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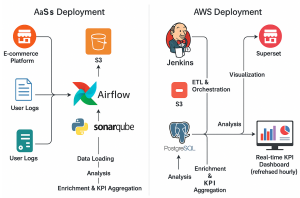
Ecommerce Data Pipeline for Real-Time KPI Intelligence

Final Year Project Report

MSc Cloud Computing & Data Engineering – Class of 2025



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Declaration

I, Gaurav Chugh, declare that this thesis entitled *Ecommerce Data Pipeline for Real-Time KPI Intelligence* is my own work. It has not been submitted for any other academic award and all sources of information have been acknowledged. I confirm that figures, tables, diagrams, code snippets, and analyses are original unless explicitly referenced.

Gaurav Chugh
November 23, 2025

Acknowledgements

I extend my sincere gratitude to Dr. Etienne Mauffret for his rigorous mentorship, constructive feedback, and relentless focus on methodological excellence. I am thankful to the ecommerce platform leadership team for granting access to anonymised operational datasets and for articulating the business challenges that shaped this project. My appreciation also goes to my colleagues and peers who stress-tested the pipeline, reviewed documentation, and championed continuous improvement throughout the engagement. Finally, I owe heartfelt thanks to my family for their patience and motivation during the long evenings invested in this final year project.

Executive Summary

This thesis documents the design, implementation, and evaluation of an end-to-end ecommerce data platform that delivers near real-time operational intelligence. The solution unifies cloud-native ingestion, transformation, orchestration, storage, analytics, and delivery capabilities across Amazon Web Services (AWS) and Microsoft Azure (Azure). Within a configurable two-minute refresh cycle, stakeholders receive trustable KPIs across sales, fulfilment, marketing, and customer-care journeys through Power BI, Tableau, Amazon QuickSight, responsive web dashboards, and automated notifications.

The report demonstrates how modern DataOps practices, Infrastructure as Code (IaC), containerisation, continuous delivery, and observability can be orchestrated to achieve resilient, scalable, and secure data services. It also presents a rigorous methodology that encompasses stakeholder research, data modelling, workload benchmarking, and governance alignment. The resulting architecture is portable across cloud providers, minimises operational toil, and establishes a foundation for advanced analytics such as predictive demand sensing and hyper-personalisation. Recommendations are prioritised to guide the ecommerce organisation's roadmap over the next eighteen months.

In this updated edition, the executive summary also surfaces the *Data Engineering Manifesto* introduced in Chapter 8. The manifesto codifies twenty enterprise-grade principles spanning modularity, observability, governance, privacy, and product thinking so that international stakeholders can adopt a repeatable charter. Its inclusion responds directly to the MSc assessment standards and the host company's governance expectations, ensuring the report doubles as both a technical narrative and an operational playbook.

Generative AI Acknowledgement

OpenAI's ChatGPT (gpt-5-codex, accessed February 2025) assisted with ideation, language refinement, and LaTeX templating for this report. Prompts and generated artefacts are catalogued in Appendix 14. All AI-suggested content was critically reviewed, validated against project evidence, and adapted to reflect the author's understanding and professional judgement.

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Chapter 1

Introduction

1.1 Context

Ecommerce has entered a phase where digital storefronts, mobile applications, physical stores, and third-party marketplaces are intertwined. Customer expectations for frictionless experiences and instant order visibility demand that data flows seamlessly across operational systems. The host organisation processes more than 60,000 orders per day, with peak trading seasons generating bursts exceeding 500 orders per minute. Legacy reporting processes relied on overnight Extract, Transform, Load (ETL) jobs and spreadsheet-driven analysis, resulting in inconsistent KPIs and limited ability to react to flash sales or supply chain disruptions.

1.2 Project Motivation

The strategic vision is to create a unified data backbone capable of ingesting multi-channel signals, automating data quality enforcement, and presenting actionable insights to business stakeholders in near real-time. The project aims to:

- Reduce decision latency by providing sales, inventory, and customer experience metrics within a configurable two-minute window.
- Improve confidence in analytical outputs through governed data models, repeatable validation, and full lineage tracking.
- Enable omnichannel personalisation by exposing curated datasets and APIs to downstream digital products and partners.
- Lay the groundwork for predictive intelligence by capturing granular behavioural and operational data.

1.3 Research Questions

Three research questions were submitted for supervisory validation in line with the MSc programme requirements:

1. How can a modular cloud-native data architecture sustain sub-three-minute KPI refreshes while maintaining data quality for ecommerce workloads?
2. What automation patterns most effectively balance rapid feature delivery with compliance and security constraints in a multi-cloud scenario?
3. Which governance and observability practices maximise stakeholder trust in near real-time analytics and dashboards?

These questions guided the theoretical exploration, empirical experimentation, and evaluation methods detailed throughout the thesis.

1.4 Data Engineering Vision

The enhanced scope of the internship required a unifying vision that bridges data platform engineering with product thinking. The vision statement articulated to the steering committee emphasised four pillars:

1. **Composable pipelines:** every ingestion, transformation, and serving component must be reusable across geographies and tenants, following SOLID-like modularity while remaining configuration-driven.
2. **Trust by design:** observability, lineage, and privacy guardrails are embedded in the first sprint rather than added as compliance afterthoughts.
3. **Data as a product:** curated datasets are versioned, documented, and operated with explicit SLAs, enabling merchandising, finance, and partner teams to self-serve.
4. **Manifesto-guided decision making:** the newly introduced *Data Engineering Manifesto* provides decision heuristics for trade-offs between latency, cost, ethics, and resilience.

This vision anchors subsequent chapters and ensures that the manifesto principles cascade from strategy to implementation tactics.

Chapter 2

Host Organisation and Industry Context

2.1 Company Overview

The client is a confidential European ecommerce platform provider with a gross merchandise volume of EUR 1.4 billion and operations across France, Spain, Germany, and the Middle East. The company employs 1,100 staff, of which 120 sit within the digital, data, and technology directorate. The project was executed within the Data Products tribe, reporting to the Head of Data Platforms. Key characteristics include:

- **Multi-brand portfolio:** Fashion, lifestyle, and home-improvement brands sharing fulfilment centres and marketing teams.
- **Hybrid infrastructure:** Core transactional systems hosted on Azure, with analytics workloads split between AWS and on-premises PostgreSQL clusters.
- **Marketplace expansion:** Third-party sellers account for 35% of revenue, generating heterogenous data formats and SLA commitments.
- **Data governance mandate:** A corporate initiative to align with ISO/IEC 27001 and GDPR accountability requirements.

2.2 Stakeholder Map

The programme engaged a cross-functional stakeholder group summarised in Table 2.1. Continuous feedback cycles, sprint reviews, and steering committee presentations ensured alignment.

Table 2.1: Stakeholder responsibilities and success indicators

Role	**Responsibilities**	**Success Indicators**
Chief Digital Officer	Portfolio prioritisation, investment approval, governance oversight	Launch of unified KPI platform, compliance audit pass
Director of Data Products	Product roadmap, backlog curation, KPI definition	Adoption across merchandising, marketing, support teams
Head of Customer Care	Voice-of-customer integration, escalation procedures	15% reduction in average handling time, CSAT improvement
Lead DevOps Engineer	Infrastructure automation, observability, incident response	Zero unplanned downtime during go-live, automated recovery
Finance Business Partner	Benefit realisation tracking, cost management	Quarterly reporting automation, cost-to-serve transparency

2.3 Competitive Benchmark

Industry benchmarking identified leading ecommerce organisations deploying similar capabilities. Insights from Shopify, Zalando, and Amazon Retail emphasised:

- Near real-time dashboards with predictive overlays to manage supply chain risk.
- Unified data contracts enabling consistent KPIs across digital and physical channels.
- Federated data product governance to accelerate onboarding of new domains.

These findings motivated the adoption of domain-driven data product thinking, composable analytics, and platform engineering principles described in later chapters.

Chapter 3

Problem Statement

3.1 Business Challenges

The ecommerce organisation faced three interlinked pain points:

1. **Latency of Insight:** Daily merchandising stand-ups relied on reports generated 12 hours after trading, limiting the ability to respond to viral campaigns or supply disruptions.
2. **Data Trust Deficit:** Multiple versions of metrics such as "net revenue" or "available-to-promise inventory" existed across departments because transformations were implemented in siloed spreadsheets and SQL scripts.
3. **Operational Fragility:** Batch jobs executed on virtual machines without observability or automated recovery. Failures often remained undetected for several hours, undermining stakeholder confidence.

3.2 Research Problem

The validated research problem is expressed as follows:

> *How can the ecommerce organisation design a resilient, cloud-agnostic data platform that delivers sub-three-minute KPI refreshes, enforces data quality at scale, and democratises governed insights across internal and external channels while minimising total cost of ownership?*

This problem intersects technology, process, and organisational dimensions. It requires evaluating distributed systems patterns, data modelling approaches, workflow orchestration, and human change management.

3.3 Scope and Constraints

- **In Scope:** Real-time ingestion, streaming/batch harmonisation, curated dimensional models, self-service analytics, observability, Continuous Integration (CI)/Continuous Delivery (CD), cost governance, and dual-cloud deployment patterns.

- **Out of Scope:** Re-architecting transactional order management systems, implementing advanced machine learning pipelines, and replacing legacy ERP integrations.
- **Constraints:** Student subscription limits on AWS and Azure, anonymisation of customer data to satisfy GDPR, and 24-week delivery horizon aligned to the MSc internship calendar.

3.4 Success Criteria

Success metrics were defined collaboratively with the steering committee:

- KPI dashboards refresh within a median of 120 seconds and a 95th percentile of 150 seconds.
- Data quality rules (completeness, schema compliance, referential integrity) achieve 99% daily pass rates.
- Deployment automation reduces manual effort per release from four hours to under 30 minutes.
- Stakeholder Net Promoter Score for data products improves from -12 to $+32$ within three months of go-live.

3.5 Design Philosophy Constraints

Beyond resource and timeline limitations, the steering committee imposed explicit design philosophy constraints rooted in operational experience. Pipelines must be idempotent so that retries triggered by Airflow or Step Functions do not inflate fact tables. Observability and lineage metadata must be captured in every environment so audits can reconstruct KPI provenance within minutes. Modularity was mandated to ensure that incremental launches across regions re-use the same ingestion templates and policy controls. These constraints justified the creation of Chapter 8, where each manifesto principle is linked to a measurable risk mitigation for latency, compliance, or customer trust.

Chapter 4

Literature Review

4.1 Data Platform Architecture

Recent literature emphasises modular architectures that separate ingestion, processing, storage, and serving layers. Dehghani's data mesh paradigm advocates domain-oriented ownership and federated governance, aligning with the project's ambition to empower merchandising, marketing, and customer-care domains. Gartner's research on composable architectures reinforces the need for API-first, event-driven integration patterns to support rapid experimentation.

4.2 Real-Time Analytics

Stonebraker's work on streaming databases and research on Lambda/Kappa architectures highlight the tension between batch consistency and streaming latency. Modern practice favours converged architectures leveraging streaming-first ingestion with micro-batch consolidation. Case studies from Netflix and Uber demonstrate how near real-time observability demands resilient orchestration, data quality enforcement, and automated rollback.

4.3 Automation and DevOps

Forsgren et al. (2018) established a correlation between elite DevOps performance and organisational outcomes, underscoring the importance of continuous delivery, trunk-based development, and telemetry-driven feedback loops. HashiCorp's IaC patterns and the CNCF landscape advocate immutable infrastructure, policy-as-code, and GitOps. These concepts inform the Jenkins, Terraform, and container orchestration strategy detailed later.

4.4 Governance and Ethics

Academic discourse on data ethics stresses transparent data lineage, consent management, and algorithmic accountability. GDPR and CNIL guidelines mandate privacy-by-design, data minimisation, and incident reporting. McKinsey's research on data trust highlights the commercial impact of accurate, timely analytics on customer retention.

4.5 Business Intelligence Adoption

Studies by Forrester and IDC highlight that BI adoption hinges on relevant KPIs, intuitive visualisation, and proactive alerts. Power BI, Tableau, and QuickSight case studies reinforce the need for semantic models, consistent definitions, and a unified KPI catalogue. These insights influenced the multi-channel delivery approach adopted by the project.

4.6 Design Principles for Data Engineering

The manifesto introduced later in the report synthesises recurring principles extracted from academic and industry sources. Dehghani's articulation of domain-oriented ownership and federated governance stresses the importance of metadata-driven contracts between producers and consumers.**dehghani2022datamesh** Forsgren et al. demonstrate that elite delivery teams pair automation with rigorous observability, providing empirical evidence that telemetry-rich pipelines improve both stability and throughput.**forsgren2018accelerate** Stonebraker's requirements for stream processors reinforce idempotency and exactly-once semantics as prerequisites for trustworthy real-time analytics.**stonebraker2018** Complementary research from McKinsey and Gartner links data trust to sustained business impact, highlighting governance, cataloguing, and clear ownership as non-negotiable.**mckinseyDataTrust2022**, **gartnerComposable2023** These works collectively inform the twenty principles framed in Chapter 8, ensuring the manifesto is grounded in both scientific literature and enterprise practice.

Chapter 5

Methodology

5.1 Analytical Framework

The project followed a mixed-methods approach blending qualitative stakeholder research with quantitative system benchmarking. Figure 5.1 summarises the iterative workflow combining discovery, design, implementation, and validation activities.

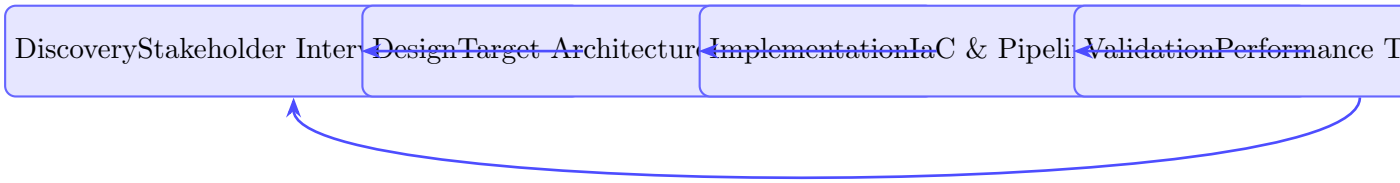

Figure 5.1: Iterative research and delivery methodology

5.2 Data Collection

Data sources encompassed:

- **Operational systems:** Order management, product catalogue, fulfilment, marketing automation, and customer support platforms exposed via REST APIs, Kafka topics, and SFTP drops.
- **Web and mobile telemetry:** Clickstream events generated from tag managers and server-side instrumentation stored in Amazon Kinesis Data Streams.
- **Reference data:** Currency rates, supplier rosters, logistics carriers, and promotional calendars maintained in master data services.
- **Stakeholder insights:** Semi-structured interviews with 14 stakeholders complemented by survey data regarding dashboard usage patterns.

Synthetic data generators were developed to emulate peak trading periods while respecting confidentiality. Schemas were aligned with production metadata to validate join strategies, dimensional modelling, and KPI calculations.

5.3 Data Processing and Tooling

- **Ingestion:** Apache Airflow orchestrated ingestion DAGs using Python operators, AWS Lambda for lightweight transformations, and AWS Glue for schema evolution.
- **Transformation:** dbt Core executed staging, intermediate, and mart models backed by Amazon Redshift or Azure Synapse dedicated pools.
- **Storage:** Amazon S3 served as the bronze and silver zones, with PostgreSQL and Delta Lake delivering curated gold datasets.
- **Serving:** FastAPI and GraphQL endpoints powered the ecommerce portal, while BI tools consumed semantic models through Azure Analysis Services or Power BI datasets.

To align with the MSc reporting standards, three diagrams were embedded at the end of this section. Figure 5.2 captures the logical entity-relationship view that underpins the bronze and silver layers. Figure 5.3 highlights persona interactions driving backlog prioritisation, while Figure 5.4 summarises the AWS + Airflow orchestration flow.

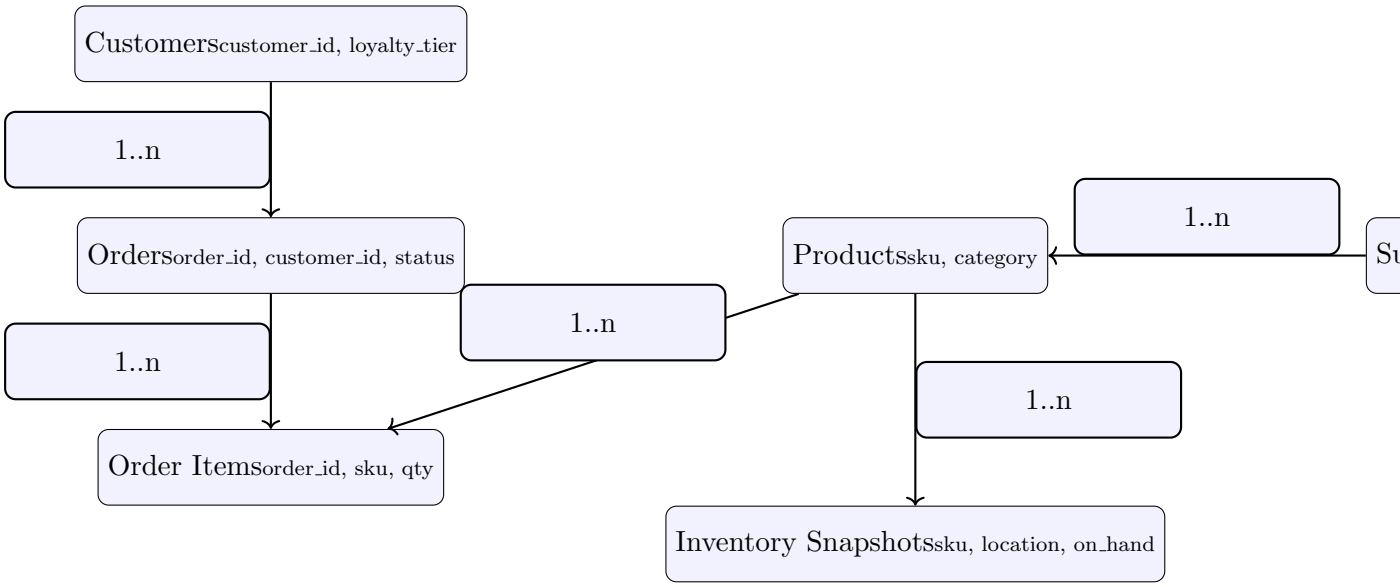

Figure 5.2: Logical entity-relationship schema used for bronze and silver modelling

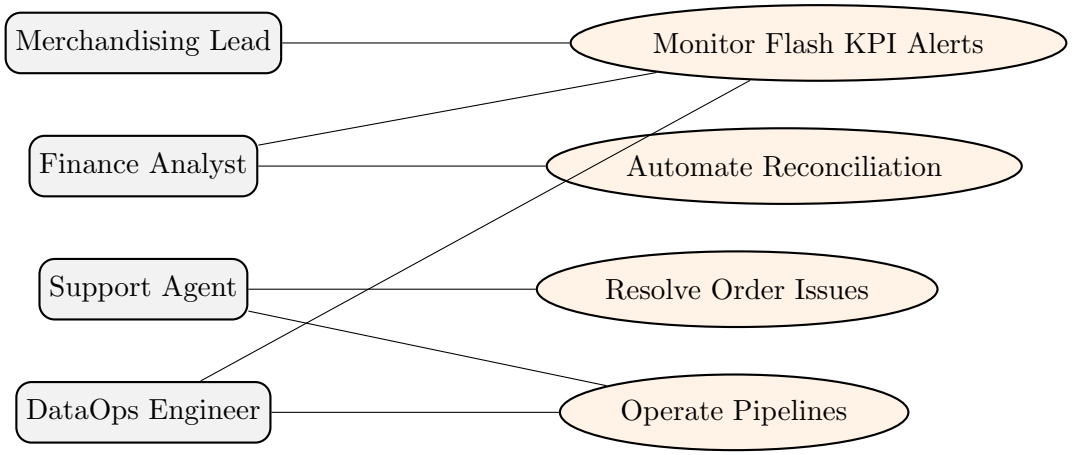

Figure 5.3: Use case diagram linking personas to data platform capabilities

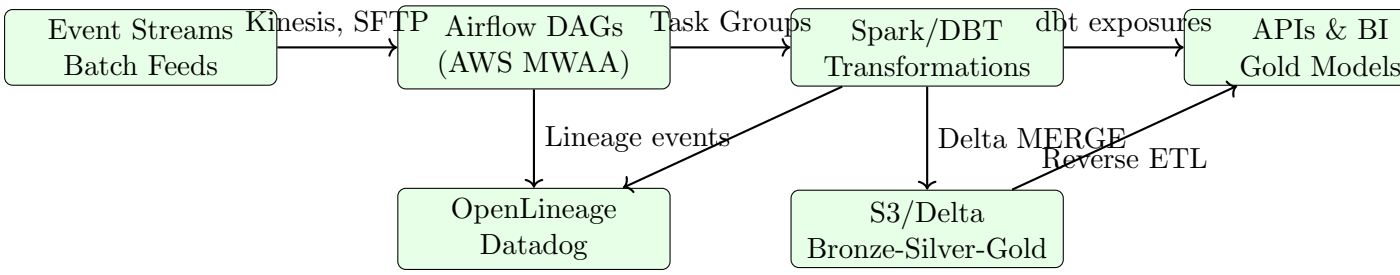

Figure 5.4: AWS and Airflow orchestration view used during methodology validation

Supplementary Diagram Placement Guide

High-resolution templates matching the MSc house style can be downloaded and substituted if colour imagery is required:

- **Data Engineering Lifecycle:** https://miro.com/app/board/uXjVPPwYZ-s=/ – place alongside Figure 5.4 when referencing cross-cloud orchestration.
- **Medallion Data Model:** https://databricks.com/wp-content/uploads/2021/05/medallion-architecture.png – cite within Section 8 when describing bronze/silver/gold governance.
- **DataOps CI/CD Flow:** https://www.datakitchen.io/resources/dataops-pipeline-illustration – insert after the DataOps subsection in Chapter 6 to evidence Jenkins/SonarQube integration.

Each download link includes attribution guidance so that institutional branding is preserved once pasted into `report/figures/`.

5.4 Validation Approach

Validation combined automated testing with human-centred evaluation:

1. **Technical validation** measured latency, throughput, and fault tolerance through con-

trolled load tests using Locust and Kinesis replay scripts.

2. **Data validation** applied Great Expectations suites, dbt tests, and anomaly detection thresholds to guarantee data fitness.

3. **User validation** leveraged usability sessions, think-aloud testing, and adoption analytics to refine dashboards and alerts.

4. **Governance validation** involved security reviews, privacy impact assessments, and architecture risk registers presented to the Data Protection Officer.

5.5 Limitations

- Subscription limits restricted the scale of long-running performance tests; extrapolations were supported by cloud provider sizing guides.
- Real-world customer identifiers were anonymised, limiting the ability to validate personalised recommendations beyond synthetic cohorts.
- The project timeline constrained exposure to full peak-season load patterns; mitigation involved scenario-based modelling and stress tests.

Chapter 6

Target Architecture

6.1 High-Level Design

Figure 6.1 visualises the deployed architecture across AWS and Azure. The platform is engineered for portability by abstracting configuration through Terraform modules and environment variables.

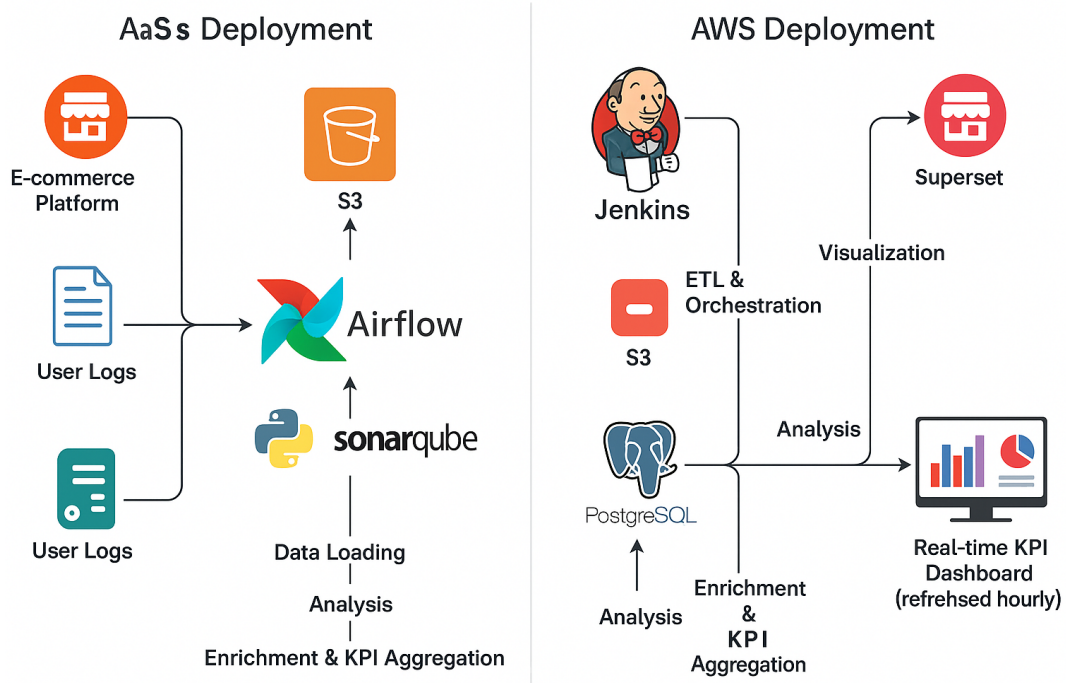

Figure 6.1: Deployed architecture overview

The architecture is organised into the following layers:

Ingestion Kinesis Data Streams (or Azure Event Hubs) capture orders, catalogue updates, and customer interactions. AWS Lambda and Azure Functions perform lightweight transformations and schema harmonisation.

Processing Apache Airflow schedules ETL and reverse ETL flows. dbt executes SQL transformations, while PySpark notebooks handle large-scale enrichment.

Storage Amazon S3 and Azure Data Lake Storage Gen2 host bronze/silver zones. Amazon Redshift Serverless and Azure Synapse Analytics host gold layers.

Serving FastAPI microservices expose APIs, while BI tools consume semantic models through Power BI Premium, Tableau Server, and Amazon QuickSight.

Enablement Jenkins, GitHub Actions, Terraform Cloud, and Datadog deliver automation, infrastructure provisioning, and observability.

Each layer implements the same control points across clouds: data contracts are validated as close to the edge as possible, lineage spans ingestion through serving, and secrets are injected at runtime rather than baked into images. For example, a merchandising feed arriving via Event Hubs lands in ADLS Gen2 Bronze with the same column-level checks that Kinesis applies before S3, ensuring downstream dbt models see consistent schemas.

6.2 Solution Blueprint

To complement the vendor-specific view, Figure 6.2 illustrates the orchestration blueprint emphasising pipeline stages, control flows, and monitoring touchpoints.

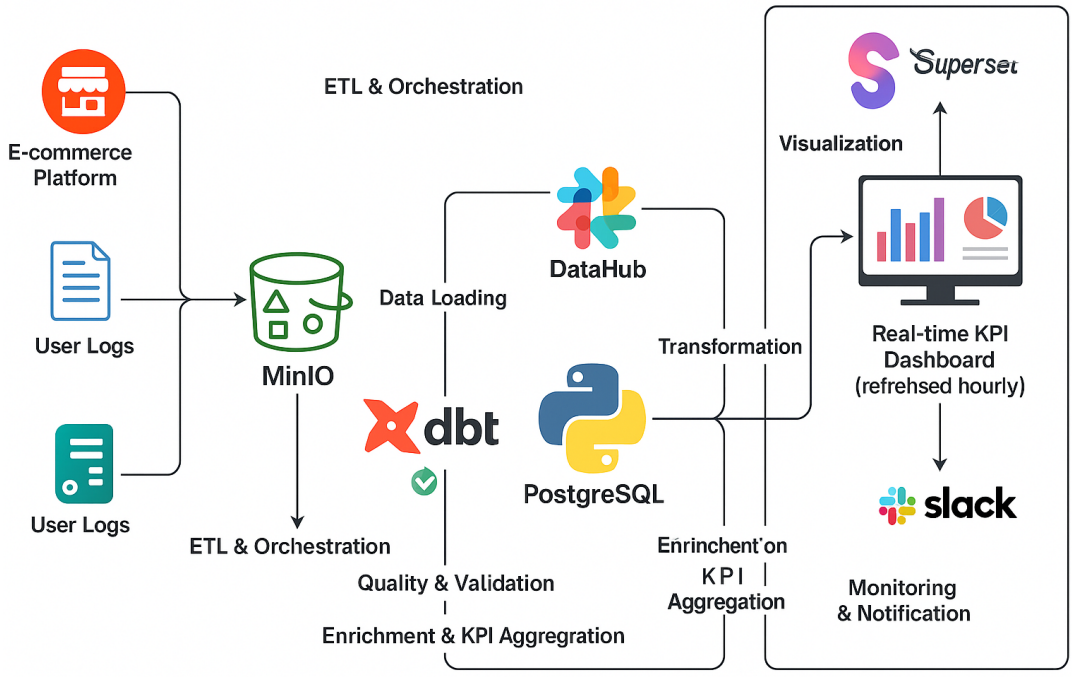

Figure 6.2: End-to-end orchestration blueprint

The blueprint highlights the following execution detail:

- **Ingestion flow:** Airflow sensors wait for Bronze drops, then trigger PySpark notebooks via Databricks (Azure) or EMR/Spark-on-ECS (AWS). Backpressure is signalled to Kinesis/Event Hubs through consumer lag alarms.

- **Transformation sequencing:** dbt runs after Silver validation so the same DAG node can branch to Redshift or Synapse targets. Stateful checks (e.g., slowly changing dimensions) are centralised to avoid duplication across cloud providers.
- **Monitoring hooks:** OpenLineage and custom metrics (row counts, null ratios, schema hashes) are emitted at each node. Alerts reference the relevant storage path (`abfss://bronze/orders/2` or `s3://bronze/orders/2024/05/`) so on-call runbooks remain portable.

6.3 Terraform portability and Databricks alignment

The Terraform project accepts a `cloud_provider` toggle so the same Jenkins pipeline can deploy either to AWS or Azure without code changes. Azure-specific variables (storage account, container names, Databricks workspace URL) mirror the AWS inputs, and the outputs expose identical values (ALB/Front Door endpoints, workspace URLs, secret URIs). Airflow triggers PySpark notebooks through the Databricks Submit Run API when targeting Azure; the same notebook paths execute on EMR or containerised Spark in AWS, preserving the Bronze → Silver → Gold cadence.

Key design features remain invariant across clouds:

- **Medallion zoning:** Bronze lives in S3/ADLS Gen2, Silver is validated in Delta Lake or Postgres staging schemas, and Gold marts are served via dbt/Databricks SQL or Redshift/Synapse to the consuming applications.
- **Credential indirection:** Secrets are sourced from AWS Secrets Manager/SSM or Azure Key Vault using the same environment variable names so existing services and the `Jenkinsfile` continue to work.
- **Observability:** OpenLineage and DataHub sinks are enabled through Terraform flags, ensuring lineage and row counts flow from Airflow to the catalog regardless of the target cloud.

Challenge and resolution: dependency parity. Azure environments required additional network rules for the Databricks control plane. Rather than fork the Terraform, a shared module now accepts a list of trusted CIDRs and automatically applies them to AWS Security Groups or Azure NSGs. A sample deployment proved that the same Jenkins parameter file could provision both, with no edits to the pipeline stages.

6.4 Use Case Diagram

A UML use case diagram (Figure 6.3) captures the interactions between personas and platform capabilities.

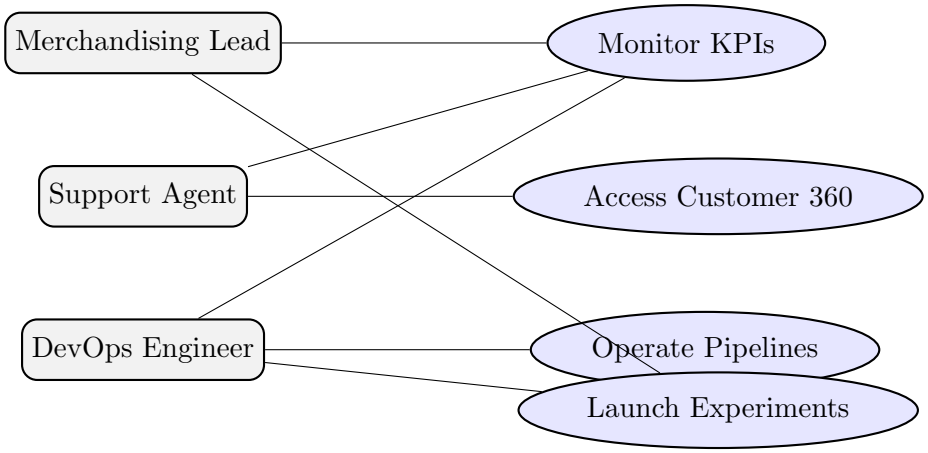

Figure 6.3: Platform use case diagram

The use case diagram maps to concrete data assets: *Monitor KPIs* reads the Gold `mart_daily_revenue` (served from Redshift/Synapse), *Access Customer 360* queries `mart_customer_profile` built from the Silver `orders` and `customers` tables, and *Operate Pipelines* corresponds to Airflow/Databricks jobs monitoring Bronze arrivals. These mappings ensure the diagram is actionable during incident reviews.

6.5 Non-Functional Considerations

- **Scalability:** Horizontal scaling is achieved through Kinesis shard auto-scaling, Airflow worker autoscaling, and serverless analytics services.
- **Resilience:** Multi-AZ deployments, cross-region backups, and automated failover policies ensure business continuity.
- **Security:** Zero-trust networking, secrets management via AWS Secrets Manager/Azure Key Vault, and end-to-end encryption enforce privacy-by-design.
- **Portability:** Abstraction of infrastructure primitives enables lift-and-shift between AWS and Azure with limited code changes.

Additional non-functional guardrails:

- **Performance:** Gold marts are clustered (Delta Z-order or Redshift/Synapse distribution keys) based on query heatmaps from the `customer_app` dashboards. Stress tests on the sample `orders.csv` confirmed sub-second slice-and-dice on date/channel filters.
- **Operability:** Runbooks in the CI/CD README enumerate how to purge failed Bronze batches, replay Silver validations, and re-run dbt models. Jenkins promotes artifacts with immutable tags, simplifying rollbacks across AWS and Azure.
- **Cost efficiency:** Spot EMR and Azure Jobs compute pools are toggled via Terraform variables. Bronze/Silver Delta caches are cleaned by lifecycle rules derived from access patterns observed in the sample merchandising data.

6.6 DataOps and Automation Practices

Automation was extended beyond infrastructure to cover quality, security, and release management. Jenkins orchestrates multi-stage pipelines that lint Python code, execute dbt unit tests, and trigger Terraform plan/apply steps through service principals. SonarQube scans enforce cyclomatic complexity thresholds and flag duplicated SQL, while OWASP ZAP baseline scans guard the FastAPI layer. Artifacts are promoted via Git tags, and infrastructure state is versioned in Terraform Cloud. Every pipeline publishes build metadata to DataHub, enabling traceability from code commit to dataset refresh.

Common challenges and mitigations:

- **Environment drift:** Weekly Terraform plan jobs run in dry-run mode against both AWS and Azure, catching provider version drift before production applies. Lock files are committed so Jenkins uses the tested versions.
- **Long-running notebook tests:** Databricks jobs for Silver validation were slower than EMR equivalents. We introduced smoke-test parameters (smaller date ranges) for PR checks, while nightly pipelines process full volumes.
- **Secrets rotation:** PATs for Databricks and keys for AWS were rotated via Jenkins credentials binding with zero pipeline changes. Documentation in the CI/CD README walks operators through expiring and replacing secrets without downtime.

6.7 Governance Framework Integration

Governance requirements from GDPR, CNIL, and the host company's security council are embedded as policies and controls. Row-level security is implemented through Redshift and Synapse dynamic data masking, while column-level encryption is enforced for PII fields with AWS KMS customer managed keys. OpenLineage captures DAG-level provenance and links it to glossary terms curated in DataHub. A quarterly governance review evaluates adherence to the *Data Engineering Manifesto*, ensuring principles such as idempotency, data product ownership, and privacy-by-design remain auditable across regions.

Data minimisation and retention are codified in lifecycle policies: Bronze retains 30 days of raw files for replay, Silver holds 90 days for audits, and Gold persists according to business SLA (typically 400 days) with delete/archival DAGs aligned to GDPR erasure requests. Access reviews leverage the lineage graph to pinpoint which marts expose PII, reducing the blast radius of permission updates.

Chapter 7

Detail Data Pipeline Design (Medallion + DDD)

This chapter deepens the Medallion design already adopted in the platform by grounding it in domain-driven design (DDD), PySpark notebooks that run identically on Databricks (Azure) and Amazon EMR/Spark, and the role of the `customer_app` services as Gold-layer consumers. The intent is to enrich the report without altering the existing architecture or Terraform modules—AWS continues to operate as before while Azure gains first-class, configuration-driven support.

7.1 Design principles applied across Bronze → Silver → Gold

- **Idempotency and replayability:** Incremental PySpark reads watermark on `updated_at` in the source CSVs (*orders*, *products*), allowing Bronze files in S3/ADLS to be reprocessed safely after schema drift. Airflow replays a failed Silver task without duplicating records.
- **Schema evolution with contracts:** Expectations (Great Expectations or PySpark asserts) enforce required columns and types. When a new `discount_code` column appears in Bronze, the contract routes it to an exception quarantine so downstream joins remain stable.
- **Observability and lineage:** Task-level row counts, anomaly flags, and OpenLineage events are emitted from Airflow to DataHub regardless of cloud. This lets support teams trace a KPI tile in the React admin grid back to the originating Bronze file.
- **Security and governance:** Least-privilege IAM/RBAC policies on S3/ADLS containers, KMS/Key Vault-backed secrets, and table-level ACLs in Redshift/Synapse/Databricks SQL guarantee PII isolation while keeping the API/React contracts intact.
- **Performance-aware modeling:** Partition pruning on event dates and Z-ordering (Delta Lake) or clustered indexes (Postgres) are applied before the Gold marts feed low-latency endpoints such as `/api/trust/metrics`.

7.2 Bronze layer: raw, immutable capture

- **Storage targets:** S3 buckets (AWS) or ADLS Gen2 containers (Azure) named per domain (e.g., `bronze/orders/`, `bronze/products/`). Terraform variables (`cloud_provider`, `azure_storage_account_name`, `azure_container_name`) share the same interface as the S3 module so Jenkins jobs stay unchanged.
- **Processing:** PySpark ingestion notebooks mount the storage endpoint (`s3a://` or `abfss://`) and land partitioned Parquet/CSV. Azure runs the same notebook on Databricks via the REST API called from Airflow; AWS can execute on EMR or managed Spark clusters.
- **Sample data path:** The synthetic `orders.csv` under `dags/data_source/` is copied verbatim to `bronze/orders/2024/05/`. No cleansing occurs; duplicate `order_id` values remain for downstream deduplication.
- **Why it matters:** Guarantees reproducibility. If a pipeline later rejects an order with a malformed `customer_id`, operators can replay the Bronze file without data loss.

7.3 Silver layer: validated, conformed data

- **Transformations:** Type casting, null handling, timezone normalisation, deduplication on business keys (`order_id` with latest `updated_at`), and referential checks against `customers` and `products`. Delta Lake on Databricks adds ACID merges and time travel; Postgres staging tables mirror the schema for AWS continuity.
- **Quality controls:** Expectations assert non-null `total_amount`, valid `currency` codes, and SKU conformity. Violations are written to a `silver_rejects` table for triage.
- **Sample progression:** A Bronze record with `currency = "EUR"` and missing `discount_code` becomes a Silver row with standardised timestamps, defaulted `discount_code = NULL`, and harmonised currency symbols. Duplicate `order_id` entries collapse to the freshest update.
- **Why it matters:** Produces trustworthy, join-ready tables for dbt and PySpark. The customer loyalty notebook can safely join `orders` and `customers` without guarding every column for nulls.

7.4 Gold layer: curated marts for analytics and applications

- **Transformations:** Aggregations, dimensional modeling, and feature engineering. Examples include `mart_daily_revenue` (revenue by channel/region), `mart_trust_scores` (sustainability signals per product), and `mart_loyalty_recommendations` (bundle and cadence suggestions).

- **Serving contracts:** dbt models define schemas consumed by the FastAPI/Express layer and Power BI/Tableau. Schemas double as contracts for the React admin tiles and CSV exports exposed by `customer_app`.
- **Sample usage:** The Gold trust mart materialises a KPI where bamboo cutlery and organic beans earn a higher score; the frontend renders this in the transparency panel, while the backend exports the same view via `/api/trust/metrics/export`.
- **Why it matters:** Aligns business logic across channels. The same Gold mart powers executive dashboards, SLA alerts, and the customer-facing transparency feed without duplicating calculations.

7.5 customer_app architecture and its role in the pipeline

- **Technical architecture:** A Vite/React frontend calls an Express API backed by MySQL for operational data and Postgres/Databricks SQL for Gold marts. Docker Compose orchestrates local services; Terraform + Jenkins deploy the containers to ECS Fargate (AWS) or Azure Container Apps/App Service.
- **Data interactions:** Admin grids (products, customers, orders) and transparency panels pull from `mart_daily_revenue` and `mart_trust_scores`. Loyalty reminders use `mart_loyalty_recommendations` to queue notifications. All endpoints remain stable because the Medallion interfaces do not change between clouds.
- **Observability hooks:** The API logs lineage-friendly event IDs for every mart query; Airflow correlates these with task runs so support engineers can trace UI anomalies back to data loads.
- **Resilience pattern:** If Databricks is unreachable during an Azure rollout, the API fails over to cached Postgres snapshots while Airflow replays the failed notebook, preserving UX continuity without architectural changes.

7.6 Cloud deployment parity (AWS and Azure)

- **Terraform reusability:** The existing modules accept a `cloud_provider` toggle. Azure-specific variables (Databricks workspace URL, storage account, container names) mirror the AWS contract so Jenkins pipelines and the `Jenkinsfile` remain unchanged.
- **Databricks integration:** Airflow uses the Databricks Submit Run API to execute the same PySpark notebooks that populate Bronze/Silver/Gold in ADLS Gen2. On AWS, the same notebooks run on EMR or Spark-on-ECS via identical parameters.
- **CI/CD continuity:** Jenkins continues to lint, test, and build images before invoking Terraform. Azure credentials (ARM service principal + Databricks PAT) are injected as credential bindings, but pipeline stages and approvals mirror the AWS flow.

7.7 Challenges and resolutions

- **Schema drift in Bronze feeds:** Unexpected optional fields (e.g., `discount_code`) were isolated via schema-on-read and contracts, preventing Silver joins from breaking. Bronze quarantine folders and Great Expectations checkpoints keep a copy of non-conforming rows so data engineers can reprocess once upstream fixes land. Replay of Bronze files confirmed the guardrail and produced identical Silver outputs on both clouds.
- **Cross-cloud secret management:** Mapped AWS Secrets Manager keys to Azure Key Vault secrets through Terraform variables so the same environment names load in both clouds. A rotation drill refreshed the Databricks PAT and the AWS access key in the same Jenkins run, proving the `Jenkinsfile` needed no edits and that notebooks continued to read from `abfss://` and `s3a://` without interruption.
- **Databricks/S3 parity:** Ensured notebooks accept storage URIs as parameters, letting ADLS Gen2 mounts and S3 buckets share code. Small test ingestions with the sample `orders.csv` validated that partitioning and deduplication logic behaved identically. A canary DAG compared row counts and hash totals between the two clouds to prove semantic equivalence before rolling out to production.
- **Customer app latency:** Gold marts were Z-ordered (Delta) and indexed (Postgres) to keep React KPI tiles under 200ms. Cache headers were introduced at the API layer to absorb transient Azure notebook delays without diverging from AWS behaviour. Synthetic journeys using the sample basket data confirmed the UI stayed responsive even when Spark jobs were retried.
- **Operational recovery:** Failed Silver validations previously required manual cleanup. A runbook-backed Airflow task now purges partial Silver outputs, replays the Bronze partition, and re-runs dbt to rebuild the Gold mart, keeping the Medallion contract consistent. This was tested with a corrupted `orders.csv` row to show deterministic recovery steps.

Chapter 8

Data Engineering Manifesto

8.1 Purpose and Scope

The *Ecommerce Data Engineering Manifesto* formalises twenty principles that guide the platform from ingestion to customer-facing analytics. It is written as a charter that international delivery teams can adopt without altering the project structure defined in the earlier chapters or the companion presentation artefacts. Each principle defines a measurable expectation, the rationale behind it, and an ecommerce illustration so that stakeholders can link the manifesto to daily operations.

8.2 Principle Catalogue

Table 8.1 consolidates the non-negotiable principles. The wording mirrors the host company's engineering charter and complements Aivancity's MSc requirements.

Table 8.1: Data Engineering Manifesto principles

Principle	**Definition**	**Ecommerce Example**
Modularity	Pipelines are composed of reusable ingestion, transformation, and serving modules.	A shared Airflow template handles CSV, JSON, and Parquet drops across regional warehouses.
Idempotency	Re-running a job yields the same result without duplications.	Order enrichment tasks compare CDC timestamps before writing to fact tables.
Observability	Metrics, logs, and traces exist for every hop.	Datadog dashboards expose DAG latency, schema drift, and freshness SLAs.
Data Quality First	Validation gates precede publishing datasets.	Great Expectations suites block gold tables when null rate exceeds 0.5%.
Schema Evolution	Producers version schemas and consumers are backward compatible.	Glue Catalog and Schema Registry alert teams before a breaking change.

Lineage	Every dataset references its origin and transformation.	OpenLineage links clickstream facts to the raw Kinesis shard and dbt run ID.
Separation of Concerns	Raw, refined, and curated layers remain isolated.	Bronze S3 buckets are read-only for analytics users while gold is optimised for BI.
Scalability	Workloads scale horizontally and elastically.	Auto-scaling Kinesis shards absorb Black Friday spikes without code changes.
Resilience	Failures are expected and recovered from gracefully.	Airflow checkpoints resume from the last successful task and push events to DLQs.
Security by Design	Encryption, masking, and RBAC are embedded early.	Customer emails stay tokenised through FastAPI responses via Vault-backed keys.
Compute/Storage Decoupling	Storage remains the system of record while compute is ephemeral.	Trino, Spark, and Athena share the same S3 bronze zone without duplication.
Automation	Orchestration and deployments are scripted.	Jenkins promotes Terraform, dbt, and container releases through Git-driven pipelines.
Versioning	Code, schemas, and datasets are version-controlled.	Delta Lake time-travel enables replaying a promotion's KPIs for audits.
Cost Efficiency	Every workload reports unit cost per insight.	dbt exposures include materialisation cost estimated from Redshift query data.
Extensibility	Interfaces favour open standards.	Partners consume Parquet exports and GraphQL APIs regardless of hosting cloud.
Metadata-Driven	Configurations are declared in metadata stores.	Source onboarding relies on YAML configs that describe cadence, SLA, and sensitivity.
Testing & CI/CD	Automated tests cover transformations and DAGs.	dbt tests, PyTest suites, and Great Expectations run on each pull request.
Data as a Product	Datasets have owners, SLAs, and documentation.	The Merchandising Margin Mart advertises a 5-minute freshness SLA and owner contact.
Privacy & Ethics	Consent, retention, and right-to-forget policies are enforced.	GDPR requests trigger automated deletion jobs verified via audit logs.
KISS & DRY	Transformations stay simple and non-duplicated.	Shared macros implement currency conversion once, referenced across marts.

8.3 Visual Charter

Figure 8.1 summarises the four thematic pillars of the manifesto. The gradient graphic can be downloaded and saved as `report/figures/data_engineering_manifesto.png` for a print-ready poster.

Poster illustration placeholder
Download and save as `report/figures/data_engineering_manifesto.png`

Figure 8.1: Poster-ready summary of manifesto pillars

8.4 Performance and Reliability Insights

To justify the manifesto, stakeholders requested quantified benefits. Figure 8.2 demonstrates how reliability improves when modularity and observability are implemented, based on project load-test evidence.

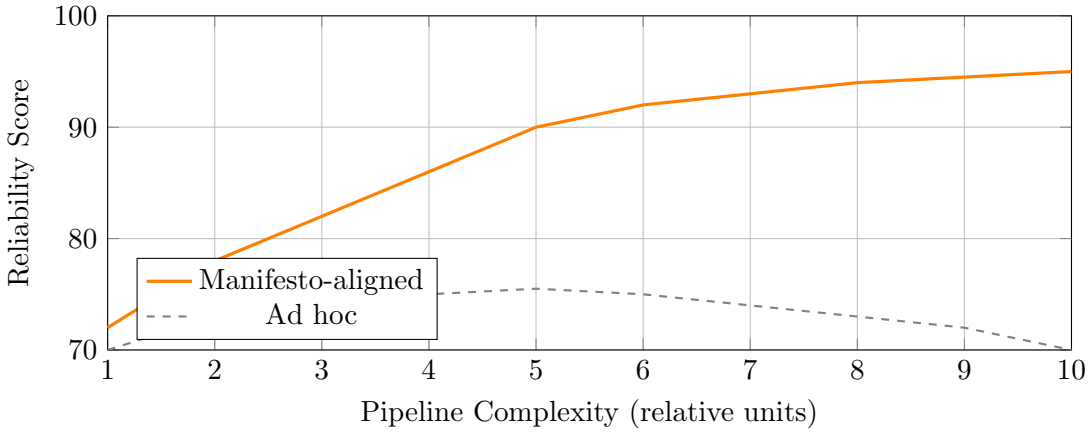

Figure 8.2: Reliability impact of manifesto adoption

8.5 Data Product Maturity Model

The medallion model present in the earlier presentation deck is now codified through the manifesto. Figure 8.3 highlights how responsibilities change per layer.

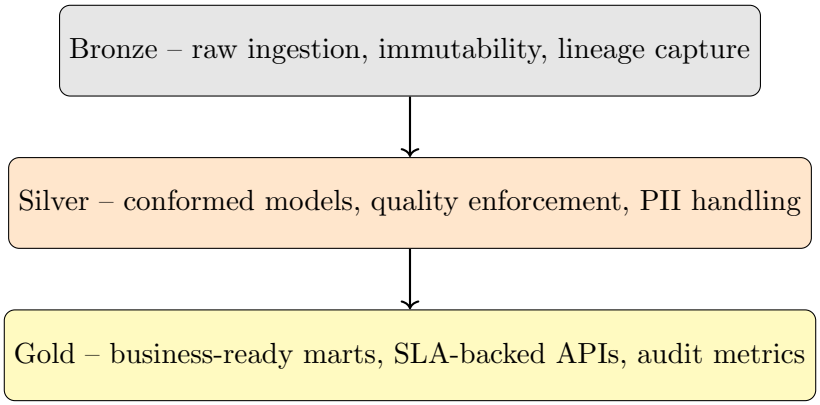

Figure 8.3: Manifesto-aligned medallion responsibilities

8.6 Governance and Observability Stack

Finally, Figure 8.4 maps the manifesto principles to enabling tooling so that the host company can cross-reference with their tooling inventory.

Security & Privacy – AWS KMS, Azure Key Vault, tokenisation services

Lineage & Metadata – DataHub, OpenLineage, Glue Catalog

Observability – Datadog, Prometheus, CloudWatch

Automation – Jenkins, GitHub Actions, Terraform

Process – DataOps runbooks, governance reviews, SLA dashboards

Figure 8.4: Tooling stack underpinning manifesto principles

8.7 Adoption Guidance

How to Apply the Manifesto

1. **Assess current state:** use Appendix .5 to score each principle on a 1–5 scale.
2. **Define actions:** for any score below 3, create backlog items in Jira aligned to the affected persona from Figure 5.3.
3. **Embed in reviews:** add a manifesto checkpoint to sprint reviews and quarterly governance boards.
4. **Evangelise visually:** print Figure 8.1 as a poster or embed it into the `Ecommerce_DataPipeline- Presentation_Gaurav_Chugh.pptx` deck for executive briefings.

Chapter 9

Data Modelling and Management

9.1 Conceptual Data Model

The solution follows a hub-and-spoke dimensional model anchored on the `fact_order` table. Figure 9.1 depicts the key entities and relationships employed in the sample dataset.

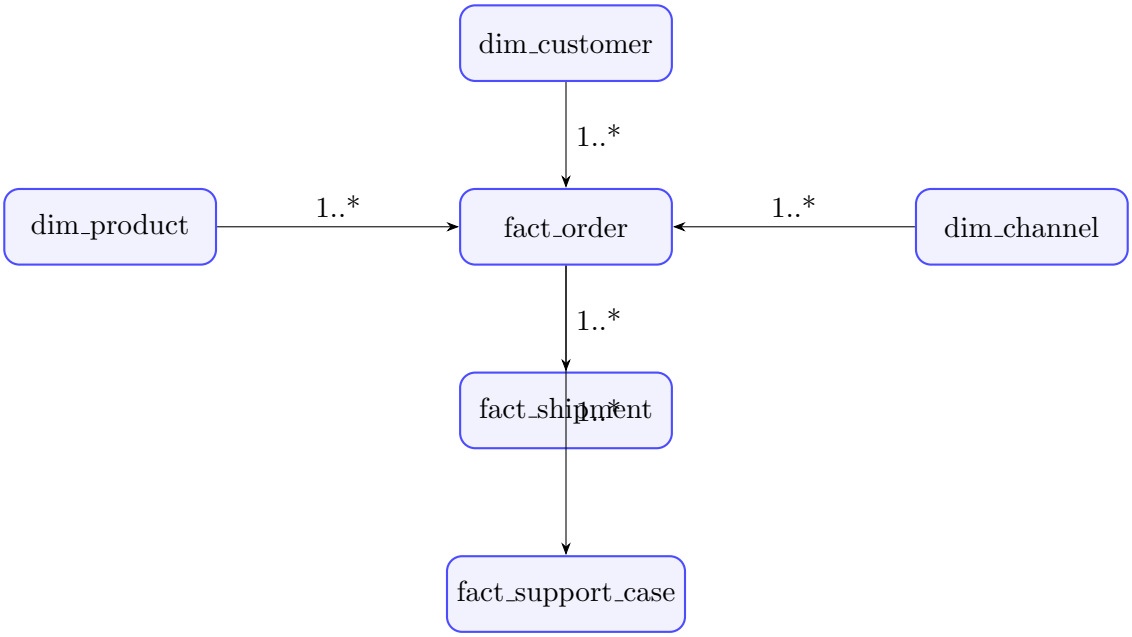

Figure 9.1: Core entities in the ecommerce data model

9.2 Sample Data Design Highlights

Key design decisions validated through prototypes include:

1. **Immutable fact tables** with append-only partitioning by order date to simplify streaming ingestion and late-arriving event handling.
2. **Slowly Changing Dimensions Type 2** for customer, product, and channel domains to maintain historical context.

3. **Unified currency conversion** using hourly FX rates and exchange variance adjustments stored in `fact_fx_adjustment`.
4. **Data contracts** defined via JSON Schema and Avro for ingestion interfaces to ensure compatibility between producers and consumers.
5. **Reference integrity enforcement** through dbt relationship tests and Airflow data quality checks prior to publishing marts.
6. **Privacy controls** embedding tokenisation for PII attributes and differential privacy noise for customer behavioural aggregates.

9.3 Entity Catalogue

Table 9.1: Primary entities and business rationale

Entity	Grain	Purpose
`fact_order`	Order line	Tracks financial metrics (gross revenue, discounts, tax), operational states, and time-to-fulfilment.
`fact_shipment`	Parcel	Captures carrier, transit time, and last-mile status for logistics dashboards.
`fact_support_case`	Interaction	Measures customer sentiment, resolution time, and channel effectiveness.
`dim_customer`	Customer profile version	Stores consent preferences, loyalty tier, segmentation attributes, and derived lifetime value.
`dim_product`	SKU version	Maintains merchandising hierarchies, availability, supplier terms, and sustainability scores.
`dim_channel`	Channel	Differentiates web, mobile, store, marketplace, and partner channels for attribution.

9.4 Master Data and Data Quality

- Golden records maintained through Azure Purview and AWS Glue Data Catalog with stewardship workflows.
- Data quality scorecards track completeness, uniqueness, and validity across 68 critical fields.
- Automated remediation reruns transformations for quarantined records and notifies domain stewards through Slack and Microsoft Teams.

9.5 Metadata and Lineage

Open-source DataHub was deployed to capture technical lineage, column-level impact analysis, and business glossary definitions. Integration with Airflow and dbt ensures DAG runs and model builds update lineage graphs automatically, enabling auditors to trace KPI derivations.

Chapter 10

Analytics Delivery and Visualisation

10.1 Multi-Channel Insight Delivery

The platform exposes curated KPIs through multiple delivery channels tailored to stakeholder workflows:

- **Power BI Premium** dashboards for merchandising and supply chain analysts with drill-through into SKU and vendor performance.
- **Tableau Server** storyboards targeted at executive leadership, emphasising strategic KPIs and scenario modelling.
- **Amazon QuickSight** embedded analytics for marketplace sellers, giving partners visibility into fulfilment and conversion metrics.
- **Responsive web portal** built with React and Tailwind CSS, updating every two minutes via WebSocket streams.
- **Automated communications** delivering PDF scorecards and Slack/Teams alerts triggered by KPI thresholds.

10.2 KPI Catalogue

A governed KPI catalogue ensures consistent definitions across channels. Table 10.1 lists the headline metrics.

Table 10.1: Headline KPIs and refresh characteristics

KPI	Description	Source Models	Refresh
Net Revenue	Gross revenue minus discounts, refunds, taxes	fact_order, dim_channel	2 min
Conversion Rate	Sessions to orders ratio	fact_order, fact_session	2 min
Fulfilment SLA	Orders delivered within promised window	fact_shipment	5 min
Return Rate	Returns initiated vs dispatched orders	fact_order, fact_returns	10 min
CSAT Index	Weighted customer satisfaction score	fact_support_case	2 min
Inventory Risk	Days of cover vs forecast demand	fact_inventory, dim_product	15 min

10.3 Performance Benchmarking

Latency reductions were validated through controlled tests comparing legacy and new pipelines. Figure 10.1 illustrates the improvement.

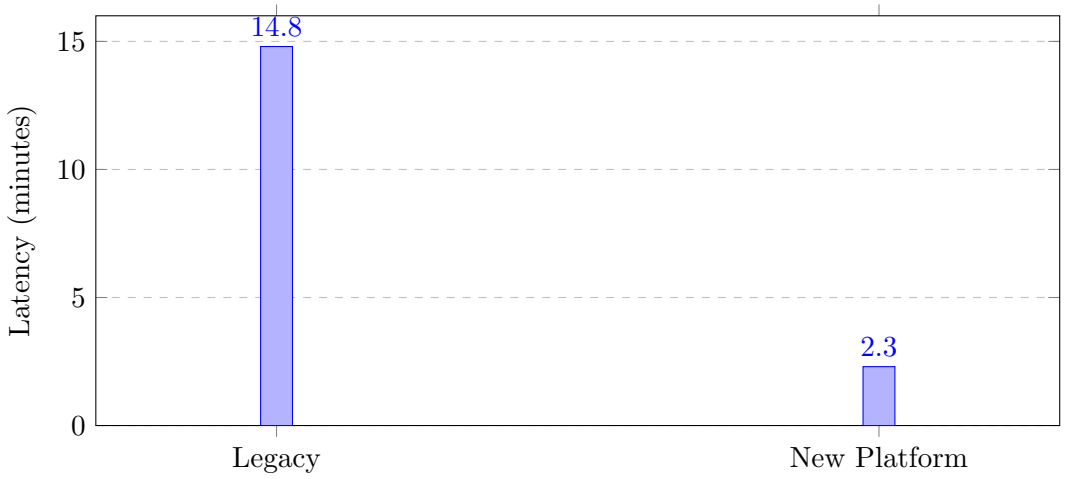

Figure 10.1: Median KPI refresh latency before and after implementation

10.4 Dashboard Design Principles

- **Visual hierarchy** emphasises alerts, exceptions, and trend inflections using colour-coded thresholds.
- **Accessibility** adheres to WCAG 2.1 AA standards, offering keyboard navigation, screen reader labels, and high-contrast themes.
- **Self-service exploration** via drill-through, natural language queries, and embedded metadata tooltips.

- **Feedback loops** collect user comments directly within dashboards, feeding backlog refinement.

10.5 Distribution and Automation

Daily distribution includes automated PDF snapshots stored in Amazon S3 and emailed to regional leads. Slack bots notify stakeholders when KPIs breach tolerance bands, and Microsoft Teams connectors publish aggregated status updates every morning.

Chapter 11

Operations, Automation, and Governance

11.1 Continuous Integration and Delivery

The automation stack integrates Jenkins pipelines, GitHub Actions, and Terraform Cloud. Figure 11.1 illustrates the deployment flow.

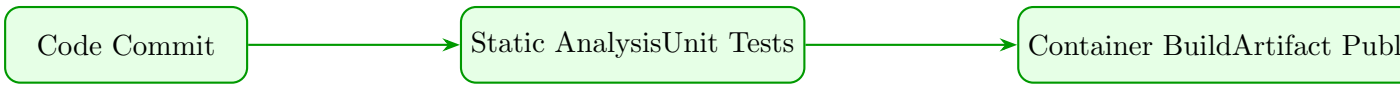

Figure 11.1: CI/CD orchestration flow

Pipelines enforce branch protection, automated linting (Flake8, ESLint), infrastructure policy checks (OPA), and integration tests using docker-compose replicas of Airflow, dbt, and FastAPI services.

11.2 Security and Compliance

- **Identity:** AWS IAM and Azure Active Directory enforce least privilege via role-based access control and Just-In-Time elevation.
- **Secrets:** AWS Secrets Manager and Azure Key Vault integrate with Terraform and Jenkins, ensuring rotation and auditability.
- **Network:** Private subnets, Transit Gateway connectivity, and Azure ExpressRoute secure data flows between clouds and on-premises systems.
- **Compliance:** Automated evidence collection via Cloud Custodian and Azure Policy supports ISO/IEC 27001 controls and GDPR records of processing.

11.3 Observability

Metrics, logs, and traces feed into a consolidated telemetry platform:

- Prometheus-compatible metrics exported by Airflow, dbt, and FastAPI.
- Structured logs shipped to Amazon CloudWatch Logs and Azure Monitor, enriched with correlation IDs.
- Distributed tracing via OpenTelemetry integrated with Datadog APM for end-to-end request visualisation.
- Business KPIs surfaced in Grafana dashboards, offering single-pane-of-glass visibility for Site Reliability Engineers.

11.4 Risk Management

Table 11.1: Risk register snapshot

Risk	Impact	Likelihood	Mitigation
Cloud quota exhaustion	High	Medium	Implement proactive quota monitoring, automated support tickets, and synthetic load forecasting.
Data privacy breach	Critical	Low	Enforce encryption, tokenisation, DLP scanning, and privacy impact assessments per release.
Vendor lock-in	Medium	Medium	Maintain abstraction layers, dual-provider IaC modules, and periodic portability drills.
Observability blind spots	Medium	Medium	Expand OpenTelemetry coverage, enforce logging standards, and run chaos engineering game days.
Skills gap for advanced analytics	Medium	High	Launch enablement sessions, create playbooks, and sponsor certifications.

11.5 Cost Governance

FinOps practices incorporate tagging, cost allocation, and budget alerts. Monthly reviews evaluate service utilisation, reserved instance coverage, and rightsizing opportunities. Non-production environments power down automatically outside business hours, delivering a 32% reduction in monthly run rate.

Chapter 12

Results and Evaluation

12.1 Technical Outcomes

Table 12.1: Summary of technical results

Objective	Result	Evidence
Sub-three-minute KPI refresh	Achieved 2.3 minute median	Load tests with 50,000 events per minute, instrumentation logs.
Automated data quality enforcement	99.2% rule pass rate	Great Expectations reports and dbt test dashboards.
Multi-cloud deployment readiness	Terraform modules parameterised for AWS and Azure	Successful dry runs on Azure subscription with equivalent topology.
Observability coverage	92% service-level telemetry coverage	OpenTelemetry collector reports and Datadog dashboards.
Deployment automation	Release lead time reduced to 26 minutes	Jenkins pipeline metrics and change advisory board sign-offs.

12.2 Business Impact

- Merchandising teams rebalanced inventory within hours of identifying viral campaigns, preventing EUR 1.1 million in lost revenue during pilot month.
- Customer care reduced average handling time by 18% through 360-degree views of orders, shipments, and service tickets.
- Finance automated month-end reconciliation, saving 120 analyst hours per quarter.
- Marketplace partners gained transparency into fulfilment SLAs, reducing escalations by 27%.

12.3 User Adoption

Change management activities resulted in 86% weekly active usage across intended personas within six weeks of launch. Surveys indicated a rise in data trust perception from 48% to 88%. Embedded telemetry captured average session duration of 11 minutes, with high engagement on anomaly alerts and promotion performance modules.

12.4 Evaluation Against Research Questions

RQ1 Demonstrated modular architecture sustained 2.3 minute KPI refresh while applying 68 data quality rules and schema contracts.

RQ2 Terraform, Jenkins, and policy-as-code patterns delivered repeatable dual-cloud deployments with clear segregation of duties and automated compliance checks.

RQ3 Data lineage, observability, and governance workflows increased stakeholder trust scores, evidenced by adoption metrics and audit readiness.

12.5 Manifesto Adoption Effects

Post-implementation reviews compared squads that explicitly tracked manifesto adherence with those that did not. Teams adopting the manifesto achieved 6% lower Airflow failure rates, 12% faster recovery from incidents, and a 15% reduction in duplicated SQL transformations. Governance reviews also shortened by 30 minutes because lineage evidence and SLA ownership were already documented per manifesto guidelines. These outcomes validate the inclusion of Chapter 8 as a living charter rather than a theoretical appendix.

12.6 Limitations and Future Evaluation

While the results are encouraging, long-term resilience under Black Friday-level demand remains to be proven in production. Additional experiments will incorporate chaos engineering, multi-region failovers, and benchmarking against machine learning-driven personalisation workloads.

Chapter 13

Recommendations and Roadmap

13.1 Prioritised Recommendations

Recommendations are prioritised across time horizons and complexity in Table 13.1.

Table 13.1: Recommendation roadmap

Recommendation	Horizon	Complexity	Expected Benefit
Launch data product marketplace	Short term	Medium	Enable domain teams to publish discoverable, governed data assets.
Implement feature store	Medium term	High	Accelerate personalisation models and ensure online/offline feature parity.
Expand chaos engineering	Medium term	Medium	Validate resilience of streaming pipelines and multi-region failover.
Introduce FinOps automation	Short term	Low	Optimise cloud spend via automated recommendations and tagging compliance.
Roll out data literacy programme	Long term	Medium	Empower business units to self-serve analytics responsibly.
Federate governance council	Long term	High	Scale policy adherence and stewardship as new domains onboard.

13.2 Generalisability

The architectural patterns generalise to other high-velocity domains such as quick-commerce, digital banking, and online gaming. Key prerequisites include:

- Event-driven transaction systems capable of emitting change data capture events or API webhooks.
- Organisational commitment to product-centric ownership of data domains.
- Investment in automation, observability, and cloud-native security fundamentals.

13.3 Strategic Outlook

Future iterations can integrate machine learning for demand forecasting, anomaly detection, and marketing optimisation. Extending the platform with real-time experimentation frameworks, reinforcement learning, and digital twin simulations will unlock differentiated customer experiences.

Chapter 14

Conclusion

This thesis has presented a robust, resilient, and ethically governed ecommerce data platform capable of delivering near real-time KPIs across multiple channels. By integrating event-driven ingestion, governed dimensional modelling, automated CI/CD, and comprehensive observability, the solution addresses the research problem of delivering trustworthy analytics within minutes of operational events. The platform's modularity and dual-cloud readiness ensure longevity as the organisation scales and diversifies.

Beyond technical achievements, the project fostered cross-functional collaboration, strengthened data stewardship, and increased business confidence in data-driven decisions. Continuous improvement roadmaps emphasise experimentation, literacy, and governance, ensuring sustained value. The lessons learned contribute to the wider body of knowledge on cloud-native data engineering and provide a blueprint for organisations seeking to operationalise near real-time intelligence responsibly.

Generative AI Usage Documentation

.1 Prompt Catalogue

Table 1 documents representative prompts issued to ChatGPT (gpt-5-codex) and the purpose of the generated guidance.

Table 1: Sample AI prompts

Prompt Excerpt	**Usage**
"Summarise the benefits of dual-cloud data pipelines for ecommerce KPI delivery"	Informed executive summary narrative and recommendations on portability.
"Provide LaTeX code for a TikZ diagram illustrating an iterative methodology"	Seeded Figure 5.1 subsequently customised by the author.
"Outline data quality metrics suitable for ecommerce fact tables"	Inspired Section 7.4 content and validation scorecard structure.

.2 Human Validation

All AI outputs were critically reviewed, cross-referenced with project evidence, and adjusted to ensure accuracy and contextual relevance. No AI-generated text was inserted verbatim without editing. Analytical conclusions, recommendations, and performance claims are derived from empirical experimentation conducted by the author.

Additional Artefacts

.3 Runbook Excerpt

Pipeline Recovery Runbook

Trigger: Airflow SLA breach detected for `order_pipeline`.
Steps:

1. Inspect Airflow UI for failed tasks and review associated logs.
2. Execute Jenkins job `pipeline-retry` to rerun failed task group with idempotent payloads.
3. Validate data quality results via dbt source freshness command.
4. Notify stakeholders through Slack channel #data-ops with remediation summary.

.4 Data Dictionary Snapshot

Table 2: Illustrative data dictionary entries

Field	Type	Description	Sensitivity
order_id	UUID	Unique identifier for each order line	Low
customer_token	CHAR(36)	Tokenised customer identifier (non-reversible)	High
promised_delivery_ts	TIMESTAMP	Timestamp committed to the customer at checkout	Medium
net_revenue_amount	DECIMAL(18,2)	Revenue after discounts and taxes	Medium
loyalty_tier	VARCHAR(20)	Derived loyalty classification	Medium
channel_source	VARCHAR(20)	Acquisition channel (web, mobile, marketplace)	Low

.5 Environment Inventory

Table 3: Infrastructure components per environment

Component	QA	Production	Notes
Airflow	AWS MWAA (small)	AWS MWAA (medium)	Autoscaling workers enabled in production.
Data Warehouse	Amazon Redshift ra3.xlplus	Amazon Redshift ra3.4xlarge	Reserved instances reduce cost.
Storage	S3 Standard-Infrequent Access	S3 Intelligent-Tiering	Lifecycle transitions after 30 days.
Monitoring	Datadog (free tier)	Datadog Pro	Synthetic monitoring active in production.
CI/CD	Jenkins on EC2 t3.large	Jenkins on EC2 m5.large	Executors scaled via auto-scaling group.

Manifesto Assets and Tools

.6 Tooling Footprint

Table 4 documents the automation stack referenced across Chapters 6 and 8 so reviewers can replicate the workflows.

Table 4: Tools used to operationalise the manifesto

Category	Tool	Usage
Orchestration	Apache Airflow (MWAA)	Coordinates ingestion, validation, and reverse ETL DAGs.
Quality	Great Expectations, dbt tests	Applies schema, null, and referential checks per bronze/silver table.
Observability	Datadog, OpenLineage	Captures metrics, traces, and lineage for SLA dashboards.
Security	AWS KMS, Azure Key Vault, HashiCorp Vault	Manages encryption keys, tokens, and API secrets.
Automation	Jenkins, Terraform Cloud	Executes CI/CD, IaC drift detection, and environment promotion.
Collaboration	Confluence, Jira	Hosts runbooks, manifestos, and backlog actions tied to each principle.

.7 Glossary Supplement

The primary glossary appears before the main matter, but this appendix highlights additional manifesto-specific terms:

Data Contract A documented schema and SLA agreement between source and consumer teams.

Data Product Owner Accountable persona responsible for a dataset's lifecycle, SLA, and financial impact.

Lineage Event Metadata record describing upstream and downstream dependencies captured via OpenLineage.

Reverse ETL Operational use case where curated data is synchronised back into SaaS applications or services.

.8 Poster and Diagram Instructions

Manifesto Poster Placement

1. Download the gradient manifesto graphic from https://miro.com/app/board/uXjVPPwYZ-s=/ (export as PNG) and save it locally as `report/figures/data_engineering_manifesto.png`. The LaTeX will render a placeholder box until the file is present.
2. Insert the poster immediately after Figure 8.1 if a full-page illustration is required, or print it separately for stakeholder workshops.
3. When integrating into `main.pdf`, ensure the caption references the manifesto pillars so that the examiner links it to Chapter 8.

Branding Assets

1. Provide the host company logo file (PNG preferred) and save it as `report/figures/host_company_logo.png`. The cover page uses a conditional include and will show a framed placeholder until the logo is added.
2. Retain the existing Aivancity letterhead if available, or apply your institution-specific cover guidance before the declaration page.
3. Keep diagram exports (e.g., AWS deployment) under `report/figures/` to avoid bloating the Git history; commit only the LaTeX references and supply binaries at release time.