

Modernizing Enterprise Data Architecture: From Traditional Data Warehouses to Scalable Information Platforms

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Abstract

Enterprise data architecture is undergoing a significant transformation as organizations increasingly require scalable, flexible, and intelligent systems to manage growing volumes of structured, semi-structured, and unstructured data. Traditional data warehouses have played a central role in enterprise reporting, business intelligence, and historical data analysis; however, their limitations in scalability, real-time processing, data integration, and support for advanced analytics have created the need for more adaptable information platforms. This paper examines the evolution of enterprise data architecture from conventional warehouse-centric models toward modern, cloud-native, and distributed data platforms. It explores key architectural approaches, including data lakes, data lakehouses, cloud data warehouses, data mesh, and data fabric, highlighting their capabilities in data storage, integration, governance, and analytical processing. The study also discusses enabling technologies such as distributed computing, automated data pipelines, metadata management, application programming interfaces, and artificial intelligence-driven analytics. Particular attention is given to interoperability, data quality, security, privacy, governance, and cost optimization as essential considerations in designing sustainable enterprise information ecosystems. Furthermore, the paper presents a conceptual framework for modernizing legacy data infrastructure through phased migration, architectural standardization, workload optimization, and continuous performance monitoring.

Keywords: Enterprise Data Architecture; Data Warehouse Modernization; Scalable Information Platforms; Cloud Data Warehousing; Data Lakes

1. Introduction

In the contemporary digital economy, data has become a strategic organizational asset that influences business planning, operational efficiency, customer engagement, risk management, and innovation. Enterprises across industries generate enormous volumes of data through transactional systems, enterprise resource planning (ERP) applications, customer relationship

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management (CRM) platforms, Internet of Things (IoT) devices, web applications, mobile services, and external information sources. The increasing diversity, velocity, and complexity of this data have created new demands on enterprise data architecture. Organizations must not only store and manage information efficiently but also integrate heterogeneous data sources, support real-time analytics, maintain data quality, and provide secure access to reliable information for decision-making. Consequently, traditional data management approaches are being reconsidered in favor of scalable, flexible, and interoperable information platforms capable of supporting evolving business and technological requirements.

Historically, enterprise data warehouses have served as the foundation of business intelligence and analytical reporting. Traditional warehouse architectures typically collect data from operational systems through extract, transform, and load (ETL) processes, standardize it according to predefined schemas, and store it in a centralized repository optimized for analytical queries. This approach has provided important advantages, including structured data organization, consistency in enterprise reporting, historical analysis, and centralized governance. By integrating information from multiple operational systems, data warehouses enable organizations to develop standardized performance indicators, monitor business activities, and identify long-term trends. Their structured design and established management practices have made them particularly suitable for applications requiring consistent definitions, controlled access, and repeatable analytical processes. However, as enterprise data environments have expanded, the limitations of conventional warehouse-centric architectures have become increasingly apparent.

One significant limitation of traditional data warehouses is their dependence on predefined data models and transformation processes. Although schema-based approaches improve consistency, they can reduce flexibility when organizations need to accommodate new data sources, rapidly changing business requirements, or unstructured information such as documents, images, sensor readings, and application logs. The integration of these diverse data types may require substantial preprocessing and additional infrastructure. Furthermore, conventional architectures can struggle to support use cases requiring low-latency data ingestion, continuous streaming analytics, machine learning, and large-scale exploratory analysis. The cost of scaling proprietary infrastructure, maintaining complex ETL pipelines, and managing separate analytical environments can also increase as data volumes and processing requirements grow.

Cloud computing has played a major role in this architectural transformation. Cloud-based storage and processing services enable organizations to scale computing resources according to workload requirements rather than relying exclusively on fixed-capacity infrastructure. Cloud data warehouses provide managed analytical environments, while data lakes support the storage of diverse data formats at scale. More recently, data lakehouse architectures have emerged to combine aspects of data lakes and warehouses, including flexible storage,

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structured data management, transactional consistency, and analytical processing. These architectural models offer enterprises greater flexibility in supporting business intelligence, data science, artificial intelligence, and operational analytics within interconnected environments. Nevertheless, the benefits of cloud adoption depend on appropriate workload management, security controls, cost governance, and integration with existing enterprise systems.

Another important development is the movement toward distributed and domain-oriented approaches to data management. Data mesh emphasizes treating data as a product, assigning domain-level ownership, and establishing shared governance standards across organizational boundaries. Data fabric focuses on connecting distributed data environments through metadata, automation, integration mechanisms, and intelligent data discovery. Although these approaches differ in their implementation principles, both address challenges associated with fragmented information systems and centralized bottlenecks. In large enterprises, a modern information platform may incorporate elements of several architectural models rather than depend on a single design.

Data integration represents another critical dimension of enterprise modernization. Organizations frequently operate legacy databases, on-premises applications, cloud services, third-party platforms, and real-time event-processing systems simultaneously. Without a consistent integration strategy, these environments can create data silos, duplicate records, inconsistent business definitions, and delays in analytical reporting. Modern architectures address these issues through reusable data pipelines, application programming interfaces (APIs), change data capture (CDC), event streaming, and automated orchestration. Batch processing remains appropriate for many historical reporting workloads, while streaming and incremental processing enable more timely insights when business requirements demand them.

Data governance, security, and quality are equally important in the transition toward scalable information platforms. Expanding data access across distributed environments increases the need for clearly defined ownership, metadata standards, lineage tracking, access policies, retention controls, and monitoring mechanisms. Enterprises must ensure that information remains accurate, traceable, appropriately classified, and accessible only to authorized users. Data quality management should address completeness, consistency, validity, uniqueness, and timeliness throughout the data lifecycle. Metadata management and data cataloging help users discover relevant datasets, understand their meaning, and assess their suitability for particular analytical tasks.

The emergence of artificial intelligence and machine learning further strengthens the case for modern enterprise data architecture. Predictive modelling, generative AI, intelligent automation, and retrieval-augmented generation require access to trustworthy, relevant, and appropriately governed information. Traditional warehouses remain valuable for structured analytical datasets, but AI-enabled applications may also require documents, knowledge

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repositories, vector representations, event streams, and operational data. A scalable information platform can connect these resources through controlled ingestion, transformation, indexing, and retrieval processes. However, AI capabilities cannot compensate for fundamentally poor data quality or inadequate governance.

Despite the availability of modern technologies, enterprise data modernization presents substantial organizational and technical challenges. Legacy application dependencies, incompatible data formats, undocumented transformation logic, vendor lock-in, workforce skill gaps, and migration costs can complicate implementation. Moving large volumes of historical data without disrupting business operations requires careful planning, validation, rollback strategies, and phased execution. Enterprises must also evaluate whether particular workloads should remain on existing infrastructure, move to the cloud, or operate in hybrid environments.

Against this background, the present paper examines the modernization of enterprise data architecture from traditional data warehouses toward scalable information platforms. It explores the evolution of enterprise data management, the capabilities of emerging architectural models, the technologies that enable integration and distributed processing, and the governance practices required to maintain trustworthy information environments. The paper also develops a conceptual approach to modernization that combines legacy-system assessment, platform selection, data integration, governance implementation, workload migration, and continuous performance evaluation. The central proposition is that enterprise data modernization should be understood as a strategic transformation of how information is collected, managed, shared, and used rather than as a simple infrastructure replacement exercise.

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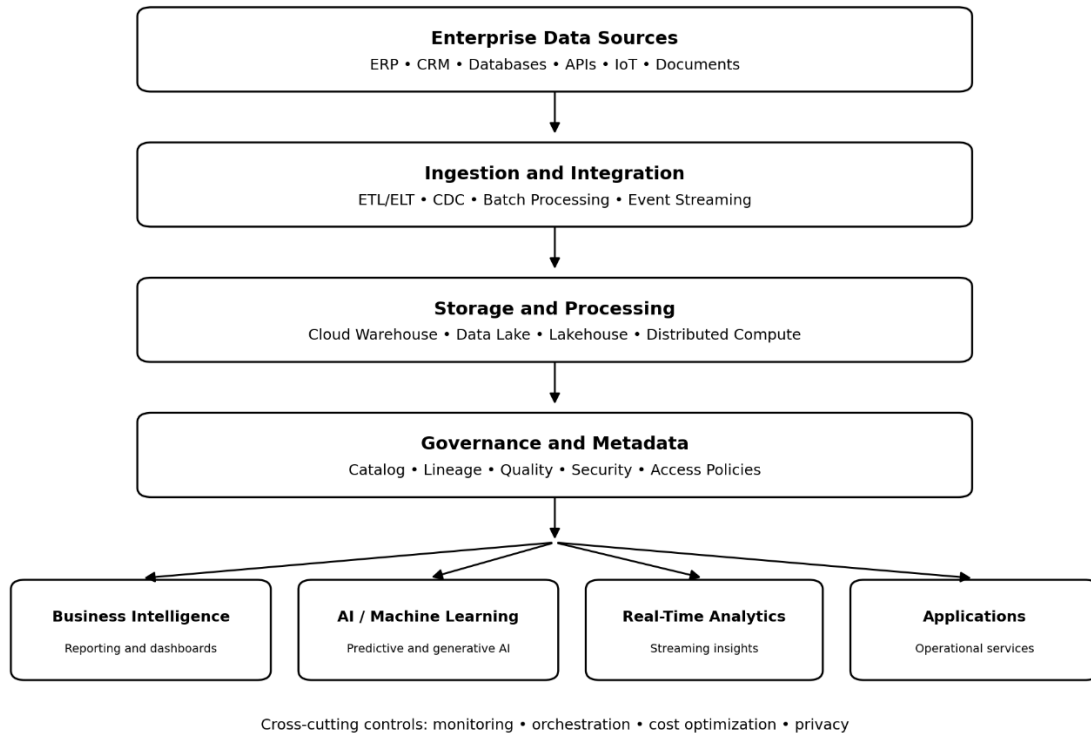


Figure 1. Evolution toward a scalable enterprise information platform. Source: Author's conceptual representation.

1.1 Research Objectives

1. To examine the limitations of traditional enterprise data warehouse architectures in contemporary data-intensive environments.
2. To evaluate modern architectural approaches, including cloud data warehouses, data lakes, lakehouses, data mesh, and data fabric.
3. To identify technologies and integration mechanisms required for scalable, interoperable, and efficient enterprise information platforms.
4. To analyze the importance of data governance, quality, security, privacy, and cost management in modernization initiatives.
5. To propose a conceptual modernization framework that aligns enterprise data architecture with advanced analytics, artificial intelligence, and long-term business objectives.

2. Literature Review: Evolution of Enterprise Data Architecture and Scalable Information Platforms

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2.1 Traditional Data Warehouse Architectures

Traditional data warehouses have historically provided the foundation for enterprise business intelligence, decision support, and historical data analysis. Their primary objective is to consolidate information from heterogeneous operational systems into a centralized repository that supports consistent reporting and analytical queries. Conventional architectures generally employ ETL processes to extract data from transactional databases, transform it into standardized formats, and load it into a warehouse organized around predefined schemas. Dimensional modelling approaches, including star and snowflake schemas, have been widely adopted to simplify analytical queries and improve the interpretability of business information. Inmon (2005) emphasized integrated, subject-oriented, time-variant, and non-volatile data repositories, while Kimball and Ross (2013) developed dimensional modelling practices for organizing analytical data around business processes and measurable facts. These approaches support consistent definitions and historical analysis, but can be less responsive when new sources, unstructured information, or low-latency workloads must be accommodated.

2.2 Cloud Computing and Modern Data Warehousing

Cloud computing has influenced enterprise data architecture by separating storage and computing resources and allowing organizations to scale infrastructure according to workload requirements. Armbrust et al. (2010) examined opportunities and challenges associated with cloud computing, including elasticity alongside concerns about availability, security, and cost management. Cloud data warehouses extend conventional capabilities through managed infrastructure, elastic compute resources, automated maintenance, and integration with cloud-native services. However, cloud migration does not automatically resolve data integration, governance, or performance problems. Poorly designed pipelines, excessive data movement, inefficient queries, and uncontrolled resource consumption can increase operating costs. Enterprises should evaluate platforms according to workload characteristics, security requirements, interoperability, service-level expectations, and total cost of ownership.

2.3 Data Lakes and the Management of Diverse Data

Data lakes provide a flexible approach for storing large volumes of structured, semi-structured, and unstructured information in native or minimally transformed formats. Dixon (2010) popularized the data lake concept in enterprise information management. Distributed storage and processing have enabled data lakes to support exploratory analytics, machine learning, log analysis, and retention of historical data. However, without ownership, documentation, validation, metadata, and lifecycle policies, a lake can become difficult to navigate and unreliable. Modern implementations therefore incorporate metadata catalogues, lineage tracking, access policies, automated validation, and standardized ingestion processes.

2.4 Data Lakehouse Architecture

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The data lakehouse seeks to combine flexible data-lake storage with management and analytical capabilities associated with warehouses. Armbrust et al. (2021) described lakehouse systems as bringing warehouse-like data management to open data-lake storage, including transactional guarantees, schema enforcement, versioning, and efficient analytical processing. A shared data foundation can support SQL reporting, exploratory analysis, machine learning, and AI workloads while reducing unnecessary copies. Yet performance still depends on file organization, metadata management, workload isolation, query optimization, and compatibility with existing tools. The lakehouse is an architectural option rather than a universal replacement for every warehouse or lake.

2.5 Data Mesh and Domain-Oriented Data Management

Data mesh distributes responsibility for analytical data among business domains while relying on shared platform capabilities and governance standards. Dehghani (2022) identifies domain-oriented ownership, data as a product, a self-service data platform, and federated computational governance as core principles. Domain teams can use their contextual knowledge to maintain quality and documentation, while shared rules support consistency. The approach can reduce centralized bottlenecks but requires clear ownership boundaries, interoperability standards, platform engineering, and collaboration. Data mesh is therefore a socio-technical model, not simply a storage technology.

2.6 Data Fabric and Intelligent Data Integration

Data fabric connects information distributed across databases, cloud platforms, applications, and organizational environments through integration, metadata management, automation, and governance. It can include cataloguing, semantic models, lineage analysis, policy enforcement, API-based access, and orchestration. Such capabilities improve discovery and access without requiring every dataset to be physically consolidated. However, automation cannot by itself correct inaccurate source information, unclear ownership, or conflicting business definitions. Metadata quality, interoperability, performance, and distributed access policies remain essential.

2.7 Distributed Processing, Streaming, and Real-Time Analytics

Distributed computing enables processing of datasets that exceed the capacity of individual machines. Dean and Ghemawat (2008) introduced MapReduce as a programming model for large-scale cluster processing, while Zaharia et al. (2016) described Apache Spark as a unified engine for big-data workloads. Kreps, Narkhede, and Rao (2011) described Kafka as a distributed messaging system for high-volume data streams. Batch processing remains useful for scheduled reporting and historical aggregation, while streaming supports continuous ingestion and event processing. The choice depends on latency, volume, reliability, cost, and business criticality; real-time processing is not always necessary.

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2.8 Data Governance, Quality, and Security

Data governance defines policies and controls that ensure enterprise information is reliable, appropriately managed, and responsibly used. Khatri and Brown (2010) examined governance through decision rights and accountability. Effective governance includes ownership, metadata standards, lineage, classification, quality monitoring, access controls, retention, and compliance. Quality issues such as duplicates, missing values, and undocumented transformations can undermine analytics and AI. Security practices should include identity management, least-privilege access, encryption, auditing, and suitable masking. Governance is most effective when embedded in platform design and automated workflows.

2.9 Enterprise Data Architecture for Artificial Intelligence

AI has expanded enterprise data requirements beyond structured reporting datasets. Machine learning requires appropriate training data, reproducible transformations, feature management, and monitoring; generative AI may require documents, knowledge repositories, semantic search, and retrieval-augmented generation. A modern platform can connect warehouse data with unstructured documents, streams, and applications. However, AI readiness also requires data provenance, access controls, retrieval evaluation, and safeguards against exposure of sensitive information. A modern platform alone does not guarantee accurate AI outcomes.

2.10 Comparative Analysis and Research Gap

The literature shows an evolution from centralized, schema-oriented warehouses toward flexible and distributed information environments. Warehouses provide consistent reporting; cloud warehouses add managed elasticity; lakes accommodate diverse formats; lakehouses unify multiple analytical workloads; data mesh distributes domain ownership; and data fabric emphasizes cross-environment integration. Each approach has limitations, and none resolves every enterprise challenge independently. The research gap addressed here is the need for a unified conceptual modernization framework connecting legacy assessment, architectural selection, integration, governance, migration, performance optimization, and AI readiness. The framework is intended to guide decisions according to business requirements rather than encouraging adoption of technologies in isolation.

Table 1. Comparative overview of enterprise data architectures

Architecture	Primary strength	Major limitation
Traditional data warehouse	Consistent reporting and structured analytics	Less flexible for diverse data and some real-time workloads

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Cloud data warehouse	Managed infrastructure and elastic analytical capacity	Cost, vendor dependency, and integration considerations
Data lake	Flexible storage of diverse formats	Governance and discoverability challenges
Data lakehouse	Shared foundation for multiple analytical workloads	Requires careful performance and data-management design
Data mesh	Domain ownership and data-product accountability	Organizational and governance complexity
Data fabric	Integration and discovery across distributed environments	Metadata quality and implementation complexity

3. Research Methodology and Proposed Modernization Framework

3.1 Research Design

This study adopts a conceptual and analytical research methodology to examine the modernization of enterprise data architecture from traditional data warehouses to scalable information platforms. It draws upon literature on data warehousing, cloud computing, distributed processing, data lakes, lakehouse architectures, data mesh, data fabric, and governance. The research follows literature analysis, architectural comparison, identification of modernization requirements, framework development, and definition of performance evaluation criteria. It does not claim empirical results from a production deployment; instead, it presents a conceptual framework that organizations can adapt to their infrastructure and business objectives. Five dimensions guide the analysis: scalability, interoperability, governance, analytical performance, and operational efficiency.

3.2 Assessment of Existing Enterprise Data Infrastructure

The first stage assesses existing architecture, technical capabilities, limitations, dependencies, and priorities. The assessment covers data sources and formats; ETL pipelines, APIs, CDC, batch and streaming integrations; storage and processing capacity; query performance; metadata, lineage, ownership and access controls; reporting latency and AI requirements; and cost and operational complexity. The findings establish a baseline for modernization decisions. For example, reporting delays may prioritize incremental ingestion and query optimization, while fragmented datasets may require stronger metadata management and common business definitions.

3.3 Proposed Enterprise Information Platform Architecture

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The proposed architecture combines traditional warehouse capabilities with cloud storage, distributed processing, automated integration, and shared or federated governance. The source layer includes databases, ERP and CRM systems, APIs, IoT devices, documents, and third-party services. The integration layer uses ETL/ELT, CDC, batch processing, and event streaming as appropriate. The storage and processing layer may combine warehouses, lakes, lakehouses, and distributed compute. Governance and metadata capabilities cover cataloguing, lineage, quality, security, access policies, and monitoring. Finally, the consumption layer supports business intelligence, AI and machine learning, real-time analytics, and operational applications. Not every enterprise needs every component; selection should be based on workload and business needs.

3.3.1 Data Source Layer

The data source layer contains operational and external systems from which information originates. Source systems retain their operational roles while exposing information through suitable, documented integration mechanisms.

3.3.2 Data Ingestion and Integration Layer

This layer transfers information into the analytical environment. Batch ingestion suits scheduled reporting and historical consolidation, while CDC and streaming can support more frequent updates. Standardized interfaces, schema validation, error handling, retry mechanisms, and observability improve pipeline reliability.

3.3.3 Storage and Processing Layer

Storage and processing technologies should be selected according to data characteristics and workload requirements. Warehouses support governed SQL analytics; lakes retain diverse source information; lakehouses can provide a shared foundation for analytics; and distributed processing supports large-scale transformation. The architecture should avoid unnecessary duplication and complexity.

3.3.4 Governance and Metadata Layer

The governance layer provides shared policies for quality, security, metadata, lineage, retention, and access. Catalogues support discovery, lineage records source-to-output relationships, and automated validation improves reliability. Governance may be centralized, federated, or hybrid, depending on organizational needs.

3.3.5 Analytics and Consumption Layer

This layer makes governed information available to BI tools, reporting applications, machine-learning workflows, monitoring systems, and AI-enabled applications. Standardized interfaces and documented data products reduce repeated integration work and improve reuse.

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3.4 Architectural Selection and Modernization Strategy

Architectural decisions should follow business requirements rather than technology trends. Scalability may require elastic storage and distributed compute; data diversity may require lake or lakehouse capabilities; reporting consistency may require governed warehouses and semantic models; freshness requirements may justify CDC and streaming; and AI use cases may need governed access to structured and unstructured information. A hybrid approach can preserve critical reporting while new capabilities are introduced incrementally.

3.5 Phased Implementation Methodology

The framework uses six phases: (1) discovery and assessment of systems, workloads, dependencies, and risks; (2) target architecture design, including integration and governance; (3) a pilot using a representative business use case; (4) migration and validation through record reconciliation and workload testing; (5) optimization of queries, orchestration, cost, and adoption; and (6) continuous monitoring of reliability, freshness, quality, security, cost, and business outcomes. Each phase should include acceptance criteria and documented decisions. Critical migration steps should be supported by rollback and recovery plans.

3.6 Data Governance and Quality Management

Governance is a continuous capability, not a final project stage. Recommended practices include assigning data owners and custodians; maintaining metadata and business definitions; recording lineage; validating completeness, validity, consistency, uniqueness, and timeliness; applying least-privilege access and encryption; defining retention and recovery procedures; and monitoring failures or policy violations. Quality rules should reflect intended use: financial reporting may require strict reconciliation, while exploratory analysis may tolerate incomplete data if limitations are documented.

3.7 Performance Evaluation Metrics

Evaluation should use consistent technical, operational, governance, and business metrics. Query response time measures analytical performance; data latency measures freshness; pipeline success rate measures integration reliability; data-quality compliance measures validation outcomes; availability measures service continuity; cost per workload supports cost analysis; and data reuse rate helps assess adoption. Additional business measures can include time to onboard a data source, effort to produce recurring reports, and time to make governed data available to AI applications. Baselines should be collected before migration and compared under comparable workload conditions.

3.8 Analytical Approach and Validation

The framework can be validated through a controlled pilot, workload benchmarking, architecture reviews, stakeholder assessment, and baseline-to-post-implementation

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comparisons. A pilot might consolidate customer transaction data from multiple operational systems into a governed analytical environment. The existing and modernized processes can be compared on processing time, failures, maintenance effort, and reporting delays, provided test conditions are comparable. Numerical targets should be treated as project-specific acceptance criteria. Because this study is conceptual, it does not claim measured performance gains.

3.9 Summary

The methodology combines infrastructure assessment, architectural selection, phased migration, integrated governance, and continuous evaluation. It treats scalability, interoperability, quality, security, cost, and AI readiness as connected design concerns. The framework provides a basis for enterprises to build and validate reliable information platforms according to their own data, infrastructure, and business requirements.

Phased Enterprise Data Modernization

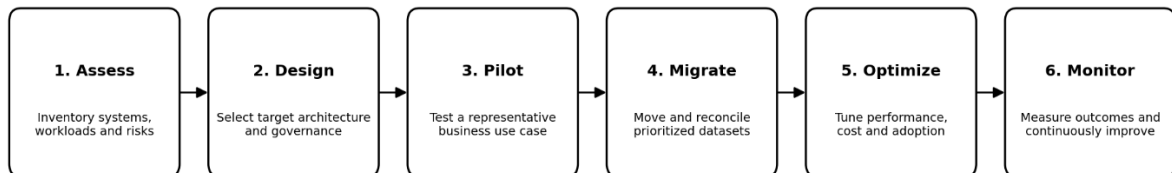


Figure 2. Six-phase enterprise data modernization methodology. Source: Author's proposed framework.

Table 2. Suggested performance evaluation metrics

Metric	Definition	Evaluation purpose
Query response time	Time required to complete an analytical query	Measure analytical performance
Data latency	Time between source availability and target availability	Assess freshness

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Pipeline success rate	Successful executions / total executions $\times 100$	Measure integration reliability
Data quality compliance	Records passing validation / records tested $\times 100$	Assess reliability
Platform availability	Available service time / scheduled service time $\times 100$	Measure continuity
Cost per workload	Costs attributable to a defined workload	Evaluate cost efficiency
Data reuse rate	Reuse of governed datasets across analytical use cases	Assess platform adoption

4. Conclusion

The modernization of enterprise data architecture represents a strategic shift from traditional, warehouse-centric systems toward scalable, flexible, and interoperable information platforms. This paper examined the limitations of conventional data warehouses and explored the capabilities of cloud data warehouses, data lakes, lakehouse architectures, data mesh, and data fabric in addressing the growing demands of contemporary enterprises. The proposed modernization framework integrates data ingestion, distributed storage and processing, metadata management, data governance, security, and analytical services into a unified architectural approach. It also emphasizes the importance of phased migration, systematic infrastructure assessment, data quality validation, workload optimization, and continuous performance monitoring. The study highlights that successful modernization depends not only on adopting advanced technologies but also on aligning architectural decisions with business objectives, organizational responsibilities, regulatory requirements, and operational capabilities. Furthermore, establishing governed and reusable data assets can strengthen the foundation for business intelligence, machine learning, and generative artificial intelligence applications. Since the framework is conceptual, its effectiveness must be validated through practical implementations and empirical evaluation using measurable performance indicators. Overall, modern enterprise information platforms offer a pathway toward improved data accessibility, operational resilience, analytical flexibility, and informed decision-making when supported by appropriate governance and sustainable implementation strategies.

5. Future Work

Future research should focus on implementing and empirically validating the proposed modernization framework across enterprises of different sizes, industries, and technological maturity levels. Experimental studies could compare traditional data warehouses, cloud-native architectures, and lakehouse platforms using standardized workloads to measure query performance, data latency, scalability, reliability, and total cost of ownership. Further

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investigation is also needed into AI-driven data management, including automated data quality assessment, intelligent metadata discovery, anomaly detection, and predictive workload optimization. The integration of generative AI and retrieval-augmented generation with enterprise information platforms presents additional opportunities for developing secure, context-aware knowledge systems supported by traceable and governed data sources. Future work should also examine federated governance models, privacy-preserving analytics, confidential computing, and automated compliance monitoring to address the challenges of distributed data environments. Another important direction is the development of quantitative maturity models that help organizations assess their readiness for modernization and prioritize investments according to business value, implementation risk, and operational complexity. Finally, long-term case studies could evaluate the effects of modernization on organizational productivity, data reuse, decision-making speed, and sustainability, including the energy consumption associated with large-scale storage and computation. These investigations would provide stronger empirical evidence for refining the proposed framework and establishing practical guidelines for developing secure, cost-effective, and AI-ready enterprise information platforms.

References

- Armbrust, M., Fox, A., Griffith, R., Joseph, A. D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, I., & Zaharia, M. (2010). A view of cloud computing. *Communications of the ACM*, 53(4), 50–58. <https://doi.org/10.1145/1721654.1721672>
- Armbrust, M., Ghodsi, A., Xin, R., & Zaharia, M. (2021). Lakehouse: A new generation of open platforms that unify data warehousing and advanced analytics. *Proceedings of the Conference on Innovative Data Systems Research (CIDR)*. https://www.cidrdb.org/cidr2021/papers/cidr2021_paper17.pdf
- Batini, C., & Scannapieco, M. (2016). *Data and information quality: Dimensions, principles and techniques*. Springer. <https://doi.org/10.1007/978-3-319-24106-7>
- Bernstein, P. A., & Haas, L. M. (2008). Information integration in the enterprise. *Communications of the ACM*, 51(9), 72–79. <https://doi.org/10.1145/1378727.1378745>
- Codd, E. F. (1970). A relational model of data for large shared data banks. *Communications of the ACM*, 13(6), 377–387. <https://doi.org/10.1145/362384.362685>
- Dean, J., & Ghemawat, S. (2008). MapReduce: Simplified data processing on large clusters. *Communications of the ACM*, 51(1), 107–113. <https://doi.org/10.1145/1327452.1327492>
- Dehghani, Z. (2022). *Data mesh: Delivering data-driven value at scale*. O'Reilly Media.
- Dixon, J. (2010, October 14). Pentaho, Hadoop, and data lakes. James Dixon's Blog. <https://jamesdixon.wordpress.com/2010/10/14/pentaho-hadoop-and-data-lakes/>

Journal of AI & Innovation (AJAI)

Impact Factor: 16.4

Peer Reviewed Refereed Journal

ISSN-3245-459x (Online)

Acceptance Rate: below 5%

Elmasri, R., & Navathe, S. B. (2016). Fundamentals of database systems (7th ed.). Pearson.

Fowler, M., & Lewis, J. (2014). Microservices: A definition of this new architectural term. MartinFowler.com. <https://martinfowler.com/articles/microservices.html>

Garcia-Molina, H., Ullman, J. D., & Widom, J. (2008). Database systems: The complete book (2nd ed.). Pearson.

Gray, J., & Reuter, A. (1993). Transaction processing: Concepts and techniques. Morgan Kaufmann.

Hey, T., Tansley, S., & Tolle, K. (Eds.). (2009). The fourth paradigm: Data-intensive scientific discovery. Microsoft Research.

Inmon, W. H. (2005). Building the data warehouse (4th ed.). Wiley.

Khatri, V., & Brown, C. V. (2010). Designing data governance. Communications of the ACM, 53(1), 148–152. <https://doi.org/10.1145/1629175.1629210>

Kimball, R., & Ross, M. (2013). The data warehouse toolkit: The definitive guide to dimensional modeling (3rd ed.). Wiley.

Kleppmann, M. (2017). Designing data-intensive applications: The big ideas behind reliable, scalable, and maintainable systems. O'Reilly Media.

Kreps, J., Narkhede, N., & Rao, J. (2011). Kafka: A distributed messaging system for log processing. Proceedings of the NetDB Workshop.

Marz, N., & Warren, J. (2015). Big data: Principles and best practices of scalable real-time data systems. Manning Publications.

Melnik, S., Gubarev, A., Long, J. J., Romer, G., Shivakumar, S., Tolton, M., & Vassilakis, T. (2010). Dremel: Interactive analysis of web-scale datasets. Proceedings of the VLDB Endowment, 3(1–2), 330–339. <https://doi.org/10.14778/1920841.1920886>

Stonebraker, M., & Çetintemel, U. (2005). One size fits all: An idea whose time has come and gone. Proceedings of the 21st International Conference on Data Engineering, 2–11. <https://doi.org/10.1109/ICDE.2005.1>

Strengtholt, P. (2023). Data management at scale: Best practices for building large-scale data solutions. O'Reilly Media.

Zaharia, M., Chowdhury, M., Franklin, M. J., Shenker, S., & Stoica, I. (2010). Spark: Cluster computing with working sets. Proceedings of the 2nd USENIX Conference on Hot Topics in Cloud Computing.

Journal of AI & Innovation (AJAI)

Impact Factor: 16.4

Peer Reviewed Refereed Journal

ISSN-3245-459x (Online)

Acceptance Rate: below 5%

Zaharia, M., Xin, R. S., Wendell, P., Das, T., Armbrust, M., Dave, A., Meng, X., Rosen, J., Venkataraman, S., Franklin, M. J., Ghodsi, A., Gonzalez, J., Shenker, S., & Stoica, I. (2016). Apache Spark: A unified engine for big data processing. *Communications of the ACM*, 59(11), 56–65. <https://doi.org/10.1145/2934664>

Zikopoulos, P., Eaton, C., deRoos, D., Deutsch, T., & Lapis, G. (2012). *Understanding big data: Analytics for enterprise class Hadoop and streaming data*. McGraw-Hill.

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