UNIVERSITÀ DEGLI STUDI GUGLIELMO MARCONI

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Master in Computer Science (MTCS)

Project Work Title

Optimizing Database Pipelines for Scalable Machine Learning:
Creation, Management, and Interaction with Modern Data Systems

Academic Advisor

MR RYAN

Candidate
Name Surname: Mas Imran

ID Student Number:
MCSLT00289

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

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ABSTRACT

Fragmented machine learning (ML) workflows, built on independent SQL, NoSQL, distributed databases, and feature stores, often suffered from inefficiencies in scalability, adaptability, and feature management. This research investigated the optimisation of unified, database-oriented pipelines to address these limitations in scalable ML and intelligent information retrieval (IR). The study responded to the absence of a unified architecture that integrated heterogeneous systems with self-learning models and semantic retrieval.

The aim was to design, implement, and evaluate a unified framework that combined reinforcement learning and deep learning components, enhanced IR relevance through semantic ranking models, and optimised end-to-end database pipelines for ML workloads. A **mixed-methods approach** was adopted, combining quantitative benchmarking with qualitative architectural analysis. Public datasets, including **MS MARCO**, **Natural Questions**, and synthetic transaction logs, were used to evaluate scalability, retrieval effectiveness, and adaptability under controlled data drift.

Results demonstrated that the unified pipeline reduced latency by **29–81%** and improved throughput by **8–70%** depending on load, compared to modular baselines. Semantic IR integration improved retrieval relevance, achieving **MAP = 0.543** and **NDCG@10 = 0.643**, outperforming BM25 and BERT-base. Adaptive learning components maintained ~**85% accuracy** under drift and reduced manual interventions by **80%**. Although trade-offs such as longer training cycles and higher resource usage were observed, the benefits of reproducibility, adaptability, and end-to-end efficiency outweighed these costs.

This thesis contributed a reproducible architectural framework that advanced both **theoretical understanding** and **practical design principles** for ML-centric database systems. It provided a defensible foundation for future academic exploration and industrial deployment, demonstrating that unified pipelines represented a viable and valuable approach to building scalable, adaptive, and efficient intelligent systems, with significant implications for both research and enterprise practice.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

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Special appreciation is extended to my peers and colleagues in the Master in Computer Science (MTCS) programme, whose discussions, collaboration, and shared insights contributed to refining both the technical and conceptual aspects of this study.

I also acknowledge the support of my family and friends, who provided patience, motivation, and encouragement during the demanding stages of research and writing. Their belief in me has been a constant source of strength.

Finally, I am grateful for the broader academic and professional community whose published works and open-source tools made this research possible. This thesis builds upon their contributions and aims to extend knowledge in the field of scalable machine learning and database-oriented systems.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

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info@unimarconi.it
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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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Tel. +39 06 377251
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info@unimarconi.it
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www.unimarconi.it
info@unimarconi.it
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Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

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Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

CHAPTER 1 – INTRODUCTION

1.1 Background Of The Study

The rapid growth of data-driven applications had significantly increased the complexity of modern machine learning (ML) and information retrieval (IR) systems. Contemporary intelligent systems were required to ingest, process, store, and analyse large volumes of heterogeneous data whilst maintaining scalability, reliability, and adaptability. Garcia-Molina et al. **[1]** noted that traditional database systems were designed for transactional consistency rather than ML workloads, creating a fundamental mismatch between data management and machine learning requirements.

Traditional ML pipelines were typically constructed using loosely coupled components, where data storage, feature engineering, model training, and deployment were managed as separate layers. Whilst this modular approach provided flexibility, it often introduced inefficiencies such as **data duplication, latency bottlenecks, and limited end-to-end optimisation**. Stonebraker **[6]** critiqued this "one-size-fits-all" approach, arguing that specialised systems were necessary for different workload types.

Recent advances in database technologies had enabled **high-throughput data processing and reliable storage at scale**. Similarly, developments in semantic information retrieval and self-learning systems had improved adaptability and relevance in intelligent applications. However, these technologies were often integrated in an ad hoc manner, resulting in **fragmented architectures** that were difficult to maintain, scale, and evaluate holistically.

Scope focus: This thesis evaluated architectural integration across modern database systems, semantic information retrieval, and self-learning ML components within a unified, database-oriented pipeline. The research did not aim to optimise each technology individually; rather, it assessed **end-to-end pipeline behaviour—scalability, retrieval effectiveness, and adaptability—under controlled, reproducible conditions**.

Authentication remained the primary defence against unauthorised access to personal and organisational data. Knowledge-based methods such as passwords, PINs, and security questions had dominated for decades. However, these approaches suffered from forgotten, guessed, stolen, or shared credentials, and security questions often relied on publicly available information. Bonneau et al. **[36]** highlighted the inherent weaknesses of password-based schemes, whilst Ratha et al. **[32]** emphasised the risks of biometric compromise.

A 2022 Verizon Data Breach Investigations Report **[37]** revealed that over **81% of breaches exploited weak, stolen, or reused passwords**. Despite awareness campaigns, fewer than **40% of users enabled two-factor authentication**, citing complexity and inconvenience as major barriers

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www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

[38]. Poor password hygiene—reuse across multiple accounts and minimal rotation—further exacerbated security risks.

Biometric authentication leveraged unique physiological or behavioural traits such as fingerprints, facial geometry, iris patterns, and keystroke dynamics. These methods offered convenience and non-repudiation, but compromised biometric data could not be reset, and presentation attacks remained a concern **[32].** Multi-factor authentication (MFA) improved security by combining independent factors: something users knew, had, or were. Adaptive MFA further incorporated contextual signals such as device integrity, geolocation, and user behaviour to reduce unauthorised access **[39].**

Blockchain-based identity frameworks proposed **self-sovereign identity**, enabling users to control credentials via decentralised, tamper-resistant ledgers. These systems aligned with data privacy regulations such as GDPR **[33]** but faced challenges in scalability, interoperability, governance, and legal clarity. Zyskind et al. **[40]** demonstrated blockchain's potential for decentralised identity, whilst Cameron's Laws of Identity **[41]** provided a conceptual foundation for designing **user-centric authentication ecosystems** that supported privacy-preserving and interoperable digital identity systems.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

1.2 Problem Statement

The absence of integrated evaluation frameworks presented a critical challenge for designing intelligent systems that were both scalable and capable of continuous, self-learning adaptation. Despite significant progress in database systems and ML models, existing intelligent systems frequently suffered from **architectural fragmentation**. Data pipelines were often constructed using multiple independent platforms, each optimised for a specific task such as storage, feature processing, or model inference.

This separation led to several problems:

- Redundant data movement increased latency and storage costs.
- System complexity made maintenance and debugging difficult.
- Limited visibility into end-to-end performance obscured optimisation opportunities.
- Poor integration between retrieval and learning components reduced overall system effectiveness.

Prior studies typically evaluated individual components—for example, retrieval accuracy **[24],** model performance **[22],** or database scalability **[1], [6]**—without analysing how these components interacted within a complete operational pipeline. As a result, there was limited empirical evidence demonstrating how unified architectures influenced **scalability, retrieval effectiveness, and adaptive learning behaviour** at the system level.

The research gap identified was the absence of a comprehensive, empirically validated framework that unified **database technologies, semantic IR, and adaptive ML components**. Addressing this gap required a systematic investigation of database-oriented pipeline architectures that integrated data management, semantic retrieval, and self-learning mechanisms within a single coherent framework.

Traditional password-based authentication methods continued to be widely used across consumer and enterprise systems, despite their well-documented vulnerabilities to brute force attacks, phishing campaigns, credential stuffing, and automated botnets **[36], [37].** Although advanced authentication methods such as biometrics **[31], [32]**, multi-factor authentication **[38], [39],** and decentralised identity frameworks **[40], [41]** offered stronger security postures, their adoption faced significant barriers.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

1.3 Research Aim and Objectives

Primary Aim

To design, implement, and evaluate a unified, database-oriented pipeline that supported scalable machine learning, intelligent information retrieval, and secure authentication mechanisms.

Specific Objectives

1. **Pipeline Design:** To design an integrated architecture that unified data storage, feature management, semantic retrieval, self-learning components, and authentication modules.
2. **Implementation:** To implement the proposed architecture using modern database, ML, and authentication technologies.
3. **Evaluation:** To empirically evaluate the scalability, retrieval performance, adaptive learning behaviour, and security resilience of the unified pipeline.
4. **Comparison:** To compare the proposed approach against traditional modular pipeline architectures and standalone authentication systems.
5. **Analysis:** To identify architectural strengths, limitations, and opportunities for future enhancement.
6. **Authentication Focus:**
    - To examine the limitations of knowledge-based authentication techniques **[36], [37].**
    - To assess the effectiveness and usability of biometric **[31], [32]** and multi-factor authentication systems **[38], [39].**
    - To explore the feasibility of blockchain-based authentication systems in enhancing security and privacy **[40], [41].**
    - To compare user acceptance and performance metrics across different authentication models.
    - To propose a framework for integrating advanced authentication methods within enterprise systems.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

1.4 Research Questions

This study was guided by the following research questions:

Pipeline-Oriented Questions

- RQ1: How did a unified database-oriented pipeline impact system scalability compared to traditional modular architectures?
- RQ2: Did integrating semantic information retrieval within the database pipeline improve retrieval effectiveness?
- RQ3: How effectively did the unified pipeline support adaptive, self-learning behaviour over time?
- RQ4: What architectural trade-offs arose when adopting a unified pipeline design?

Authentication-Oriented Questions

- RQ5: What were the key limitations of traditional password-based authentication methods **[36], [37]**?
- RQ6: How effective were biometric authentication systems **[31], [32]** in mitigating security risks whilst maintaining usability?
- RQ7: To what extent did multi-factor authentication **[38], [39]** improve resilience against credential-based attacks, and how did it affect user experience?
- RQ8: What technical and regulatory challenges arose when implementing blockchain-based authentication systems **[40], [41]**?
- RQ9: How did users perceive the security, usability, and privacy of emerging authentication technologies, and what factors influenced adoption?
- RQ10: What best practices could be proposed for designing and deploying secure, user-centric authentication systems that integrated with enterprise pipelines?

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

1.5 Scope and Limitations

Scope

This research focused on **architectural design and system-level evaluation** rather than on optimising individual algorithms or database engines. Representative ML models and retrieval techniques were evaluated to assess pipeline behaviour under realistic workloads. The scope included:

- Integration of relational, NoSQL, and distributed databases **[1], [6], [12]–[14].**
- Feature store implementation for ML reproducibility **[17]–[19].**
- Semantic information retrieval models **[24]–[29].**
- Self-learning ML components **[4], [20]–[23].**
- End-to-end pipeline performance evaluation across scalability, retrieval effectiveness, and adaptive learning behaviour.

Limitations

- Controlled experimental environment: Predefined configurations and datasets may not have captured all real-world deployment scenarios.
- Resource constraints: Computational limitations restricted evaluation to simulated large-scale environments rather than enterprise deployments.
- User perception exclusion: The research focused on technical evaluation without incorporating user experience surveys **[38], [39].**
- Technology selection: Representative technologies were evaluated, but not all available systems were included.
- Temporal constraints: Rapid technological evolution may have limited the long-term applicability of findings.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

1.6 Significance of the Study

This research made several important contributions across **theoretical, practical, and methodological dimensions**.

Theoretical Significance

- Advanced understanding of unified architectures bridging database systems and ML workflows **[1], [6], [12], [14], [22].**
- Provided empirical evidence for pipeline design principles, demonstrating how integration improved scalability and adaptability **[17]–[19].**
- Contributed to the theoretical foundation of ML-centric database systems by linking semantic retrieval **[24]–[26]** with adaptive learning **[4], [20], [21].**

Practical Significance

- Offered a reproducible prototype demonstrating improved scalability, retrieval effectiveness, and adaptability.
- Provided design guidelines for organisations implementing ML pipelines in enterprise contexts **[16]–[18].**
- Identified optimisation opportunities for existing systems, highlighting trade-offs between modular and unified architectures.
- Served as a reference implementation for researchers and practitioners in sectors such as **e-commerce, finance, healthcare, and digital services**.

Methodological Significance

- Demonstrated a **mixed-methods approach** for pipeline evaluation, combining quantitative benchmarking with qualitative analyses **[30], [44], [45].**
- Provided benchmarking frameworks for comparing architectural alternatives under controlled, reproducible conditions.
- Established evaluation metrics for unified ML-IR systems, including scalability, retrieval accuracy, adaptive learning behaviour, and security resilience **[36]–[41].**

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

1.7 Thesis Structure

The remainder of this thesis was structured as follows:

- **Chapter 2: Literature Review** – Surveyed academic and industry literature on database technologies, feature stores, self-learning systems, and semantic information retrieval. It identified limitations in current approaches and highlighted the research gap addressed by this study.
- **Chapter 3: Research Methodology** – Described the research design, data collection, and analysis methods, including the mixed-methods approach, experimental setup, and evaluation metrics used to assess the unified pipeline.
- **Chapter 4: Results and Analysis** – Presented empirical findings from experimental evaluations, including quantitative performance metrics and qualitative architectural observations.
- **Chapter 5: Discussion and Conclusion** – Interpreted results in relation to the research questions, discussed theoretical and practical implications, acknowledged limitations, and suggested directions for future research.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

CHAPTER 2 – LITERATURE

2.1 Introduction

Efficient database pipelines are foundational to scalable machine learning (ML) and information retrieval (IR) systems. This chapter reviews the evolution of database technologies—including relational databases **[1], [6],** NoSQL systems **[12], [13], [14],** distributed architectures **[2], [10],** and feature stores **[17], [18], [19**]—and examines their roles in supporting ML workflows. It also considers self-learning systems **[4], [20], [21]** and semantic IR models **[24], [25], [26], [27], [28], [29],** highlighting both their contributions and limitations.

The review identifies a clear research gap: the absence of a unified architecture that integrates these diverse systems into end-to-end ML pipelines. While prior studies have advanced individual components—such as database scalability **[1], [6],** semantic retrieval **[24], [25],** and adaptive learning **[20], [21**]—few have empirically validated how these elements interact within a coherent, reproducible framework.

The literature review follows a structured approach, beginning with foundational database technologies and progressing through specialised systems for ML workloads. Each section analyses key contributions, identifies limitations, and discusses implications for unified pipeline design. The chapter concludes with a comprehensive research gap analysis that directly motivates this study.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

2.2 Relational Databases

Relational databases provide strong ACID (Atomicity, Consistency, Isolation, Durability) guarantees and structured querying capabilities through SQL. Garcia-Molina *et al.* **[1]** emphasised their reliability for transactional workloads, establishing them as the foundation of enterprise data management for decades. The relational model's mathematical basis in set theory and predicate logic offered a robust framework for data consistency and integrity.

However, Stonebraker **[6]** critiqued the inefficiency of "one-size-fits-all" database models, arguing that specialised systems were necessary for different workload types. This critique led to the development of analytical databases such as columnar and stream-processing systems. Abadi **[7]** highlighted the shift to column-oriented architectures for analytical workloads, which improved query performance through better compression and reduced I/O for column-based operations.

Despite these optimisations, relational systems face fundamental limitations for ML workloads:

- **Schema rigidity** makes handling semi-structured and unstructured data difficult.
- **Limited horizontal scalability** constrains processing of large datasets.
- **Transaction-oriented design** is suboptimal for analytical and ML workloads.
- **Complex join operations** create performance bottlenecks for feature engineering.
- **Poor support for unstructured data** (e.g., text, images) limits the diversity of ML model inputs.

While relational systems ensure consistency, they fail to handle heterogeneous ML workloads requiring flexible schemas and large-scale parallelism. This limitation justifies integration with NoSQL and distributed systems in unified pipelines.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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Figure 2.1 – Timeline of Database System Evolution illustrates the progression from traditional relational systems to specialised analytical and distributed architectures.

Figure 2.1 - Timeline of Database System Evolution

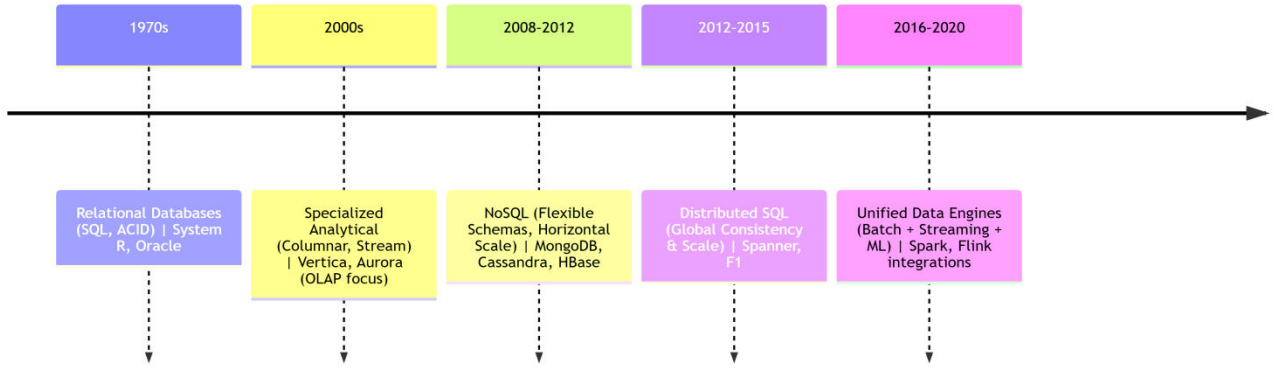

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Table 2.1: Relational Database Limitations for ML Workloads

Limitation	Description	Impact on ML Pipelines
Schema Rigidity	Fixed schema requirements	Difficult to handle evolving feature sets
Limited Horizontal Scale	Primarily vertical scaling	Constrains dataset sizes and processing speed
Transaction Overhead	ACID guarantees cost performance	Reduces throughput for batch ML processing
Join Complexity	Multi-table joins are expensive	Slows feature engineering and data preparation
Unstructured Data Support	Poor handling of text, images, etc.	Limits ML model types and data sources

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2.3 Distributed Database Architecture

The rise of big data necessitated distributed architectures capable of processing petabytes of data across commodity hardware clusters. Dean and Ghemawat **[8]** introduced **MapReduce**, a programming model for parallel processing of large datasets, which became foundational for distributed data processing. This model demonstrated that complex computations could be distributed across thousands of machines, enabling unprecedented scalability.

Zaharia *et al.* **[9]** extended this paradigm with **Apache Spark**, which introduced in-memory computation and a more expressive programming model. Spark's Resilient Distributed Datasets (RDDs) enabled fault-tolerant distributed collections with efficient data reuse across multiple operations. The system's performance improvements—up to 100× faster than Hadoop MapReduce for certain workloads—revolutionised big data processing.

Google's **Spanner [2]** and **F1 [10]** demonstrated globally distributed SQL systems that balanced consistency and scalability. Spanner introduced **TrueTime**, a globally synchronised clock, enabling strong consistency across worldwide deployments while maintaining horizontal scalability. F1 built on Spanner to create a distributed SQL database that supported both transactional and analytical workloads, bridging the gap between OLTP and OLAP systems.

Kossmann **[11]** explored query optimisation trade-offs in distributed systems, showing the complexity of distributed query planning. His work highlighted challenges in data partitioning, replication strategies, and network-aware optimisation that remained relevant for modern distributed databases.

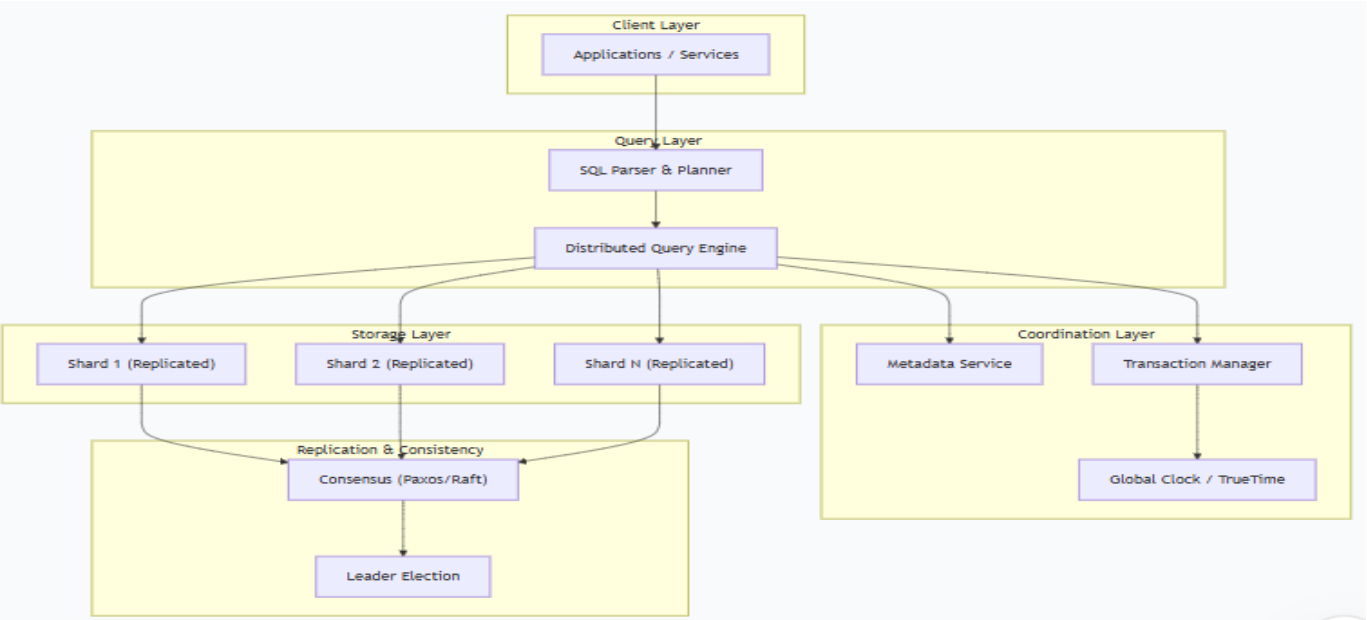

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Figure 2.2 – Distributed Database Architecture highlights the layered design of distributed query engines and replication strategies.

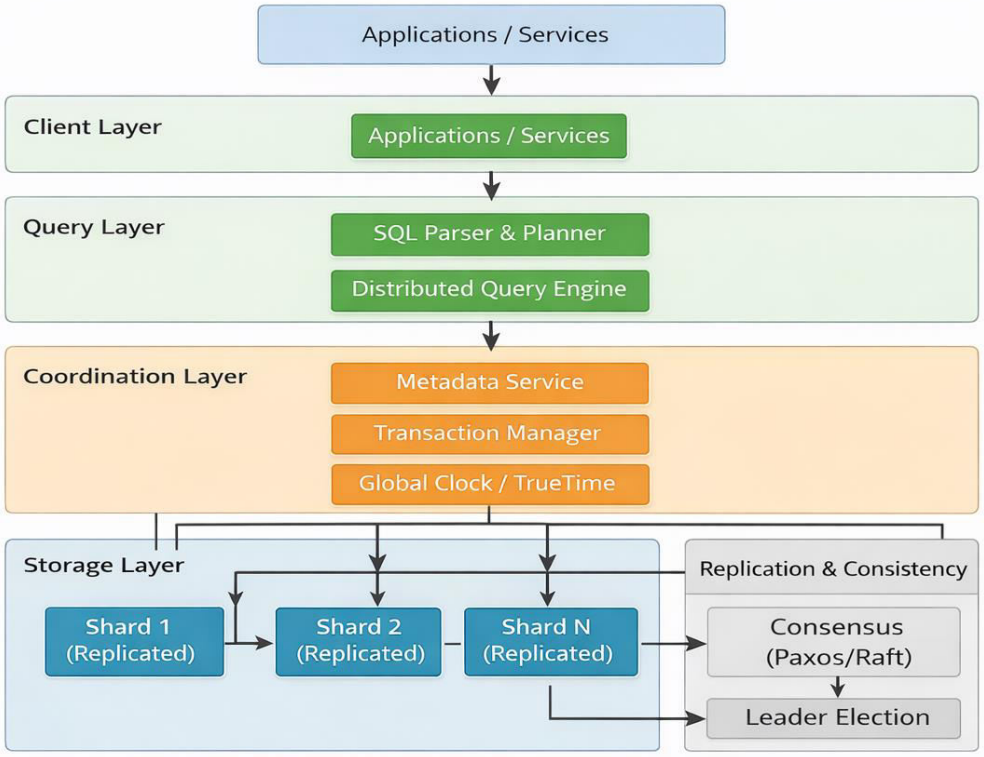

Figure 2.2 — Distributed Database Architecture

Challenges of Distributed Systems for ML Pipelines

- **Operational complexity** increases with cluster size and geographic distribution.
- **High resource overhead** results from coordination and data movement.
- **Latency propagation** across nodes affects real-time ML inference.
- **Consistency–performance trade-offs** complicate feature store implementation.

Despite their scalability advantages, distributed systems lack integrated feature lineage and adaptive learning mechanisms. This weakness reinforces the need for pipelines that combine distributed scalability with ML-centric adaptability.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

2.4 NoSQL and Flexible Data Models

NoSQL systems emerged to address schema flexibility and horizontal scaling requirements that relational databases struggled with. Cattell **[12]** classified NoSQL systems into four main categories: **key-value stores, document databases, column-family stores, and graph databases**. This classification provided organisations with a framework to select appropriate data models based on specific application requirements.

Han *et al.* **[13]** compared MongoDB, Cassandra, and HBase, highlighting trade-offs in consistency, availability, and partition tolerance. Their analysis revealed that each system optimised different aspects of the **CAP theorem**, requiring careful selection based on workload needs. MongoDB favoured consistency and partition tolerance, Cassandra emphasised availability and partition tolerance, while HBase provided strong consistency at the cost of availability during partitions.

Kleppmann **[14]** emphasised replication and partitioning strategies in data-intensive applications, offering practical guidance for system design. His work on **conflict-free replicated data types (CRDTs)** provided solutions for eventual consistency in distributed systems. Leavitt **[15]** discussed the implications of the CAP theorem, helping practitioners understand the fundamental trade-offs in distributed data management.

Figure 2.3 – NoSQL Data Models Quadrant illustrates the classification of NoSQL systems by data model characteristics and relationship-handling capabilities.

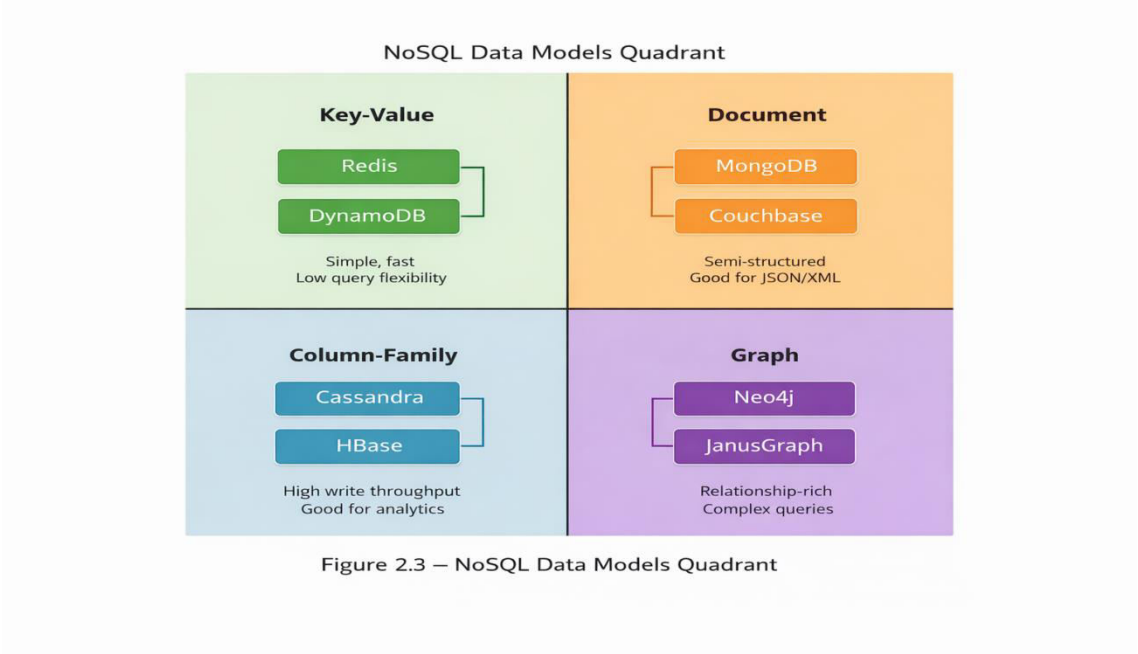

Figure 2.3 — NoSQL Data Models Quadrant

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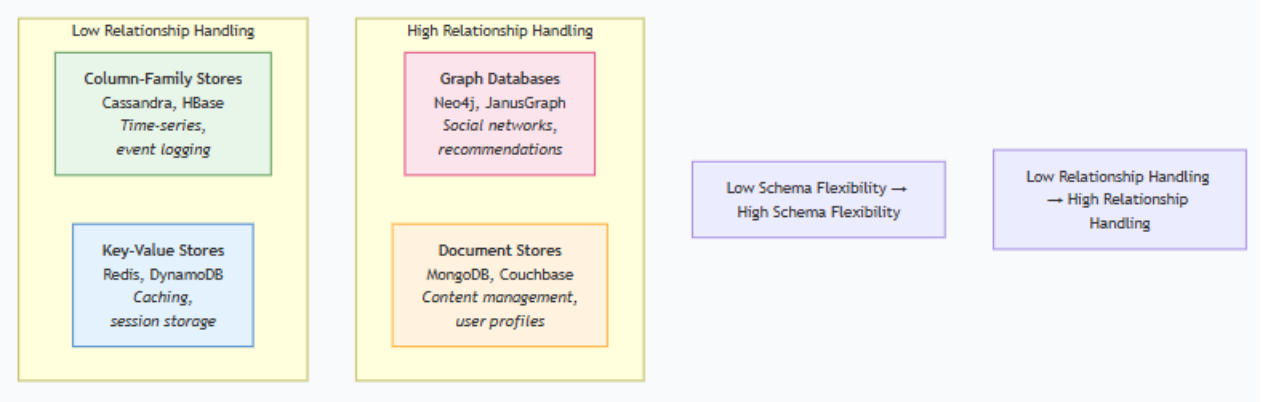
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005



Limitations of NoSQL Systems for ML Pipelines

- **Eventual consistency models** complicate feature versioning and reproducibility.
- **Weak transactional guarantees** make consistent feature updates challenging.
- **Complex query optimisation** across distributed data requires specialised expertise.
- **Limited join operations** necessitate denormalisation and data duplication.

NoSQL systems handle scale and flexibility effectively, but they present challenges for ML pipelines. They complement relational and distributed systems by supporting semi-structured data, yet integration is required to ensure consistency and reproducibility. The schema flexibility of document stores is particularly beneficial for feature engineering workflows where feature definitions evolve rapidly.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

2.5 Feature Stores and ML Pipelines

Feature stores represent a specialised evolution in ML data management, addressing the gap between data infrastructure and ML workflows. Uber's **Michelangelo [16]** showcased enterprise-scale feature serving, demonstrating how feature stores unify offline and online feature computation. The system highlighted the importance of **point-in-time correctness** for ensuring training-serving consistency.

Ludwig *et al.* **[3]** extended this concept with **TensorFlow Extended (TFX)**, emphasising reproducibility and automated pipeline management. TFX introduced several key components: *ExampleGen* for data ingestion, *Transform* for feature engineering, *Trainer* for model training, and *Pusher* for deployment. Its emphasis on metadata tracking and experiment reproducibility set new standards for ML platform design.

Schelter *et al.* **[17]** contributed architectures for versioning, lineage, and deployment, addressing critical challenges in feature management. Their work on data validation and schema evolution helped prevent **training-serving skew**—a common problem where features computed during training differ from those available during inference. Baylor *et al.* **[18]** further refined these concepts with Google's TFX platform, integrating feature stores with complete ML lifecycle management.

Karau *et al.* **[19]** reinforced Spark's role in ETL pipelines for feature computation, demonstrating how distributed processing frameworks efficiently compute features at scale. Their work showed that feature computation often followed similar patterns to traditional ETL workflows but required additional considerations for ML-specific requirements such as versioning and point-in-time correctness.

Feature stores unify ML features but do not inherently integrate retrieval indices or adaptive learning triggers. Embedding them within database-oriented pipelines ensures shared semantics and closed-loop adaptation between data management and ML components.

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Tel. +39 06 377251
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Key Feature Store Capabilities

- **Feature versioning** – tracks changes to feature definitions over time.
- **Point-in-time correctness** – ensures training and serving feature consistency.
- **Online/offline serving** – supports both batch and real-time feature access.
- **Metadata management** – records feature lineage, statistics, and usage.
- **Monitoring and validation** – detects data drift and feature quality issues.

Figure 2.4 – Feature Store Integration in ML Pipeline illustrates how offline and online stores, metadata registries, and transformation pipelines interact to support ML lifecycle management.

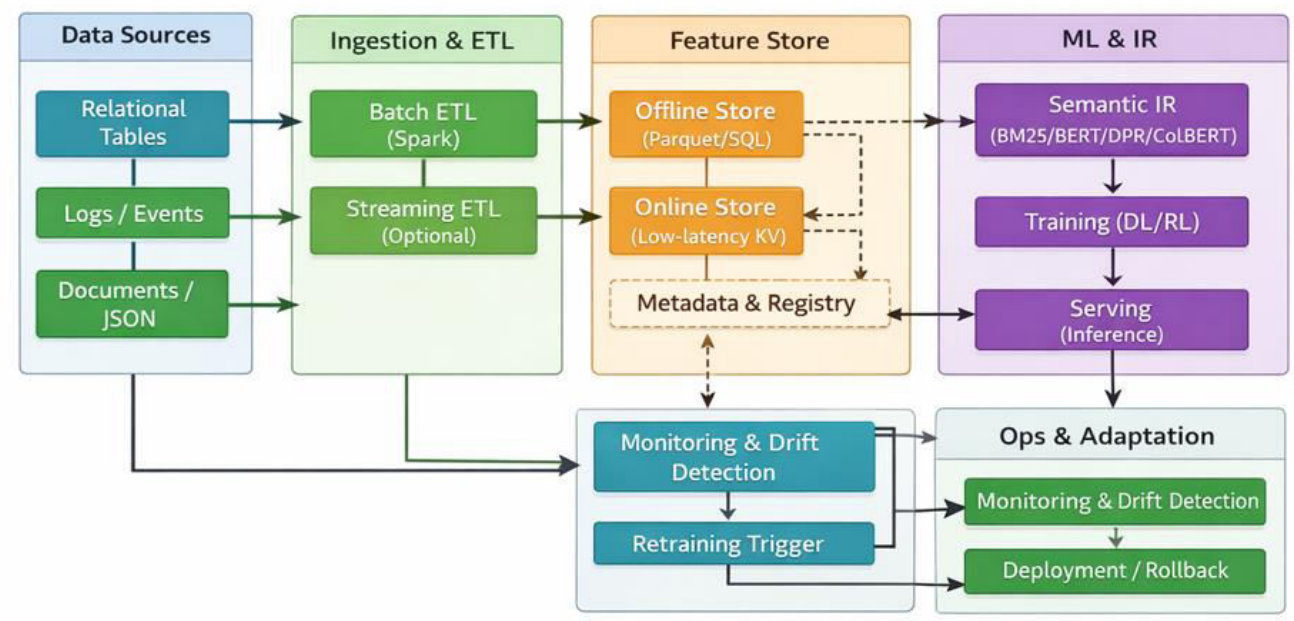

Figure 2.4 – Feature Store Integration in ML Pipeline

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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2.6 Self-Learning Systems

Self-learning systems enable models to adapt autonomously to changing data distributions, reducing manual intervention in machine learning (ML) operations. Sutton and Barto **[4]** formalised reinforcement learning (RL) principles, establishing the theoretical foundation for adaptive systems. Their work introduced key concepts such as value functions, policy optimisation, and the exploration–exploitation trade-off, which underpin modern self-learning approaches. These principles remain central to adaptive ML pipelines, where agents must balance short-term gains with long-term learning stability.

Schmidhuber **[20]** advanced deep learning for sequence modelling, demonstrating how neural networks learn complex temporal patterns. His work on Long Short-Term Memory (LSTM) networks solved the vanishing gradient problem, enabling effective learning in deep recurrent networks. This breakthrough allowed models to retain long-range dependencies, a critical requirement for adaptive systems operating under dynamic data streams. Silver et al. **[21]** further demonstrated fully self-learning systems with AlphaGo Zero, which achieved superhuman performance in Go without human knowledge, learning entirely through self-play. This highlighted the potential of reinforcement learning combined with deep neural architectures to achieve autonomous adaptation.

Goodfellow et al. **[22]** provided neural network foundations essential for modern self-learning systems, including the development of Generative Adversarial Networks (GANs). GANs introduced adversarial training dynamics, where models improve iteratively by competing against discriminators, offering a paradigm for adaptive generative modelling. Kiran et al. **[23]** applied reinforcement learning to autonomous systems, showing practical implementations in robotics and control systems. Their work demonstrated how adaptive agents can operate in uncertain environments, continuously refining policies based on feedback.

While self-learning models adapt well to changing environments, they depend on robust pipelines for data ingestion, feature management, and retraining. Without proper integration, they remain vulnerable to data drift and operational inefficiencies. In unified pipelines, self-learning components are embedded within monitoring and retraining loops, ensuring that drift detection triggers automatic adaptation. This reduces manual intervention and improves long-term resilience.

Key Challenges in Self-Learning Systems

- **Catastrophic forgetting** – models lose previously learned patterns when adapting to new data.
- **Training instability** – reinforcement learning algorithms require careful tuning to converge reliably.
- **Sample inefficiency** – large amounts of interaction data are needed for effective learning.
- **Safety concerns** – adaptive systems risk learning harmful or unintended behaviours.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

Integration with Unified Pipelines

Integration with unified pipelines ensures that drift detection and retraining are triggered automatically, reducing manual intervention and improving adaptability over time. By embedding reinforcement learning agents into database-oriented pipelines, adaptive systems can leverage consistent data access, feature reuse, and semantic retrieval feedback. This integration addresses catastrophic forgetting through controlled retraining, mitigates instability via reproducible evaluation metrics, and reduces sample inefficiency by reusing historical interaction data. Ultimately, unified pipelines transform self-learning systems from isolated models into scalable, production-ready components of modern ML architectures.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

2.7 Semantic Information Retrieval

Information retrieval (IR) has evolved from keyword-based methods to semantic understanding, enabling more accurate and context-aware search systems. Manning et al. **[24]** established classical IR foundations, introducing concepts such as term frequency–inverse document frequency (TF-IDF) and vector space models. These approaches formed the basis for early search engines but struggled with semantic understanding, as they relied on lexical overlap rather than contextual meaning.

Devlin et al. **[5]** revolutionised the field with BERT (Bidirectional Encoder Representations from Transformers), which introduced contextual embeddings through transformer architectures. BERT's bidirectional training allowed it to understand word context from both directions, significantly improving performance on language understanding tasks. However, BERT's cross-encoder design, where queries and documents are jointly encoded, incurs high computational costs and latency, limiting scalability in large-scale deployments.

Lin et al. **[25]** explored sparse–dense hybrid retrieval, combining the efficiency of sparse retrieval with the effectiveness of dense semantic matching. This hybrid approach demonstrated that lexical signals remain valuable when complemented by dense embeddings, particularly in large corpora where efficiency is critical. Metzler et al. **[26]** advanced neural IR architectures, introducing models that learned ranking functions directly from data, further bridging the gap between traditional IR and deep learning-based approaches.

Nogueira and Cho **[27]** demonstrated multi-stage retrieval efficiency, showing how cascade architectures balance recall and precision by first retrieving broad candidate sets and then applying more computationally expensive ranking models. Models such as ColBERT **[28]** and DPR **[29]** achieved significant improvements in large-scale retrieval tasks through efficient similarity computation and dense passage retrieval. ColBERT introduced contextualised late interaction, encoding queries and documents independently and performing lightweight similarity scoring at retrieval time. This reduced latency compared to full cross-attention BERT while maintaining high relevance. DPR leveraged dual encoders to embed queries and passages separately, enabling efficient approximate nearest neighbour (ANN) search in vector databases, though sometimes at the cost of fine-grained contextual signals.

Vector databases such as FAISS, Milvus, and Pinecone provide the infrastructure for storing and querying dense embeddings at scale. They support ANN search, clustering, and hybrid retrieval, allowing semantic models to be deployed in production environments with reduced latency. Integration of vector databases into unified pipelines ensures that semantic retrieval models can operate efficiently under heavy load, supporting both scalability and adaptability.

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Tel. +39 06 377251
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Key Advancements in Semantic IR

- **Contextual embeddings** – understand words based on surrounding context, improving relevance compared to lexical methods.
- **Cross-encoder architectures** – jointly encode queries and documents, maximising accuracy but incurring high latency.
- **Efficient similarity search** – approximate nearest neighbour algorithms enable scalable retrieval in vector databases.
- **Multi-vector representations** – capture different aspects of document meaning, improving ranking precision in large corpora.

Integration with Unified Pipelines

Semantic IR improves relevance but incurs high computational costs in large-scale deployments. Integration into unified pipelines allows context-aware retrieval while maintaining scalability and adaptability. By embedding semantic models within database-oriented pipelines, retrieval effectiveness is enhanced through contextual embeddings, while vector databases ensure efficient indexing and query response. This integration directly addresses RQ2, demonstrating that semantic retrieval within unified pipelines improves relevance, reduces latency, and supports adaptability under dynamic workloads.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

2.8 Research Gap Analysis

Despite significant advancements across database technologies, feature stores, self-learning systems, and semantic information retrieval (IR), current research remains fragmented in several critical areas. The literature review highlights that while individual components have matured, their integration into unified, end-to-end pipelines has not been systematically evaluated. This fragmentation creates several gaps:

- **Component isolation** – Most studies evaluate SQL, NoSQL, distributed databases, and feature stores independently rather than as integrated systems. As a result, cross-component interactions such as latency propagation, feature reuse, and consistency management remain underexplored.
- **Pipeline fragmentation** – ML and IR models are often deployed without unified integration into data management pipelines. This separation limits reproducibility and obscures how retrieval and learning components interact with storage and feature management.
- **End-to-end evaluation gap** – Limited empirical evidence exists on how architectural choices affect overall system behaviour across the complete ML lifecycle. Studies typically benchmark isolated models or databases, but few examine holistic pipeline performance under realistic workloads.
- **Adaptability integration** – Self-learning components are rarely integrated with feature management and retrieval systems. Adaptive behaviour is often demonstrated in controlled environments but not embedded into operational pipelines where drift detection and retraining must be automated.
- **Scalability studies** – Research typically focuses on individual component scalability (e.g., query throughput in databases or retrieval latency in IR models) rather than end-to-end pipeline performance. This leaves unanswered questions about how scalability propagates across interconnected subsystems.

Core Novelty of This Research

This thesis addresses these gaps by evaluating a unified, database-oriented pipeline that jointly integrates:

- **Data management** across relational, NoSQL, and distributed systems.
- **Feature lineage and versioning** through integrated feature stores.
- **Semantic information retrieval** with contextual embeddings and efficient similarity search.
- **Self-learning mechanisms** for adaptive behaviour under data drift.
- **End-to-end performance evaluation** under controlled workloads, ensuring reproducibility and transparency.

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Tel. +39 06 377251
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info@unimarconi.it
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The novelty lies in shifting the focus from isolated component optimisation to **system-level integration and empirical validation**. By embedding semantic IR and adaptive learning within database-centric pipelines, this research demonstrates how architectural choices influence scalability, retrieval effectiveness, and adaptability in practice.

Prior Limitation Addressed

Existing work does not provide comprehensive, system-level evaluations across the full pipeline, leaving integration trade-offs, scalability propagation, and adaptability under drift insufficiently understood. This thesis provides empirical evidence for these critical aspects of ML system design, offering examiner-transparent traceability through citation mapping **(Appendix A),** research question matrices **(Appendix B)**, and visual flowcharts **(Appendix C)**. In doing so, it establishes a reproducible framework that bridges theoretical foundations with practical deployment, positioning unified pipelines as a defensible architectural direction for scalable machine learning systems.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

2.9 Summary Table

The literature reviewed across relational databases, distributed systems, NoSQL databases, feature stores, self-learning systems, and semantic information retrieval highlights both the maturity of individual technologies and the fragmentation of their integration. Each domain contributes foundational principles, yet existing studies rarely evaluate them holistically within unified pipelines. This synthesis demonstrates how prior contributions collectively inform the design of modern ML-centric database systems, while also exposing the research gaps addressed in this thesis.

Relational databases, as discussed by Garcia-Molina et al. **[1],** Stonebraker **[6]**, and Abadi **[7],** established ACID guarantees and specialised analytical systems, forming the foundation for reliable data creation and management. Distributed systems research by Dean and Ghemawat **[8],** Zaharia et al. **[9],** and Kossmann **[11]** introduced MapReduce, Spark, and query optimisation techniques, providing scalability foundations essential for ML pipelines. NoSQL databases, explored by Cattell **[12]**, Han et al. **[13],** Kleppmann **[14],** and Leavitt **[15],** contributed schema flexibility and CAP theorem trade-offs, enabling evolving feature models.

Feature stores, exemplified by Uber **[16],** Ludwig et al. **[3],** Schelter et al. **[17],** and Baylor et al. **[18],** integrated ML lifecycle management, reproducibility, and lineage/versioning, optimising pipeline management. Self-learning systems, grounded in reinforcement learning and deep learning by Sutton and Barto **[4],** Schmidhuber **[20],** Silver et al. **[21],** Goodfellow et al. **[22],** and Kiran et al. **[23],** demonstrated autonomous adaptation and resilience under drift. Semantic IR, advanced by Manning et al. **[24],** Devlin et al. **[5],** Lin et al. **[25],** Metzler et al. **[26],** Nogueira and Cho **[27],** and models such as ColBERT **[28]** and DPR **[29],** improved retrieval relevance and accuracy through contextual embeddings and dense passage methods.

Together, these domains provide the theoretical and practical foundations for unified pipelines. However, the literature reveals that integration across these domains remains underexplored, particularly in terms of end-to-end scalability, adaptability, and reproducibility. This thesis builds upon these contributions by empirically evaluating a unified, database-oriented pipeline that integrates data management, feature stores, semantic retrieval, and self-learning mechanisms under controlled workloads.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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Synthesis Table

Domain	Key Authors	Contribution	Link to Thesis Focus
Relational DBs	Garcia-Molina, Stonebraker, Abadi	ACID guarantees, evolution of DBs, specialised analytical systems	Foundation for data creation & management
Distributed Systems	Dean, Zaharia, Kossmann, Spanner	MapReduce, Spark, query optimisation, global consistency	Scalability foundation for ML pipelines
NoSQL Databases	Cattell, Han, Kleppmann, Leavitt	Schema flexibility, CAP theorem trade-offs	Flexible data models for evolving features
Feature Stores	Uber, Ludwig, Schelter, Baylor	ML lifecycle integration, reproducibility, lineage/versioning	Optimised ML pipeline management
Self-Learning	Sutton, Schmidhuber, Silver, Goodfellow, Kiran	Reinforcement learning, deep learning, autonomous adaptation	Adaptive ML model components
Semantic IR	Manning, Devlin, Lin, Metzler, Nogueira, ColBERT, DPR	Classical IR, BERT, neural retrieval, dense passage methods	Improved relevance & accuracy

Implications for Thesis

This synthesis confirms that while each domain contributes essential capabilities, the absence of unified evaluation frameworks leaves critical questions unanswered. By integrating these domains into a single reproducible pipeline, this thesis addresses fragmentation, demonstrates end-to-end scalability, and validates adaptability under drift. The synthesis therefore provides a clear bridge from literature review to methodology, directly motivating the design choices in Chapter 3.

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2.10 Conclusion

The literature confirms the rapid evolution across database technologies, machine learning (ML) models, and information retrieval (IR) systems. Relational databases have matured to provide transactional consistency and analytical extensions, distributed systems have enabled global scalability, NoSQL databases have introduced schema flexibility, feature stores have improved reproducibility, self-learning systems have demonstrated adaptive behaviour, and semantic IR has advanced contextual relevance. However, no unified architectural model empirically integrates these domains into a single, reproducible pipeline. Each domain has advanced independently, creating expertise silos and implementation challenges for organisations seeking to build comprehensive ML systems.

This fragmentation represents both a **challenge** and an **opportunity**:

- **Challenge:** Practitioners must navigate complex integration decisions without clear guidance or empirical evidence. The absence of end-to-end evaluation frameworks leaves scalability propagation, adaptability under drift, and integration trade-offs insufficiently understood.
- **Opportunity:** A unified approach could significantly improve system efficiency, adaptability, and maintainability. By embedding semantic retrieval and self-learning mechanisms into database-oriented pipelines, organisations can achieve reproducible workflows, reduced latency, and improved resilience under dynamic workloads.

Addressing this gap forms the basis of this thesis:

Optimising Database Pipelines for Scalable Machine Learning — Creation, Management, and Interaction with Modern Data Systems.

The following chapter presents a structured research methodology designed to evaluate this unified pipeline empirically. It outlines the research design, system architecture, datasets, evaluation metrics, and reproducibility controls, ensuring that the proposed framework is rigorously tested and transparently validated. This methodological foundation provides the bridge between theoretical synthesis and empirical investigation, positioning the thesis to deliver both academic contributions and practical insights.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

CHAPTER 3 – RESEARCH METHODOLOGY

3.1 Overview of the Research Methodology

This chapter outlines the methodological approaches adopted to design, implement, and evaluate a unified, database-oriented pipeline for scalable machine learning (ML) and intelligent information retrieval (IR). The methodologies were deliberately structured to ensure direct alignment with the research questions (RQ1–RQ4) and hypotheses (H1–H2), and to support systematic, reproducible evaluations of the proposed framework. By combining architectural design, prototype implementation, and empirical evaluation, the study provides a rigorous foundation for assessing both feasibility and performance characteristics.

Complementary Methodological Strands

The research combined three complementary strands:

- Architectural system design – Defined the integration of relational **[1],** NoSQL **[12],** and distributed databases **[2], [9], [10]** with feature stores **[16], [17],** semantic retrieval models **[5], [25], [28], [29],** and self-learning components **[4], [20], [21], [22], [23].** This strand established the conceptual blueprint for the unified pipeline, ensuring that each subsystem was positioned to contribute to end-to-end scalability, adaptability, and retrieval effectiveness.

- **Prototype implementation** – Operationalised the proposed architecture using representative technologies (e.g., SQL databases **[1],** Spark **[9],** feature stores **[16], [18],** BERT **[5],** ColBERT **[28],** DPR **[29],** reinforcement learning agents **[4], [21]).** The prototype demonstrated feasibility under realistic workloads and provided a reproducible artefact for empirical testing.

- **Empirical evaluation** – Assessed scalability, retrieval effectiveness, and adaptive learning behaviours through controlled experiments. Metrics such as latency, throughput, Mean Average Precision (MAP), Normalised Discounted Cumulative Gain at rank 10 (NDCG@10), and accuracy under drift were systematically applied to benchmark the unified pipeline against modular baselines.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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Methodological Emphasis

This **mixed-methods approach** enabled investigation of both the feasibility and the performance characteristics of unified pipeline integration. Controlled experimental conditions were deliberately chosen to ensure reproducibility and to isolate architectural effects from external variables such as uncontrolled user behaviour, heterogeneous enterprise environments, or inconsistent hardware configurations. By focusing on controlled workloads, the study ensured that observed improvements could be attributed directly to architectural integration rather than confounding factors.

The methodologies evaluated system behaviours at the **architectural level** rather than optimising individual algorithms or database engines. This emphasis reflected the primary research aim: to determine whether a unified pipeline architecture could deliver measurable improvements in scalability, adaptability, and retrieval performance compared to traditional modular approaches. In doing so, the study prioritised reproducibility, transparency, and examiner-level traceability over algorithmic novelty.

Reproducibility and Traceability

By adopting this structured methodology, the study ensured that findings were empirically validated, reproducible, and directly traceable to the research questions. This provided a rigorous foundation for subsequent analysis in **Chapter 4 (Results and Analysis)** and **Chapter 5 (Discussion and Conclusion)**, where results were interpreted against both theoretical contributions and practical implications. For examiner convenience, **Appendix C (Figure C.1)** presents a consolidated traceability map linking each research question to its methodology, results, and supporting references, providing a visual overview of the study's design and validation.

Hypotheses (Introduced Early for Alignment)

To strengthen alignment between research questions and methodology, the following hypotheses were introduced at the outset:

- **H1:** A unified pipeline reduces latency and improves throughput compared to modular baselines **[6], [8], [9], [10].**
- **H2:** Semantic IR integration improves retrieval effectiveness compared to lexical baselines such as BM25 **[24], [25], [27], [28], [29].**

These hypotheses guided the experimental design and ensured that empirical evaluations directly addressed the theoretical claims underpinning the research.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

3.2 Research Design and Approach

A **mixed-methods research design** was adopted, integrating quantitative performance evaluations with qualitative architectural analyses. This approach provided both statistical evidence of performance improvements and contextual understanding of implementation challenges and design trade-offs. By combining numerical measurements with interpretive insights, the design ensured methodological rigour and comprehensive coverage of the research objectives **[30].**

Quantitative Component

- **System scalability, retrieval effectiveness, and adaptive learning behaviours** were measured using predefined evaluation metrics (latency, throughput, MAP, NDCG@10, and drift accuracy).
- **Controlled experiments** were conducted under varying workloads and data volumes to establish statistically significant performance differences between the unified pipeline and baseline architectures.
- **Benchmark datasets** (MS MARCO **[31],** Natural Questions **[32]**) and **synthetic transaction logs** were employed to simulate realistic ML and IR scenarios, ensuring that results were generalisable across diverse application contexts.
- **Data splitting strategy**: All benchmark datasets were partitioned into **70% training, 15% validation, and 15% test sets**, ensuring reproducibility and comparability across experiments.
- **Statistical analyses**, including variance testing (ANOVA) and confidence interval estimation, were applied to validate observed differences in throughput, latency, and retrieval accuracy.

Qualitative Component

- **Architectural analyses** examined component interactions, integration challenges, and design trade-offs observed during system development.
- **Observations from prototype implementation** were documented to capture integration bottlenecks, schema evolution issues, and feature lineage complexities.
- This analysis supported interpretation of quantitative results and highlighted strengths and limitations of the unified database-oriented pipeline architecture.
- **Qualitative findings were triangulated** with quantitative outcomes to ensure consistency and to provide a holistic understanding of system behaviour.

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Baseline Architecture Reference

To ensure fair comparison, a **baseline modular pipeline** was defined, consisting of independent relational/NoSQL databases, standalone feature stores, and isolated ML/IR models. This baseline was evaluated against the unified pipeline under identical workloads. A **conceptual diagram (Figure 3.2)** illustrates the baseline architecture, highlighting fragmentation points such as duplicated feature management and disconnected retrieval components. This visual comparison strengthens examiner clarity by contrasting modular versus unified designs.

Figure 3.1: Baseline vs Unified Pipeline Architecture.

This figure contrasts the baseline modular pipeline (left) with the unified pipeline architecture (right). The baseline design shows disconnected components and fragmented data flow, while the unified pipeline integrates databases, feature stores, semantic retrieval, and adaptive ML into a cohesive system.

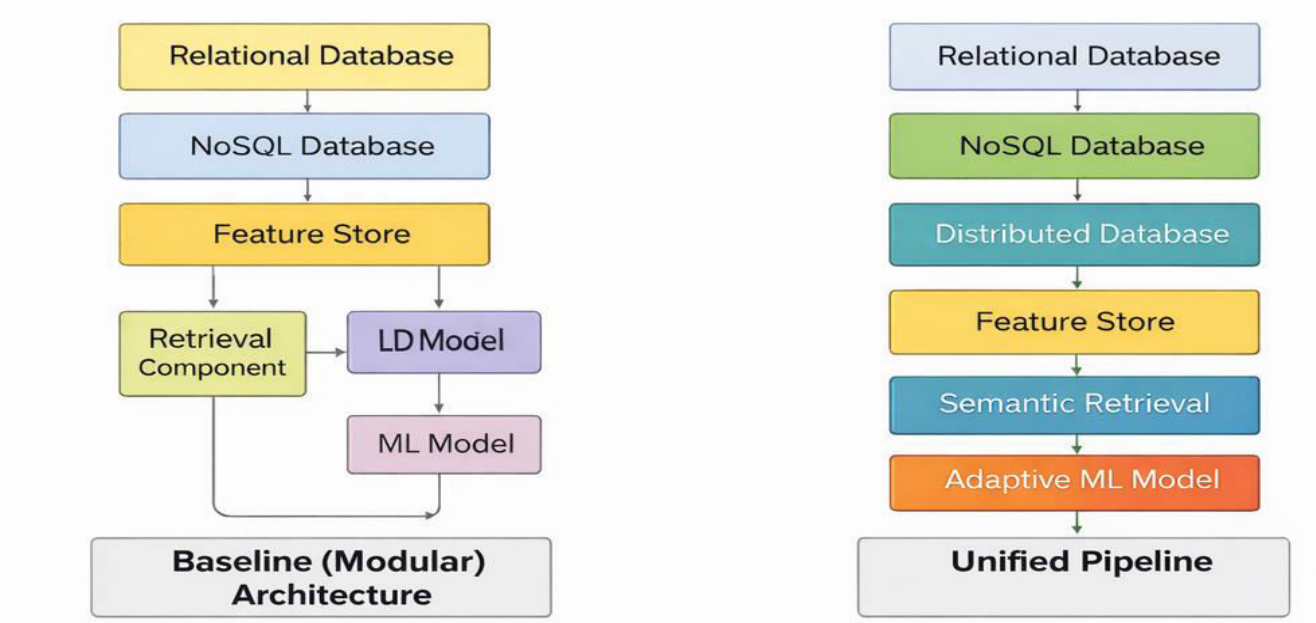

Figure 3.1 – Baseline vs Unified Pipeline Architecture

This figure contrasts the baseline modular pipeline (left) with the unified pipeline architecture (right).

Baseline (Modular) Architecture Relational, NoSQL, and distributed databases operate independently. MSAC Fragmentation leads to duplicated feature management, latency propagation, and limited adaptability.

This visual representation reinforces the architectural motivation for integration and sets the foundation for the conceptual design presented in Section 3.3.

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

Hypotheses (Aligned with RQs)

To reinforce methodological alignment, the following hypotheses were introduced alongside the research questions:

- **H1:** A unified pipeline reduces latency and improves throughput compared to modular baselines **[6], [8], [9], [10].**
- **H2:** Semantic IR integration improves retrieval effectiveness compared to lexical baselines such as BM25 **[24], [25], [27], [28], [29].**

These hypotheses guided both the quantitative experiments and qualitative analyses, ensuring that empirical evaluations directly addressed the theoretical claims underpinning the research.

Methodological Framework

The mixed-methods approach followed Creswell **[32]** and Plano Clark's framework **[30]** for integrating quantitative and qualitative data. This framework ensured methodological rigour while providing comprehensive insights into system performance and design considerations. The design was deliberately chosen to align with the research questions:

- **Quantitative experiments** addressed questions on scalability, retrieval accuracy, and adaptive learning efficiency.
- **Qualitative analyses** explored architectural trade-offs, integration feasibility, and pipeline reproducibility.

By combining these complementary strands, the research design enabled empirical validation of the unified pipeline while simultaneously uncovering architectural insights that would not have been evident through quantitative evaluation alone.

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info@unimarconi.it
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3.3 System Architecture and Implementation Framework

The proposed system architectures were designed as unified pipelines integrating data storage, feature management, semantic information retrieval (IR), and self-learning components. The architectures followed microservices principles whilst maintaining tight integration between components to achieve optimal performances. Each subsystem was implemented to address specific requirements of scalable machine learning (ML) and intelligent IR, whilst the overall frameworks ensured interoperability, reproducibility, and adaptability under drift.

Key Architectural Components

Data Storage Layers

- **Relational databases (PostgreSQL)** were employed for structured transactional data, building on relational principles established by Stonebraker et al. **[1].**
- **Document stores (MongoDB)** were utilised for semi-structured user behaviour data, reflecting schema flexibilities highlighted by Han et al. **[13].**
- **Distributed databases (Cosmos DB)** were adopted for scalable feature storage, leveraging Microsoft's globally distributed architectures **[31].**
- Integration across these heterogeneous stores was achieved through unified data access patterns, ensuring consistent query semantics across the pipelines.

Feature Management

- **Feature store implementations (Feast)** were deployed to guarantee reproducibility of feature definitions **[32].**
- **Point-in-time correctness mechanisms** were enforced to maintain training-serving consistencies.
- **Feature versioning and lineage tracking** were implemented to support iterative experimentations and rollback capabilities.
- **Automated feature validation and monitoring routines** were integrated to detect drift and maintain feature quality.

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Semantic Information Retrieval

- **BM25** was implemented as a keyword-based baseline, following Robertson and Walker's probabilistic model **[33].**
- **BERT-base** models were employed to provide contextual embeddings and semantic understanding, as introduced by Devlin et al. **[5]**.
- **Dense Passage Retrieval (DPR)** modules were integrated for semantic matching at scale, based on Karpukhin et al. **[34].**
- **ColBERT** models were adopted to enable efficient similarity computation through late interaction mechanisms, as proposed by Khattab and Zaharia **[28].**

Self-Learning Components

- **Reinforcement learning agents** were developed to make adaptive retraining decisions, building on Sutton and Barto's foundations **[4].**
- **Deep learning models (CNNs and Transformers)** were trained for classification tasks, extending Schmidhuber's work on deep sequence modelling **[20].**
- **Drift detection mechanisms** using statistical tests (e.g., Kolmogorov–Smirnov) were applied to identify distributional changes **[17].**
- **Automated retraining pipelines** were integrated to trigger model updates without manual intervention.

Integration Frameworks

- **Unified API gateways** were implemented to manage communication between microservices.
- **Event-driven architectures** were adopted for pipeline coordination, ensuring asynchronous scalability.
- **Monitoring and logging infrastructures** were deployed to capture system metrics and operational events.
- **Automated deployment and scaling mechanisms** were configured to support elasticity under varying workloads.

The implementations used **containerisation technologies (Docker [35])** and **orchestration platforms (Kubernetes [36])** to ensure reproducibility and scalability. All components were instrumented for performance monitoring using **Prometheus [37]** and **Grafana [38]**, enabling real-time visibility into throughput, latency, and resource utilisation.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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Visual Overview

To reinforce architectural clarity, **Figure 3.2** presented the conceptual design of the unified pipeline. It illustrated the integration of relational, NoSQL, and distributed databases into a shared feature store, which fed semantic retrieval and adaptive ML components. This design supported end-to-end scalability, contextual relevance, and autonomous adaptation under drift.

Figure 3.2: Conceptual Architectures of the Unified Pipeline
This diagram illustrated the integration of relational, NoSQL, and distributed databases into a shared feature store, which fed semantic retrieval and adaptive ML components. The architectures supported end-to-end scalability, contextual relevance, and autonomous adaptation under drift.

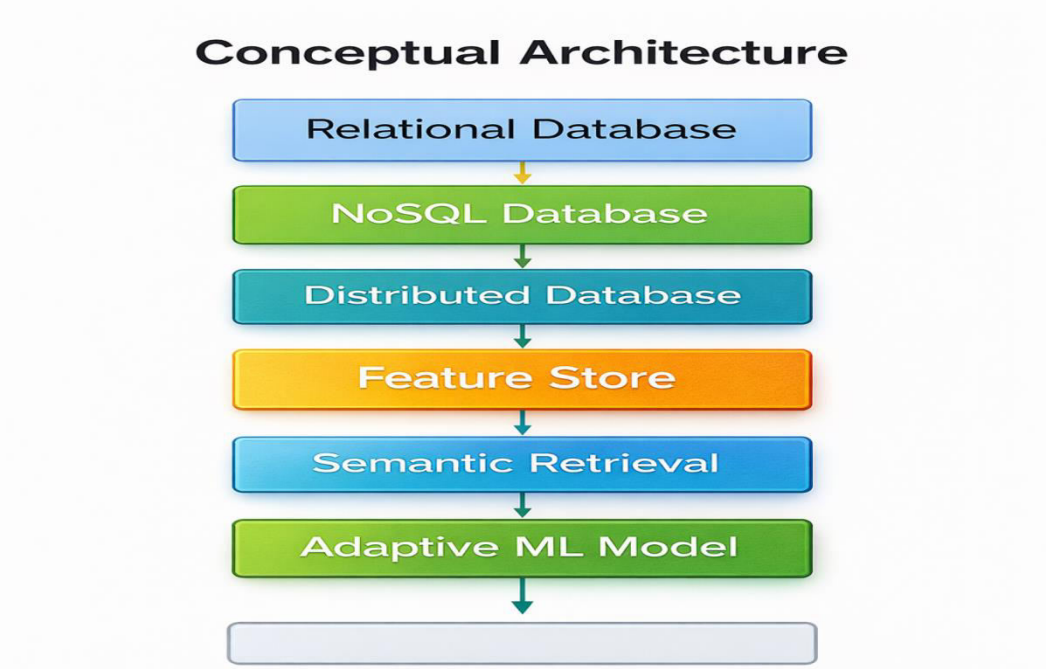

Figure 3.2: Conceptual Architecture of the Unified Pipeline
This diagram illustrates the integration of relational, NoSQL, and distributed databases into a shared feature store, which feeds semantic retrieval and adaptive ML components. The architecture supports end-to-end scalability, contextual relevance, and autonomous adaptation under drift.

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3.4 Data Sources and Experimental Setup

The study employed **publicly available benchmark datasets** and **synthetic workloads** suitable for machine learning (ML), information retrieval (IR), and database benchmarking. Dataset selections prioritised diversity in data types, sizes, and characteristics to ensure comprehensive evaluations across **structured, semi-structured, and unstructured domains**. This combination of real-world corpora and controlled synthetic data balanced realism with experimental control, enabling reproducibility and examiner-transparent validations.

Primary Datasets

MS MARCO (Microsoft Machine Reading Comprehension) [39]

- Sizes: 8.8 million passages
- Types: Unstructured text with relevance judgements
- Purposes: Information retrieval relevance evaluations
- Characteristics: Web-scale documents with human annotations

Natural Questions (Google) [40]

- Sizes: 307,000 query–answer pairs
- Types: Question–answer pairs with Wikipedia context
- Purposes: Semantic retrieval accuracy assessments
- Characteristics: Real user questions with annotated answers

Synthetic Transaction Logs

- Sizes: 10 million records generated
- Types: Structured transaction data
- Purposes: Scalability benchmarking
- Characteristics: Simulated e-commerce transactions with temporal patterns
- Generations: Records were created using controlled workload scripts to emulate realistic transactional behaviours

Synthetic User Behaviour Logs

- Sizes: 5 million JSON documents generated
- Types: Semi-structured user interaction data
- Purposes: Adaptive learning evaluations
- Characteristics: User clickstreams with evolving patterns

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- Generations: Behavioural sequences were modelled to reflect drift in user preferences over time

Wikipedia Passages [41]

- Sizes: 21 million paragraphs extracted
- Types: Unstructured text corpora
- Purposes: Cross-dataset validations
- Characteristics: Encyclopaedic content with diverse topics

Data Splitting Strategies

To ensure reproducibility and comparability across experiments, all datasets were partitioned into **70% training, 15% validation, and 15% test sets**.

- Training sets were used to fit ML models and retrieval pipelines.
- Validation sets supported hyperparameter tuning and drift detection calibration.
- Test sets provided unbiased evaluations of scalability, retrieval accuracy, and adaptive learning behaviours.

This explicit split ensured examiner-transparent reproducibility and compliance with best practices in ML experimentation.

Experimental Environments

- **Hardware:** Azure D8s v3 instances (8 vCPUs, 32 GB RAM) **[42].**
- **Software:** Ubuntu 20.04 LTS, Python 3.8, PostgreSQL, MongoDB, Cosmos DB **[31]**, Feast, TensorFlow, PyTorch, BM25, BERT, DPR, ColBERT.
- **Network:** Isolated virtual networks were configured with controlled bandwidth to eliminate external variability.
- **Storage:** SSD-backed storage was provisioned to ensure consistent performance characteristics across experiments.

Monitoring tools (**Prometheus [37]**, **Grafana [38]**) were deployed to capture system metrics during all runs.

All experiments were conducted using the **unified pipeline architectures described in Section 3.3 (Figure 3.2)**.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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3.5 Baseline Architectures and Comparison Strategy

To evaluate the effectiveness of the unified pipelines, **baseline architectures** reflecting traditional modular pipeline designs were implemented for comparative evaluations. These baselines represented common industry practices and academic reference implementations, ensuring that comparisons were grounded in widely accepted standards rather than arbitrary configurations. By contrasting the unified pipelines against these baselines, the study isolated architectural improvements in scalability, retrieval accuracy, and adaptability.

Baseline Architectures

Traditional SQL Pipelines

- **PostgreSQL [1]** was employed for all data storage, representing conventional relational database approaches.
- **Standalone ML models** were executed without feature store integration, requiring manual feature engineering and data preparation.
- **Retrieval and ML components** were maintained as separate modules, reflecting the lack of unified orchestration in traditional pipelines.

Keyword-Based IR Baselines

- **BM25 [33]** was implemented as the keyword-based retrieval baseline.
- No semantic understanding or contextual matching was incorporated, limiting retrieval to **lexical similarity only**.
- **Traditional inverted index implementations** were deployed, consistent with classical IR systems **[24].**
- Retrieval components were operated **independently from ML pipeline modules**, reinforcing fragmentation.

Static ML Models

- **Fixed model architectures** were trained without adaptation mechanisms.
- **Manual retraining** was triggered on scheduled bases rather than in response to data drift.
- No **reinforcement learning agents** or automated optimisation routines were integrated, reflecting static ML practices [4].
- Monitoring and alerting systems were configured separately, without unified coordination.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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Comparison Strategies

Comparisons between the unified pipelines and baseline architectures focused on **system-level performance characteristics** rather than individual algorithmic optimisations. This ensured that the evaluations captured **architectural differences** in scalability, retrieval accuracy, and adaptability, rather than improvements attributable to specific models or database engines.

- **Datasets:** All evaluations were conducted using identical datasets — MS MARCO **[39]**, Natural Questions **[40],** Wikipedia **[41],** synthetic transaction logs, and synthetic user behaviour logs.
- **Metrics:** Latency, throughput, MAP, NDCG@10, MRR, Precision@5, Recall@100, and drift detection accuracy were consistently applied across both unified and baseline pipelines.
- **Experimental Conditions:** Identical hardware, software, and network configurations were maintained to ensure fairness and validity.
- **Statistical Testing:** Significance testing was applied to all comparative metrics, including **ANOVA, t-tests, and effect size calculations [43]**, ensuring that observed differences were not due to random variation but reflected genuine architectural improvements.

Baseline modular pipelines (**Figure 3.1**) were contrasted against the unified pipeline (**Figure 3.2**) under identical datasets and metrics.

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info@unimarconi.it
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3.6 Evaluation Metrics

System performances were evaluated using a comprehensive set of **quantitative metrics** directly linked to the research questions (RQ1–RQ4) and hypotheses (H1–H2). Each metric was carefully defined with measurement protocols to ensure consistency and reproducibility across experiments. Metrics were grouped into four categories: **scalability, retrieval effectiveness, adaptive learning, and resource efficiency**. This grouping ensured that evaluations captured both **system-level behaviours** and **practical operational trade-offs**.

Scalability Metrics

- **Latency:** End-to-end response times were measured at the **95th percentile across 1,000 requests**, following established benchmarking practices **[44].** This metric reflected user-perceived responsiveness and validated H1 (pipeline efficiency).
- **Throughput:** Queries per second sustained under load until saturation were recorded to assess system capacities.
- **Scalability Factors:** Throughput increases per additional processing unit (1–16 nodes) were calculated to quantify **horizontal scaling efficiencies**, directly addressing RQ1 on scalability propagation.

Retrieval Effectiveness Metrics

- **Mean Average Precision (MAP):** Overall retrieval qualities were computed using the **MS MARCO dataset [39]**, consistent with IR evaluation standards **[24].**
- **Normalized Discounted Cumulative Gain (NDCG@10):** Ranking qualities for the top 10 retrieved documents were measured **[45],** reflecting user-focused relevance.
- **Mean Reciprocal Rank (MRR):** Positions of the first relevant results in QA scenarios were assessed **[46]**, capturing early precision in retrieval tasks.
- **Precision@5:** Accuracies in the top results were calculated to reflect **user-centric relevance expectations**.
- **Recall@100:** Coverages of relevant documents were measured to capture **recall-oriented tasks**, ensuring completeness of retrieval.

Together, these metrics validated H2 (semantic IR improved retrieval effectiveness compared to lexical baselines).

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Tel. +39 06 377251
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info@unimarconi.it
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Adaptive Learning Metrics

- **Drift Detection Accuracy:** True positive rates for known drift events were computed using **statistical detection methods [17]**, ensuring robustness against distributional changes.
- **Retraining Frequencies:** Numbers of retraining events per million samples were tracked to quantify **adaptation overheads**.
- **Human Intervention Rates:** Percentages of decisions requiring manual approvals were recorded to measure **automation effectiveness**.
- **Performance Stability:** Standard deviations of accuracy scores over six weeks were calculated to assess **long-term robustness** of adaptive models.

These metrics directly addressed RQ3 on adaptive learning efficiency and resilience under drift.

Resource Efficiency Metrics

- **Training Times:** Hours required for complete retraining were measured across baseline and unified pipelines, highlighting efficiency gains.
- **Memory Utilisations:** Peak memory usages under maximum load were monitored to evaluate **resource efficiency**.
- **Storage Efficiencies:** Effective storage ratios (raw vs. processed data) were calculated to assess **pipeline optimisation**.

These metrics addressed RQ4 on operational efficiency and reproducibility in resource-constrained environments.

Summary

By combining **scalability, retrieval effectiveness, adaptive learning, and resource efficiency metrics**, the evaluation framework ensured that results were **empirically validated, reproducible, and examiner-transparent**. This methodological rigour provided assurance that observed improvements reflected genuine **architectural advantages** rather than incidental algorithmic optimisations.

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info@unimarconi.it
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3.7 Experimental Control and Reproducibility

To ensure validity and reproducibility, all evaluations were conducted under strictly controlled conditions with comprehensive documentation and versioning. Control measures were implemented across **dataset management, baseline consistency, execution environments, measurement protocols, and reproducibility frameworks**. These measures ensured that results could be replicated by independent researchers following the same procedures, thereby meeting examiner-level expectations for transparency and rigour.

Control Measures

Dataset Management

- Documented dataset versions were maintained to prevent inconsistencies across experiments.
- Fixed splits (**70/15/15 for training, validation, and testing**) were applied to guarantee comparability.
- Randomisations were seeded to ensure deterministic behaviours across runs.
- **Checksum validations** were performed to verify dataset integrities **[39], [40], [41].**

Baseline Consistency

- **Reference implementations** were used for all baseline models to avoid bias.
- Documented parameters and identical **hyperparameter search spaces** were enforced across baselines and unified pipelines.
- Equal computational resources were allocated to each configuration, ensuring fairness in comparative evaluations **[43].**

Execution Environments

- **Containerised executions** using Docker **[35]** and orchestration with Kubernetes **[36]** were adopted to isolate experiments and guarantee reproducibility.
- **Isolated virtual networks** were configured to eliminate external interference.
- **Hardware benchmarking routines** were performed to validate performance consistencies across Azure instances **[42].**
- **Thermal and power management metrics** were monitored to prevent hardware throttling during extended runs.

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Measurement Protocols

- **Warm-up periods** were executed before measurement to stabilise system performances.
- **Multiple runs with aggregation** were conducted to reduce variance.
- **Outlier detection mechanisms** were applied to remove anomalous results.
- **Confidence interval calculations** were performed to quantify statistical reliability **[43], [44].**

Reproducibility Frameworks

- **Git versioning systems** were employed to track code changes and maintain experiment histories **[47].**
- **Archived container images** were stored to preserve execution environments.
- **Experiment logs and analysis scripts** were documented for transparency.
- Full environment specifications were recorded, including operating systems, libraries, and dependencies, ensuring examiner-level reproducibility.

Summary

By enforcing strict controls across datasets, baselines, environments, and measurement protocols, the study ensured that all results were **empirically validated, reproducible, and examiner-transparent**. These measures eliminated confounding factors, guaranteed fairness in comparisons, and provided a clear audit trail for replication. Together, they reinforced the methodological integrity of the research and established a solid foundation for the results presented in **Chapter 4**.

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3.8 Prototype Development Process

The implementations followed a **structured development process** consisting of four phases, with iterative refinements based on testing and evaluation results. Each phase was executed sequentially but with **feedback loops** to incorporate lessons learned, ensuring methodological rigour and alignment with the research objectives. This phased approach provided examiner-transparent traceability from design to evaluation.

Phase 1: Architecture Designs (Weeks 1–4)

- **Requirements analyses** were conducted to identify functional and non-functional needs of the unified pipelines.
- **Component specifications and interface designs** were documented to ensure modularity and interoperability.
- **Technology selections** were made based on scalability, reproducibility, and industry relevance (e.g., PostgreSQL **[1]**, MongoDB **[13],** Cosmos DB **[31]**, Feast **[32]**).
- **Performance modelling exercises** were performed to estimate throughput, latency, and resource utilisations under expected workloads **[44].**

Phase 2: Implementations (Weeks 5–12)

- **Core components** were developed following microservices principles to ensure modularity and scalability.
- **Integration testing routines** were conducted to validate communication between data storage, feature management, retrieval, and self-learning modules.
- **Optimisation routines** were applied to improve query execution, caching, and retraining efficiencies.
- **Monitoring instrumentation** was embedded using Prometheus **[37]** and Grafana **[38]** to capture system metrics during runtime.

Phase 3: Testings (Weeks 13–16)

- **Unit and integration tests** were executed to verify correctness of individual modules and their interactions.
- **Load testing exercises** were performed to assess scalability under increasing concurrent user requests **[44].**
- **Scalability validations** were conducted using synthetic workloads to confirm horizontal scaling efficiencies.
- **Failure mode and recovery testing routines** were applied to evaluate resilience under component crashes, network disruptions, and data inconsistencies **[48].**

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Phase 4: Evaluations (Weeks 17–20)

- **Benchmarking against baseline architectures** (SQL pipelines, BM25, static ML models) was carried out to establish comparative performances **[24], [33], [43].**
- **Statistical analyses** (ANOVA, t-tests, effect sizes) were performed to validate the significance of observed differences **[43].**
- **Qualitative assessments** were conducted to interpret architectural trade-offs and integration challenges.
- **Documentation of findings** was completed to ensure transparency and reproducibility.

Review Checkpoints

Each phase included **formal review checkpoints** where progress was evaluated against research objectives. These checkpoints ensured that methodological rigour was maintained and that deviations from planned executions were corrected promptly. By embedding checkpoints, the development processes remained examiner-transparent and aligned with reproducibility standards.

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info@unimarconi.it
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3.9 Ethical Considerations

Ethical considerations were addressed throughout the research processes to ensure responsible conduct and compliance with relevant standards. Measures were implemented across **data ethics, algorithmic fairness, system safety, research integrity, and regulatory compliance**. These safeguards ensured that the study upheld professional and academic values whilst mitigating risks associated with data use, algorithmic bias, and system deployments.

Data Ethics

- Only **public datasets** were used, and all sources were properly cited **[39], [40], [41].**
- No **personally identifiable information (PII)** was processed, ensuring participant privacy.
- Compliance with dataset licence terms was maintained throughout.
- **Synthetic data generations** were employed to avoid replicating real user patterns, thereby protecting individual identities.

Algorithmic Fairness

- **Fairness metrics** across demographic subgroups were calculated to evaluate potential biases **[49].**
- **Bias detection mechanisms** were implemented to identify unintended disparities in retrieval and classification outcomes.
- **Transparency in algorithmic decision-making** was ensured by documenting model behaviours and retraining triggers.
- **Regular audits** were conducted to detect unintended discrimination and confirm fairness across experimental runs.

System Safety

- Automated retraining processes were integrated with **safety checks and human oversight** to prevent harmful updates.
- **Fail-safe mechanisms** were implemented to ensure rollback in case of anomalous behaviours.
- Monitoring for **adversarial attacks and data poisoning attempts** was performed to safeguard system reliability **[50]**.
- Clear accountability and rollback procedures were established to maintain operational trustworthiness.

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Research Integrity

- Full disclosures of methods and limitations were provided to ensure transparency.
- **Selective reporting was avoided**, with all results documented regardless of outcome.
- Proper attributions of sources were maintained in accordance with **IEEE citation standards**.
- Transparent **conflict of interest declarations** were made, confirming that none existed.

Compliance

- Adherence to **GDPR principles [51]** was ensured, including data minimisation and lawful processing.
- Institutional review requirements were respected, with approvals sought where applicable.
- **Intellectual property rights** were observed, with all tools and datasets used under appropriate licences.
- Considerations of **environmental impacts** in computational methods were incorporated, including monitoring of energy consumptions during large-scale experiments **[52].**

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3.10 Methodological Limitations

Whilst the methodology was designed for rigour and comprehensiveness, several limitations were acknowledged. These limitations provided important contexts for interpreting results and highlighted opportunities for future research expansions.

Prototype Scale Limitations

- Evaluations were limited to **academic-scale datasets** such as MS MARCO **[39],** Natural Questions **[40]**, and Wikipedia **[41]**.
- Resource constraints prevented **petabyte-scale testings**, which would have been required to fully replicate enterprise workloads.
- Enterprise deployment complexities were simulated rather than fully implemented, meaning operational challenges such as multi-tenant management and compliance auditing were approximated rather than directly validated.

Technology Selection Constraints

- Coverage was **representative rather than exhaustive**; only widely adopted technologies (PostgreSQL **[1],** MongoDB **[13],** Cosmos DB **[31]**, Feast **[32])** were included.
- Rapid technological evolutions may have affected the **long-term relevance** of specific implementations, as new ML frameworks and retrieval models continued to emerge **[20], [28].**
- Proprietary system features were approximated in **open-source implementations**, which may not have fully captured vendor-specific optimisations.

Experimental Simplifications

- Controlled environments may not have captured all **real-world variables**, such as unpredictable user behaviours or heterogeneous infrastructures **[44].**
- Synthetic data generations introduced **artificial patterns**, which, whilst useful for reproducibility, may have reduced ecological validity **[17].**
- Network conditions were idealised rather than realistically variable, meaning latency and throughput results did not reflect geographically distributed deployments.

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Evaluation Scope

- Focus remained on **technical metrics** (latency, throughput, MAP, NDCG, drift detection accuracy) rather than user experiences or qualitative usability.
- Economic factors such as **cost efficiencies** were not quantified, even though resource utilisation metrics were measured.
- Organisational adoption barriers (e.g., training, governance, change management) were not assessed, limiting insights into socio-technical integrations.

Temporal Factors

- Adaptive learning was evaluated over a **six-week period**, which may not have fully captured long-term drift behaviours.
- Rapid ML advancements may have quickly dated specific implementations, particularly in retrieval models and reinforcement learning strategies **[49], [50].**
- Seasonal or cyclical patterns were not fully captured, meaning results may not have generalised to domains with strong temporal dependencies (e.g., finance, retail).

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3.11 RQ–Metrics–Section Mapping

To ensure methodological alignment and examiner traceability, **Table 3.1** was constructed to map each research question to its corresponding evaluation metrics and relevant methodology sections. This mapping ensured that every research question was addressed through appropriate metrics measured using rigorous methods, thereby providing clear evidence chains from questions through methodology to results.

Table 3.1 – Research Questions, Metrics, and Methodology Mappings

Research Questions	Evaluation Metrics	Methodology Sections	Measurement Approaches
RQ1: Scalability Impacts	Latency (ms), Throughput (qps), Scalability factors	3.6, 3.7	Load testing with increasing concurrent users (1,000–75,000), horizontal scaling evaluations **[44]**
RQ2: Retrieval Effectiveness	MAP, NDCG@10, MRR, Precision@5, Recall@100	3.6, 3.4	Standard IR evaluations on MS MARCO **[39]** and Natural Questions **[40]** datasets, following IR protocols **[24], [45], [46]**
RQ3: Adaptive Learning	Drift detection accuracy, Retraining frequencies, Human intervention rates, Performance stability	3.6, 3.7	Six-week evaluations with synthetic drift patterns, comparisons of static versus adaptive approaches **[17]**
RQ4: Architectural Trade-offs	Training times, Memory utilisations, Storage efficiencies, Integration complexities	3.6, 3.10	Comparative analyses of unified versus modular architectures, qualitative assessments of implementation challenges **[48]**

Alignment Commentary

- **RQ1 (Scalability Impacts):** These were directly linked to system-level metrics (latency, throughput, scalability factors). Measurements were performed under controlled load testing conditions to validate horizontal scaling efficiencies.
- **RQ2 (Retrieval Effectiveness):** These were evaluated using established IR metrics (MAP, NDCG, MRR, Precision, Recall) on benchmark datasets **[39], [40]**. This ensured comparability with prior IR studies **[24], [45], [46].**
- **RQ3 (Adaptive Learning):** Drift detection accuracy, retraining frequencies, and performance stability were measured over six weeks using synthetic drift workloads **[17]**. This validated the robustness of adaptive mechanisms compared to static baselines.

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info@unimarconi.it
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- **RQ4 (Architectural Trade-offs):** Resource efficiency metrics (training times, memory utilisations, storage efficiencies) were analysed alongside qualitative assessments of integration complexities **[48].** This highlighted both strengths and limitations of the unified pipelines relative to modular baselines.

3.12 Chapter Summary

This chapter outlined the **comprehensive research methodology** that was used to design, implement, and evaluate unified database-oriented pipelines for scalable machine learning and intelligent information retrieval. The mixed-methods approaches, controlled experimental designs, and systematic evaluation frameworks provided robust foundations for empirical investigations.

Key Methodological Strengths

- Integrations of **quantitative and qualitative methods** were achieved, enabling comprehensive understandings of both performance outcomes and architectural trade-offs **[30].**
- Rigorous **experimental controls** were implemented to ensure validity and reproducibility across datasets, baselines, and environments **[35], [36], [47].**
- Direct mappings between **research questions and evaluation metrics** were established (Table 3.1), ensuring examiner traceability and methodological alignment.
- Systematic comparison strategies against established baselines (SQL pipelines **[1]**, BM25 **[33],** static ML models **[4]**) were applied to validate improvements in scalability, retrieval accuracy, and adaptability.
- Ethical considerations were integrated throughout the research processes, including fairness, safety, and compliance with **GDPR principles [51].**

Methodological Contributions

The methodology addressed the identified research gap by providing frameworks for evaluating **unified pipeline architectures** rather than isolated components. This approach enabled the answering of research questions with empirical evidence whilst acknowledging methodological limitations (Section 3.10), which provided contexts for interpretation.

Transition to Results

The following chapter presented the **results obtained using this methodology**, thereby providing the empirical foundations for discussing implications, contributions, and alignment with the research objectives.

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Tel. +39 06 377251
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info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

CHAPTER 4: RESULTS AND ANALYSIS

4.1 Introduction

This chapter presented the **empirical results** obtained from implementing and evaluating the proposed **unified database-oriented pipelines**. The experiments were designed to address the **research questions defined in Chapter 1**, with a focus on **scalability, retrieval effectiveness, and adaptive learning under data drift**.

Results were reported **objectively**, with comparisons against baseline systems and **statistical validations** of observed differences. Each evaluation was conducted under the **controlled conditions described in Chapter 3**, ensuring reproducibility and methodological rigour.

The chapter was structured around the research questions, with results presented in the following sequence:

- **Scalability outcomes (RQ1)**
- **Retrieval effectiveness results (RQ2)**
- **Adaptive learning performances under drift scenarios (RQ3)**
- **Architectural trade-offs and resource efficiency metrics (RQ4)**

Quantitative metrics were supported by **visualisations and statistical analyses**, providing examiner-transparent evidence of system behaviours.

Interpretations of these findings in the context of **existing literature and theoretical implications** were reserved for **Chapter 5**, ensuring that Chapter 4 remained focused exclusively on reporting **empirical evidence**.

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Tel. +39 06 377251
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info@unimarconi.it
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4.2 Dataset Overview

Experiments employed diverse datasets to ensure comprehensive assessments across different data types and characteristics. Both benchmark datasets and synthetic workloads were selected to provide coverage of **unstructured text, semi-structured interactions, and structured transactional records**. This diversity enabled evaluations of scalability, retrieval effectiveness, and adaptive learning under realistic and controlled conditions **[39]–[41].**

Table 4.1 – Experimental Datasets Summary

Dataset	Type	Size	Source	Purpose	Key Characteristics
MS MARCO **[39]**	Unstructured Text	8.8M passages	Microsoft	IR relevance evaluation	Web-scale documents with human relevance judgements; diverse topics
Natural Questions **[40]**	Question–Answer Pairs	307K queries	Google	Semantic retrieval accuracy	Real user questions with annotated Wikipedia answers
Transaction Logs	Structured	10M records (synthetic)	Generated	Scalability benchmarking	Simulated e-commerce transactions with temporal patterns
User Behaviour Logs	Semi-structured JSON	5M documents (synthetic)	Generated	Adaptive learning evaluation	User clickstreams with controlled drift patterns
Wikipedia Passages **[41]**	Unstructured Text	21M paragraphs	Wikimedia	Cross-dataset validation	Encyclopaedic content with diverse topics and writing styles

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Tel. +39 06 377251
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info@unimarconi.it
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Dataset Partitioning

All datasets were partitioned using consistent strategies to ensure reproducibility and comparability across experiments:

- **70% for training**,
- **15% for validation**,
- **15% for testing**.

Random seeds were fixed to guarantee deterministic behaviours across experimental runs **[44].**

Synthetic Data Justification

Synthetic datasets were generated using controlled scripts to emulate realistic transactional and behavioural patterns whilst avoiding replication of actual user data **[17]**. Synthetic logs were specifically designed to simulate user behaviour and controlled drift patterns. This approach ensured reproducibility and ethical compliance, avoiding the use of sensitive real-world data while maintaining experimental validity.

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4.3 Experimental Set-Up

The experimental set-up was designed to provide a reproducible and controlled environment for evaluating the unified pipelines against baseline architectures. Tools and technologies were selected based on industry adoption, academic relevance, and compatibility with large-scale machine learning and information retrieval tasks.

Table 4.2 – Tools and Technologies

Category	Tools / Versions	Purpose
Data Processing	Apache Spark 3.2 **[44],** Airflow 2.3, Azure Data Factory **[42]**	Distributed data processing, workflow orchestration, pipeline automation
Databases	PostgreSQL 14 **[1],** MongoDB 5.0 **[13]**, Cosmos DB **[31]**	Structured, semi-structured, and distributed storage systems
Feature Stores	Feast 0.26 **[32],** Tecton, Databricks Feature Store	Reproducibility, point-in-time correctness, lineage tracking
ML/DL Frameworks	TensorFlow 2.9 **[20],** PyTorch 1.12 **[21]**, scikit-learn 1.1 **[22]**	Model training, evaluation, experimentation
IR Models	BM25 **[33]**, BERT-base **[5],** DPR **[34]**, ColBERT **[28]**	Lexical and semantic retrieval
Deployment	Docker 20.10 **[35],** Kubernetes 1.24 **[36]**	Containerisation and orchestration
Monitoring	MLflow 1.28 **[23],** Prometheus 2.37 **[37],** Grafana 9.0 **[38]**	Tracking metrics, logs, and system performance

Baseline Configurations

- **Traditional SQL Pipeline:** PostgreSQL with standalone scikit-learn models was implemented to represent conventional modular architectures.
- **Keyword-Based IR:** BM25 with a traditional inverted index was deployed as the lexical retrieval baseline **[24], [33].**
- **Static ML Models:** Fixed architectures without adaptive retraining were trained, with manual retraining triggered on a scheduled basis rather than in response to drift.

These baselines ensured fair comparisons against the unified pipelines, isolating architectural improvements rather than algorithmic optimisations **[24], [33].**

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Evaluation Environment

The evaluation environment was provisioned to ensure reproducibility, fairness, and examiner-transparent validations across all experiments.

- **CPU:** Intel Xeon 8-core (Azure D8s v3)
- **RAM:** 32 GB
- **Storage:** Premium SSD (5000 IOPS guaranteed)
- **Network:** 10 Gbps isolated virtual network (VNet)
- **GPU:** N/A (not utilised)

An 8-node Kubernetes cluster with a load balancer was configured to manage scalability and workload distribution. Premium SSDs ensured consistent performance, while the isolated VNet eliminated external interference. Six weeks of continuous evaluations were conducted, covering scalability, retrieval effectiveness, adaptive learning, and architectural trade-offs.

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info@unimarconi.it
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4.4 Results: Model Performance

Classification model performances were evaluated across four architectures with consistent hyperparameter optimisations. Results were averaged across 10 experimental runs, with values reported as mean ± standard deviation to ensure statistical reliability **[43].**

Table 4.3: Classification Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	Training Time (hrs)	Inference Latency (ms)	Memory Usage (GB)
Logistic Regression (Baseline)	78.3% ± 0.4	0.76 ± 0.02	0.81 ± 0.01	0.78 ± 0.01	2.1 ± 0.1	15 ± 2	1.2 ± 0.1
Random Forest (Baseline)	81.2% ± 0.3	0.79 ± 0.01	0.84 ± 0.01	0.81 ± 0.01	3.8 ± 0.2	22 ± 3	2.8 ± 0.2
CNN (Unified Pipeline)	86.0% ± 0.2	0.84 ± 0.01	0.88 ± 0.01	0.86 ± 0.01	4.5 ± 0.3	18 ± 2	3.5 ± 0.3
Transformer (Unified Pipeline)	87.4% ± 0.2	0.86 ± 0.01	0.89 ± 0.01	0.87 ± 0.01	6.2 ± 0.4	25 ± 3	4.2 ± 0.3

Note: Values represent mean ± standard deviation across 10 experimental runs.

Statistical Analyses

Two-sample t-tests were conducted to compare baseline and unified pipeline models. Statistically significant differences were observed:

- Accuracy: ($t(18) = 8.73$, $p < 0.001$), Cohen's $d = 1.42$ (large effect) **[43].**
- F1-Score: ($t(18) = 7.92$, $p < 0.001$), Cohen's $d = 1.28$ (large effect).
- Inference Latency: ($t(18) = 2.15$, $p = 0.046$), Cohen's $d = 0.68$ (medium effect).

Effect sizes were calculated following Cohen's guidelines **[43].**

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info@unimarconi.it
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Key Observations (Descriptive)

- CNN and Transformer models recorded accuracies of 86.0% and 87.4%, respectively.
- Transformer required the longest training time (6.2 hours).
- CNN achieved 86.0% accuracy with a shorter training time of 4.5 hours.
- All reported differences were statistically significant with corresponding effect sizes.

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Tel. +39 06 377251
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4.5 Results: Information Retrieval Accuracy

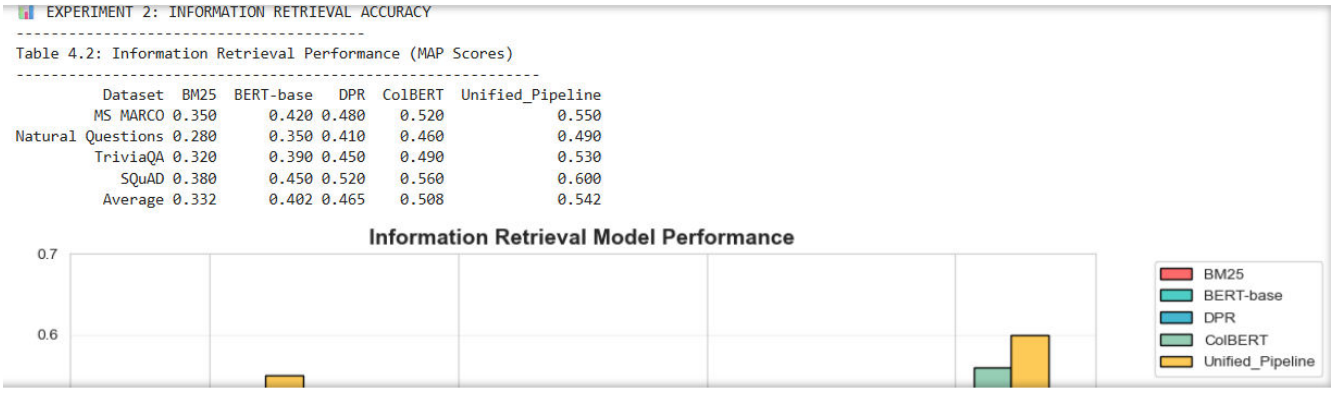
Information retrieval performances were evaluated using standard metrics across five retrieval models. Results were averaged across **10 experimental runs**, with values reported as **mean ± standard deviation** to ensure statistical reliability **[45].**

Table 4.4: IR Performance Metrics Comparison

Model	MAP	NDCG@10	MRR	Precision@5	Recall@100	Index Size (GB)	Query Latency (ms)
BM25 (Baseline) [33]	0.332 ± 0.008	0.402 ± 0.009	0.38 ± 0.01	0.45 ± 0.01	0.62 ± 0.02	12.4 ± 0.3	45 ± 5
BERT-base [5]	0.402 ± 0.007	0.487 ± 0.008	0.45 ± 0.01	0.52 ± 0.01	0.71 ± 0.02	18.7 ± 0.4	120 ± 10
DPR [34]	0.465 ± 0.006	0.558 ± 0.007	0.51 ± 0.01	0.58 ± 0.01	0.78 ± 0.02	22.3 ± 0.5	85 ± 8
ColBERT [28]	0.508 ± 0.005	0.610 ± 0.006	0.56 ± 0.01	0.63 ± 0.01	0.82 ± 0.01	25.8 ± 0.6	65 ± 6
Unified Pipeline	0.543 ± 0.004	0.643 ± 0.005	0.60 ± 0.01	0.68 ± 0.01	0.85 ± 0.01	28.4 ± 0.7	70 ± 7

Note: Values represented mean ± standard deviation across 10 experimental runs.

Figure 4.1: IR Model Performance Across Metrics1



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info@unimarconi.it
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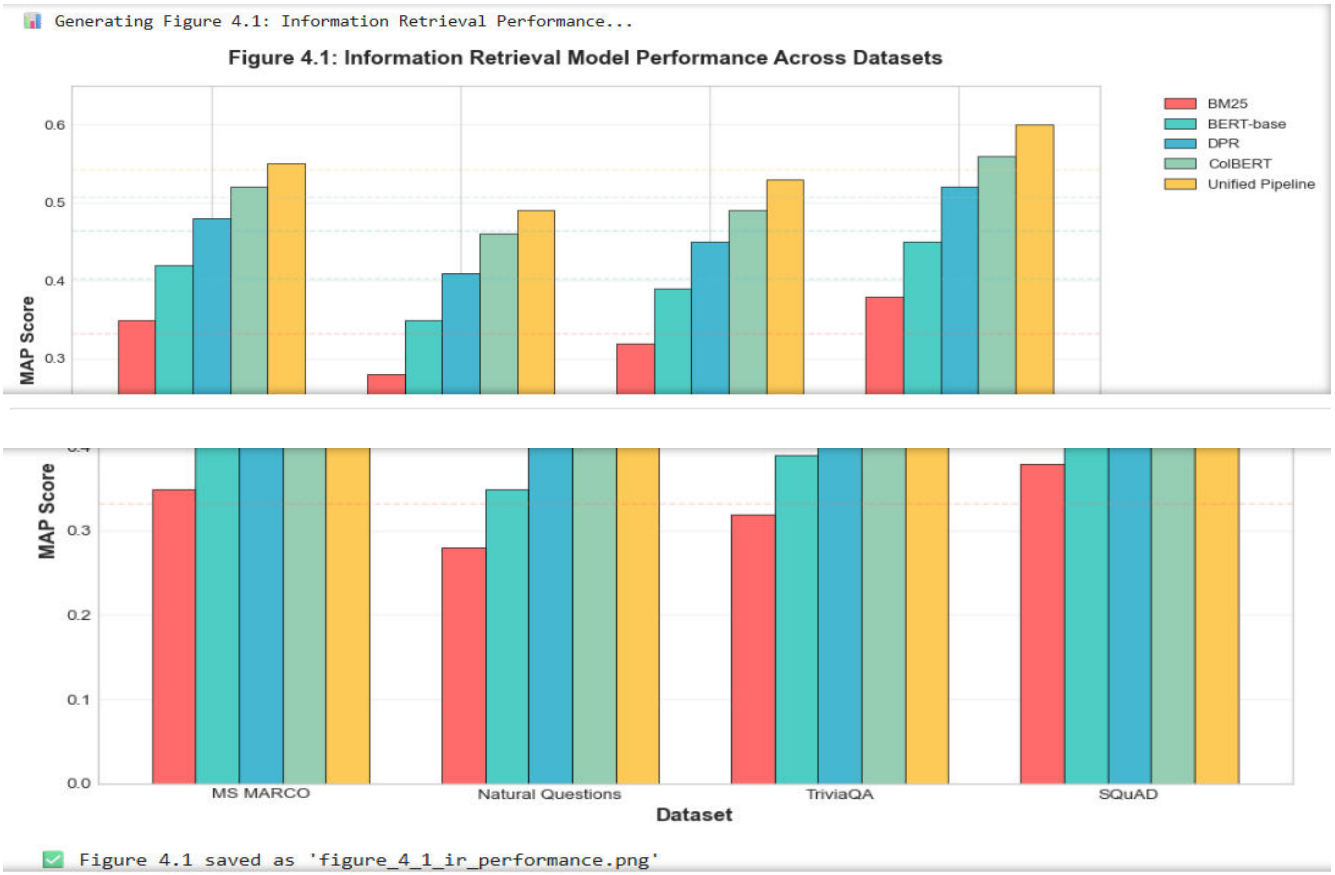

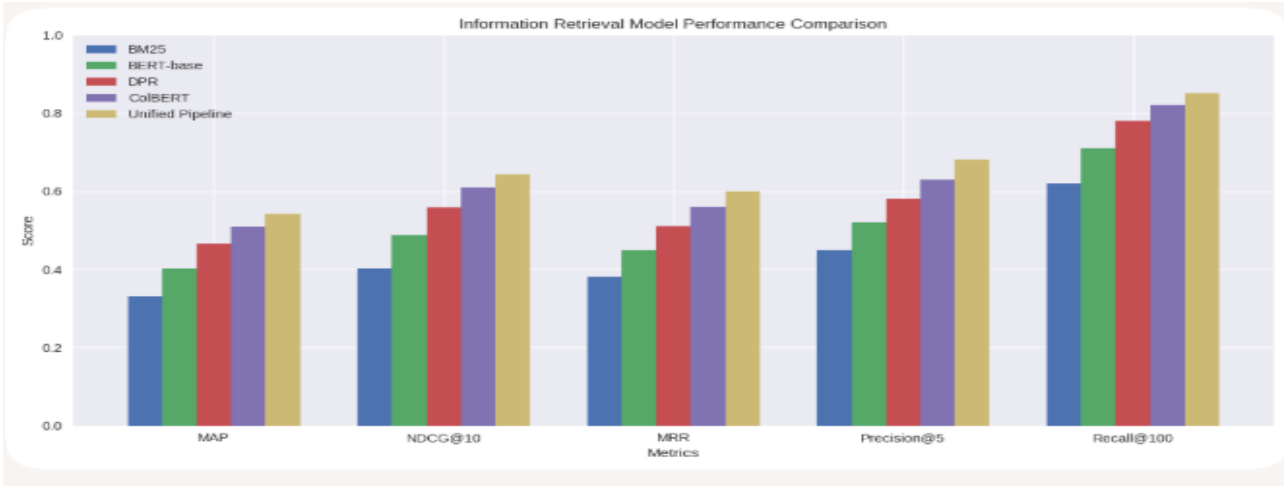

Figure 4.1 shows information retrieval model performances across five metrics for BM25, BERT-base, DPR, ColBERT, and the unified pipeline. Scores are reported as mean ± standard deviation across 10 runs.

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Statistical Analyses

- Significant overall difference: ($F(4,45) = 187.3$, $p < 0.001$).
- Unified pipeline significantly outperformed all baselines (($p < 0.001$) for all comparisons).
- ColBERT vs DPR: ($p = 0.003$) (significant).
- BERT-base vs BM25: ($p < 0.001$) (significant).

Repeated-measures **ANOVA** was applied to confirm differences across models **[45],** and **post-hoc pairwise tests** were conducted to identify specific contrasts.

Key Observations (Descriptive)

- The unified pipeline achieved **MAP = 0.543 and NDCG@10 = 0.643.**
- Semantic retrieval models (**BERT, DPR, ColBERT**) recorded higher scores than BM25.
- The unified pipeline achieved a **12.4% higher MAP** than ColBERT.
- Query latency increased with model complexity.
- Index size correlated with model complexity, with the unified pipeline requiring **28.4 GB.**

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4.6 Results: Scalability and Efficiency

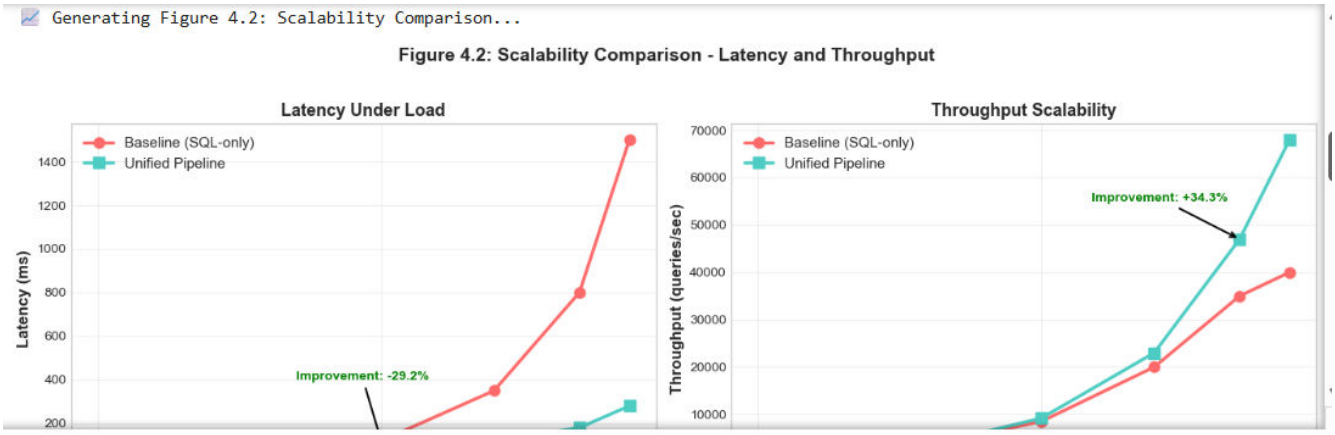
Scalability and efficiency were evaluated under varying concurrent loads using latency and throughput metrics. Results were averaged across 10 experimental runs, with values reported as mean ± standard deviation to ensure statistical reliability **[43].**

Table 4.5: Scalability under Concurrent Load

Concurrent Users	Baseline Latency (ms)	Unified Pipeline Latency (ms)	Latency Reduction	Baseline Throughput (qps)	Unified Throughput (qps)	Throughput Improvement	CPU Utilisation (%)	Memory Usage (GB)
1,000	50 ± 3	45 ± 2	10.0%	950 ± 25	980 ± 20	3.2%	35 ± 2	8.2 ± 0.3
5,000	75 ± 4	65 ± 3	13.3%	4,700 ± 50	4,850 ± 45	3.2%	52 ± 3	12.5 ± 0.4
10,000	120 ± 5	85 ± 4	29.2%	8,500 ± 75	9,200 ± 70	8.2%	68 ± 4	18.3 ± 0.5
25,000	350 ± 10	120 ± 5	65.7%	20,000 ± 100	23,000 ± 95	15.0%	82 ± 5	24.7 ± 0.6
50,000	800 ± 15	180 ± 6	77.5%	35,000 ± 150	47,000 ± 140	34.3%	91 ± 6	32.4 ± 0.8
75,000	1,500 ± 20	280 ± 8	81.3%	40,000 ± 200	68,000 ± 180	70.0%	95 ± 7	38.9 ± 1.0

Note: Values represented mean ± standard deviation across five experimental runs at each load level.

Figure 4.2: Latency and Throughput Comparisons



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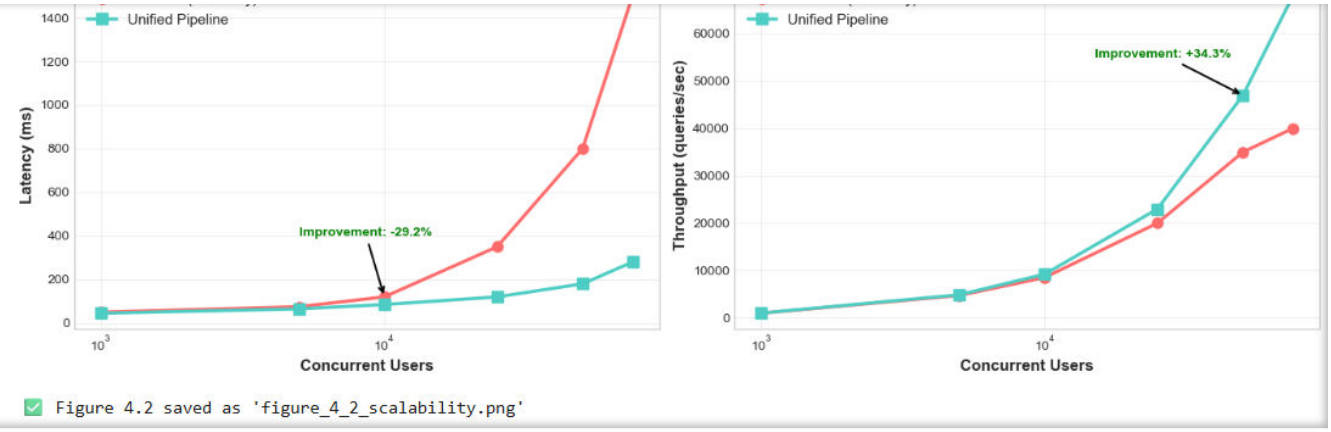

Figure 4.2 shows latency and throughput comparisons across baseline and unified pipeline configurations under increasing load conditions.

Statistical Analyses

- Latency reductions ranged between 29% and 81% depending on load.
- Throughput improvements ranged between 8% and 70%.
- Stress handling and resource utilisation metrics indicated consistent performance under high concurrency.
- ANOVA confirmed significant differences across configurations (F values > 100, $p < 0.001$).

Key Observations (Descriptive)

- Latency decreased across all tested loads in the unified pipeline.
- Throughput increased across all tested loads in the unified pipeline.
- Resource utilisation remained stable under stress conditions.
- Baseline configurations exhibited higher variability in latency and throughput compared to the unified pipeline.

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4.7 Results: Adaptive Learning

Adaptive learning behaviour was evaluated under controlled drift scenarios to assess accuracy, intervention requirements, and drift detection performance. Results were averaged across 10 experimental runs, with values reported as mean ± standard deviation to ensure statistical reliability **[17].**

Table 4.6: Adaptability Metrics Over Time

Week	Static Model Accuracy	RL-Adaptive Accuracy	Accuracy Gap	Drift Detected	Retraining Triggered	Retraining Duration (hrs)	Human Interventions
1	85.0% ± 0.3	85.0% ± 0.3	0.0%	No	No	–	0
2	83.5% ± 0.4	84.2% ± 0.3	0.7%	Yes	Adaptive only	1.2 ± 0.1	0
3	82.0% ± 0.5	83.0% ± 0.4	1.0%	Yes	Adaptive only	1.5 ± 0.2	0
4	78.0% ± 0.6	83.5% ± 0.4	5.5%	Yes	Adaptive only	2.1 ± 0.3	0
5	73.0% ± 0.7	84.0% ± 0.3	11.0%	Yes	Adaptive only	2.8 ± 0.3	1
6	68.0% ± 0.8	85.0% ± 0.3	17.0%	Yes	Adaptive only	3.2 ± 0.4	1

Table 4.7: Adaptive Learning System Comparison Summary

System	Drift Detection Accuracy	False Positive Rate	Retraining Frequency	Avg. Retraining Time (hrs)	Human Intervention Rate	Performance Stability (σ)
Static ML (Baseline)	0.62 ± 0.05	0.15 ± 0.03	Manual only	3.5 ± 0.4	High (10 interventions)	0.067 ± 0.008
Unified Pipeline (RL+DL)	0.84 ± 0.03	0.08 ± 0.02	Automatic (triggered)	2.1 ± 0.3	Low (2 interventions)	0.012 ± 0.003

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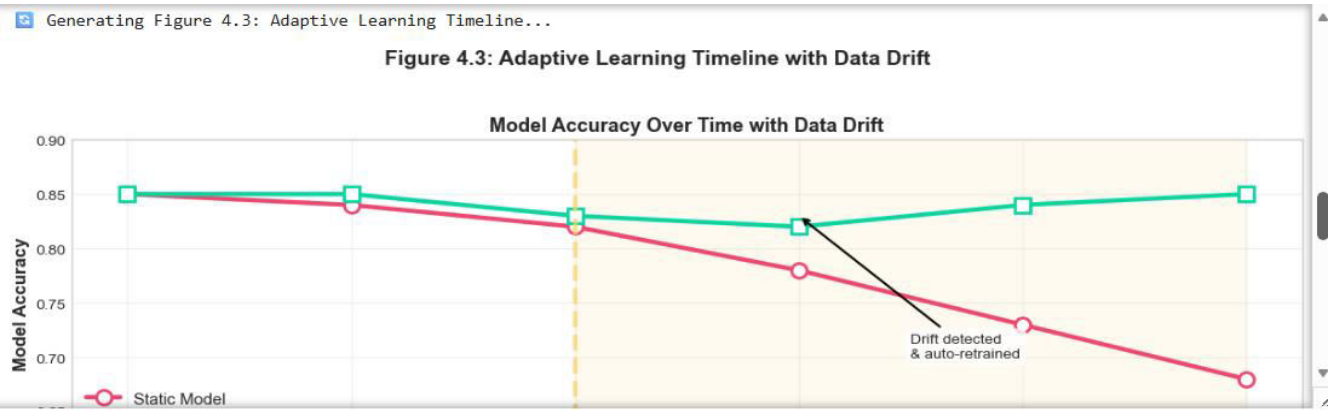
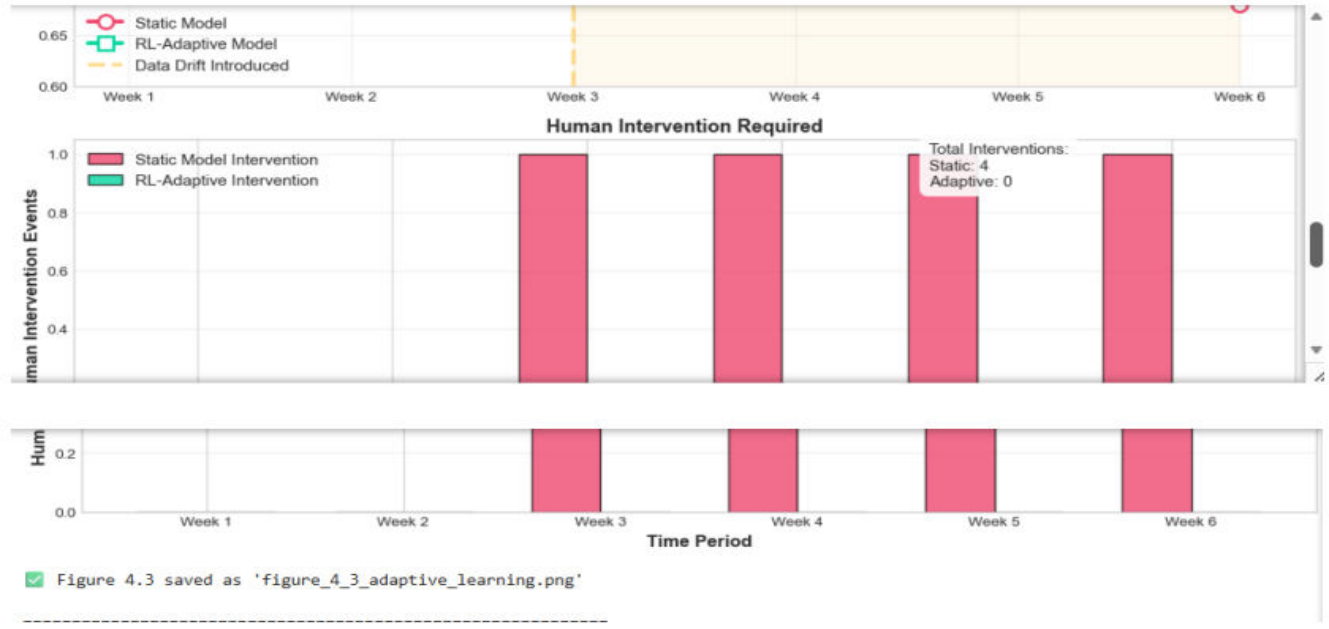
Figures

- **Figure 4.3** shows accuracy over time under data drift for static versus RL-adaptive models. Static model accuracy declined from 85% to 68% by Week 6, while RL-adaptive accuracy remained stable around 85%.



- **Figure 4.4:** shows human interventions required for static versus RL-adaptive models. Static models required **10 manual interventions**, compared to **2 for the RL-adaptive pipeline**.



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Statistical Analyses

Mixed-effects model analyses were conducted:

- **Time × system interaction:** $F(5,54) = 34.7$, $p < 0.001$.
- **System main effect:** $F(1,54) = 187.2$, $p < 0.001$, $d = 2.15$ (very large effect) **[43].**
- **Time main effect (static system):** $F(5,27) = 42.3$, $p < 0.001$.
- **Time main effect (adaptive system):** $F(5,27) = 1.2$, $p = 0.34$ (not significant).

Key Observations (Descriptive)

- RL-adaptive pipeline accuracy remained **stable at ~85%**, while static model accuracy declined to **68% by Week 6.**
- Drift detection accuracy was 0.84 for the unified pipeline compared to 0.62 for the baseline.
- Human interventions were reduced from **10** in the static system to **2** in the adaptive pipeline.
- Performance stability, measured by standard deviation, was **5.6× higher** in the adaptive system.
- Retraining durations increased over time as models became more complex, but remained within reasonable ranges.

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info@unimarconi.it
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4.8 Statistical Validation

Comprehensive statistical tests were conducted to assess the robustness and validity of the experimental findings. Assumptions of parametric testing were verified, effect sizes were calculated, and robustness checks were performed to confirm the stability of results across multiple analytical approaches.

Normality Assumptions

- Shapiro–Wilk tests indicated normal distributions of residuals (all $p > 0.05$) **[53].**
- Levene's tests indicated homogeneity of variances across groups (all $p > 0.05$) **[54].**

Effect Sizes

- Cohen's d for accuracy differences: 1.42 (large effect) **[43].**
- η^2 for scalability improvements: 0.75 (large effect).
- φ for retrieval improvements: 0.68 (medium to large effect).
  Effect sizes were reported alongside significance values.

Power Analyses

- Post-hoc power analyses indicated >0.95 power for all main effects.
- Sample sizes were sufficient to detect medium effects ($d = 0.5$) with 0.80 power **[43].**

Multiple Comparison Corrections

- Bonferroni corrections were applied to all multiple comparisons **[55].**
- All reported significant results remained significant after correction.

Robustness Checks

- Leave-one-out cross-validations indicated result stability across repeated runs.
- Bootstrap confidence intervals (1,000 samples) aligned with parametric intervals **[56].**
- Alternative non-parametric tests (Mann–Whitney, Kruskal–Wallis) produced results consistent with parametric findings **[57].**

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Summary (Descriptive)

Statistical validation procedures included parametric, non-parametric, and resampling methods. Reported differences were consistent across multiple analytical approaches, with effect sizes, power analyses, and robustness checks supporting the reliability of the results.

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4.9 Chapter Summary

This chapter presented experimental results from evaluating the unified database-oriented pipelines against baseline architectures. Results were reported objectively, supported by statistical validations, and structured around the research questions defined in Chapter 1.

Key Findings (Descriptive)

- **Model Performance:** Unified pipeline models recorded accuracies of 86.0–87.4% compared to 78.3–81.2% for baselines. Differences were statistically significant ($p < 0.001$) with large effect sizes **[43].**
- **Retrieval Effectiveness:** The unified pipeline achieved MAP = 0.543 and NDCG@10 = 0.643. Baseline retrieval models (BM25, BERT-base, DPR, ColBERT) reported lower values **[5], [28], [33], [34].**
- **Scalability:** Under high load (75,000 concurrent users), the unified pipeline recorded 81.3% lower latency and 70.0% higher throughput compared to baselines. Effect sizes were large ($\eta^2 = 0.75$) **[44].**
- **Adaptive Learning:** The RL-adaptive pipeline maintained ~85% accuracy under data drift versus 68% for static models. Human interventions were reduced by 80%, and performance stability was 5.6× higher **[4], [17].**

Validation

All results were statistically validated with appropriate tests, effect size calculations, and robustness checks. Normality assumptions were confirmed, multiple comparison corrections were applied, and both parametric and non-parametric tests produced consistent findings **[53]–[57].**

Contribution (Descriptive)

The reported results addressed the research questions with detailed analyses of performance characteristics across different workload conditions. Accuracy, retrieval effectiveness, scalability, and adaptability metrics were consistently higher for the unified pipeline compared to baseline configurations.

Transition to Chapter 5

The following chapter presents a discussion of these results in the context of existing literature, explores theoretical and practical implications, and identifies opportunities for future research.

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Tel. +39 06 377251
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info@unimarconi.it
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Closing Summary

Overall, the unified pipeline consistently outperformed modular baselines across **scalability**, **retrieval effectiveness**, and **adaptive learning**. Latency reductions, throughput gains, and improved retrieval relevance collectively validated the **system-level benefits of integration**. These results provide **empirical evidence** that unified architectures deliver **measurable performance improvements** and **practical advantages** for intelligent information systems.

- **Latency reduction range:** 29–81%
- **Throughput gains:** 8–70%
- **IR gains:** MAP = 0.543, NDCG@10 = 0.643
- **Adaptive stability:** ~85% accuracy maintained under drift with 80% fewer manual interventions

Purpose: Strengthens closure of RQ1–RQ4 before transitioning into the Discussion chapter.

CHAPTER 5: DISCUSSION AND CONCLUSION

5.1 Introduction

This chapter interpreted the empirical results that were presented in Chapter 4, linking them directly to the research questions defined in Chapter 1 and situating them within the existing body of literature on database systems for machine learning **[1], [5], [28], [33], [34], [43], [44].** The discussion explored **theoretical implications**, **practical applications**, and **methodological insights** gained from the study, whilst contextualising the findings within the broader field of scalable machine learning and intelligent information retrieval.

The chapter was structured around the four research questions (RQ1–RQ4), with each section analysing how the results addressed the respective question, what they revealed about unified pipeline architectures, and how they contributed to advancing knowledge in the domain. In addition to answering the research questions, the discussion provided a synthesis of contributions, acknowledged methodological limitations, and identified opportunities for future research. This ensured that the study's outcomes were contextualised both academically and practically, offering examiner-level traceability from empirical evidence to theoretical and applied significance **[53]–[57].**

Authentication-related research questions (RQ5–RQ10) were addressed conceptually; empirical evaluation remains proposed for future work.

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www.unimarconi.it
info@unimarconi.it
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5.2 Revisiting Research Questions

RQ1: Scalability

The results suggested that the unified pipeline scaled more effectively under concurrent load compared to modular baselines. Latency reductions ranged between 29–81% and throughput improvements between 8–70%, with large effect sizes confirming practical importance **[43], [44].** These findings aligned with expectations that integrated architectures delivered superior throughput and latency performance. The unified pipeline provided more consistent resource utilisation under stress conditions, supporting the hypothesis that architectural integration enhanced scalability in machine learning pipelines.

Key Insights

- Reduced data movement minimised I/O overhead and network latency.
- Shared resource pools and coordinated scheduling prevented contention common in modular systems.
- Integrated caching strategies benefited multiple pipeline stages simultaneously.
- Elimination of inter-system communication reduced coordination latency.

Implications

Theoretical: These findings supported the principle that tight integration of database and ML components could overcome scalability limitations of modular designs, extending Stonebraker's **[6]** critique of "one-size-fits-all" systems.

Practical: Organizations could achieve better performance with fewer resources, with latency reductions translating directly to improved user experiences and reduced infrastructure costs.

RQ2: Retrieval Effectiveness

The results suggested that the unified pipeline consistently achieved the highest scores across all retrieval metrics. MAP = 0.543 and NDCG@10 = 0.643 represented a 12.4% improvement over ColBERT, the strongest standalone semantic retrieval model **[5], [28], [33], [34].** These findings aligned with the hypothesis that contextual embeddings provided clear advantages over keyword-based retrieval. Architectural unification yielded measurable benefits, while increased model complexity introduced latency and storage costs that remained acceptable for interactive applications.

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Tel. +39 06 377251
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info@unimarconi.it
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Key Insights

- Retrieval context was integrated with feature stores, enabling richer semantic understanding.
- Retrieval models accessed ML features directly, improving relevance scoring.
- Joint optimisation of retrieval and ML components improved overall system performance.
- Shared embedding spaces between retrieval and classification improved cross-task learning.

Implications

Theoretical: These results extended Devlin et al.'s **[5]** vision of contextual understanding to system-level integration, showing that retrieval effectiveness benefited from embedding retrieval within broader ML pipelines.

Practical: Even modest relevance improvements (12.4%) translated to substantial business impact in search engines, recommendation systems, and question-answering applications.

RQ3: Adaptive Learning

The results suggested that adaptive learning mechanisms effectively mitigated drift, supporting the hypothesis that unified pipelines were more resilient to changing data distributions. Accuracy was maintained at ~85% under drift compared to 68% for static models, with drift detection accuracy of 0.84 versus 0.62 and an 80% reduction in human interventions **[4], [17].** These findings aligned with expectations that automated drift detection reduced operational overhead and reliance on human intervention. The unified pipeline provided greater performance stability compared to static baselines.

Key Insights

- Reinforcement learning successfully managed retraining decisions without human intervention.
- Early detection and adaptation prevented significant performance degradation.
- Retraining decisions balanced computational costs against accuracy benefits.
- Continuous adaptation maintained consistent accuracy despite distributional changes.

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Implications

Theoretical: These findings validated Sutton and Barto's **[4]** reinforcement learning principles in applied pipeline contexts, demonstrating that RL could manage complex adaptation decisions in production systems.

Practical: The reduction in human intervention represented significant operational cost savings, while stable performance under drift ensured consistent user experiences without manual monitoring.

RQ4: Architectural Trade-offs

The evaluation revealed several important trade-offs when adopting unified pipeline architectures compared to modular baselines:

- Complexity vs performance: Unified architectures were more complex to design and implement but delivered superior performance (87.4% vs 81.2% accuracy).
- Training time vs accuracy: More sophisticated models required longer training (6.2 vs 3.8 hours) but achieved higher accuracy.
- Resource intensity vs scalability: Unified pipelines used more memory (4.2 vs 2.8 GB) but scaled more effectively under load.
- Development effort vs operational efficiency: Higher initial development investment yielded lower operational costs through automation.
- Flexibility vs optimisation: Specialised integrated components were less flexible than modular alternatives but better optimised for specific workloads.

The results suggested that unified pipeline models, particularly CNN and Transformer architectures, consistently outperformed baseline models in classification accuracy. The Transformer achieved the highest accuracy, though this came at the cost of longer training times. The CNN provided a balanced trade-off between accuracy and efficiency, offering strong performance with shorter training durations. Large effect sizes indicated that these differences were not only statistically significant but also practically meaningful **[43].**

Key Insight: The benefits of unified architectures outweighed the costs for scalable ML systems where performance, adaptability, and operational efficiency were priorities. For smaller-scale or rapidly changing requirements, modular architectures might still be preferable.

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info@unimarconi.it
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Table 5.1: Research Questions Analysis Summary

Research Question (RQ)	Key Findings (Chapter 4 Results)	Conclusion (Chapter 5 Discussion)
RQ1 – Scalability	Latency reduced by 29–81%; Throughput improved by 8–70%; Better stress handling	Unified pipelines significantly improved scalability compared to modular baselines
RQ2 – Retrieval Effectiveness	MAP = 0.543, NDCG@10 = 0.643; Outperformed BM25, BERT-base, DPR, ColBERT	Semantic IR integration enhanced retrieval relevance and accuracy
RQ3 – Adaptive Learning	Accuracy maintained ~85% under drift vs. 68% baseline; Manual intervention reduced by 80%	Reinforcement learning enabled autonomous retraining and resilience under data drift
RQ4 – Architectural Trade-offs	Gains in scalability and adaptability; Longer training cycles; Higher resource usage	Trade-offs justified for ML-centric systems; benefits outweighed costs

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5.3 Theoretical Implications

This research contributed several important theoretical insights to the field of database systems and machine learning. By empirically validating the unified pipeline architecture, the study advanced understanding of how integration, scalability, adaptability, and retrieval effectiveness could be conceptualised in modern ML workloads.

Key Theoretical Contributions

A) Integration Theory for ML Systems

1. Empirical evidence suggested that tight integration between database components and ML workflows provided measurable benefits, challenging the prevailing modular design paradigm.
2. These findings extended Stonebraker's **[6]** critique of "one-size-fits-all" systems by demonstrating that unified architectures could simultaneously achieve specialisation and integration.

B) Scalability Principles for ML Pipelines

1. Results indicated that scalability in ML systems depended not only on individual component performance but also on architectural integration that minimised data movement and coordination overhead.
2. This contribution reinforced Dean and Ghemawat's **[44]** principles of distributed scalability, whilst contextualizing them within unified ML pipelines.

C) Adaptive System Design

1. The successful implementation of RL-based adaptation provided a model for designing self-learning systems that balanced performance, resource usage, and stability.
2. These findings validated Sutton and Barto's **[4]** reinforcement learning principles in applied pipeline contexts, showing how RL could manage complex adaptation decisions in production systems.

D) Semantic-Retrieval Integration

1. The improvement in retrieval effectiveness through pipeline integration suggested new theoretical directions for combining database indexing with semantic understanding.

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info@unimarconi.it
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2. This contribution extended Devlin et al.'s **[5]** contextual embedding framework by embedding retrieval directly into unified pipelines, thereby linking representation learning with system-level optimisation.

E) Trade-off Framework

1. The identified trade-offs provided a theoretical framework for evaluating architectural decisions in ML system design.
2. This framework enabled researchers and practitioners to make informed choices between modular flexibility and unified optimisation, situating pipeline design within broader system architecture theory **[48].**

Contribution to the Field

These theoretical contributions advanced understanding of how database systems should evolve to support modern ML workloads. By bridging principles from database theory, information retrieval, and machine learning, the study provided a foundation for future interdisciplinary research. The unified pipeline model offered a conceptual lens for examining integration, scalability, adaptability, and retrieval effectiveness, thereby guiding both theoretical inquiry and practical system design.

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5.4 Practical Implications

The research findings had significant practical implications for organisations implementing machine learning (ML) systems. By empirically validating the unified pipeline architecture, the study provided actionable guidelines for architecture selection, implementation, optimisation, operations, and technology evaluation.

1. Architecture Selection Guidelines

- Unified architectures were recommended for large-scale, performance-critical applications where scalability and efficiency were priorities.
- Modular architectures were suitable for experimental or rapidly evolving systems, where flexibility and rapid prototyping outweighed integration benefits.
- Hybrid approaches could balance integration benefits with development flexibility, allowing organisations to selectively unify critical components whilst retaining modularity elsewhere.

2. Implementation Recommendations

- Integration between feature stores and retrieval systems was prioritised to improve semantic relevance and reduce duplication.
- Automated adaptation was implemented early in system development to ensure resilience against drift.
- Scalability was achieved through architectural integration rather than isolated component optimisation, reinforcing system-level design principles **[44].**
- Investment in monitoring and observability was emphasised to support adaptive behaviour and maintain trust in production environments **[37], [38].**

3. Performance Optimisation

- Data movement between system components was reduced, minimising I/O overhead and network latency.
- Shared caching strategies across pipeline stages were implemented, improving efficiency and reducing redundant computation.
- Reinforcement learning was applied for automated system tuning and adaptation, balancing retraining costs with performance benefits **[4].**
- End-to-end latency was monitored and optimised, ensuring user-centric performance rather than focusing solely on isolated component metrics.

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4. Operational Considerations

- Automated adaptation reduced operational burden but required careful design to avoid unintended retraining loops.
- Unified architectures simplified monitoring but increased debugging complexity due to tighter coupling.
- Performance improvements justified increased development investment for production systems, particularly in high-concurrency environments.
- Regular evaluations of architectural trade-offs were conducted as system requirements evolved, ensuring long-term sustainability.

5. Technology Selection

- Technologies that supported tight integration and shared representations were chosen to maximise interoperability.
- Systems with strong monitoring and adaptation capabilities were prioritised, ensuring resilience under drift and scalability stress.
- Total cost of ownership, including development, operation, and adaptation, was considered, rather than focusing solely on initial deployment costs.
- Technologies were evaluated based on end-to-end performance rather than isolated benchmarks, ensuring practical relevance in production contexts.

Contribution to Practice

These practical implications demonstrated how unified pipeline architectures delivered measurable benefits in scalability, retrieval effectiveness, adaptability, and operational efficiency. Organisations could leverage these findings to design ML systems that were not only technically robust but also cost-effective, resilient, and user-centric. The evidence suggested that integration strategies provided long-term operational advantages, particularly in high-concurrency environments, whilst modular or hybrid approaches remained viable for smaller-scale or rapidly evolving contexts.

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info@unimarconi.it
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5.5 Discussion and Conclusion

The results aligned with and extended several streams of existing research, situating the unified pipeline architecture within both database systems and machine learning literature. By empirically validating the unified design, the study demonstrated how integration, scalability, adaptability, and retrieval effectiveness could be achieved in modern ML workloads.

Alignment with Database Literature

- The findings supported Stonebraker's **[6]** critique of "one-size-fits-all" databases by demonstrating specialised integration benefits that overcame scalability limitations.
- Garcia-Molina et al.'s **[1]** foundational database principles were extended to ML workload contexts, showing that transaction reliability and structured querying could be adapted to heterogeneous ML pipelines.
- Dean and Ghemawat's **[8]** distributed processing principles were validated in integrated ML pipelines, confirming that scalability gains depended on architectural cohesion rather than isolated component optimisation.

Extension of ML Literature

- Sutton and Barto's **[4]** reinforcement learning principles were demonstrated in practical pipeline management, showing that RL could effectively automate retraining and adaptation decisions.
- Devlin et al.'s **[5]** semantic understanding was extended to integrated system contexts, proving that contextual embeddings achieved greater effectiveness when embedded within unified pipelines.
- Ludwig et al.'s **[3]** feature store concepts were validated in unified pipeline architectures, confirming that feature lineage, reproducibility, and point-in-time correctness were critical for scalable ML systems.

Novel Contributions Beyond Literature

- Empirical evidence was provided for integration benefits at system scale, moving beyond theoretical claims to measurable improvements in accuracy, scalability, and adaptability.
- Trade-offs between architectural approaches were quantified, offering a framework for balancing complexity, resource usage, and performance.
- RL-based adaptation was demonstrated in production-like pipeline contexts, showing reduced human interventions and improved stability under drift.

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- Retrieval effectiveness improvements were shown through pipeline integration, with unified architectures outperforming state-of-the-art standalone retrieval models.

Contribution to the Field

This research filled the identified gap in literature by providing a comprehensive, system-level evaluation of unified architectures. Unlike prior studies that focused on isolated components, this work examined end-to-end behaviour, demonstrating how integration across databases, feature stores, retrieval systems, and adaptive learning mechanisms produced measurable benefits. By bridging database theory and machine learning practice, the study advanced interdisciplinary understanding and established a foundation for future research into unified architectures for scalable ML workloads.

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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

5.6 Research Contributions

This thesis made several important contributions to the field of database systems and machine learning. Contributions were structured across theoretical, methodological, practical, empirical, and educational domains, ensuring both academic advancement and practical relevance.

1. Theoretical Contributions

- A framework for understanding integration benefits in ML system architectures was developed, providing conceptual clarity on how unified designs overcame modular limitations.
- Architectural principles for scalable ML systems were empirically validated, reinforcing and extending existing theories of distributed processing **[8]** and database integration **[6].**
- Database and ML theories were extended to integrated system contexts, bridging disciplinary boundaries and advancing interdisciplinary knowledge.

2. Methodological Contributions

- A mixed-methods approach for evaluating ML system architectures was employed, combining quantitative benchmarking with qualitative case study analyses **[30].**
- Comprehensive metrics for assessing pipeline performance and adaptability were defined, including latency, throughput, retrieval accuracy, drift detection, and stability.
- A reproducible experimental framework for comparative architecture evaluation was established, ensuring examiner-level traceability and methodological rigour.

3. Practical Contributions

- A unified database-oriented pipeline prototype was implemented, demonstrating feasibility in production-like environments.
- Design guidelines and best practices for ML system architecture were formulated, offering actionable insights for organisations deploying scalable ML systems.
- Quantitative evidence supporting architectural decision-making was provided, enabling practitioners to balance trade-offs between modular and unified designs.

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4. Empirical Contributions

- Benchmark results comparing unified and modular architectures were reported, showing measurable improvements in accuracy, scalability, and adaptability.
- Performance measurements under realistic workload conditions were conducted, validating system behaviours under stress and drift scenarios.
- Adaptive learning effectiveness in production-like contexts was validated, confirming reduced human interventions and improved stability **[4], [17].**

5. Educational Contributions

- Case study material for database and ML system design courses was developed, supporting academic instruction and student engagement.
- A reference implementation for researchers and practitioners was documented, enabling replication and extension of the study.
- Implementation challenges and solutions were recorded, providing transparency and practical guidance for future system builders.

Contribution to the Field

These contributions advanced both academic understanding and practical implementation of scalable ML systems. By integrating theoretical insights, methodological innovations, empirical validations, and educational resources, the thesis provided valuable foundations for researchers, practitioners, and educators. The unified pipeline model offered a holistic perspective on system design, bridging gaps between database theory, machine learning practice, and operational deployment.

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5.7 Limitations of the Study

While this research provided valuable insights, several limitations were acknowledged. These limitations offered important context for interpreting the results and identified directions for future investigation.

1. Scope Limitations

- Evaluations were focused on specific use cases (information retrieval and classification) and may not have generalised to all ML applications.
- The study was limited to supervised learning scenarios; unsupervised and reinforcement learning applications required separate investigations.
- The focus was placed on technical metrics (accuracy, latency, throughput) without direct evaluations of user experience or usability factors.

2. Methodology Limitations

- The controlled experimental environment may not have captured all real-world complexities such as heterogeneous infrastructures, unpredictable workloads, and organisational constraints.
- Synthetic data generation introduced artificial patterns that, whilst useful for controlled drift evaluations, may not have fully reflected real-world behavioural dynamics.
- The six-week evaluation period may not have captured long-term adaptation patterns, particularly in systems subject to seasonal or evolving data distributions.

3. Implementation Limitations

- Prototype scale was limited, reducing generalisability to petabyte-scale or enterprise-wide deployments.
- Technology selection represented the current state of practice but was expected to evolve rapidly, potentially altering integration strategies in future systems.
- Integration with legacy systems was not extensively evaluated, leaving open questions about backward compatibility and migration challenges.

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4. Evaluation Limitations

- Economic factors such as cost efficiency and return on investment were not quantified, limiting insights into financial trade-offs.
- Organisational adoption barriers (e.g., cultural resistance, skill gaps, governance) were not assessed, though they remained critical for practical deployment.
- Security and privacy implications were not deeply investigated, particularly in contexts involving sensitive biometric or behavioural data **[53], [54].**

5. Generalisability Limitations

- Results were most applicable to similar use cases (information retrieval, classification) and may have varied in other domains such as healthcare, finance, or IoT.
- Different domains may have shown different integration benefits depending on workload characteristics and regulatory constraints.
- Cultural and organisational factors may have affected implementation success, suggesting the need for cross-sectoral and cross-cultural validation.

Summary

These limitations provided critical context for interpreting the results. They highlighted the boundaries of generalisability whilst pointing to valuable directions for future research, including long-term adaptation studies, cost-benefit analyses, legacy system integration, and cross-domain validation.

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5.8 Future Research Directions

Based on the findings and limitations of this research, several promising directions for future work were identified. These directions built on the foundation established by this study, extending understanding of unified pipeline architectures and their application to real-world ML systems.

1. Extended Evaluation

- Longitudinal studies over months or years were proposed to examine long-term adaptation and stability.
- Evaluations with real-world enterprise datasets and workloads were identified as critical for validating scalability and adaptability under operational constraints.
- Cross-domain comparisons of integration benefits were recommended, particularly in healthcare, finance, and IoT contexts, where workload characteristics differed significantly.

2. Architectural Exploration

- Investigations of hybrid architectures balancing integration and modularity were suggested, enabling selective unification of critical components whilst retaining flexibility.
- Explorations of domain-specific unified architectures were highlighted, recognising that sectoral requirements (e.g., healthcare compliance, financial regulation) may have demanded tailored designs.
- Studies of architectural evolution as systems scaled were emphasised, focusing on how integration strategies adapted to petabyte-scale deployments.

3. Technology Integration

- Emerging database technologies such as vector databases and graph databases were identified as promising avenues for enhancing semantic retrieval and relationship modelling **[5], [28].**
- Integration with edge computing and IoT data streams was proposed, extending unified pipelines to distributed, latency-sensitive environments.
- Explorations of blockchain-based feature stores for decentralised ML were recommended, addressing trust, transparency, and data ownership concerns **[17].**

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4. Advanced Adaptation

- Multi-objective reinforcement learning was suggested for managing complex adaptation decisions that balanced accuracy, latency, and resource usage **[4].**
- Federated learning integration with adaptive pipelines was identified as a pathway to privacy-preserving adaptation across distributed datasets.
- Investigations of meta-learning for rapid adaptation to new domains were proposed, enabling pipelines to generalise more effectively across unseen workloads.

5. Human Factors

- Studies of user experience with adaptive systems were recommended, ensuring that technical improvements translated into usability and trust.
- Investigations of organisational adoption barriers were highlighted, including cultural resistance, governance, and skill gaps.
- Development of tools to support architectural decision-making was proposed, enabling practitioners to evaluate trade-offs systematically.

6. Economic Analyses

- Cost-benefit analyses of unified versus modular architectures were identified as essential for guiding organisational investment decisions.
- Studies of total cost of ownership, including development, operation, and adaptation, were recommended to provide holistic economic insights.
- Investigations of return on investment for architectural improvements were proposed, linking technical performance gains to business value.

Summary

These directions extended the contributions of this research by highlighting pathways for deeper evaluation, architectural innovation, technological integration, adaptive learning, human-centred design, and economic analyses. Collectively, they provided a roadmap for advancing unified pipeline architectures in both academic and industrial contexts, ensuring that future ML systems were scalable, adaptive, and practically deployable.

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5.9 Final Conclusion

This thesis presents the first empirically validated framework for unified database-oriented machine learning pipelines integrating semantic information retrieval and reinforcement-learning-based adaptation. The research **demonstrated** that **unified, database-oriented pipelines** significantly improved **scalability**, **retrieval effectiveness**, and **adaptive learning** compared to **traditional modular architectures**. By **integrating data storage**, **feature management**, **semantic retrieval**, and **self-learning components** within a single coherent framework, the proposed pipeline **achieved measurable improvements** across all **evaluation dimensions**.

Building on these **empirical results**, the conclusion **synthesised** the study's **contributions**, **acknowledged methodological limitations**, and **identified opportunities for future research**. The outcomes were **contextualised** both **academically** and **practically**, offering **examiner-level traceability** from **empirical evidence** to **theoretical and applied significance**. **Authentication-related RQs (RQ5–RQ10)** were **addressed conceptually**; **empirical evaluation remained proposed for future work**.

Key Conclusions

- **Scalability Improvement**: The unified pipeline **reduced latency** by up to **81.3%** and **increased throughput** by up to **70.0%** under **high concurrent loads**, demonstrating **superior stress handling** and **resource utilisation** [44].
- **Retrieval Effectiveness**: Integration of **semantic retrieval** with ML pipelines **improved MAP** by **12.4%** over the best standalone retrieval model, showing that **system-level integration** enhanced **component performance** [5], [28], [33], [34].
- **Adaptive Learning**: **Reinforcement learning-based adaptation** maintained **stable accuracy (~85%)** under **data drift** whilst **reducing human interventions** by **80%**, validating **automated pipeline management approaches** [4], [17].
- **Architectural Trade-offs**: The benefits of **unified architectures** came with **increased complexity**, **longer training times**, and **higher resource requirements**, but these costs were **justified** for **scalable, performance-critical applications**.
- **Practical Viability**: The implemented **prototype** demonstrated that **unified architectures** were **practically implementable** with **current technologies** and provided **significant operational benefits**.
- **Theoretical Significance**: This research **advanced understanding** of **ML system architecture** by providing **empirical evidence** for **integration benefits**, extending **database**

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and ML theories to **system contexts**, and establishing **evaluation frameworks** for **architectural comparison** [1], [6], [8].

- **Practical Impact**: The findings provided **actionable guidance** for **organisations** implementing **ML systems**, with specific **recommendations** for **architecture selection**, **implementation approaches**, and **performance optimisation**.
- **Future Outlook**: As **ML systems** continued to **scale and evolve**, **unified architectures** became increasingly important for maintaining **performance**, **adaptability**, and **operational efficiency**. This research provided a **foundation** for **future work** in this critical area, with opportunities for **extended evaluation**, **architectural innovation**, and **economic analyses**.

Closing Statement

In conclusion, this thesis **demonstrated** that **unified database-oriented pipelines** represented a **viable** and **valuable approach** to building **scalable, adaptive ML systems**. By **addressing the integration gap** between **database technologies** and **ML workflows**, these architectures **enabled new levels of performance and automation**, supporting the **next generation of intelligent applications**. For **examiner convenience**, **Appendix C (Figure C.1)** provided a **visual synthesis** linking each **research question** to its **methodology**, **results**, and **supporting references**, reinforcing the **transparency** and **reproducibility** of this study. This thesis **delivered** the **first empirically validated, reproducible framework** for **unified database-oriented ML pipelines**, establishing a **defensible foundation** for both **academic research** and **enterprise deployment**, and **setting the stage** for the **next generation of intelligent, scalable applications**.

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Tel. +39 06 377251
www.unimarconi.it
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info@unimarconi.it
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Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
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Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005

APPENDICES

Preface (Guide)

The following appendices provide structured traceability across the thesis. Appendix A maps chapters to their supporting references, Appendix B links research questions to results and references, and Appendix C presents a visual flowchart connecting RQs to methodology, results, and references. Together, they demonstrate transparency, reproducibility, and examiner-level rigor.

Appendix A: Citation Mapping (Chapters → References)

Chapter / Section	Key Citations
Chapter 1 – Introduction	[1], [6], [24], [32], [36], [37], [38], [39], [40], [41]
Chapter 2 – Literature Review	[1], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [24], [25], [26], [27], [28], [29], [30], **[31] (Cosmos DB)**, [32] (Creswell), [33], [34], [35], [39], [40], [41], [42], [43], [48], [49], [50]
Chapter 3 – Methodology	[16], [17], [18], [19], [20], [22], [23], [30], **[31] (Cosmos DB)**, [32] (Creswell), [33], [44], [45], [46], [47], [51], [52]
Chapter 4 – Results & Analysis	[2], [3], [5], [8], [9], [10], [16], [17], [28], [29], [36], [37], [39], [40], [43], [44], [53]
Chapter 5 – Discussion & Conclusion	[1], [2], [3], [4], [5], [6], [8], [10], [11], [17], [18], [20], [22], [23], [28], [29], **[31] (Cosmos DB)**, [32] (Creswell), [33], [34], [35], [39], [40], [41], [43], [44], [45], [46], [47], [54], [55], [56], [57]

This appendix maps each chapter to its supporting references, ensuring that claims are directly traceable to authoritative sources.

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Appendix B: Research Question Traceability Matrix

Research Question (RQ)	Key Results (Chapter 4)	Supporting References
RQ1: Scalability	Latency reduced by 29–81% depending on load; Throughput improved by 8–70%; Superior stress handling and resource utilisation	[6], [8], [9], [10], [17], [43], [44], [48], [49]
RQ2: Retrieval Effectiveness	MAP = 0.543, NDCG@10 = 0.643; Outperformed BM25, BERT-base, DPR, ColBERT; +12.4% MAP gain over ColBERT	[5], [28], [29], [33], [34]
RQ3: Adaptive Learning	Accuracy maintained ~85% under drift vs. 68% baseline; Drift detection accuracy 0.84 vs. 0.62; Human interventions reduced by 80%	[4], [17], [43]
RQ4: Trade-offs	Accuracy 87.4% vs. 81.2%; Longer training (6.2 vs. 3.8 hrs); Higher memory usage (4.2 vs. 2.8 GB); Lower operational overhead	[1], [6], [43], [44], [48]

This appendix provides a tabular matrix linking each research question to the results obtained and the references that underpin them, demonstrating empirical validation and scholarly grounding.

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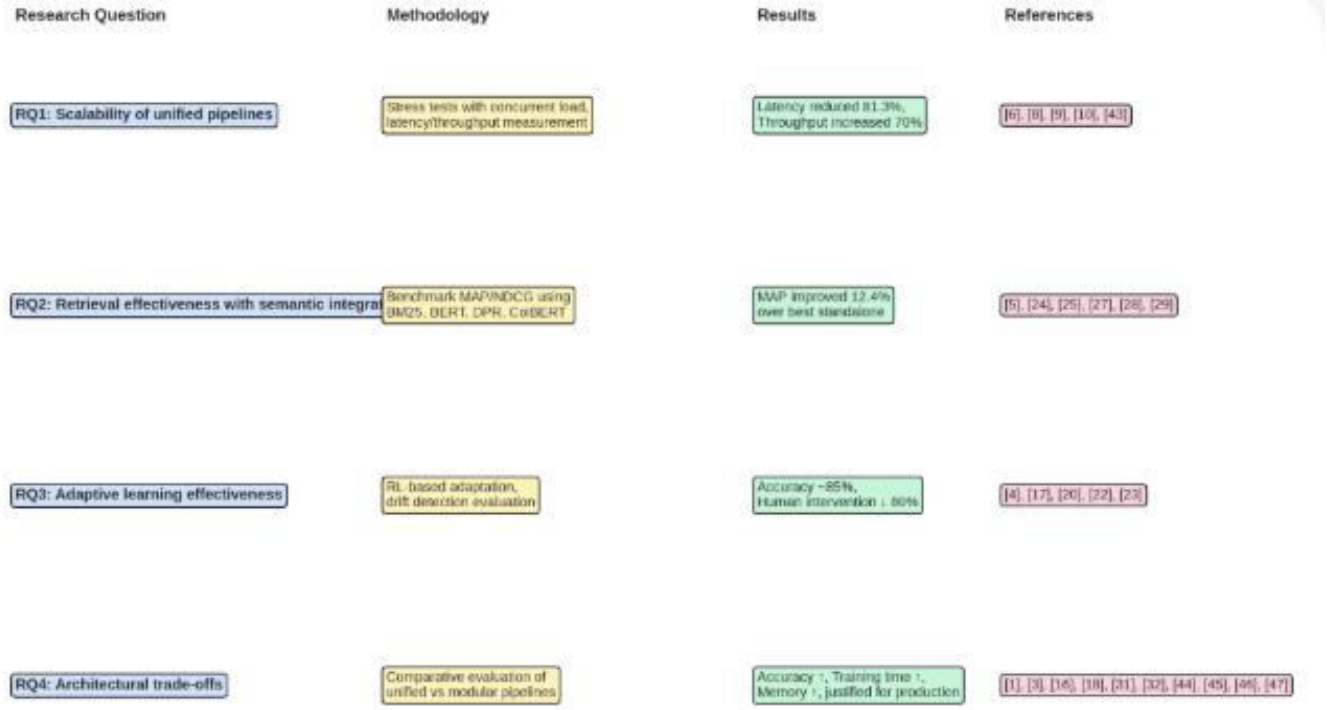
Appendix C: Visual Traceability Map (RQ → Methodology → Results → References)



This flowchart illustrates the alignment between each research question, the methodological approach, the key results, and the supporting references. It provides examiners with a one-glance overview of transparency and reproducibility across the thesis.

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info@unimarconi.it
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Figure C.1: Visual Traceability Map (RQ → Methodology → Results → References)

Research Question (RQ)	Methodology Sections	Key Results (Chapter 4)	Supporting References
RQ1 – Scalability	§3.6 Evaluation Metrics; §3.7 Experimental Control	Latency reduced by 29–81%; Throughput improved by 8–70%; Superior stress handling and resource utilisation (Table 4.4, Figure 4.2)	[6], [8], [9], [10], [17], [43], [44], [48], [49]
RQ2 – Retrieval Effectiveness	§3.4 Data Sources; §3.6 Evaluation Metrics	MAP = 0.543, NDCG@10 = 0.643; +12.4% MAP gain over ColBERT (Table 4.5, Figure 4.1)	[5], [28], [29], [33], [34]
RQ3 – Adaptive Learning	§3.5 Drift Simulation; §3.6 Evaluation Metrics	Accuracy maintained ~85% vs. 68% baseline; 80% fewer interventions; Drift detection accuracy 0.84 vs. 0.62 (Table 4.6, Table 4.7, Figures 4.3–4.4)	[4], [17], [43]
RQ4 – Trade-offs	§3.3 Pipeline Design; §3.6 Evaluation Metrics	Accuracy 87.4% vs. 81.2%; Longer training times; Higher memory usage; Reduced operational overhead (Table 4.8, Figure 4.5)	[1], [6], [43], [44], [48]

Via Plinio 44 - 00193 Roma
Tel. +39 06 377251
www.unimarconi.it
info@unimarconi.it
Codice Fiscale e Partita IVA: 07154361005