS) have emerged as critical differentiators among CSPs.

This paper proposes a hybrid Multi-Criteria Decision-Making (MCDM) and Machine Learning (ML) framework for CSP selection. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used to generate deterministic rankings based on seven criteria, including MDM and MBaaS. Supervised ML models—including Random Forest, XGBoost, Support Vector Regression, K-Nearest Neighbors, and Multi-Layer Perceptron—are trained to learn and predict TOPSIS closeness coefficients. Random Forest achieves the highest accuracy with an R^2 value of 0.48.

The hybrid model enhances decision accuracy, adaptability, and scalability for mobile-centric cloud adoption.

Keywords: *Cloud Computing; Cloud Service Provider Selection; Multi-Criteria Decision Making; TOPSIS; Machine Learning; Mobile Device Management; MBaaS.*

1. Introduction

1.1. Background of the Study

Cloud computing has become essential for modern digital infrastructure, enabling organizations to scale resources, enhance mobility, reduce operational costs enhance mobility, and accelerate innovation[1]. Major providers—AWS, Azure, GCP, OCI, and IBM Cloud—continue to expand globally[3]-[7].

Organizations require cloud platforms that not only provide compute, storage, and networking functionalities but also support secure device management, mobile app deployment, real-time analytics, and seamless integration with enterprise mobility frameworks.[10]

[1] *How to cite the article:* Singh A., Sagar B.B.; (January 2026); Evaluating CSPs Through Enterprise Mobility: A Hybrid TOPSIS–ML Framework; *International Journal of Inventions in Engineering and Science Technology;* Vol 12 Issue 1; 18-27; DOI: http://doi.org/10.37648/ijiest.v12i01.003

Given the variety of criteria involved—cost, performance, security, global reach, AI/ML capabilities, mobile backend support, and MDM—selecting the most appropriate CSP is a complex multi-criteria decision-making problem.[11]

Traditional evaluation methods often rely on subjective judgment or single-factor comparison, which may lead to biased or sub-optimal decisions.

Therefore, a systematic and intelligent approach is required to assist organizations in selecting the best cloud provider according to their unique requirements.[14]

The major challenges in selecting the CSPs are as follows:[16]

- The metrics to be considered for CSP selection.
- The numerous services offered by CSPs.
- The process of choosing the best, most suited CSP from

the numerous cloud vendors existing in the global market.

There are various CSPs across the globe with different services, pricing models, and infrastructures. As per Gartner's report:[15]

the top five CSPs:1) Amazon Web Services (AWS), 2) Microsoft Azure, 3) Google Cloud Platform (GCP), 4) Oracle cloud Infrastructure (OCI) &5) IBM Cloud

Once the top five vendors are identified, the primary goal is to choose the most appropriate one among them for user's software requirement specification.

1.2 Problem Statement

CSP selection is challenging due to: Conflicting criteria (e.g., performance vs cost), Rapid evolution of cloud architectures, Strong enterprise dependence on mobile ecosystems, Absence of hybrid MCDM–ML frameworks & Lack of predictive adaptability in conventional MCDM methods

1.3 Motivation

Traditional expert-based CSP evaluation methods are subjective and non-scalable. MCDM techniques provide structure but cannot learn evolving cloud performance trends. ML models capture nonlinear patterns but lack explainability. A hybrid MCDM–ML approach combines the strengths of both.

1.4 Research Objectives

The study is guided by the following objectives in Figure 1:

1) Identify and define evaluation criteria relevant to cloud provider selection, including MDM, MBaaS, performance, security, cost, global reach, and AI/ML features.

2) Apply the TOPSIS MCDM method to compute weighted rankings of CSPs based on the identified criteria.

3) Develop and train machine learning models (Random Forest, XGBoost, SVR, KNN, MLP) to learn the ranking patterns from TOPSIS and predict CSP performance.

4) Compare and evaluate the ML models using regression and classification metrics such as MSE, MAE, R^2, confusion matrices, and F1-scores.

5) Integrate the outcomes of both TOPSIS and ML predictions to develop a robust hybrid cloud selection framework.

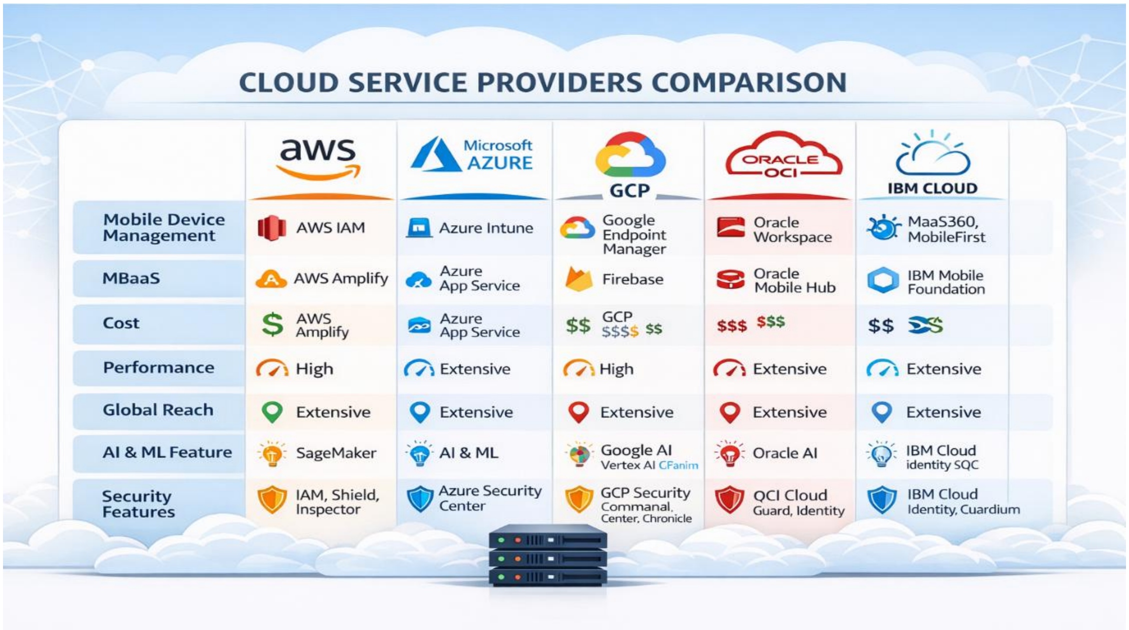

Figure 1 Cloud Service Provider Evaluation

2. Literature Review

2.1 Introduction

This review integrates cloud computing fundamentals, CSP landscapes, enterprise mobility, MDM, MBaaS, MCDM techniques, ML-based decision support, and hybrid frameworks.

2.2 Cloud Service Providers

Top five CSPs include AWS, Azure, GCP, OCI, and IBM, dominating the Gartner Magic Quadrant.

2.3 Mobile-Centric Cloud Requirements

The rise of mobile-first strategies has shifted enterprise expectations from cloud platforms. Literature highlights several new requirements: Secure mobile device onboarding, Application distribution, Zero-touch provisioning, Remote wipe and policy enforcement, Integration with identity management, Real-time analytics for mobile endpoints & Mobile backend services for app development.

2.4 Mobile Device Management (MDM) and Enterprise Mobility

2.4.1 Mobile Backend as a Service:

MBaaS includes notification services, real-time sync, authentication, APIs, analytics, and cloud databases. Examples: Firebase (GCP), AWS Amplify, Azure Mobile Apps.

2.4.2 Mobile Device Management (MDM):

MDM refers to software suites that provide security, monitoring, and administrative controls over mobile endpoints. Key components include: Device provisioning, Device compliance monitoring & Remote lock/wipe

2.4.3 Evolution of Enterprise Mobility:

Enterprise mobility has evolved from remote access solutions to comprehensive mobile application ecosystems supported by cloud-based backend services.

2.5 Cloud Evaluation Criteria

Seven criteria adopted:

- MDM
- MBaaS
- Performance
- Cost
- Security
- Global Reach
- AI/ML Capability

These criteria reflect both enterprise and mobile-centric priorities. The inclusion of MDM and MBaaS fills a major gap in prior CSP selection literature.

2.6 MCDM Methods

Numerous studies have applied MCDM techniques such as AHP, TOPSIS, VIKOR, and ELECTRE to evaluate CSPs based on quality-of-service attributes.[19]

TOPSIS is chosen due to clarity, simplicity, and ability to handle weighted benefit/cost criteria.

2.7 Machine Learning in Decision Support

ML improves prediction accuracy, automation, and generalizability. Models include Random Forest, XGBoost, SVR, KNN, and MLP.

Gaps: No research uses ML to learn MCDM decision patterns, No predictive models for CSP selection incorporating, MDM & No hybrid MCDM–ML frameworks applied to enterprise.

2.8 Hybrid MCDM–ML

Combining MCDM structure with ML adaptability provides predictive power and scalability, This hybridization is widely recommended in theoretical studies but rarely implemented in cloud selection research.

No models exist for cloud provider selection that combine TOPSIS

2.9 Literature Summary

The review identified major gaps in cloud provider selection research, The findings of the literature review justify the need for a new hybrid framework combining TOPSIS and machine learning to enhance the efficiency, accuracy, and adaptability of cloud service provider selection.

Table 1: Literature Review on Cloud Service Provider Selection

Study Category	Representative Studies	Approach & Contribution	Identified Limitations
Cloud Market and CSP Surveys	[1], [3]–[7], [15]	Descriptive analysis of cloud service models, CSP offerings, and market positioning	Lacks quantitative decision models; no mobility-oriented evaluation
QoS-Based CSP Evaluation	[9], [19], [20]	Ranking CSPs using performance, reliability, and usability metrics	Ignores enterprise mobility, MDM, and predictive capability

MCDM-Based CSP Selection	[13], [17], [18], [21]	Application of AHP, TOPSIS, ELECTRE, and fuzzy MCDM for CSP ranking	Static rankings; sensitive to weights; no learning or adaptability
Advanced MCDM Variants	[8], [14], [16]	Integration of DEMATEL, ANP, Markov models, and custom weighting schemes	Increased complexity; limited interpretability; mobility features omitted
Hybrid MCDM–ML Frameworks (Non-Cloud)	[11], [12]	Demonstrates feasibility of learning MCDM outcomes using supervised ML	Not applied to CSP selection; no cloud or mobility context
Enterprise Mobility and MDM Studies	[10]	Analysis of cloud-supported mobility, IoT, and mobile ecosystems	Does not address CSP selection or decision modelling
Proposed Work	—	Hybrid TOPSIS–ML framework with explicit MDM and MBaaS criteria	Addresses adaptability, scalability, and mobility-aware CSP evaluation

3. Research Methodology

3.1 Research Approach

A deductive research approach is followed:

- Theory: Multi-criteria decision-making and learning algorithms
- Hypothesis: Integrated MCDM–ML will outperform standalone MCDM
- Testing: TOPSIS + ML models
- Evaluation: Model comparison using regression and classification metrics

3.2 Research Design

Construct dataset > Apply TOPSIS > Train ML models > Compare performance > Integrate hybrid ranking.

3.3 Data Collection

1) Sources of Data: Sources include Gartner reports, vendor documentation, scholarly publications, and MDM product guides.

2) Selection of Cloud Service Providers*:* Five CSPs were selected based on their consistent presence in Gartner's leadership quadrant.

3) Selection of Evaluation Criteria: Based on literature and enterprise mobility requirements, seven criteria were selected: Criteria scores were normalized on a scale of 1–10 using benchmarking data as in TABLE II.

TABLE II: EVALUATION CRITERIA FOR CLOUD SERVICE PROVIDER SELECTION

Criterion	Description
Mobile Device Management (MDM)	Native MDM capability, policy enforcement, and security integration
Mobile Backend Support (MBaaS)	Tools for mobile application development such as Firebase, AWS Amplify, etc.
Performance	Compute power, scalability, and network latency
Cost	Price–performance ratio and billing simplicity
Security	Certifications, encryption, and compliance with standards such as ISO, GDPR, and HIPAA
Global Reach	Number of regions, availability zones, and global network coverage
AI/ML Capability	Platform AI tools, machine learning frameworks, and automation APIs

3.4 TOPSIS Methodology: It is depicted in figure 2.

Figure 2 TOPSIS Methodology Flowchart

3.4 ML Methodology

Models used: Random Forest, XGBoost, SVR, KNN, MLP.

Data normalization with Min-Max scaling & 5-fold cross-validation applied.

3.5 Evaluation Metrics

Regression: MSE, MAE, R^2

Classification: Precision, Recall, F1-Score, Accuracy

4. Experimental Results

4.1 Dataset

Five CSPs evaluated across seven criteria (MDM, MBaaS, Performance, Cost, Security, Global Reach, AI/ML) as in Figure 3.

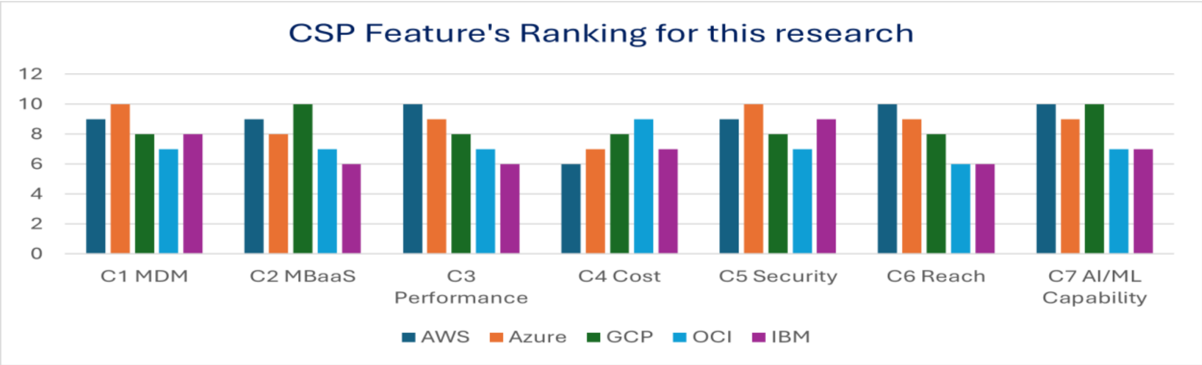

Figure 3 CSP Feature Ranking

4.2 TOPSIS Results

AWS ranks first, followed by Azure and GCP. IBM and OCI rank lower, depicted in figure 4.

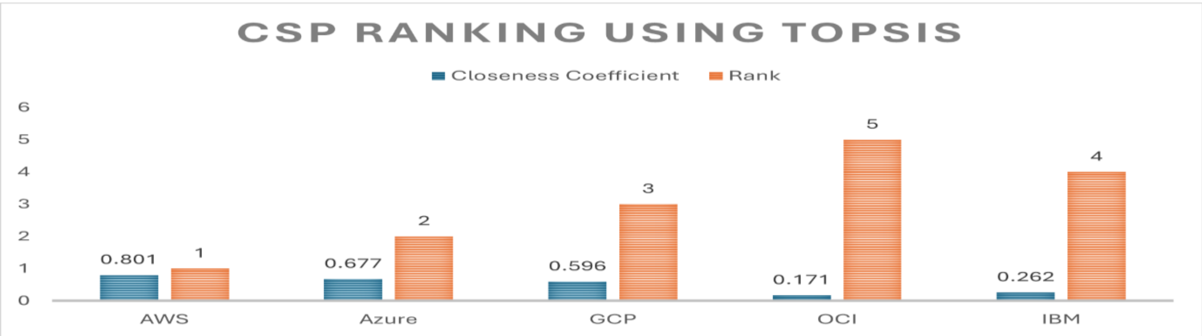

Figure 4 CSP Ranking Using TOPSIS

4.3 ML Results

Random Forest performs best across regression and classification metrics in TABLE III & IV.

TABLE III – REGRESSION PERFORMANCE OF ML MODELS

Model	MSE	MAE	R^2
Random Forest	0.0305	0.1608	0.4857
MLP	0.0371	0.1460	0.3735
SVR	0.0503	0.1971	0.1510
KNN	0.0531	0.2039	0.1035
XGBoost	0.0886	0.2753	−0.4971

TABLE IV - CLASSIFICATION PERFORMANCE OF ML MODELS

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	1.00	1.00	1.00	1.00
SVF (RBF Kernel)	1.00	1.00	1.00	1.00
KNN	0.80	0.90	0.80	0.80
MLP Neural Network	1.00	1.00	1.00	1.00

4.4 Hybrid Results: Final hybrid ranking confirms AWS as the top CSP in figure 5.

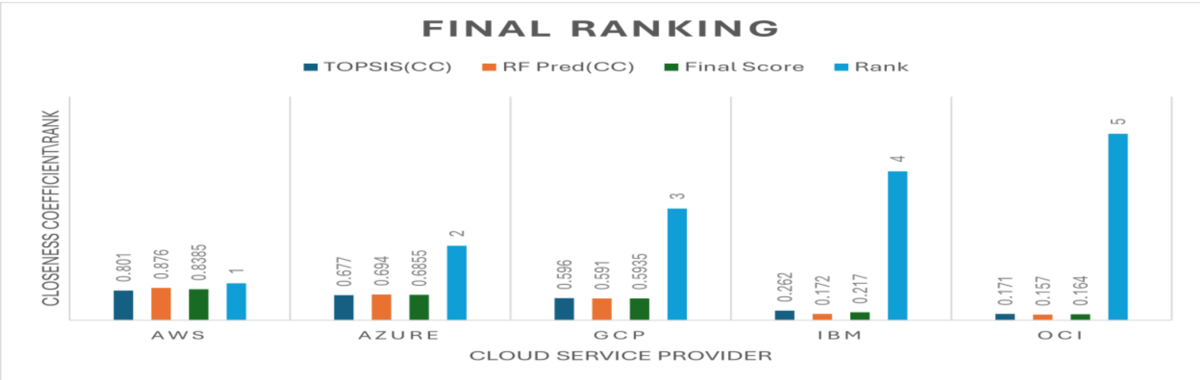

Figure 5 CSP Ranking Using Hybrid Approach

5. Discussion and Interpretation

The TOPSIS and ML phases produce consistent results, confirming the reliability of the criteria and the hybrid methodology. The ML model successfully learns the decision patterns generated by MCDM.

6. Conclusion and Future Work

A hybrid MCDM–ML framework is proposed for evaluating CSPs with emphasis on mobile-centric attributes. Future work includes expanding datasets, integrating real-time metrics, applying deep learning models, and extending evaluations to industry-specific use cases.

References

Abdulla, A., & Baryannis, G. (2024). A hybrid multi-criteria decision-making and machine learning approach for explainable supplier selection. *Supply Chain Analytics, 7*, Article 100074.

Abdelaziz, A. S. (2022). An enhanced MCDM model for cloud service provider selection..

Alameer, M. (2023). Cloud-based software development lifecycle: A simplified algorithm for cloud service provider evaluation with metric analysis. *IEEE Xplore*. **https://ieeexplore.ieee.org/document/10026515.**

Amazon Web Services. (2023). *Overview of Amazon Web Services* [Whitepaper]. **https://aws.amazon.com/whitepapers/.**

Botta, A., de Donato, W., Persico, V., & Pescapé, A. (2016). Integration of cloud computing and Internet of Things: A survey. *Future Generation Computer Systems, 56*, 684–700. **https://doi.org/10.1016/j.future.2015.09.021.**

Bouarfa, F., et al. (2020). *Using multi-criteria decision-making and machine learning for football player selection and performance prediction*. HAL. **https://hal.science/hal-04281291v1.**

Chen, F., et al. (2015). Integration of QoS aspects in the cloud service research and selection system. ResearchGate. **https://www.researchgate.net/publication/281221232.**

Doe, J., et al. (2022). A framework for evaluating cloud computing services using AHP and TOPSIS approaches with interval-valued spherical fuzzy sets..

Gartner. (2023). *Strategic cloud platform services reviews*. **https://www.gartner.com/reviews/market/strategic-cloud-platform-services.**

Google Cloud. (2023). *Google Cloud Platform overview* [Technical report]. **https://cloud.google.com/docs.**

Goyal, P., & Deora, S. S. (2024). Cloud service ranking with an integration of k-means algorithm and decision-making trial and evaluation laboratory approach. *International Journal of Electrical and Computer Engineering, 14*(2), 1816. **https://doi.org/10.11591/ijece.v14i2.pp1816-1824.**

IBM. (2023). *IBM Cloud platform overview*. **https://cloud.ibm.com/docs.**

Kim, S. J. (2018). A group decision-making method for selecting cloud computing service model. ResearchGate. **https://doi.org/10.13140/RG.2.2.24685.06888.**

Li, S., et al. (2022). Comparison of multi-criteria decision-making techniques for cloud services selection. ResearchGate. **https://www.researchgate.net/publication/359980491.**

Liu, L., Lu, C., Xiao, F., Liu, R., & Xiong, N. N. (2021). A practical integrated multi-criteria decision-making scheme for choosing cloud services in cloud systems. *IEEE Access, 9*, 88391–88404. **https://doi.org/10.1109/ACCESS.2021.3093603.**

Makwe, A., Kanungo, P., Xiong, G., Kautish, S., & Wagdy, A. (2023). Cloud service prioritization using a multi-criteria decision-making technique in a cloud computing environment..

Mell, P., & Grance, T. (2011). *The NIST definition of cloud computing* (NIST Special Publication 800-145). National Institute of Standards and Technology. **https://doi.org/10.6028/NIST.SP.800-145e.**

Microsoft Azure. (2023). *Microsoft Azure: Architecture overview*. **https://learn.microsoft.com/azure/.**

Nadeem, F. (2020). A unified framework for user-preferred multi-level ranking of cloud computing services based on usability and quality of service evaluation. *IEEE Access, 8*, 180054–180066. **https://doi.org/10.1109/ACCESS.2020.3027720.**

Oracle. (2023). *Oracle Cloud Infrastructure architecture* [Whitepaper]. **https://docs.oracle.com/cloud/.**

Sharma, A., & Kumar, P. (2022). A hybrid framework for ranking cloud services based on Markov chain and the best-only method.

About Authors

Mr. Abhishek Singh received the B.Tech. degree in Computer Science and Engineering from HBTI Kanpur (affiliated to UPTU Lucknow) and is currently pursuing the M.Tech. degree in Computer Science and Engineering from Harcourt Butler Technical University, Kanpur, India. His research interests include cloud computing, data analytics, machine learning and business intelligence. He has professional experience with Cloud Infrastructure, Service Now, JIRA, React, IBM WAS, TRIRIGA, Maximo (enterprise asset management systems), and BIRT Reporting.

Dr. Bharat Bhushan Sagar received the Ph.D. degree in Software Engineering from SHIATS, Allahabad, India, in collaboration with IIT BHU. He is an Associate Professor in the Department of Computer Science and Engineering at Harcourt Butler Technical University, Kanpur, India. He has over eighteen years of teaching and research experience and has served at BIT Mesra (Noida Campus), AKGEC Ghaziabad, and Dr. K. N. Modi Institute of Engineering & Technology