Modern Data Architectures: Evaluation Framework for Selecting Suitable Data Platforms

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ABSTRACT

Purpose: This paper addresses the challenge of selecting a suitable modern data architecture in the context of growing data complexity, increased demand for real-time analytics, and evolving business needs.

Methodology/Approach: The study follows the DSR process. The paper presents a structured evaluation framework based on clearly defined criteria across technical, organisational, and economic dimensions. The framework supports decision-makers in comparing data architectures, including Data Warehouse, Data Lake, and Data Lakehouse, through a weighted scoring system.

Findings: The outcome highlights the advantages of the Data Lakehouse paradigm for the evaluating organisation, which sought to combine flexibility, scalability, and advanced analytics capabilities. This paper contributes a practical and adaptable methodology that aligns enterprise and data architecture decisions.

Research Limitation/Implications: Since each question may hold varying importance for the evaluator, it is recommended that each individual question be weighted. The evaluator must possess the necessary knowledge to assign weights.

Originality/Value of paper: The methodology provides a foundation for further research on data architectures and their evaluation. It can serve as a starting point for the development of analytical tools and the implementation of case studies.

Category: Case study

Keywords: modern data architecture; data warehouse; data lakehouse; enterprise architecture; data quality

Research Areas: Management of Technology and Innovation; Quality by Innovation

1 INTRODUCTION

Over the past decades, the exponential growth of data and the increasing complexity of information systems have significantly transformed the role of data in organisations. Modern enterprises are no longer merely data-generating entities but are increasingly becoming data-driven in both strategic planning and daily operations (European Commission, 2020). This evolution has brought about a paradigm shift from traditional data handling practices to sophisticated architectural frameworks designed to harness the full potential of data assets (Wang & Zhao, 2024).

The proliferation of innovative technologies – such as the Internet of Things (IoT), cloud computing, and artificial intelligence (AI) has further intensified the demand for robust and adaptable data architectures. These technologies generate high volumes of diverse and fast-moving data that challenge the capabilities of conventional systems, particularly those reliant on structured data. As a result, selecting an appropriate data architecture has become a critical decision for organisations aiming to support real-time analytics, scalability, integration of heterogeneous data sources, and compliance with regulatory standards (Rashed & Drews, 2021).

Although various architectural models, such as Data Warehouses (DWH), Data Lakes (DL), and Data Lakehouses (DLH), have emerged, organisations continue to struggle with choosing the most appropriate solution for their data and analytics needs. (Serra, 2024) There is limited consensus on a systematic methodology for evaluating and selecting the most suitable architecture. Organisations often face uncertainty in aligning their architectural choices with business goals, technological constraints, and operational contexts. This gap underscores the need for a structured decision-making framework that incorporates both qualitative and quantitative evaluation criteria (Masaryk University, 2025).

The objective of this research is not only to present the methodology but also to demonstrate its practical utility. The goal is to support decision-makers— particularly in data-intensive sectors with a tool that integrates enterprise architecture perspectives, data governance, technology constraints, and business priorities into a coherent evaluation model.

Accordingly, the research is guided by the following questions:

- RQ1: Is it possible to define a set of relevant and comprehensive criteria for selecting a modern data architecture?
- RQ2: Can a methodology be established that enables the parameterisation of these criteria based on an organisation's specific context?

2 LITERATURE REVIEW

The rapid growth in data volume, variety, and velocity has challenged traditional approaches to storing and processing data. In response, new architectural paradigms have emerged, each addressing various aspects of data management, analytical performance, and business flexibility (Sebastian-Coleman, 2018).

While Data Warehouses represent a well-established and governed solution for structured analytics, Data Lakes, and Data Lakehouses have emerged in response to the evolving needs for flexibility, scalability, and multi-format data handling.

Data Warehouses have long served as the backbone of analytical ecosystems in enterprises (Brackett, 1994). They are optimised for structured data and support complex queries, aggregations, and reporting functions across historical datasets. Based on Extract, Transform, Load (ETL) processes, DWHs enforce strict schema-on-write logic, which ensures data integrity, consistency, and quality.

The strengths of DWHs include mature governance models, robust performance for business intelligence (BI), and alignment with compliance requirements. However, their rigidity in schema design and limited support for unstructured or semi-structured data make them less suited to modern use cases such as data science, real-time analytics, or IoT data processing.

Data Lakes emerged to address the limitations of DWHs by offering scalable storage for a broad range of data formats, including raw, semi-structured, and unstructured data (Sá et al., 2015). Based on schema-on-read principles, DLs enable users to apply data models during query time, thus increasing flexibility and supporting exploratory analysis.

The architecture of a DL typically relies on low-cost distributed storage systems (e.g., Hadoop, cloud object storage) and can accommodate streaming data ingestion. While highly adaptable, DLs often suffer from data governance challenges, including data quality, cataloguing, and security. Without proper controls, a DL can quickly devolve into a "data swamp" – a repository of poorly curated, hard-to-use data (Harby & Zulkernine, 2025; Serra, 2024).

The Data Lakehouse architecture seeks to unify the strengths of DWHs and DLs. It combines scalable, low-cost storage with the transactional guarantees, metadata handling, and performance optimisation traditionally associated with DWHs. DLHs support both BI-style reporting and advanced data science workloads within a single platform. (Wang & Jiang & Cosenz, 2025)

Technologies such as Delta Lake, Apache Iceberg, and Databricks exemplify this hybrid approach by providing ACID compliance, time-travel queries, and schema enforcement on top of flexible data lakes. DLHs reduce data duplication, simplify data pipelines, and enable a consistent data governance model across the organisation.

DLHs are particularly attractive to organisations aiming to centralise analytics without compromising flexibility or performance. However, this model remains new, and its successful implementation requires careful platform selection, operational maturity, and alignment with business goals (Gerber et al., 2020).

The choice among these architectures should not be based solely on technical capabilities but must also reflect the organisation's analytical goals, compliance environment, and operational readiness.

There are many criteria that are key to deciding on a suitable architecture. During the research phase, we could not find a publication that deals with setting specific criteria. The search identified publications that mentioned some of the key criteria mentioned below, but did not address the selection itself (Serra, 2024; Noran & Bernus, 2017; Mušić & Hribar & Fortuna, 2024).

3 METHODOLOGY

This research adopts a Design Science Research (DSR) methodology, which is particularly suited for developing and validating practical artefacts in information systems. DSR enables researchers to iteratively design, implement, and evaluate solutions to real-world problems through a structured and reflective process. In this study, the artefact under development is an evaluation framework for selecting modern data architectures based on multidimensional criteria.

Problem Identification and Motivation is the growing complexity of data environments and the lack of structured decision support in architectural selection, prompting the need for a comprehensive evaluation framework.

The primary objective was to develop a methodology that integrates technical, organisational, and economic considerations into a unified scoring and decision model. Two research questions guided the work.

A set of criteria was formulated through literature review, expert consultation, and analysis of significant business needs. The criteria were organised into three categories and operationalised using a weighted scoring model.

The framework was applied in a real enterprise setting to guide architecture selection. Stakeholder workshops, expert interviews, and scoring exercises were conducted to ensure the framework's relevance, usability, and adaptability.

The methodology was evaluated based on its ability to:

- support transparent decision-making,
- align with business and IT needs,
- be customised for different contexts.

The organisation's strategic and operational needs must be translated into weights for the evaluation model, which is then applied to three competing architectures: DWH, DL, and DLH.

Individual architecture alternatives are then scored against each criterion on a fixed scale (e.g., 0 to 100). The final score is computed as a weighted average:

$$Score\_architecture = \Sigma\ (weight\_i \times score\_i) \quad (1)$$

Where:

- weight_i = weight of the i-th criterion or question
- score_*i* = score of the i-th criterion or question
- precondition: weights are normalised, meaning: ∑ (weight_*i*) = 1

This flexible approach allows any organisation to reflect their unique priorities in the evaluation process. For instance, an enterprise with strict compliance requirements may assign higher weights to governance-related criteria, while a startup may prioritise low initial cost and fast time-to-value.

4 SOLUTION DESIGN: EVALUATION CRITERIA

The selection of an appropriate data architecture is a multidimensional problem involving not only technical capabilities but also strategic alignment, organisational readiness, cost considerations, and governance maturity. To support systematic and transparent decision-making, this study proposes a structured set of evaluation criteria, which the authors grouped into three main categories:

- Technical Criteria (TC),
- Organisational Criteria (OC),
- Economic Criteria (EC).

Each category contains specific factors that reflect practical concerns in real-world environments. These criteria serve as the foundation for the comparative evaluation framework developed in this research.

Technical Criteria (TC): These criteria reflect the system's architectural and technological capabilities:

- Data Integration,
- Performance and Scalability,
- Support for Data Science and AI,
- Data Governance and Security,
- Tooling and Platform Maturity.

Organisational Criteria (OC): These criteria relate to the architecture's compatibility with internal processes and human resources:

- Ease of Adoption,

- Team Expertise Fit,
- Implementation Timeframe,
- Operational Complexity.

Economic Criteria (EC): These criteria reflect financial and strategic resource constraints:

- Initial Investment Cost,
- Operational Costs,
- Return on Investment (ROI) Potential,
- Vendor Lock-in Risk.

Several approaches can be used in terms of weighting the criteria, for example, the Pairwise comparison method, the method of estimating weights, etc. The elaboration of these methods is beyond the scope of this case study.

The evaluation criteria need to be assessed, and we developed two matrices to support the evaluation process. An example of the matrix used for calculating the weight of each question is shown below.

Table 1 – Evaluation: Requirements and Weighting Scheme

Questions	**Requirement - company expectations**	**The weight of the question**	**Recalculated question weight**
1 - Why do you need a data solution?			
2 - Future data use and use cases?			
3 - Type of processed data?			
4 - Processing speed?			

The second matrix is developed for assignment rating to defined questions.

Table 2 – Example: Assessment Results - Requirement Fulfilment Using Standardised Weights

			Expected fulfilment of the requirement		
Questions	**The weight of the question**	**Recalculated question weight**	**DWH - MS SQL**	**DL - Azure**	**DLH - Azure Databricks**
1 - Why do you need a data solution?					
2 - Future data use and use cases?					
3 - Type of processed data?					
4 - Processing speed?					

Both tables should be filled for all relevant questions defined by the evaluators.

Based on the analysis conducted, the criteria identified, and the proposed way of evaluation, it can be concluded that research question R01 has been confirmed, and it is possible to define a set of relevant and comprehensive criteria for selecting a modern data architecture.

5 RESULTS AND DISCUSSION

The proposed framework was tested within a Central European Company in the Financial industry, which is currently in a phase of digital transformation. Key stakeholders included IT architects and data governance professionals.

The company has approximately. Two hundred employees provide services worldwide. The company is using an on-premises solution, but is open to using a cloud one too.

Data was collected through:

- structured interviews,
- stakeholder workshops,
- comparative scoring exercises,
- internal documentation review.

The research was done between September and October 2024.

The evaluation framework was applied to compare three data architecture alternatives: Data Warehouse (DWH), Data Lake (DL), and Data Lakehouse (DLH). The organisation under study, a company from the financial sector, was seeking a scalable, integrated platform to support reporting, advanced analytics, and real-time capabilities.

The analysis was conducted in close cooperation with internal stakeholders, including enterprise architects, data governance specialists, and business users. Each architecture was evaluated using the previously defined criteria, with weights assigned based on strategic priorities identified through stakeholder workshops.

Weights were assigned to each criterion to reflect organisational priorities, with an emphasis on data governance, integration capabilities, and cost efficiency. Each architecture was then scored on a scale from 0 (poor) to 100 (excellent) for each criterion.

5.1 Evaluation Questions and Scales

As part of the validation of the proposed approach, the requirements and expectations for each question were set. Twenty-five selected criteria from fifty criteria are presented in the following table.

Table 3 – Requirements and Weighting Scheme

Questions	Requirement - company expectations	The weight of the question	Recalculated question weight
1 - Why do you need a data solution?	We need to improve the decision-making process, include unstructured data in the process, and start using ML, AI. How much will the approach support this goal?	100	6%
2 - Future data use and use cases?	The new scenarios are not yet specified but are expected to meet the requirements of standard regulatory reporting, the processing of complex calculations and the creation of ML models. An important parameter is the Self-Service approach. To what extent will the already known scenarios be fulfilled?	100	6%
3 - Type of processed data?	All types of data will be processed. Data structured from primary systems has a significant predominance. Unstructured/semi-structured data in the form of contracts is supplementary material. We do not foresee the processing of videos, voice, etc. What percentage of requirements on the 0-100 scale will be met?	100	6%
4 - Processing speed?	We want real-time processing of all data. To what extent is real-time processing feasible, and how complex is the implementation? The lower the complexity and the higher the processing speed, the higher the value on the 0-100 scale.	50	3%
5 - Architectural form and technological design	Our goal is to become a fully cloud-based organisation, with a preference for Microsoft Azure. While we favour SaaS solutions, we also anticipate the need to adopt IaaS and PaaS approaches where appropriate. How well does the proposed architecture natively align with cloud-based environments?	70	4%
6 - What is the need for integration with existing and planned systems	The solution must be able to connect to the existing data infrastructure in the form of primary systems and the existing data warehouse running on-premises. Today, only structured data is processed. Unstructured data resides on file share and on primary systems. What percentage of requirements are fulfilled?	90	5%
7 - What support/integration of data sources are available	The solution must support connection to MS SQL databases, API, and FTP, FTPS, SFTP. What percentage of the requirements are fulfilled?	100	6%
8 - Latency and performance requirements	Performance expectations will be lower in the initial stages of building the platform, but will grow dynamically as the volume of data increases. Latency needs to be low, especially when users will be accessing the data platform. Is the solution scalable without significant intervention? The simpler the extension and the lower the latency, the higher the fill rate.	50	3%

Questions	Requirement - company expectations	The weight of the question	Recalculated question weight
9 - Horizontal and vertical expansion	The solution must support both horizontal and vertical expansion.	80	5%
10 - What are the characteristics of the processed data	Data structured from MS SQL databases, data in text files exported from various systems (e.g. SAP, Success Factors), and data processing from MS Excel and MS Access will be processed. Are the files native to the approach?	40	2%
11 - Support for open formats	The solution must allow transfer to another provider without significant additional costs. Similarly, the company must be able to operate and develop the solution in-house.	30	2%
12 - Optimisation for analysis	Data analytics in the form of ML, AI is a key reason for deploying the solution.	100	6%
13 - Functional and non-functional requirements	The solution must satisfy XYZ.	80	5%
14 - Returns on solutions	We expect a return on investment of 5 years.	20	1%
15 - Total costs	The maximum amount of investment costs and related operating costs over a five-year horizon must not exceed CZK XY.	60	4%
16 - How easy it is to use the platform	The data and technology architecture represented by the solution must support Self Service BI, be understandable to the user, and the user must be able to learn the basic principles during the two-day training.	80	5%
17 - Required visualisation tools	The solution must support Microsoft Power BI as an enterprise visualisation platform.	90	5%
18 - What are the functional requirements	The solution must satisfy XYZ.	100	6%
19 - What are the non-functional requirements	The solution must satisfy XYZ.	60	4%
20 - What will be the design model of the data solution	The architecture will be based on Data Vault, which the solution must support.	80	5%
21 - How the organisation is ready for change	The organisation needs to be prepared for change both technically and organisationally.	30	2%
22 - How is data accountability set up?	The organisation must have a basic Data Governance set up, and the solution and architecture must be able to support it.	40	2%
23 - How is the data quality set	Data quality management processes must be set up. How important is setting up quality processes and functional data quality for a given environment? The need for higher standardisation represents a lower percentage.	40	2%
24 - Required level of security and compliance	Do the solutions/architectures meet the requirements for data access security, requirements resulting from supranational standards such as DORA, GDPR and others?	70	4%
25 - Status of metadata and data cataloguing	The company must be able to implement metadata management with all related	30	2%

Questions	Requirement - company expectations	The weight of the question	Recalculated question weight
	elements. How important is it to set up quality metadata management and functional metadata management for the environment? The need for higher standardisation represents a lower percentage.		

As a result of this phase of the research, research question RQ1 was confirmed, which focused on the possibility of defining a set of appropriate criteria for selecting a modern data architecture.

5.2 Requirement Fulfilment Using Standardised Weights

Table 4 below shows the degree of fulfilment of each requirement based on an assessment using data from structured interviews, stakeholder workshops, comparative scoring exercises, and internal documentation reviews.

Different evaluators may have different expectations, and therefore, the ratings may vary. For this reason, it is always necessary that the evaluation is conducted by a larger number of evaluators with appropriate expertise.

In the case of multiple raters, it is necessary that the weights of each question remain the same for all raters to allow comparison of results.

The final scores were calculated using a weighted average formula.

Table 4 – Assessment Results: Requirement Fulfilment Using Standardised Weights

			Expected fulfilment of the requirement		
Questions	**Weight of the question**	**Recalculated question weight**	**DWH - MS SQL**	**DL - Azure**	**DLH - Azure Databricks**
1 - Why do you need a data solution?	100	6%	30	50	90
2 - Future data use and use cases?	100	6%	50	80	80
3 - Type of processed data?	100	6%	50	80	100
4 - Processing speed?	50	3%	100	60	80
5 - Architectural form and technological design	70	4%	40	100	100
6 - What is the need for integration with existing and planned systems	90	5%	100	80	80
7 - What support/integration of data sources are available	100	6%	100	100	100
8 - Latency and performance requirements	50	3%	70	50	70
9 - Horizontal and vertical expansion	80	5%	60	100	100
10 - What are the characteristics of the processed data	40	2%	100	100	100
11 - Support for open formats	30	2%	50	80	80
12 - Optimisation for analysis	100	6%	50	80	100

			Expected fulfilment of the requirement		
Questions	**Weight of the question**	**Recalculated question weight**	**DWH - MS SQL**	**DL - Azure**	**DLH - Azure Databricks**
13 - Functional and non-functional requirements	80	5%	100	100	100
14 - Returns on solutions	20	1%	50	30	40
15 - Total costs	60	4%	80	50	60
16 - How easy it is to use the platform	80	5%	80	30	50
17 - Required visualisation tools	90	5%	100	50	100
18 - What are the functional requirements	100	6%	100	100	100
19 - What are the non-functional requirements	60	4%	100	100	100
20 - What will be the design model of the data solution	80	5%	100	0	80
21 - How the organisation is ready for change	30	2%	80	20	40
22 - How is data accountability set up?	40	2%	80	50	50
23 - How data quality is set	40	2%	60	30	40
24 - Required level of security and compliance	70	4%	100	80	80
25 - Status of metadata and data cataloguing	30	2%	70	0	0
Resulting			76	69	84

5.3 Discussion

The final scores were calculated using a weighted average formula. The evaluation results showed that the Data Lakehouse platform under consideration, implemented on Azure Databricks, achieved the highest score, namely eighty-four points. Relational Data Warehouse on the MS SQL Server platform scored seventy-six points, placing it in second place. The Data Lake platform built on Azure achieved the lowest score, at 69 points. Each solution was evaluated based on weighted criteria covering both technical and organisational aspects, with the differences in scores reflecting the key characteristics and capabilities of each platform.

While the DWH performed well in governance and ease of implementation, it fell short in flexibility and support for modern analytics. The DL excelled in data science support but was penalised for governance and operational risk.

The DLH architecture achieved the highest overall score, striking a balance between advanced capabilities and manageable complexity.

The results suggest that no single architecture is universally superior; rather, suitability depends on organisational context and priorities. In the case study, the DLH emerged as the most balanced option, offering support for both BI and data science, while maintaining reasonable governance standards and cost predictability.

However, the framework also helped highlight risk areas and implementation challenges, prompting discussion about resource planning, skill development, and platform selection.

Stakeholders reported that the structured evaluation:

- increased confidence in architectural decisions,
- fostered alignment between IT and business,
- provided transparency for budget justification and roadmap planning.

The methodology proved especially useful in facilitating consensus in a multi-stakeholder environment and allowed for repeatable use in future decision scenarios.

Based on the identified criteria, the evaluation table, and the practical evaluation, it can be concluded that the research questions RQ1 and RQ2 stated in the introduction have also been confirmed, and the methodology enables the parameterisation of the criteria based on an organisation's specific context.

6 CONCLUSIONS

As organisations increasingly depend on data for strategic advantage, the choice of a suitable data architecture becomes a critical determinant of their analytical capabilities, agility, and long-term competitiveness. This paper addressed the growing complexity of architectural decision-making by introducing a structured evaluation framework that supports the comparison and selection of modern data platforms. Both research questions were confirmed.

The proposed framework integrates technical, organisational, and economic dimensions into a unified scoring model, allowing stakeholders to assess Data Warehouse, Data Lake, and Data Lakehouse architectures in a transparent and repeatable manner. Grounded in Design Science Research methodology, the artefact was validated through application in a real-world enterprise context, where it facilitated decision-making, stakeholder alignment, and justification of platform investments.

The findings demonstrate that while Data Lakehouse architecture emerged as the most balanced option in the case study, the framework itself holds broader value. It empowers organisations to tailor architectural decisions to their unique contexts, priorities, and capabilities—rather than following generic trends or vendor-driven narratives.

This research contributes a practical and adaptable tool for enterprise data strategy and governance, while also laying the groundwork for future studies on architectural evaluation, decision support, and data platform evolution.

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CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest. The funders had no role in the design of the study, in the collection, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.