Project - High Level Design

on

Autonomous Retail Researcher Agent

Course Name: Agentic AI

Institution Name: *Medicaps University – Datagami Skill Based Course*

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Academic Year: **2025-2026**

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1. Introduction

This document presents the High-Level Design (HLD) for the AI-Powered Retail Intelligence Platform. It describes the overall system architecture, core components, data flows, technology choices, and the key design decisions that underpin the platform.

The platform automates competitive intelligence gathering for retail businesses by scraping product data from Amazon India and Flipkart, persisting it in a cloud database (MongoDB Atlas), and running AI-powered analysis to deliver actionable insights through a Streamlit dashboard.

1.1 Scope of the Document

This document covers the following:

- End-to-end system architecture and its major tiers
- Component design for the scraping engine, AI analysis engine, database layer, and UI dashboard
- Data flow between all internal modules and external services
- API contracts for the key modules and third-party integrations
- Non-functional requirements: performance, security, caching, and session management

The following are explicitly out of scope for this document:

- User authentication and multi-tenant access control (single-user system in the current version)
- Payment processing or direct e-commerce transaction handling
- Detailed class/method-level design (covered in the separate LLD document: docs/LLD.md)

1.2 Intended Audience

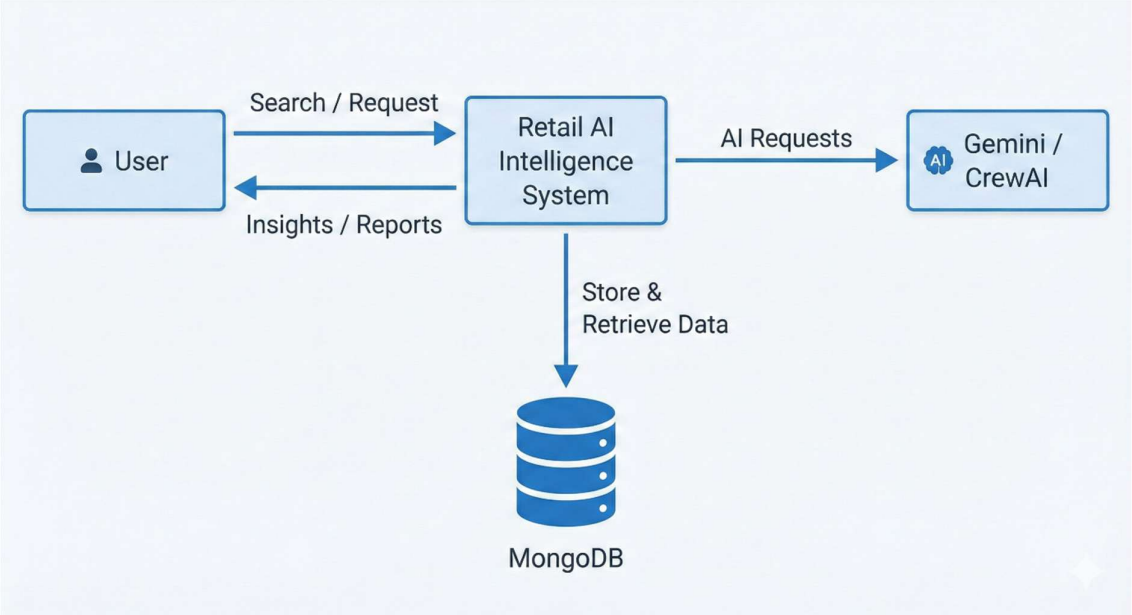
Audience	Purpose
Project Developers / Engineers	Implementation reference and architectural guidance
University Mentors	Assessment and project evaluation
Industry Mentors	Technical review and feedback
Future Contributors	On-boarding and codebase understanding

1.3 System Overview

The Retail AI Intelligence Platform is built in Python 3.11+ and composed of four principal layers:

Layer	Technology	Responsibility
Presentation	Streamlit 1.29+	Interactive dashboard – KPIs, product explorer, price charts, AI insights, report archive
Application	Python 3.11+	Scraping engine (Selenium + BeautifulSoup4), AI engine (Gemini single-agent + CrewAI multi-agent), PDF generator (ReportLab)
Data	MongoDB Atlas	Cloud NoSQL storage – products, price history, and generated reports
External Services	Gemini API, Groq API, SerpAPI	LLM inference for quick and deep market analysis; trend product search

The system is currently a single-user local application intended to be scaled to a multi-user cloud deployment in Phase 3 of the roadmap.

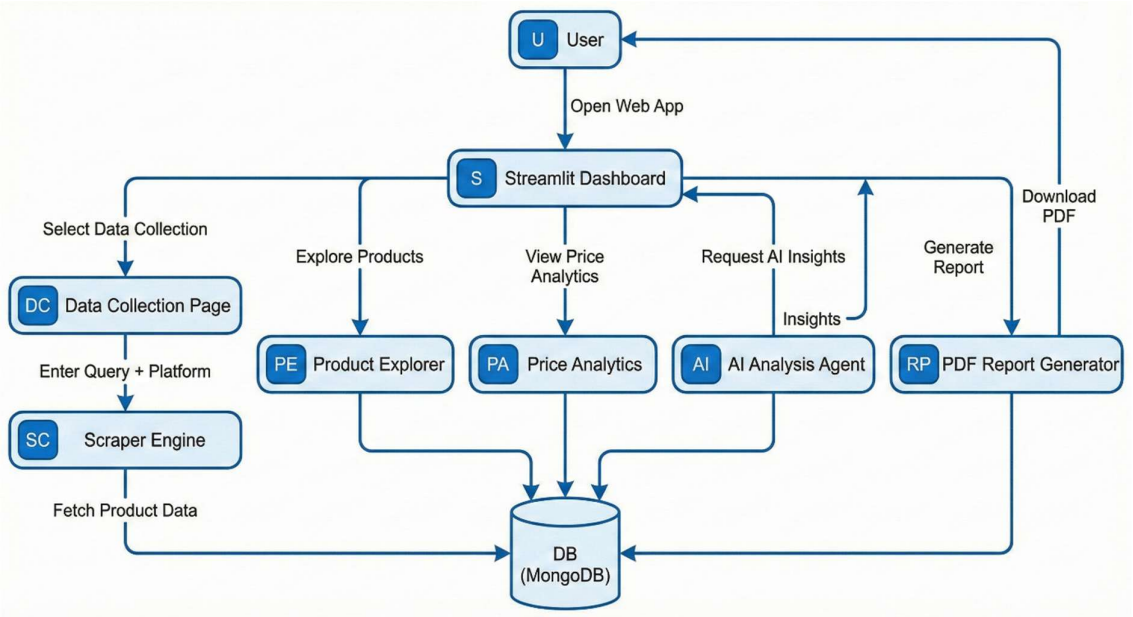


2. System Design

2.1 Application Design

The application follows a layered monolithic architecture for the current release. The three tiers interact as follows:

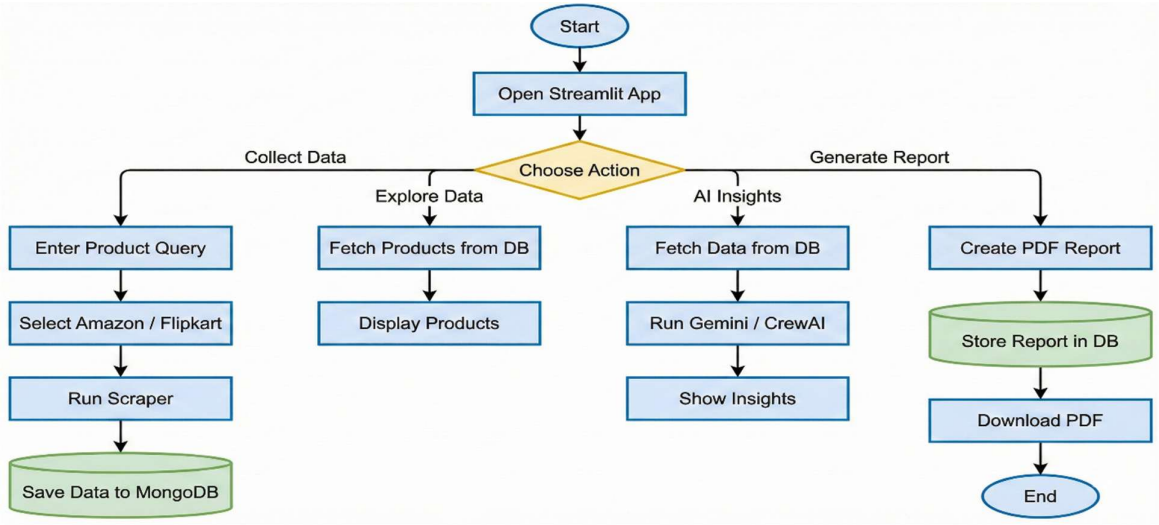
Tier	Components	Interaction
Presentation Tier	Streamlit Dashboard (dashboard.py) – 6 pages: Dashboard Home, Data Collection, Product Explorer, Price Analytics, AI Insights, Reports Archive	Browser calls Streamlit server; Streamlit calls Application tier directly (in-process function calls)
Application Tier	Scrapers (amazon_scraper.py, flipkart_scraper.py), AI Agents (analysis_agent.py, crew_manager.py), PDF Generator (pdf_generator.py), Utilities (helpers.py)	Scrapers write to MongoDB via MongoManager; AI Agents read products from MongoDB; PDF Generator writes report binary back to MongoDB
Data Tier	MongoDB Atlas – three collections: products, price_history, reports	PyMongo driver; connection string loaded from .env via Pydantic-Settings (config/settings.py)



2.2 Process Flow

The end-to-end operational flow for a standard data collection and analysis cycle:

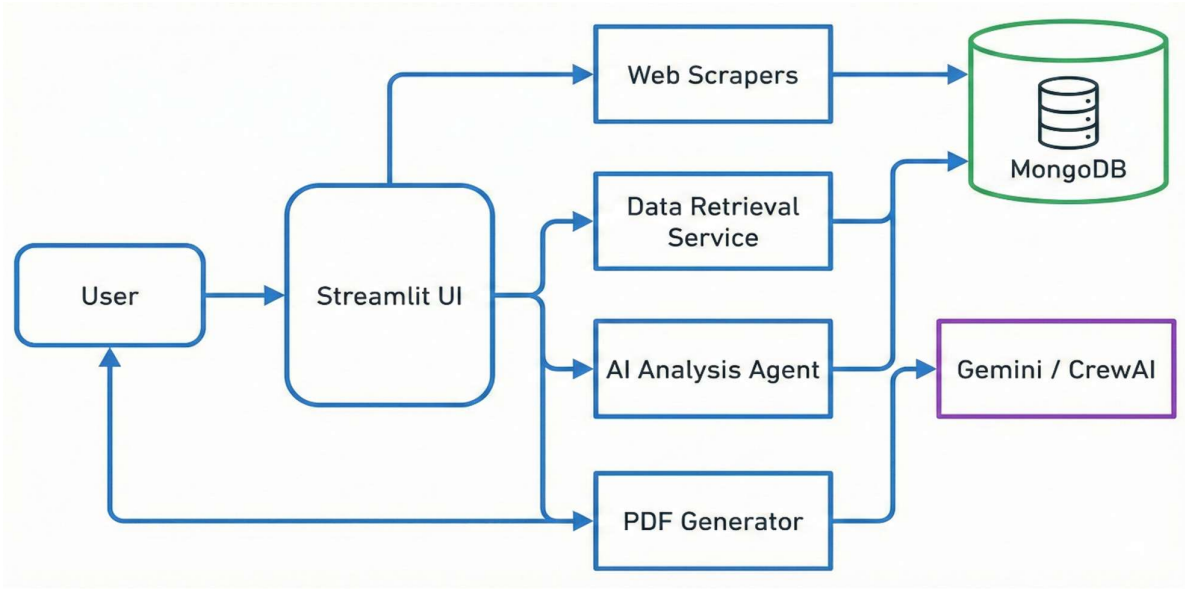
Step	Stage	Actor / Component	Output
1	User Query Entry	User via Streamlit UI	Search term, platform, and category selections
2	Web Scraping	Amazon / Flipkart Scraper (Selenium + BS4)	List of raw product dicts (name, price, rating, reviews, URL, image)
3	Deduplication & Upsert	MongoManager.upsert_product()	Products inserted or updated in products collection
4	Price History Record	MongoManager.add_price_history()	New price entry appended to price_history collection
5	Quick Analysis (optional)	AnalysisAgent – Gemini 2.5 Flash	Markdown report: price range, top-rated, best value (~5–10 s)
6	Deep Analysis (optional)	CrewManager – CrewAI + Groq Llama 3.3	Executive multi-section report via 5 specialised agents (~5–6 min)
7	PDF Generation	PDFGenerator – ReportLab	PDF binary saved to reports collection; download link shown in UI
8	Dashboard Render	Streamlit – dashboard.py	Charts, KPI cards, price tables, and download buttons rendered in browser



2.3 Information Flow

The four primary information flows through the system are described below:

Flow	Source	Destination	Data Carried
Inbound Scraping	Amazon.in / Flipkart.com	MongoDB Atlas – products	name, price, original_price, rating, reviews_count, url, image_url, platform, category, scraped_at
Price Tracking	MongoManager (on each scrape)	MongoDB Atlas – price_history	product_id, price, platform, recorded_at
AI Analysis	MongoDB Atlas – products (JSON export)	Gemini API / Groq API → AI Agents	Product list as JSON (input); Markdown insights string (output)
Report Export	AI Analysis output (Markdown)	MongoDB Atlas – reports + browser download	PDF binary, report_id, type, title, generated_at



2.4 Components Design

The application is organised into five packages inside the src/ directory. Each module has a single, well-defined responsibility:

Package	Module	Responsibility
src/scrapers/	base_scraper.py	Abstract base class: Selenium WebDriver lifecycle, retry logic (max 3x), configurable delay, user-agent rotation, explicit-wait helpers
src/scrapers/	amazon_scraper.py	Amazon India-specific CSS selectors, pagination handling, CAPTCHA detection and retry
src/scrapers/	flipkart_scraper.py	Flipkart-specific DOM selectors, category field mapping, price string normalisation
src/database/	mongo_manager.py	MongoDB Atlas connection pool management, all CRUD operations, upsert logic, price history append, report archive read/write
src/agents/	analysis_agent.py	Single-agent Gemini pipeline: builds structured system prompt with product JSON context, calls Gemini 2.5 Flash, returns Markdown string
src/agents/	crew_manager.py	CrewAI orchestration: defines 5 agents (Data Scout, Pricing Strategist, Risk Assessor, Demand Forecaster, Report Writer), 5 tasks, hierarchical process with Groq LLM
src/utils/	pdf_generator.py	ReportLab PDF construction: page layout, branded header/footer, tables, charts, section formatting
src/utils/	helpers.py	Shared utilities: price string-to-float parser, SHA-256 product_id generator, timestamp helpers, category normalisation
src/ui/	dashboard.py	Streamlit page router: sidebar navigation, per-page render functions, Plotly/Altair chart builders, session-state management
config/	settings.py	Pydantic-Settings model: typed .env loader for API keys, MongoDB URI, scrape_delay, max_retries; validated at application startup

2.5 Key Design Considerations

2.5.1 Scraping Resilience

- Selenium's webdriver-manager automatically downloads and manages the correct ChromeDriver binary.
- A configurable scrape_delay (default: 2 s) and max_retries (default: 3) with exponential back-off reduce the risk of IP-blocking.
- CAPTCHA detection triggers an automatic pause-and-retry cycle before raising a failure to the UI.

2.5.2 AI Agent Architecture

- Quick Analysis uses a single synchronous Gemini 2.5 Flash API call, keeping latency under 10 seconds.
- Deep Analysis uses CrewAI's hierarchical multi-agent process: a manager agent assigns tasks to 5 specialist agents and collates their outputs into a final executive report.
- Groq's Llama 3.3 70B model is used for CrewAI to leverage its low-latency, high-throughput inference API at zero cost.

2.5.3 Product Deduplication

- Each product is assigned a unique product_id by SHA-256-hashing the concatenation of platform name and product URL.
- MongoDB's update_one with upsert=True prevents duplicate records on repeated scrapes of the same product.
- Price history is always appended (never updated) to maintain a full audit trail of price changes over time.

2.5.4 Configuration and Secrets Management

- All credentials (API keys, MongoDB URI) are loaded at startup via Pydantic-Settings from a .env file.
- A .gitignore rule ensures the .env file is never committed to the repository.
- Environment variable names are case-insensitive, simplifying deployment across Windows, macOS, and Linux.

2.6 API Catalogue

External APIs consumed by the platform:

API / Service	Provider	Usage in Platform	Auth Method
Gemini 2.5 Flash	Google AI Studio	Quick single-agent market analysis (AnalysisAgent)	GEMINI_API_KEY (.env)
Llama 3.3 70B	Groq Cloud	Multi-agent deep analysis via CrewAI (CrewManager)	GROQ_API_KEY (.env)
MongoDB Atlas	MongoDB	All database read/write operations via PyMongo driver	MONGODB_URI connection string (.env)
SerpAPI	SerpAPI	Trending product search queries (Phase 2 roadmap feature)	SERPAPI_KEY (.env)

Key internal module interfaces:

Caller	Callee	Interface / Method	Purpose
dashboard.py	amazon_scraper.py	AmazonScraper.scrape_products(query, category)	Trigger Amazon data collection
dashboard.py	flipkart_scraper.py	FlipkartScraper.scrape_products(query, category)	Trigger Flipkart data collection
Scrapers	mongo_manager.py	MongoManager.upsert_product(product_dict)	Persist or update a scraped product
Scrapers	mongo_manager.py	MongoManager.add_price_history(product_id, price)	Record a price observation
dashboard.py	analysis_agent.py	AnalysisAgent.analyze(products_json)	Run quick AI analysis
dashboard.py	crew_manager.py	CrewManager.run_analysis(products_json)	Run deep multi-agent analysis
dashboard.py	pdf_generator.py	PDFGenerator.generate(analysis_text, title)	Build and return PDF binary

3. Data Design

3.1 Data Model

MongoDB Atlas is used as the sole persistent data store. Three collections are defined, each with a clear document schema:

Collection 1: products

Field	Type	Description
_id	ObjectId	Auto-generated MongoDB primary key
product_id	String	SHA-256 hash of platform + URL. Used as the upsert key. Unique index.
name	String	Full product title as scraped
price	Float	Current selling price in INR
original_price	Float	MRP or listed original price, if available
rating	Float	Star rating (0.0 – 5.0)
reviews_count	Integer	Total number of customer reviews
url	String	Direct URL to the product page
image_url	String	Product thumbnail image URL
platform	String	Source marketplace: 'amazon' or 'flipkart'
category	String	Normalised category label (Electronics, Clothing, etc.)
scraped_at	DateTime (UTC)	Timestamp of the most recent scrape (updated on each upsert)
created_at	DateTime (UTC)	Timestamp of the first insertion

Collection 2: price_history

Field	Type	Description
_id	ObjectId	Auto-generated primary key
product_id	String	Foreign reference to products.product_id
price	Float	Price recorded at this point in time
platform	String	Platform at the time of recording

recorded_at	DateTime (UTC)	UTC timestamp of this price observation

Collection 3: reports

Field	Type	Description
_id	ObjectId	Auto-generated primary key
report_id	String	UUID v4 identifier for external reference
title	String	Human-readable report title
type	String	Analysis type: 'quick' or 'deep'
platform	String	Platform analysed
content	String	Raw Markdown output from the LLM agent
pdf_bytes	Binary (BSON)	Serialised ReportLab PDF document
generated_at	DateTime (UTC)	Report creation timestamp

3.2 Data Access Mechanism

All database interactions are encapsulated in MongoManager (src/database/mongo_manager.py). The following access patterns and indexes are used:

Operation	PyMongo Method	Index
Insert / update product	update_one({product_id}, $set, upsert=True)	product_id – unique ascending
Record price observation	insert_one(price_record)	product_id – ascending (for range queries)
List products by platform	find({platform: x}).sort(scraped_at, -1)	platform – ascending
Fetch price history for a product	find({product_id: x}).sort(recorded_at, 1)	product_id + recorded_at – compound
Save generated report	insert_one(report_doc)	report_id – unique ascending
List all reports	find({}).sort(generated_at, -1)	generated_at – descending

The PyMongo driver maintains a connection pool (default maxPoolSize: 5) sufficient for the current single-user workload. The MongoDB URI is read from .env via Pydantic-Settings and never hard-coded.

3.3 Data Retention Policies

- products: records are retained indefinitely. The scraped_at field is refreshed on every upsert cycle.
- price_history: all records are append-only and retained without expiry to support long-term trend analysis.
- reports: retained in full (including PDF binary) until a user manually deletes a report from the Reports Archive page.
- Roadmap (Phase 2): a 180-day TTL index on price_history.recorded_at will be introduced to cap collection growth at scale.

3.4 Data Migration

No migration is required for the initial deployment as the application starts with an empty database. Future migration considerations are:

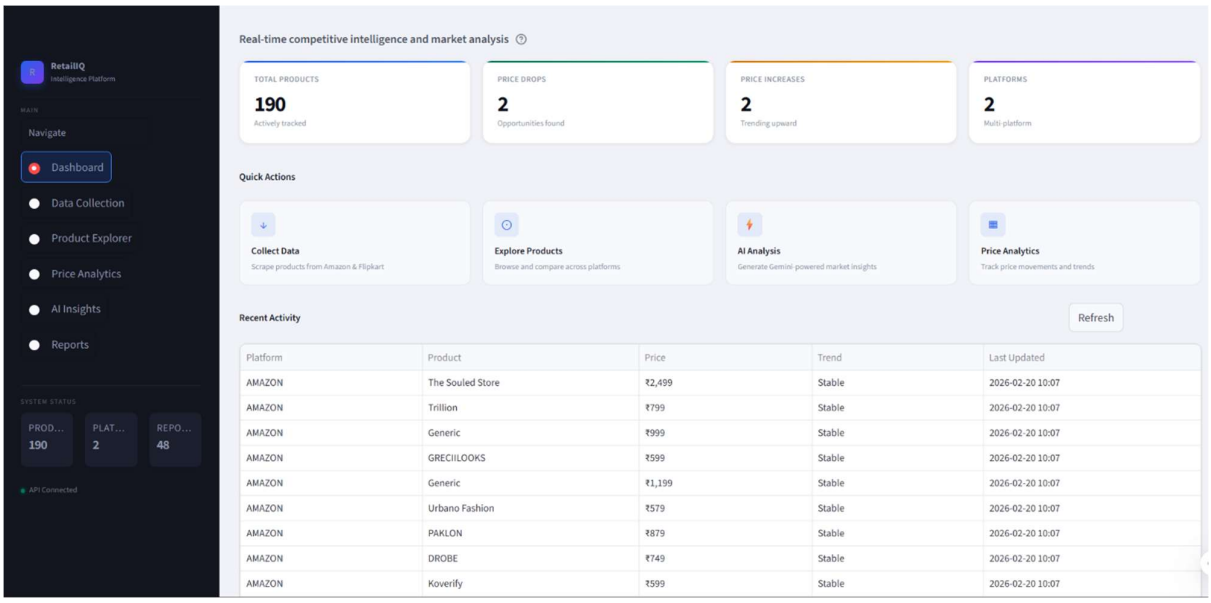
Scenario	Migration Approach
Adding new required fields to the products schema	PyMongo update_many script to back-fill default values for existing documents
Upgrading from MongoDB Atlas M0 to a paid tier	Standard mongodump / mongorestore tooling; no application code changes required
Schema versioning for breaking changes	Add a schema_version integer field to each collection; migration scripts increment the version after transformation

4. Interfaces

4.1 User Interface

The entire user interface is delivered through a Streamlit web application served at http://localhost:8501/. The dashboard has six pages, navigated via a persistent left-hand sidebar:

Page	Description
Dashboard Home	High-level KPI cards (total products, platforms, recent scrapes, price drops). Quick-action buttons to jump to other pages.
Data Collection	Form inputs: search query string, platform dropdown (Amazon / Flipkart), category dropdown. Real-time progress indicator during scraping. Post-scrape summary.
Product Explorer	Filterable and sortable data table of all stored products. Clicking a row opens a detail panel with a price history line chart.
Price Analytics	Aggregate charts: price distribution histogram, top price-drop table, platform comparison bar chart, trend sparklines.
AI Insights	Toggle between Quick Analysis and Deep Analysis. Markdown-rendered output with section headings. Download-as-PDF button.
Reports Archive	Chronological list of previously generated reports with metadata (type, platform, date). Re-download PDF. Delete report.



4.2 External Service Interfaces

Service	Interface Type	Data Format	Error Handling Strategy
Amazon.in	HTTP via Selenium (headless Chrome)	HTML DOM → Python dict	CAPTCHA detected → pause 5 s → retry; max 3 attempts before surfacing error to UI
Flipkart.com	HTTP via Selenium (headless Chrome)	HTML DOM → Python dict	Selector mismatch → log warning → skip product; scrape continues
Google Gemini API	HTTPS REST (google-genai SDK)	JSON request → Markdown string response	API error / quota exceeded → display error message in AI Insights page
Groq API (via CrewAI / litellm)	HTTPS REST	JSON request → JSON response	Timeout set to 120 s; on failure CrewAI surfaces a partial result or error message
MongoDB Atlas	TCP (PyMongo driver)	BSON documents	Connection failure → retry 3× with 2 s back-off; persistent failure shows banner in UI

5. State and Session Management

The platform uses Streamlit's built-in session_state object for in-memory, per-tab state, combined with MongoDB Atlas for all durable persistence:

State Variable	Storage	Scope	Purpose
st.session_state.scraped_products	Streamlit session_state	Per browser tab	Caches the product list returned by the most recent scrape to avoid re-querying the DB on every page re-run
st.session_state.analysis_result	Streamlit session_state	Per browser tab	Holds the last AI analysis Markdown string so the output can be re-rendered without re-calling the LLM API
st.session_state.selected_product_id	Streamlit session_state	Per browser tab	Tracks the product currently selected in the Product Explorer for the detail / price-history panel
st.session_state.active_page	Streamlit session_state	Per browser tab	Maintains the current sidebar page selection across Streamlit re-runs
All product and price data	MongoDB Atlas	Persistent / shared	Durable storage of all scraped products, price history records, and generated reports

There is no server-side user authentication or cross-session state sharing in the current release. Each browser tab is treated as an independent isolated session. Multi-user session management via a FastAPI backend layer is planned for Phase 3.

6. Caching

The following caching strategies are applied across the different layers of the platform:

Layer	Strategy	TTL / Scope	Details
Scraping	No caching (always live)	N/A	Every scrape fetches fresh data from the marketplace to ensure price accuracy. Results are written to MongoDB immediately.
Database reads	Streamlit @st.cache_data	60 seconds	Product list queries and price history queries are cached for 60 s to reduce repeated MongoDB round-trips during dashboard interactions.
AI Analysis output	Streamlit session_state cache	Per session	LLM analysis result is stored in session_state after the first API call. Re-displaying the result does not re-invoke the API.
PDF Reports	MongoDB Binary (persistent)	Indefinite	Generated PDFs are stored as BSON Binary in the reports collection and served directly on download request without regeneration.
Future – Redis (Phase 3)	Shared in-memory cache	Configurable TTL	When migrating to a multi-user cloud deployment, a Redis layer will replace Streamlit session_state caching to support shared state across instances.

7. Non-Functional Requirements

7.1 Security Aspects

Threat / Concern	Mitigation Applied
Credential exposure in source code	All API keys and the MongoDB URI are loaded exclusively from a .env file via Pydantic-Settings. A .gitignore rule prevents .env from being committed to version control.
IP blocking during scraping	Configurable scrape_delay (default: 2 s), user-agent rotation in BaseScraper, and max_retries (3) with back-off reduce the scraping footprint and detection risk.
Insecure report enumeration	Reports are referenced externally by a UUID v4 report_id rather than a sequential integer, making enumeration impractical.
Dependency vulnerabilities	The GitHub Actions CI/CD pipeline runs bandit (SAST) and flake8 (style) checks on every push. Dependency pinning via requirements-lock.txt prevents uncontrolled upgrades.
LLM prompt injection via product data	Product data is JSON-serialised and injected into the system prompt as a structured context block. Free-text user input is not passed directly into prompt templates.

7.2 Performance Aspects

Requirement	Target	Implementation Strategy
Dashboard initial render	< 2 seconds	Streamlit @st.cache_data (TTL: 60 s) on all DB read calls. Charts are rendered lazily on tab selection.
Scrape throughput	~20 products / min per platform	Sequential scraping with 2 s delay. Parallel tab-based scraping is planned for Phase 2 to double throughput.
Quick Analysis (Gemini)	< 10 seconds end-to-end	Gemini 2.5 Flash model selected for speed. Product JSON payload capped at the top 50 records.
Deep Analysis (CrewAI + Groq)	< 6 minutes end-to-end	CrewAI executes tasks in parallel where agent dependencies allow. Groq provides low-latency inference for Llama 3.3 70B.

MongoDB write latency	< 200 ms per upsert	PyMongo write concern: majority. Atlas M0 SSD-backed storage. Connection pool maintained throughout the session.
PDF generation	< 5 seconds	Synchronous ReportLab generation. The binary is persisted in MongoDB so subsequent downloads require no regeneration.

8. References

Reference	Location / URL
Project GitHub Repository	https://github.com/Nikhilgarg0/retail-ai-intelligence
Low-Level Design Document (LLD)	docs/LLD.md (within the repository)
Project Architecture Document	docs/ARCHITECTURE.md (within the repository)
Streamlit Documentation	https://docs.streamlit.io
MongoDB Atlas Documentation	https://www.mongodb.com/docs/atlas/
PyMongo Driver Documentation	https://pymongo.readthedocs.io
Google Gemini API (google-genai)	https://ai.google.dev/gemini-api/docs
CrewAI Framework Documentation	https://docs.crewai.com
Groq Cloud API Reference	https://console.groq.com/docs
Selenium WebDriver – Python	https://selenium-python.readthedocs.io
BeautifulSoup4 Documentation	https://www.crummy.com/software/BeautifulSoup/bs4/doc/
ReportLab PDF Library User Guide	https://www.reportlab.com/docs/reportlab-userguide.pdf
Pydantic-Settings Documentation	https://docs.pydantic.dev/latest/concepts/pydantic_settings/
bandit – Python Security Linter	https://bandit.readthedocs.io

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