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Aigul Meirmanova
PhD, Postdoctoral Researcher, Assistant Professor, School of Software Engineering
a.meirmanova@astanait.edu.kz; orcid.org/0000-0002-3841-3754
Astana IT University, Kazakhstan
Aibek Zhumabekov
Master's Student, School of Software Engineering
242946@astanait.edu.kz; orcid.org/0009-0002-5257-7138
Astana IT University, Kazakhstan

HIERARCHICAL DECISION MODELLING OF CLOUD ENTERPRISE DATA STORAGE SYSTEMS USING AHP

Abstract: Evaluating cloud enterprise data storage systems is mission-critical for ensuring reliability, security and compliance, interoperability, scalability, performance, vendor support, and cost-effectiveness in modern organizations where petabytes of data are stored. However, choosing the appropriate storage solution is complex, as enterprises must consider numerous strategic, technological, and operational dimensions. This article addresses these challenges by presenting a multiperspective assessment of cloud enterprise storage systems supported by multi-criteria decision making (MCDM) tool, such as Analytic Hierarchy Process (AHP). A three-tier hierarchy was constructed that organizes nine criteria into strategic, technological, and operational dimensions. Using this structure, three leading cloud storage platforms – Amazon S3, Microsoft Azure, and Google Cloud Storage – were evaluated. The opinions of twelve senior experts from National Information Technologies Joint-Stock Company (NITEC JSC) in Kazakhstan, all with experience in corporate cloud infrastructure, were collected using pairwise comparison questionnaires and summarized using the geometric mean. Local and global weights were obtained by calculating the priority based on eigenvectors with a consistency coefficient check and sensitivity analysis to confirm the reliability of the model. The results show that the criteria related to continuity and reliability prevail in decision-making, while pure productivity and manageability have a comparatively lower weights. Amazon S3 had the highest overall priority, followed by Microsoft Azure and Google Cloud Storage. This study contributes not only a practical solution for a multiperspective decision model but also a validated methodological blueprint that helps enterprises adapt continuously as technologies evolve. Future work will explore how hierarchical decision modelling can facilitate transparent and repeatable selection of enterprise cloud storage providers and can be expanded to include additional criteria such as cost and security in organization-specific applications.

Keywords: Cloud service provider selection; multi-criteria decision making (MCDM); Analytic Hierarchy Process (AHP); cloud computing; quality of service; decision analysis; reliability; performance; strategic alignment; continuity.

Introduction (Literary review)

Enterprise data storage has become a main part of today's organisational infrastructure because data keeps growing and cloud use is speeding up [1-2]. Cloud enterprise data storage systems give scalable and flexible designs, yet choosing the best provider is still a complex task due to competing strategic, technical and operational goals [3-5]. Although Amazon S3, Microsoft Azure, Google Cloud Storage provide services that appear similar at first sight, but they differ in performance, pricing and feature sets. These differences complicate the evaluation and increase the likelihood that the enterprise needs will not match what the provider offers. Such mismatches can lead to a reduced performance, security vulnerabilities, and compliance failures [4, 6].

Storage systems are usually replaced every three to five years to add new functions and reduce the risks related to outdated hardware [7-8]. Because of this, choosing an enterprise data

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storage system locks an organisation into a long-term decision that will last for years, demands a large capital investment, and involves a difficult data migration. Planners must weigh multiple separate factors – such as how well the system supports long-term goals, the reliability of the technology, and whether it can run day-to-day operations without interruption – rather than focusing only on price or rated speed [8-9]. The rapid growth of unstructured data, driven by the expanding use of Artificial Intelligence (AI) as well as Internet of Things (IoT), has turned storage from a background service into a key business resource. Analysts expect worldwide enterprise storage budgets to increase significantly, with most new spending focused on high-performance flash systems that support AI workloads [10]. However, if a company chooses the wrong product, it may face *vendor lock-in*: proprietary formats and high data-exit charges can prevent an affordable move to another platform [11]. At the same time, the surge in cyber attacks forces organizations to apply strict security checks, since poorly designed systems still face the twin risks of data loss and hijacked traffic [12-13]. To manage these competing goals, Multiple Criteria Decision Making (MCDM) provides step-by-step methods for assessment. One widely used approach, the Analytic Hierarchy Process (AHP), converts qualitative opinions into numerical scores [14]. AHP is well suited to problems that can be organized hierarchically: it breaks a decision into smaller parts and then calculates stable weights for each of them [15].

Published studies show that combined AHP-based models have already been used to guide cloud service selection and security evaluations, demonstrating that the method performs reliably in high-stakes decisions [16]. Multi-Attribute Decision Making (MADM) evaluates a predefined set of alternatives, whereas Multi-Objective Decision Making (MODM) seeks optimal solutions without relying on a fixed list. Despite these differences, AHP remains the leading approach when technology suppliers must be ranked [17]. Effective decision making requires up-to-date models that include expert views, especially when clear benchmarks are lacking [18]. Information Technology (IT) executives often extend their knowledge by consulting specialists to assess emerging technologies [19]. Structured expert elicitation transforms tacit knowledge into numbers, reduces uncertainty, and strengthens analytical rigor [20]. To address these needs, the study evaluates a multiperspective Hierarchical Decision Modeling (HDM) framework by using AHP. The proposed model integrates expert judgment with strategic, technological, and operational criteria, providing a transparent method for ranking cloud enterprise data storage systems in data-limited environments.

Methods and materials

Dataset

The study employed a fixed sequence consistent with the AHP. To collect reliable expert judgments on cloud enterprise data storage systems, a pairwise comparison instrument was developed on Saaty's 1-9 scale, where each value represents the relative importance of one element over another [14]. Experts applied this scale to evaluate both the weights of the criteria and the performance of three large services: Amazon S3, Microsoft Azure, and Google Cloud Storage.

The instrument consists of two stages that reflect the decision model:

1. Criteria Evaluation – In this stage, respondents compared criteria within each of the three groups – Strategic, Technological, Operational. For every pair, they indicated how many times one criterion outweighed the other in the selection of a data storage system.
2. Alternative Assessment – In this stage, the same experts conducted pairwise comparisons of the three cloud services for each sub-criterion. By collecting judgments at both the criterion and service levels, the study captures comprehensive expert judgments and derives weighted rankings of criteria and alternatives within the HDM framework.

To ensure that the comparisons reflected real organisational practice, the study selected participants deliberately – individuals with long-term involvement in both cloud infrastructure and enterprise architecture. Due to the limited availability of data in this area, the study followed

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established guidance indicating that experienced specialists supply the most reliable judgments [19-20]. Twelve professionals joined in the given study from National Information Technologies Joint-Stock Company (NITEC JSC) in Kazakhstan. The panel combined senior management along with hands-on technical staff to ensure so that all relevant viewpoints were appeared. Participant titles included Chief Engineer, IT Director, Senior Analyst, Solution Architect, Lead System Analyst, Senior Database Administrator, and Chief IT Architect. Each expert's responses were stored separately in order to prevent mutual influence. The aggregated pairwise comparison matrices obtained using the geometric mean, together with anonymized expert judgments, are provided as supplementary material to improve transparency and reproducibility of the study.

AHP modelling approach

The study uses a step-by-step decision method named the AHP to rate cloud enterprise data storage systems. The process follows four main stages – build the hierarchy, collect expert judgements, run the AHP calculations and automate the final instrument.

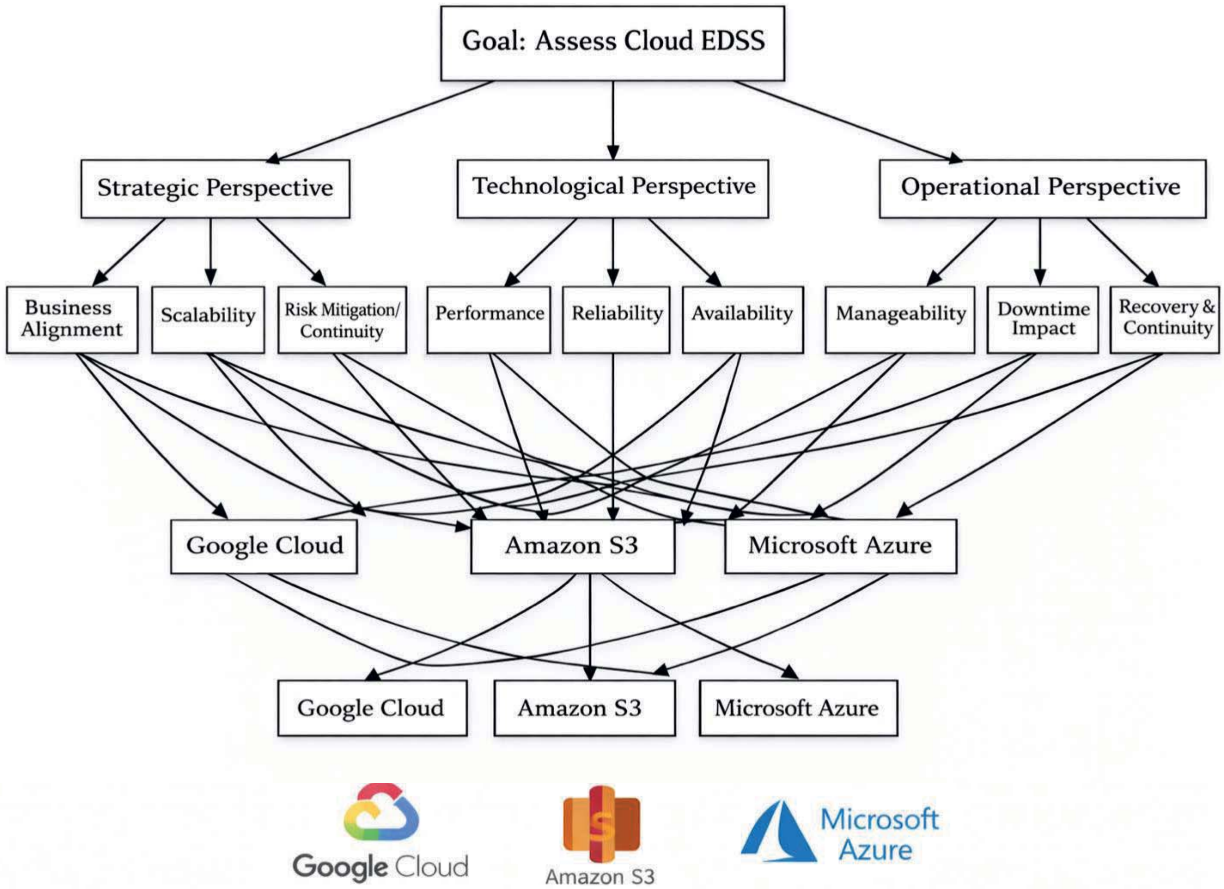

Figure 1. Hierarchical model for cloud provider selection

As shown in Figure 1 the hierarchy has three layers. The top layer defines a single objective: selecting the most appropriate Cloud Service Provider (CSP). This objective is decomposed into three dimensions, each of which is further divided into three specific evaluation criteria, resulting in a total of nine criteria.

- Strategic Perspective: Focuses on *Business Alignment*, *Scalability*, and *Risk Mitigation/Continuity*.
- Technological Perspective: Evaluates *Performance*, *Reliability*, and *Availability*.
- Operational Perspective: Assesses *Manageability*, *Downtime Impact*, and *Recovery and Continuity*.

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The alternatives evaluated against these criteria are three leading CSPs: Google Cloud, Amazon S3, and Microsoft Azure.

Data collection utilized a structured pairwise comparison questionnaire based on Saaty's 1–9 fundamental scale, where 1 represents equal importance and 9 represents extreme importance [15]. Experts performed two levels of assessment:

1. **Criteria evaluation:** Weighting the importance of criteria within the Strategic, Technological, and Operational categories.
2. **Alternative assessment:** Comparing the three CSPs (Google Cloud, Amazon S3, and Microsoft Azure) against each specific sub-criterion [14, 16].

The mathematical derivation of weights followed the standard AHP protocol [14].

(a) Pairwise Comparison Matrices

For every expert and comparison set, a reciprocal matrix A of dimension $n \times n$ was constructed, where n is the number of elements compared. The matrix is defined as:

$$A = [a_{ij}] = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix} \tag{1}$$

(b) Aggregation of Group Judgments

To synthesize the inputs from the 12 experts into a single consensus matrix, the geometric mean method was applied. This method is preferred in group AHP settings for preserving the reciprocal property of the matrix. The aggregated entry $\overline{a_{ij}}$ is calculated as:

$$(\bar{a})_{ij} = \left(\prod_{k=1}^{K} a_{ij}^{k}\right)^{\frac{1}{K}} \tag{2}$$

where $a_{ij}^{(k)}$ is the judgment of the k-th expert and $K = 12$.

(c) Priority Vector Derivation

The local weights (priority vector w) were derived by solving the principal eigenvalue problem:

$$Aw = \lambda_{max} w \tag{3}$$

where λ_{max} is the maximum eigenvalue of matrix$A$ and w is the normalized eigenvector $\sum w_i = 1$.

(d) Consistency Verification

To validate the logical consistency of the expert judgments, the Consistency Ratio (CR) was computed for every aggregated matrix. The consistency is determined using the Consistency Index (CI) and the Random Index (RI):

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

A CR below 0.10 is taken as acceptable – every aggregated matrix in the study met this requirement.

(e) Global Synthesis

The final global priorities were obtained – combining the weights throughout the hierarchy. The three top level perspectives were given equal weights of one third each. The Strategic, Technological, and Operational dimensions were initially assigned equal weights (1/3 each) to avoid introducing subjective preferences at the highest level of the hierarchy. Since no empirical evidence or prior studies suggested that one perspective should dominate the others, equal weighting provided a neutral baseline. This approach ensures that the final ranking is primarily determined by expert evaluations of the lower-level criteria rather than predefined assumptions. Future research may derive the top-level weights directly from expert pairwise comparisons. The global score for each alternative is the weighted sum of its local scores over all criteria.

Automated computational implementation

Custom calculation engine was developed using Python with NumPy library to ensure transparency and reproducibility. The code processes the experts' judgments by computing the geometric mean for each comparison group, deriving the corresponding priority vector using the eigenvalue method, evaluating the consistency of the judgments, and producing a ranked list of the service providers. As shown in Figure 2 the configuration defines the three main criteria groups and maps each group to its three evaluation criteria. It also lists the identifiers for the alternative comparisons associated with each sub-criterion, which are later used to process expert judgments.

```python
# --- Configuration ---
keys_criteria = ['strat', 'tech', 'ops']
criteria_names = {
    'strat': ['Business Align', 'Scalability', 'Risk/Continuity'],
    'tech': ['Performance', 'Reliability', 'Availability'],
    'ops': ['Manageability', 'Downtime Impact', 'Recovery/Cont.']
}

keys_alternatives = [
    'alt_ba', 'alt_sc', 'alt_rm',
    'alt_pf', 'alt_rl', 'alt_av',
    'alt_mg', 'alt_di', 'alt_rc'
]
```

Figure 2. Configurations for further calculations

As shown in Figure 3 the code maps internal keys to readable criterion names, defines the cloud providers being evaluated, and initializes data structures to store global criterion weights and provider scores.

```python
# Mapping the short data keys to the readable criteria names
criterion_key_map = dict(zip(keys_alternatives, [
    'Business Align', 'Scalability', 'Risk/Continuity',
    'Performance', 'Reliability', 'Availability',
    'Manageability', 'Downtime Impact', 'Recovery/Cont.'
]))

provider_names = ['Google Cloud', 'Amazon S3', 'Microsoft Azure']
global_criteria_weights_map = {}
provider_scores = {name: 0 for name in provider_names}

print("=== AHP Analysis Report ===")
print(f"Total Respondents: {len(respondents_data)}\n")
```

Figure 3. Data mapping

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As shown in Figure 4 this block aggregates pairwise comparison matrices across respondents using the geometric mean, computes local weights for each criterion, and converts them into global weights by applying the category weight. As shown in Figure 5 this block aggregates comparisons for each criterion, computes alternative scores, stores them in a table, and accumulates weighted scores to build each provider's final score.

As shown in Figure 6 this block sorts providers by their total weighted scores and displays the final ranking along with percentage contributions.

```
# --- Step A: Criteria Weights ---
print("1. Criteria Weights Calculation (Aggregated)")
criteria_report_data = []

for key in keys_criteria:
    # 1. Gather all matrices for this category
    matrices = [create_matrix(resp[key]) for resp in respondents_data]

    # 2. Aggregate using Geometric Mean
    agg_matrix = geometric_mean_aggregation(matrices)

    # 3. Calculate Local Weights
    weights = calculate_priority_vector(agg_matrix)

    # 4. Process Global Weights (Category Weight = 1/3)
    category_weight = 1/3
    for i, name in enumerate(criteria_names[key]):
        local_w = weights[i]
        global_w = local_w * category_weight
        global_criteria_weights_map[name] = global_w

        criteria_report_data.append({
            'Category': key.capitalize(),
            'Criterion': name,
            'Local Weight': local_w,
            'Global Weight': global_w
        })

# Display Criteria Weights Table
criteria_df = pd.DataFrame(criteria_report_data)
display(criteria_df)
```

Figure 4. Criteria weight derivation

```
# --- Step B: Alternative Weights ---
print("\n2. Alternatives Evaluation per Criterion")
alt_details_df = pd.DataFrame(index=provider_names)

for key in keys_alternatives:
    # 1. Gather all matrices for this alternative comparison
    matrices = [create_matrix(resp[key]) for resp in respondents_data]

    # 2. Aggregate
    agg_matrix = geometric_mean_aggregation(matrices)

    # 3. Calculate weights (scores for each provider on this specific criterion)
    weights = calculate_priority_vector(agg_matrix)

    # 4. Store in DataFrame
    crit_name = criterion_key_map[key]
    alt_details_df[crit_name] = weights

    # 5. Add to Final Score Calculation
    # Final Score = Sum(Alternative Score on Criterion X * Global Weight of Criterion X)
    global_weight_crit = global_criteria_weights_map[crit_name]
    for i, provider in enumerate(provider_names):
        provider_scores[provider] += weights[i] * global_weight_crit

# Display the local scores for alternatives
display(alt_details_df.T)
```

Figure 5. Alternative scoring and global synthesis

```
# --- Step C: Final Ranking ---
print("\n3. Final ranking")
final_ranking = pd.Series(provider_scores).sort_values(ascending=False)
final_ranking_df = pd.DataFrame({
    'Score': final_ranking,
    'Percentage': (final_ranking * 100).map('{:.2f}%'.format)
})
display(final_ranking_df)
```

Figure 6. Final ranking and reporting

Results

The combined expert opinions resulted in stable importance scores across all tests and cloud providers. In every case, the CR was below 0.10, demonstarting a high level of agreement among experts [14].

Criteria Priority Weights

Table 1 shows local and overall weights for each test. Overall weights equal local weights multiplied by one third because the three main groups were equally weighted. Local weights sum to 1 within groups, and overall weights sum to 1 across all tests.

Table 1. Complete hierarchy of criteria and global weights

Category	Criterion	Local Weight	Global Weight
Strategic dimension	Business Alignment	0.477	0.477*1/3=0.159
	Scalability	0.143	0.143*1/3=0.048
	Risk Mitigation/Continuity	0.380	0.380*1/3=0.127
(CR = 0.00008)			
Technological dimension	Performance	0.142	0.142*1/3=0.047
	Reliability	0.490	0.490*1/3=0.163
	Availability	0.367	0.367*1/3=0.122
(CR = 0.00164)			
Operational dimension	Manageability	0.118	0.118*1/3=0.039
	Downtime Impact	0.451	0.451*1/3=0.150
	Recovery and Continuity	0.431	0.431*1/3=0.144
(CR = 0.00550)			

Within the Strategic dimension, *Business Alignment* was evaluated as the most important factor, followed by *Risk Mitigation/Continuity*, while *Scalability* was considered significantly less important. Within the Technological dimension, *Reliability* was evaluated as the most important factor, followed by *Availability* and *Performance*. Within the Operational dimension, *Downtime Impact* was evaluated as the most important factor, followed by *Recovery and Continuity* and *Manageability*.

Evaluation of Cloud Service Providers

The three providers – Amazon S3, Microsoft Azure, and Google Cloud Storage – were compared across all tests using the weights from Table 1. Local scores were calculated for each test and then aggregated into an overall score. Selected test results, along with the final totals, are presented in Table 2.

Table 2. AHP results for cloud service provider alternatives

Cloud Provider	Business Alignment	Reliability	Downtime Impact	Performance	Overall Priority	Rank
Amazon S3	0.393	0.387	0.373	0.286	0.397	1
Microsoft Azure	0.407	0.295	0.309	0.213	0.327	2
Google Cloud	0.199	0.319	0.318	0.501	0.277	3

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Amazon S3 gained the highest total score (0.397) and placed first. Microsoft Azure scored (0.327) and placed second. Google Cloud Storage scored (0.277) and placed third.

At the level of single tests, Microsoft Azure scored highest on *Business Alignment*. Amazon S3 scored highest on *Reliability* also on *Downtime Impact*, both of which carry large overall weights. Google Cloud Storage scored highest on *Performance*, but that test has a low overall weight.

Consistency and Robustness

Every comparison matrix for the providers met the AHP consistency rule, with CR values mostly below 0.01. This shows that the experts largely agreed on how the providers compare. A sensitivity test was run – raising or lowering selected test weights within sensible limits. The order of the providers did not change – the outcome is stable within the chosen decision structure.

Discussion

The results obtained through the AHP model show that *Reliability*, *Downtime Impact*, and *Recovery and Continuity* are the most influential criteria in the evaluation of enterprise cloud storage systems. This prioritization is consistent with the operational requirements of large organizations, where uninterrupted service availability is essential for maintaining business processes and data integrity. Enterprise systems often support mission-critical workloads, and therefore system reliability and continuity mechanisms are typically considered more important than raw computational performance. Although cost and security are widely recognized as important cloud service provider selection criteria, they were intentionally excluded from the current hierarchy to maintain a compact decision model and reduce the complexity of pairwise comparisons for experts. Consequently, the proposed model emphasizes strategic, technological, and operational aspects rather than economic or regulatory considerations. Future versions of the model should explicitly incorporate cost, security, and compliance criteria to improve applicability in organization-specific decision-making scenarios.

The high weight assigned to *Reliability* (0.490) within the technological dimension reflects the fact that organizations handling large volumes of data must minimize the risk of service failures or data loss. Previous studies on cloud service provider evaluation have similarly emphasized reliability and availability as key decision criteria in enterprise environments. Reliable storage infrastructures reduce operational risks and improve long-term service stability.

Similarly, the significant weights of *Downtime Impact* (0.451) and *Recovery and Continuity* (0.431) in the operational dimension indicate that organizations are particularly sensitive to service interruptions. Even short periods of downtime can lead to financial losses, operational disruption, and reputational damage. As a result, decision makers prioritize platforms that provide strong disaster recovery mechanisms, redundancy, and rapid service restoration capabilities.

The AHP was used to rank three cloud storage services – Amazon S3, Microsoft Azure, and Google Cloud – based on evaluations by twelve senior specialists across strategic, technological, and operational dimensions. In their assessments, the specialists prioritized service stability and continuity over raw speed and feature sets.

Within the technological dimension, *Reliability* received nearly half of the total weight (0.490), while *Performance* was assigned the smallest share (0.142). A similar pattern emerged in the operational dimension: *Downtime Impact* (0.451) and *Recovery and Continuity* (0.431) dominated the weighting, leaving only (0.118) for *Manageability*.

After aggregating individual judgments, Amazon S3 ranked first with an overall score of 0.397. Its leading position was driven by strong performance on the most heavily weighted criteria – *Reliability* (0.387), *Downtime Impact* (0.373), and *Recovery and Continuity* (approximately 0.462). The panel therefore identified Amazon S3 as the safest option for minimizing service outages. Amazon S3 achieved the highest overall score (0.397) largely because it performed strongly on the criteria with the greatest importance, particularly reliability and

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downtime impact. This suggests that the expert panel perceived Amazon S3 as offering a stable and resilient infrastructure for enterprise data storage.

Microsoft Azure placed second with a score of 0.327. Although it lagged behind Amazon S3 in reliability, it outperformed both competitors in *Business Alignment* (0.407, compared with 0.393 for Amazon S3 and 0.199 for Google Cloud). Organizations requiring close integration with existing workflows may therefore favor Azure. The panel also rated Azure highest on *Manageability*, indicating that its administrative tools are perceived as particularly user-friendly. Microsoft Azure, which ranked second with a score of 0.327, performed particularly well in *Business Alignment*, indicating that experts consider it well integrated with enterprise software ecosystems and organizational workflows. This result is consistent with the widespread adoption of Azure in organizations that rely on existing Microsoft enterprise solutions.

Google Cloud ranked third with a score of 0.277. It achieved the highest *Performance* score (0.501), well ahead of Amazon S3 (0.286) and Microsoft Azure (0.213). However, because *Performance* accounted for only about 4.7% of the total weight, this advantage was insufficient to compensate for Google Cloud's lower ratings in continuity and strategic alignment. Although Google Cloud Storage achieved the highest score in *Performance* (0.501), this advantage did not significantly influence the final ranking because the overall weight assigned to performance was relatively small. This outcome demonstrates how the hierarchical weighting structure of AHP affects the final decision: criteria with greater importance exert a stronger influence on the overall ranking than those with lower weights.

The results demonstrate strong reliability: all pairwise comparison matrices produced Consistency Ratios well below the accepted 0.10 threshold – for example, 0.00164 for the technological dimension and 0.00550 for the operational dimension. Sensitivity analysis further confirmed the robustness of the ranking, which remained Amazon S3, Microsoft Azure, and Google Cloud unless the weight assigned to *Performance* was increased to unrealistic levels. While the study provides a clear quantitative ranking, it excludes cost considerations and detailed security compliance factors. In addition, the strategic, technological, and operational dimensions are weighted equally. As a result, the model favors providers with superior reliability regardless of price. Future applications should incorporate a cost dimension so that budget-constrained organizations can explicitly balance financial considerations against risk and resilience.

Conclusion

The study applied the AHP to evaluate Amazon S3, Microsoft Azure, and Google Cloud against strategic, technological, and operational criteria. Amazon S3 achieved the highest overall score, outperforming the alternatives in reliability, risk control, and service continuity. Microsoft Azure ranked second, driven primarily by its strong alignment with business objectives and ease of management. Google Cloud placed third: although it demonstrated the strongest raw performance, it scored lower on strategic weighting and resilience.

The specialists who participated in the study consistently emphasized that, for large organizations, stable and interruption-free operations are far more critical than speed. Statistical consistency tests confirmed that their judgments were coherent and reliable. This work demonstrates how a hierarchical criteria structure can transform a complex infrastructure decision into a clear, quantitative ranking. The same model can readily incorporate additional dimensions—such as cost or security—allowing it to be adapted to the specific priorities of any enterprise.

Limitations

This study has several limitations. First, all twelve experts were recruited from a single organization (NITEC JSC, Kazakhstan), which may limit the generalizability of the resulting criterion weights to organizations with different technological priorities or business environments. Second, the three top-level dimensions were assigned equal weights rather than being elicited through pairwise comparisons. Third, the model evaluates only three leading cloud storage providers and excludes cost, security, regulatory compliance, and vendor-specific contractual considerations. Finally, the study relies on expert judgment rather than empirical operational performance measurements. Future research should involve experts from multiple organizations and countries, derive top-level weights directly from expert assessments, and extend the hierarchy with additional economic and security-related criteria.

Ethical considerations

Participation in the expert survey was voluntary. All participants were informed about the purpose of the study before completing the pairwise comparison questionnaires. Individual responses were anonymized and analyzed only in aggregated form. No personal or confidential organizational information was collected or disclosed. The study involved expert opinions only and did not include human subjects requiring medical or behavioral interventions.

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