

Enabling Successful Al Initiatives with Modern Data Management

Innovative technical Approaches & Case Studies

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Agenda

Modern Data Management for Al

Emerging Best Practices for Architects

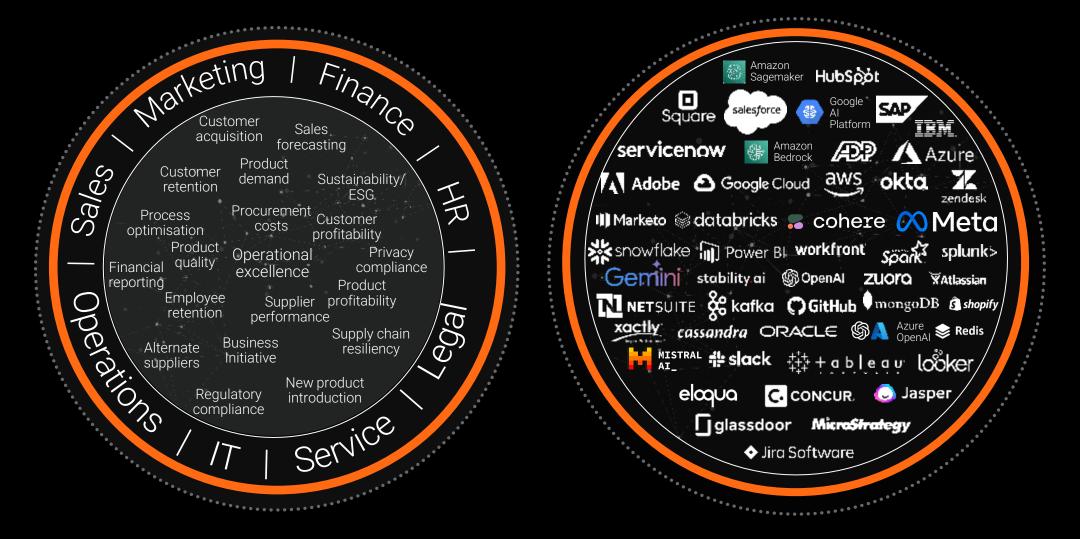
Al for Data Management & Data Democratisation



Modern Data Management for Al







"By 2026, more than 80% of enterprises will have used GenAl APIs/models and/or deployed GenAl-enabled applications in production environments, up from less than 5% in 2023."

Source: Gartner® Press Release, "Gartner Says More Than 80% of Enterprises Will Have Used Generative Al APIs or Deployed Generative Al-Enabled Applications by 2026 "October 11, 2023. GARTNER® is a registered trademark and service mark of Gartner, Inc. and/or its affiliates in the U.S. and internationally and is used herein with permission. All rights reserved. https://www.gartner.com/en/newsroom/press-releases/2023-10-11-gartner-says-more-than-80-percent-of-enterprises-will-have-used-generative-ai-apis-or-deployed-generative-ai-enabled-applications-by-2026

Data Management & Al

of organizations using AI will invest more in Al overall because of advances in Generative Al

said more than 5 percent of their digital budgets will go to Al use cases going forward

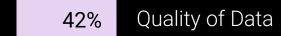
40% 63% 79%

had some exposure to gen AI at work or outside of work, and 22 percent routinely use it in their own work

say that data management is a major obstacle in scaling AI use cases

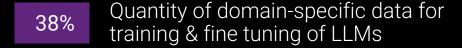
Is your data ready to empower your teams and deliver trusted data for !?

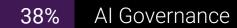
Top Generative AI Challenge

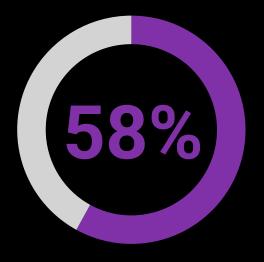








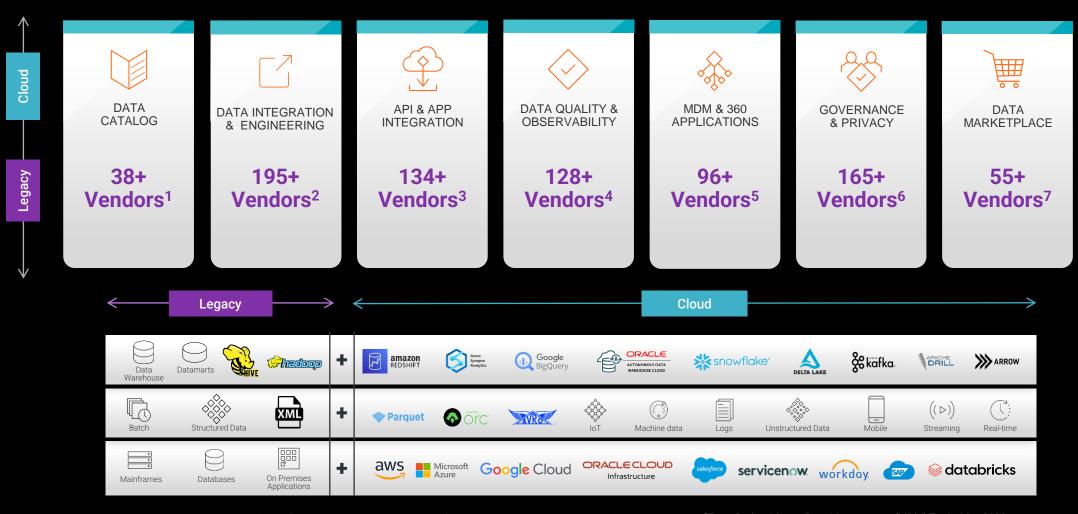




58% of those who predict data management investment will need five or more data management tools to support their priorities

Source: CDO Insights 2024: Charting a Course to Al Readiness (Informatica)





¹Trust Radius, Data Catalog Software, May 2023 ²Trust Radius, Data Integration Tools Software, May 2023 ³Trust Radius, API Management Tools, May 2023 ⁴Trust Radius, Data Quality Software, May 2023 ⁵Trust Radius Master Data Management (MDM) Tools, May 2023 ⁶Trust Radius, Data Governance Software, May 2023 ⁷Trust Radius, Data Collaboration Tools, May 2023





Example: Data Quality and Reputation

Al is at risk of bias and poor-quality outcomes unless the data is of high quality











MS Chatbot Spew Racist Tweets²

Used uncleansed X (Twitter) interactions for training ML models

Within 16 hrs, 95,000 tweets posted, and rapidly turned overtly racist, misogynist, and anti-Semitic

Bad Al → Attorney Sanctions²

GenAl used to support a new case, at least 6 cases did not exist

Zillow Home Values Corrupted²

Overpaid homes resulted in a \$304M inventory writedown 03 2021

Data & Al bias

Amazon's Al recruiting tool was found to be biased against women, as it systematically downgraded resumes that included the word "women's," such as in "women's chess club captain."

DPD caused chatbot to swear at customer³

Al used in online chat to answer queries, asked to ruin business reputation

NOTE: [1] "Car Buyer Hilariously Tricks Chevy Al Bot Into Selling A Tahoe For \$1, 'No Takesies Backsies'." (2023), <u>HotHardware.com</u> NOTE: [2] "Famous Analytics and Al Disasters." (2023), <u>CIO.com</u>

NOTE: [3] "DPD error caused chatbot to sweat at customer." (2023), <u>BBC.com</u>



Example: Al Laws in a State of Flux - Overview of the EU Al Act



First EU regulatory framework for Al proposed by European Commission



Risk Based Classification for all AI/ML Algorithms in EU Organisations



Priority that AI systems used in the EU are safe, transparent, traceable, non-discriminatory and environmentally friendly

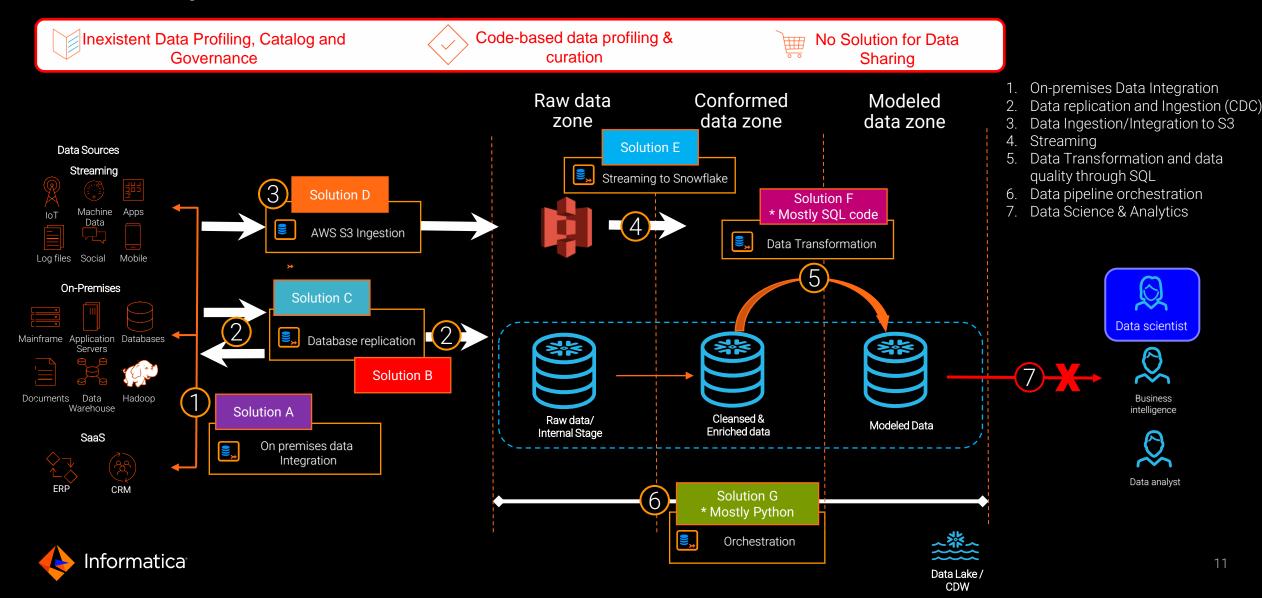
Businesses must stay abreast of relevant laws and regulations, such as intellectual property rights and data protection, to ensure compliance and mitigate legal risks.



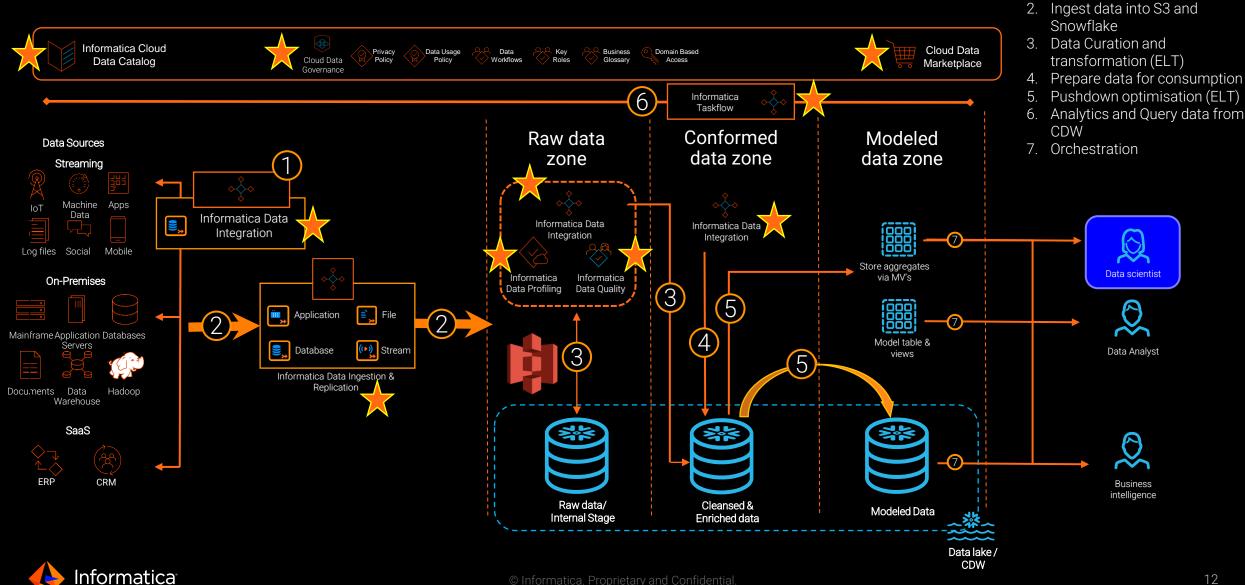
Source – European Parliament News

Example: Data Integration at Large Retailer in Australia

7 solutions just to move data around



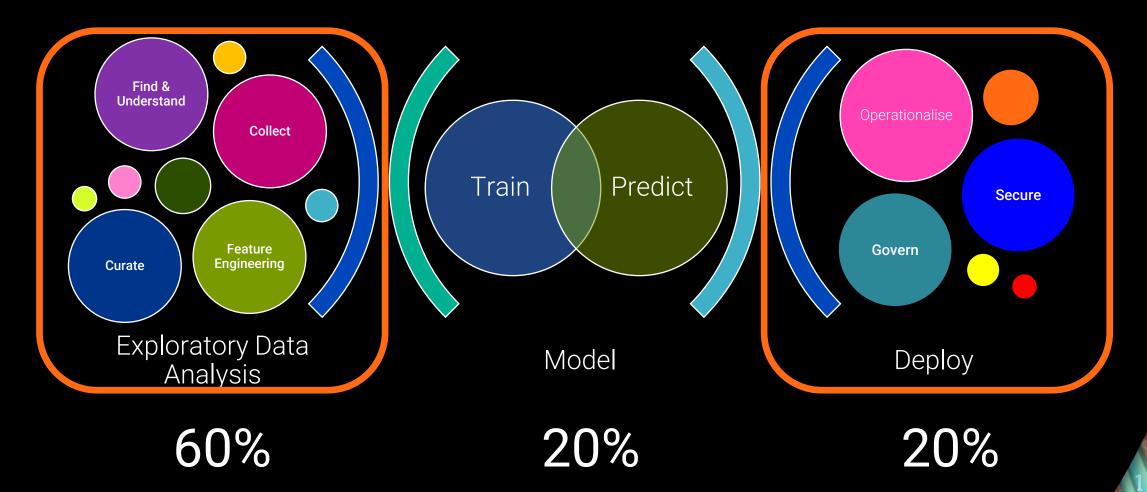
Modern Data Architecture



On-premises integration

The Data Science Workflow

Streamlined Data Management is the Data Science Supercharger

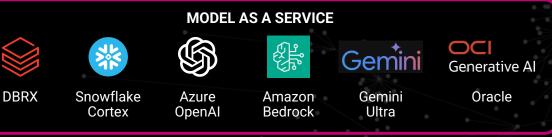




Making Sense of the Generative AI Landscape

Key building blocks and options cloud ecosystems provide





Model-as-a-Service

- There are hundreds and hundreds of open source and commercial, LLM and SLM models available today
- Model-as-a-service provide hosting of models and model management and execution

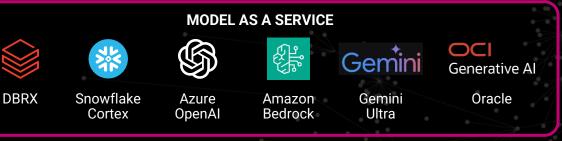




Making Sense of the Generative AI Landscape

Key ecosystem components





Front End/Application Layer

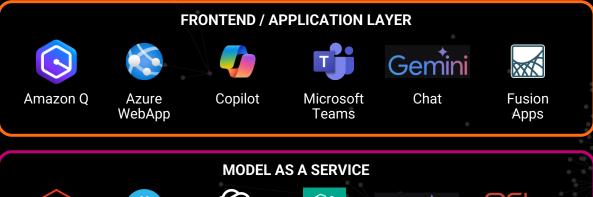
- Frameworks for building Generative Al applications
- End user collaboration end points that expose Generative AI capabilities to their users (Microsoft Teams, Microsoft Co-pilots, Amazon Q, etc...)





Making Sense of the Generative AI Landscape

Key ecosystem components





DBRX



Snowflake

Cortex









Amazon Bedrock



Gemini Ultra



Oracle

VECTOR DATABASE



Cosmos

DB



Postares

SQL





Pinecone









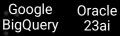


Snowflake

Vector





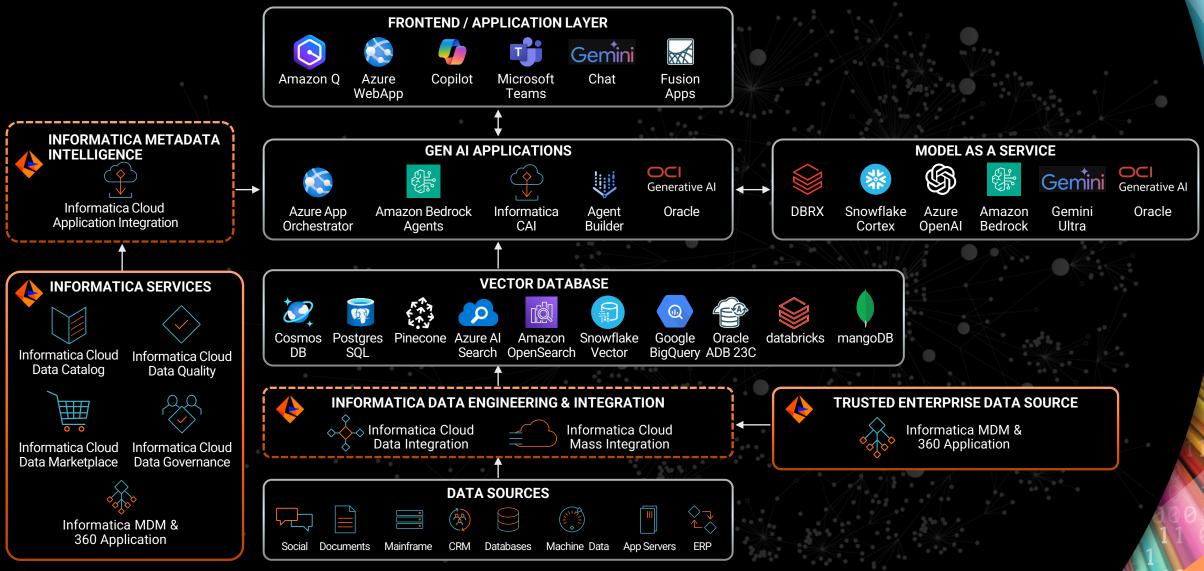


Vector Databases/Vectorization

- Key for RAG use cases to embed other data and services into Generative Al conversational applications
- Stores vectorized form of data to enable vector search to retrieve relevant data as context to inference queries
- Some ecosystems have one or more Vector Databases, others are offering new Vector column types in their database/data lake services



Enabling Enterprise Generative Al Applications





Bringing Enterprise Data to Generative Al

Emerging Best Practices for Architects



Modern Data Architecture & Al Trends in 2024



- Multi-cloud & Hybrid Data
 Management Platforms
- Data Products
- RAG & Al Agents
- Al Governance



- Modern Data Stack
- Data Mesh





State of Enterprise Data for Gen Al

Grounding Gen AI in Enterprise Data is important

Internet Data

- Majority of data that LLMs are trained on is publicly available, internet data
- Unstructured and Semi-Structured
- Optimised for Search and Retrieval (SEO)
- Accessible to anybody with an internet connection

Enterprise Data

- Estimated 90% of the world's data is private data, owned by organisations
- Enterprises are more experienced with working on structured data
- Not tagged for retrieval
- Subject to role-based access control

Simplified RAG Pipelines

Unstructured **Structured Sources Preprocess Vectorise Semantic Store** Corpus • APIs, ERP, CRM, • Extract: Includes metadata, • Chunk: Optional step to • Vector DB: Pinecone, Qdrant, • Formats: DOCX, PDF, PPT, Email, MDM, DWH, layouts, content convert long documents to Flastic manageable chunks HTML Lakehouse, Graph • Cleanse: Remove confidential • RETRO: Key Value Stores like Databases Sources: Sharepoint, data, filter spam/ads/irrelevant • Embed: Convert text to Mongo File Servers, Data text, duplicate content vectors, using embedding Lakes, Websites, models • Transform: Classify, Original Text **Email Servers** to JSON **Unstructured Data Extract** Chunk Cleanse **Generate Q&A** Source Generate Target Connectors **Training Set** Connectors **Transform Structured Data Vector Database/ Enterprise Data Sources Prepare Data Embeddings RETRO Key-Value Pairs**



Large Insurance organisation leverages RAG and Informatica MDM to provide contextual responses to customers using their Al Chatbot

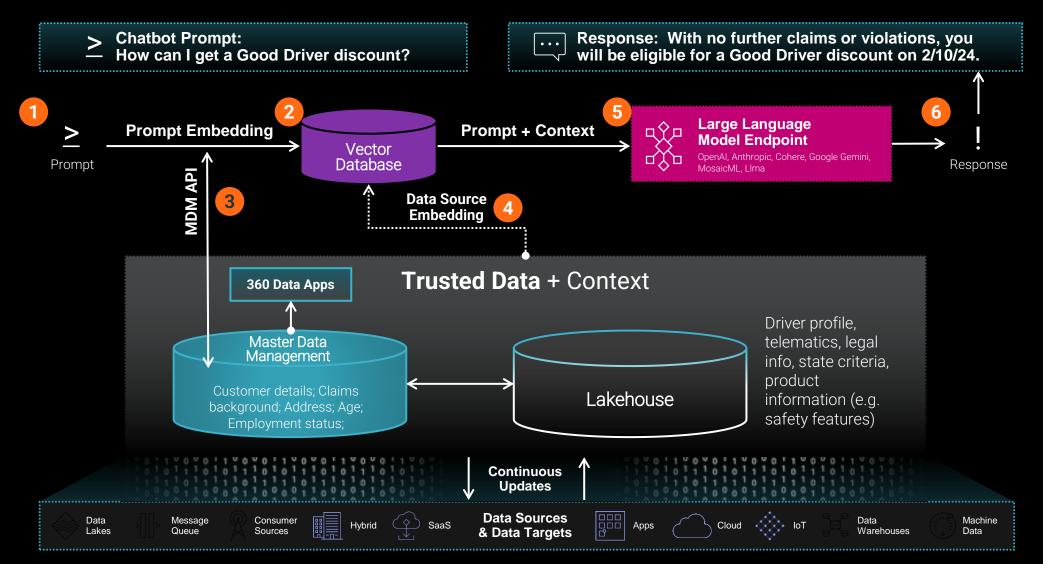
Example: User Query with No Context



- Generic response
- No context based on user
- Response is helpful, but not tailored or contextual

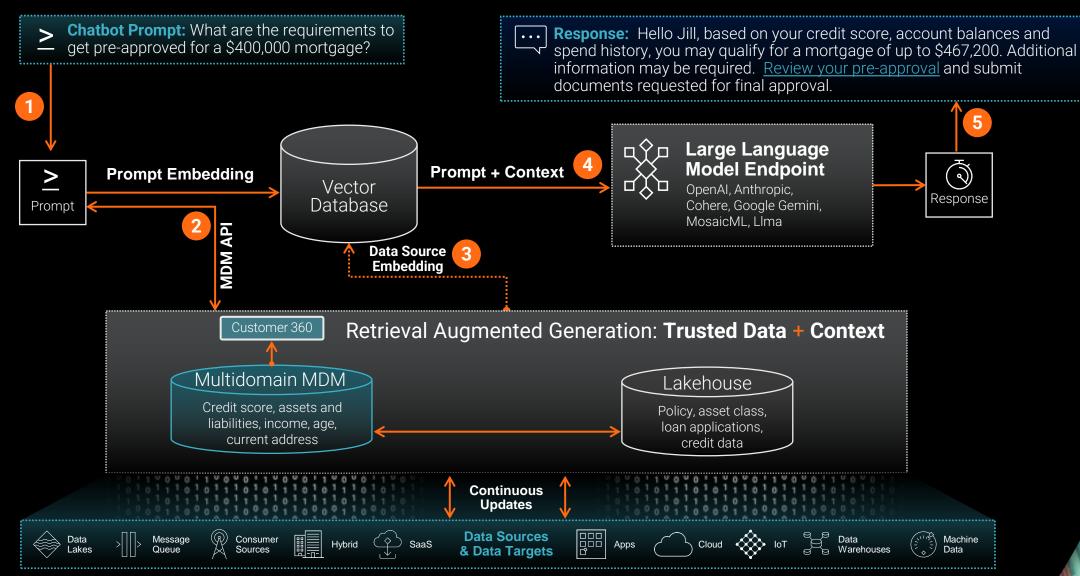


Modern Data Architecture and RAG for Trusted Data & Context



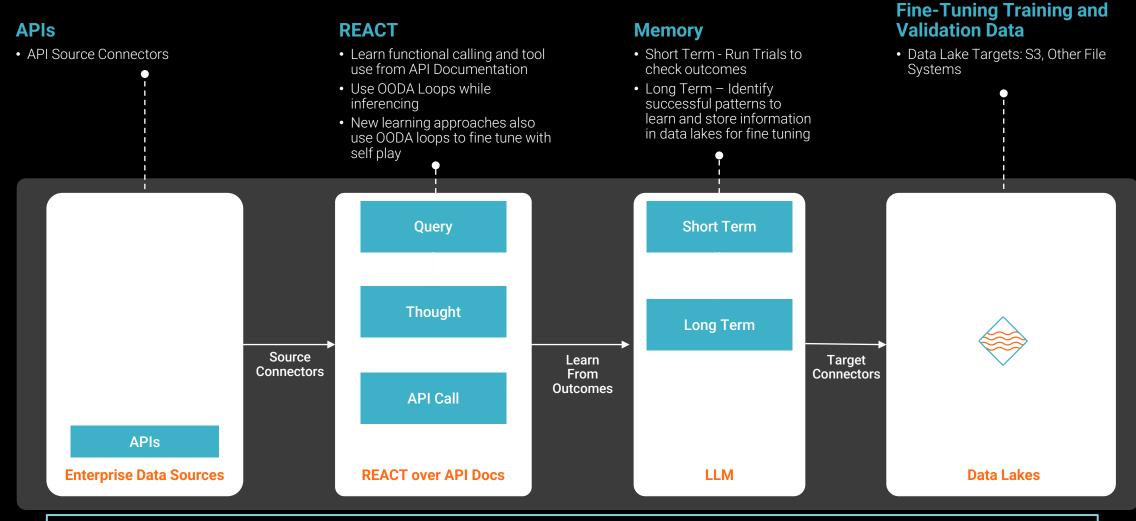


Grounding AI with Trusted Data



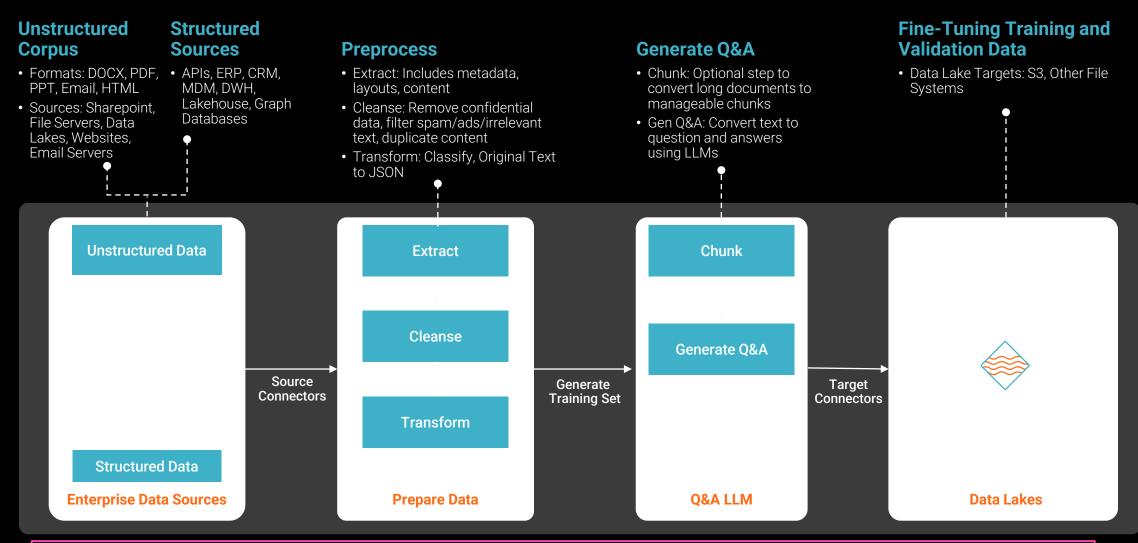


Simplified Al Agent Calling



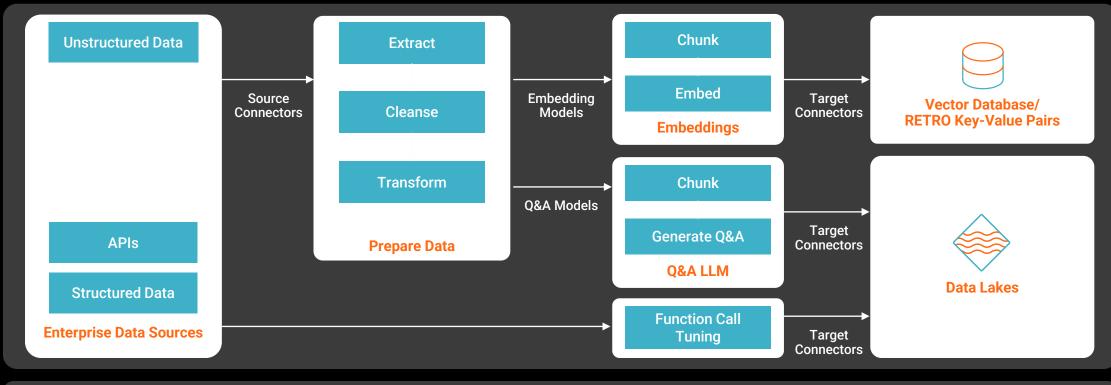
- Al system queries or "calls" external services or APIs, such as web search engines, knowledge bases, or specialised APIs, to retrieve additional information or perform specific tasks. This information are then incorporated into the AI system's response or decision-making process.
- Global Bank in APJ used Informatica's iPaaS to orchestrate AI agent calling and Google BERT models to build FinServ business processes
- A virtual assistant like Siri or Alexa might use an AI agent calling to retrieve weather information from a weather API, look up movie showtimes from a cinema database, or perform calculations using a math API.

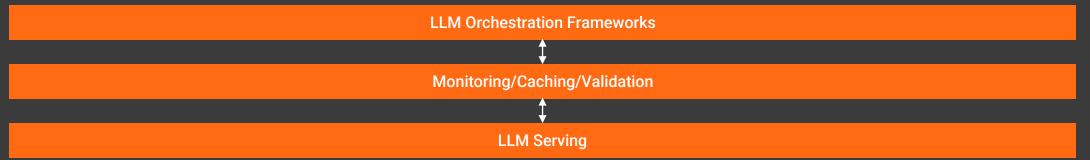
Simplified Fine-Tuning Pipelines



- 1. Start with a pre-trained model that has already learned a lot of general knowledge from a large dataset during its initial training.
- 2. Prepare a smaller, task-specific dataset related to the particular problem you want the model to solve (e.g., customer service dialogues if you want a chatbot, or medical images if you want a disease diagnosis model).
- 3. Load the pre-trained model and continue training it on the task-specific dataset, making adjustments to its knowledge and weights to better fit the new data.

Simplified Enterprise Architecture for Gen Al







How Al/GenAl Works



- Trusted, Holistic, & Governed Data
- Collection & Preparation

- Al Models
- Augment, Build or Train

- LLM Operations
- Plan, Manage, & Execute

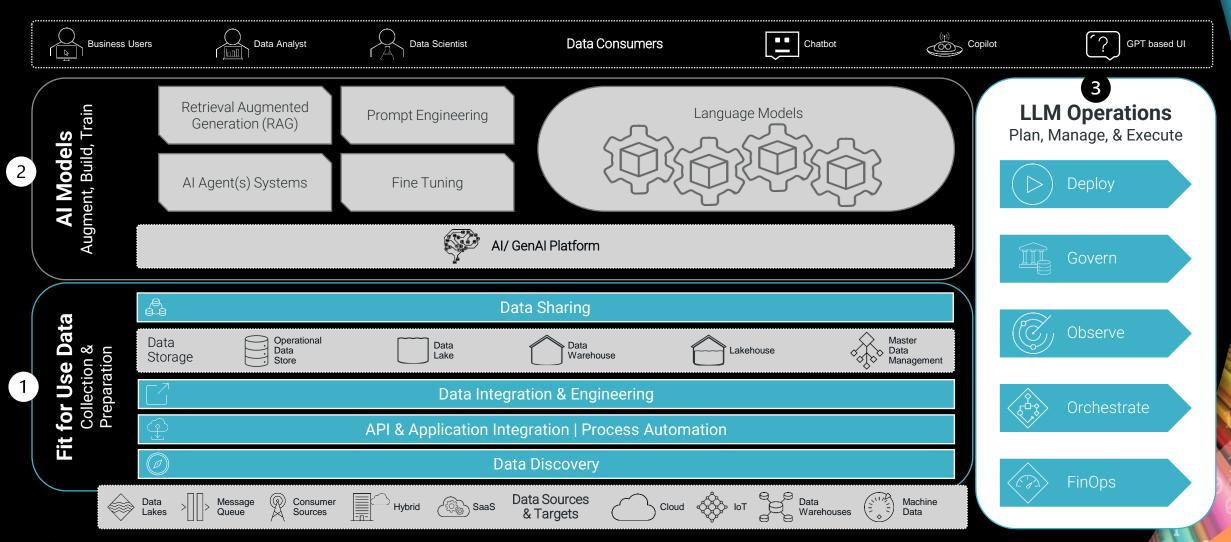
Fit for Use Data

Intelligence

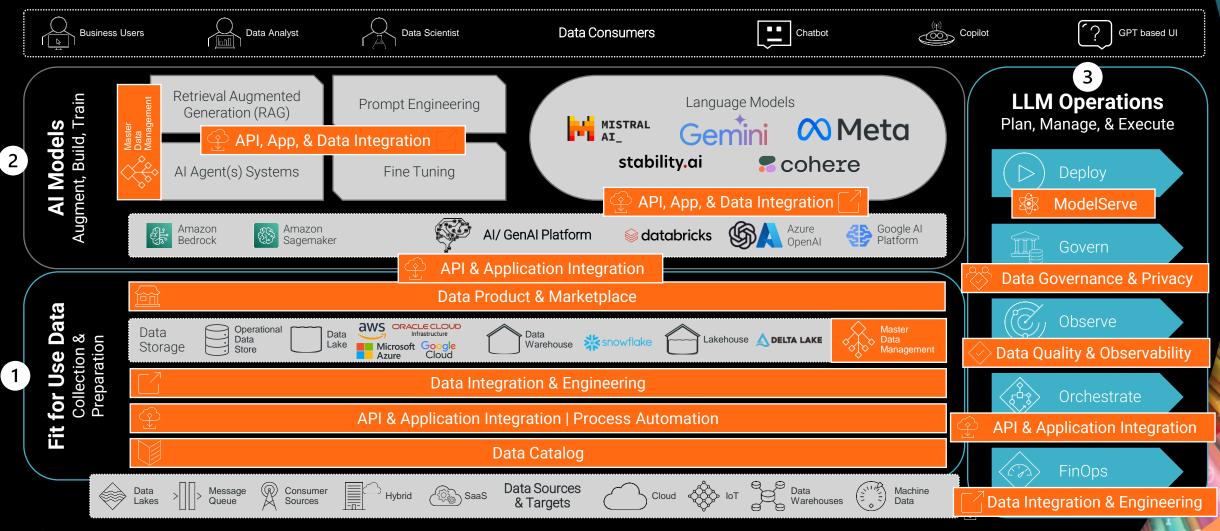
Value



Al Reference Architecture



Data Management for A





)ATA MANAGEMENT & AI STRATFGY "With Informatica, we can now promote data-driven journeys across NRMA"

Single data platform strategy to consolidate all data on Google Cloud



Driving productivity with low-code modern data management



Deliver timely access to data, automatically

VAI UF

Tenfold boost in productivity with automation; 60% Reduced Data Ingestion Time; 98% Less Time For Campaign Delivery; Selfservice functions for democratised data on a modern, single data platform for connected, trusted insights





Al for Data Management & Data Democratisation



Organisations Require "Fit for Business Use" Data

Key Business Imperatives







COMPLY WITH REGULATIONS



INCREASE BUSINESS MANAGEMENT AGILITY



Your Investments









Success Requires "Fit for Business Use" Data, and Intelligence & Automation are key enablers

TRANSPARENT

End to end visibility into the lineage of your data from creation to consumption

ACCESSIBLE

Access to data and applications that run your business

CLEAN

Clean and trustworthy data for business use

VALID

Valid and authoritative sources of the truth across systems

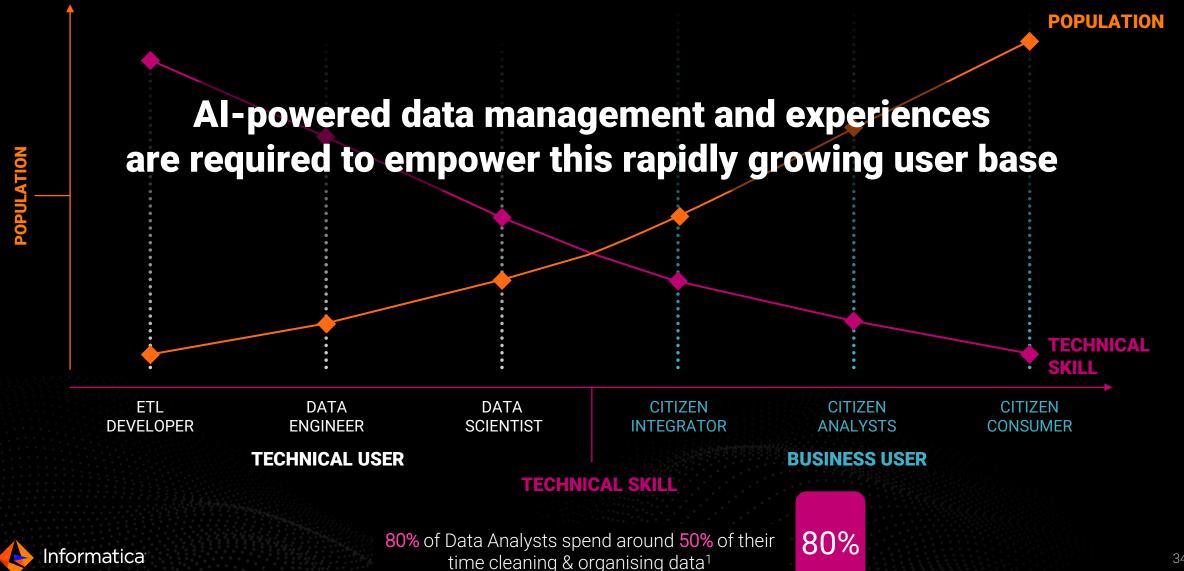
GOVERNED

Defined policies, standards, and established controls by data stewards across your business

UNDERSTOOD

Enabling every business user to get answers about the data they use every day

Inability to Address the Expanding Breadth of Data Users



CLAIRE® copilot - Data Management Intelligence & Automation





AUTOMATED

- Inferred Data Relationships
- Al Generated Data Classifications
- Inferred Data Lineage



- Al generated data pipelines
- Intelligent Structure Discovery
- Data Transformation Recommendation
- Data Masking Recommendation



AUTOMATED

- Sensitive field detection
- Auto generation of API
- Auto-match and validation of APIs
- **OBSERVABILITY** AUTOMATED

DATA QUALITY &

- Automated Data Quality Rule Creation
- Al Powered Data Quality Insights
- NLP for Data Cleansing



AUTOMATED

- Entity Matching & Relationship Inference
- Automated data pipeline generation

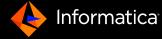


AUTOMATED

- Intelligent Glossary Association
- AI & ML powered Data Observability



 Automated Fulfillment



Latrobe University



GOAL

Develop a unified, trusted source of certified data to better service their customers, including students, partners and the community.

TA MANAGEMEN 8 AI STRATEGY "Informatica's Customer 360 enables us to have a single source of truth, a holistic 360-degree view of data we can trust from across our organization for data analytics and insights"

Automated Data Classification to improve data governance and privacy controls



Uses AI to automate onboarding & mastering of students

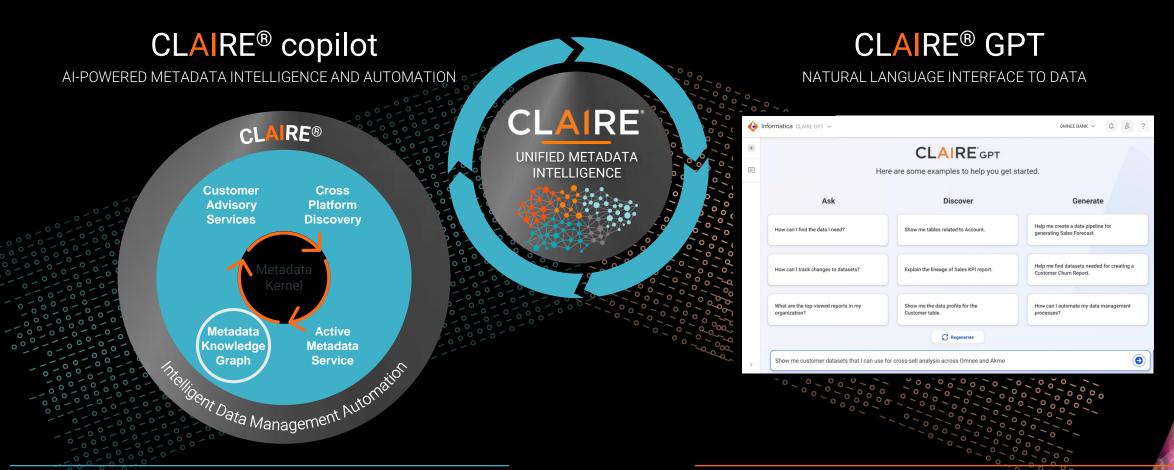


Use trusted data to provide close to realtime insights

VALUE

Their AI model can predict within two weeks of a student's failure; AI classifies data for privacy regulation; near realtime insights

CLAIRE®: Al-Powered Data Management



Data Management Automation

Generative Al-powered Data Management

Gen Al to Simplify Data Management for All Users

CLAIRE® GPT Possibilities

Business Users

Who are our most valuable customers in

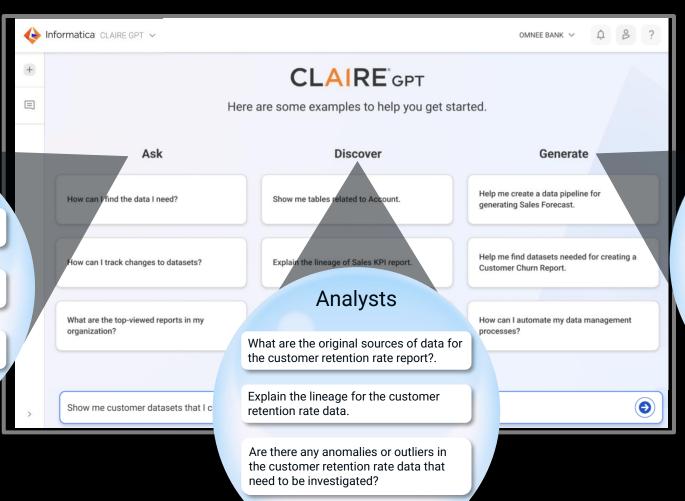
What products or services do customers

terms of spending over the last year?

frequently buy together?

What are the trends in customer

retention rate over the last 4 quarters?





Data Engineers

Where can I find the datasets I need to calculate Customer Acquisition Cost (CAC)?

Are all the datasets I need to calculate CAC connected and accessible?.

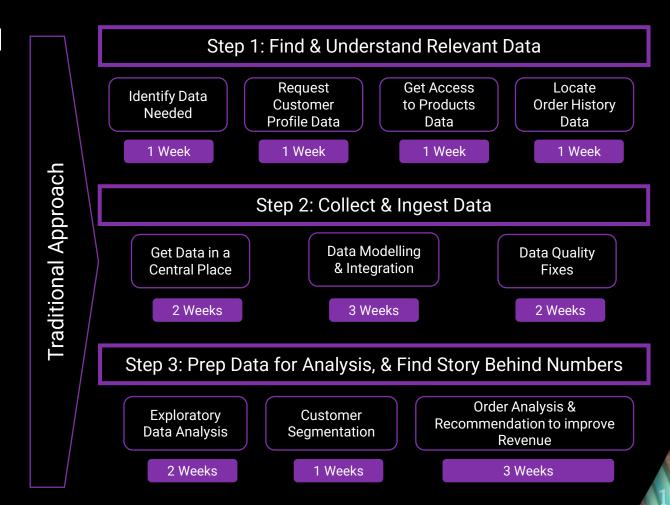
Create a pipeline that calculates CAC for different marketing channels.



Business Analysis & Revenue

Example Scenario

- Role: Business Analyst at XYZ Retail Ltd.
- Objective: Understand Customer Behavior, Analyse Past Orders, and Recommend how to Improve Revenue
- Strategy: Use data to segment customers, identify top performing products, and underperforming categories





Need help getting started? Try one of these sample prompts.

| Discover | Explore | Ask | |
|---|--|--|--|
| Show me the assets controlled by @claire GPT_DEMO | Show data preview of @CMI_SPECIALTY_CODES | How do you create a custom workflow in CDGC? | |
| Find catalog sources of type Snowflake, Databricks, and Oracle | Show data preview of @CMI_PHYSICAN | Can mass ingestion cause any restrictions when using SQL Server? | |
| | | | |

Create a mapping for

@CMI_SPECIALTY_CODES

What is CLAIRE GPT?

Show me the assets which are profiled in

last 30 days



What API can be used to get the details of

an asset in CDGC?



What is Claire GPT?



Finding out what CLAIRE GPT is

CLAIRE GPT is a business-oriented tool powered by Informatica's AI machine learning engine, CLAIRE. It allows users to process, manage, and analyze data using natural language prompts. Users can discover data and explore metadata available in Data Governance and Catalog, including metadata from various sources like databases, data integration sources, data lakes, and data warehouses. Additionally, they can discover and explore business assets such as business glossaries, data sets, policies, and processes. By performing data-driven insights based on responses from CLAIRE GPT, users can determine the data sets that best meet their business requirements and create pipelines to transform their data.

Citations:

- 1. CLAIRE GPT/Getting Started With Claire Gpt-Welcome to CLAIRE GPT
- 2. CLAIRE GPT/Using Claire Gpt-User persona based use cases
- 3. CLAIRE GPT/Administration-Administer CLAIRE GPT







Show me retail customer datasets



Searching for retail customer datasets



Generating response...





Show me retail customer datasets



Searching for retail customer datasets

Here are the retail customer datasets available across different resources.

- 1. RETAIL_CUSTOMER: This table is part of the sandbox_CDW_Snowflake resource in Snowflake. It resides under the CDW_DEMO_DB database in the SANDBOX_PUBLIC schema.
- 2. RETAIL_CUSTOMERS: This table does not have a description provided. It is part of the cpg_snowflake_retail resource in Snowflake. It resides under the RETAIL_CPG database in the PUBLIC schema.
- 3. retail_customers_202405100903.csv: This is a flat file present in the cpg_adlsg2_retail resource in Adls Gen2. It resides under the **cdpadlsgen2** storage account in the **retailcpg** container.

Found 6 of the available 10 records.

Here are the retail customer datasets found in different resources.

- 1. Datasets under the sandbox_CDW_Snowflake Snowflake resource in CDW_DEMO_DB database under the SANDBOX_PUBLIC schema:
 - CUSTOMERS: This is a table dataset.
 - DM_CUSTOMERS_SALES: This is another table dataset.
 - **CUSTOMERS_SALES**: This is also a table dataset.
- 2. Dataset under the **cpg_adlsg2_retail** Adls Gen2 resource in **cdpadlsgen2** storage account under the **retailcpg** container:
 - o retail_products_202405100903.csv: This is a flat file dataset.
- 3. Datasets under the cpg_snowflake_retail Snowflake resource in RETAIL_CPG database under the PUBLIC schema:

Show me data preview for CUSTOMERS

Show me data preview for RETAIL_CUSTOMER

Get an overview of RETAIL_CUSTOMER







Tell me more about @RETAIL_CUSTOMERS



Looking for more information about retail_customers

RETAIL_CUSTOMERS Overview

Description

RETAIL_CUSTOMERS is a table stored in a Snowflake environment. It has been profiled to assess its structure and quality comprehensively. However, no detailed description is provided.

Data Characteristics

- **Resource Type**: Snowflake
- Number of Columns: 1200
- Data Quality:
 - o Accuracy: 95%, indicating a high level of reliability.
 - Validity: 92%, showing a good level of data correctness.
 - Timeliness: 88%, suggesting that the data is updated regularly.
 - Uniqueness: 90%, indicating a high level of distinct entries.
 - o Completeness: 94%, indicating that most data entries are complete.
- Profiled: Yes
 - This indicates that RETAIL_CUSTOMERS has undergone profiling to assess its quality and structure comprehensively.



Get the data quality scores of RETAIL_CUSTO...

Find me an overview of RETAIL_CUSTO...

Find dataset with data lineage to RETAIL_CUSTO...



Key Columns

The table includes several key columns that are significant for understanding retail customer information:

- CustomerID: A unique identifier for each customer.
- CustomerName: The name of the customer.
- · Address: The address of the customer.
- Phone: The phone number of the customer.
- Email: The email address of the customer.

Glossary

It is associated with key business terms like "CustomerID" and "Email."

Data Entity Classification

It is classified under the "Customer Information" category, highlighting its importance in understanding and managing customer data.

Quality

• The quality has been assessed with metrics provided for accuracy, validity, timeliness, uniqueness, and completeness.

Stakeholdership

• RETAIL_CUSTOMERS has been profiled by the "Data Quality Assessment Team" who are responsible for maintaining its quality and structure.





Find an overview of RETAIL_CUSTO...

Find tables that can be joined with RETAIL_CUSTO...

Get dataset with data lineage to RETAIL_CUSTO...





Quality

• The quality has been assessed with metrics provided for accuracy, validity, timeliness, uniqueness, and completeness.

Stakeholdership

• RETAIL_CUSTOMERS has been profiled by the "Data Quality Assessment Team" who are responsible for maintaining its quality and structure.







Show me what glossaries are associated with @RETAIL_CUSTOMERS



Showing the glossaries associated with retail_customers

Here are the glossaries associated with RETAIL_CUSTOMERS. They are part of the Party Data domain under the Personal Data subdomain in the Data Subject Categories subdomain.

- 1. Customers (inc. historic): This term refers to individuals who have previously or currently received goods or services from the organisation.
- 2. Customer: This term refers to corporate entities or individuals that have an economic relationship of some sort with the company, excluding employment.







Find an overview of RETAIL_CUSTO...

Find tables that can be joined with RETAIL_CUSTO...

Get dataset with data lineage to RETAIL_CUSTO...



What Kind of Data Quality does @RETAIL_CUSTOMERS



Finding out the kind of data quality does RETAIL_CUSTOMERS

The RETAIL_CUSTOMERS data quality analysis reveals the following:

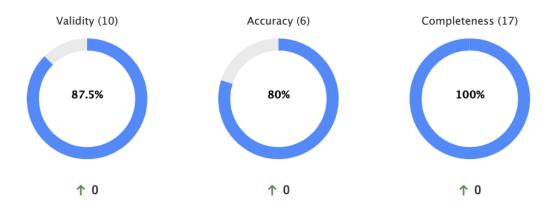
Validity (87.5): The data shows high adherence to predefined formats or rules, indicating that the data meets the established criteria for validity, enhancing its reliability for analysis.

Accuracy (80.0): This score suggests that the data accurately reflects the real-world objects or events they are intended to represent, indicating that the data is reliable for representing customer information.

Completeness (100.0): The data is completely present and accounted for, with no missing entries, ensuring a comprehensive understanding of the customer data.

Overall Data Quality (122.5): This high score encapsulates the overall data quality, reflecting minor deficiencies across the measured dimensions. It underscores the high quality of the RETAIL_CUSTOMERS data, making it trustworthy and valuable for business operations and decision-making.

Data Quality Scores:





Show me the profiling for @RETAIL_CUSTOMERS



Showing the profiling for retail_customers

The data profiling of the "RETAIL_CUSTOMERS" table provides insights into the key columns such as PHONE, ID, GENDER, LAST_NAME, RACE, FIRST_NAME, CITY, COUNTRY, and DOB. These insights are crucial for understanding the quality and robustness of the data, which significantly impacts business strategies and customer information management.

PHONE

- Data Type: String
- Analysis of 980 Entries:
 - Distinctiveness: High at 99.8%
 - Duplication: Low duplication at 0.2%
 - Data Quality: Very few nulls (0.2%), indicating high data quality.

ID

- Data Type: Integer
- Analysis of 980 Entries:
 - Distinctiveness: High at 99.8%
 - **Duplication:** Low duplication at 0.2%
 - Data Quality: Very few nulls (0.2%), indicating high data quality.



Find tables that can be joined with RETAIL_CUS...

Find me the data quality scores of RETAIL_CUS...

Show me data preview for RETAIL_CUST...



GENDER

- Data Type: String
- Analysis of 980 Entries:
 - Distinctiveness: Very low at 0.2%
 - Duplication: Very high duplication at 99.8%
 - Data Quality: Very few nulls (0.2%), indicating high data quality.

LAST_NAME

- Data Type: String
- Analysis of 980 Entries:
 - **Distinctiveness:** High at 98.8%
 - **Duplication:** Low duplication at 1.2%
 - Data Quality: Very few nulls (0.2%), indicating high data quality.

RACE

- Data Type: String
- Analysis of 980 Entries:
 - **Distinctiveness:** Low at 9.5%
 - **Duplication:** High duplication at 90.5%
 - Data Quality: Very few nulls (0.2%), indicating high data quality.

FIRST_NAME

Find tables that can be joined with RETAIL_CUS...

Find me the data quality scores of RETAIL_CUS...

Show me data preview for RETAIL_CUST...



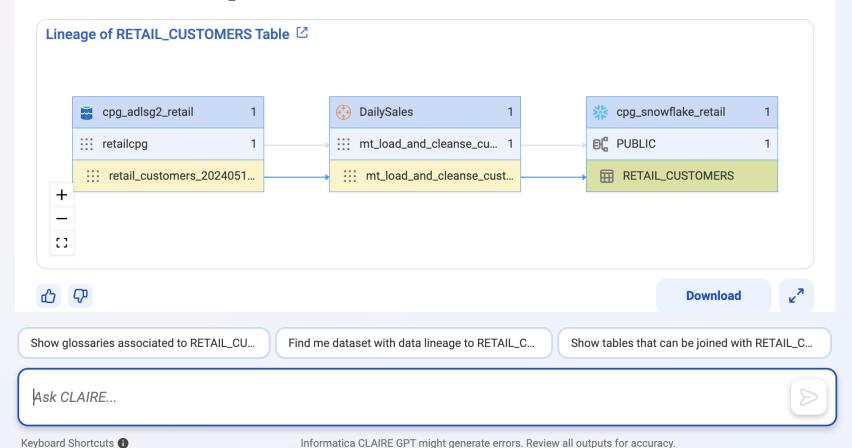


Show the lineage for @RETAIL_CUSTOMERS



Showing the lineage for retail_customers

- The lineage of RETAIL_CUSTOMERS involves a total of 2 catalog sources.
- The data flow begins from the source cpg_adlsg2_retail, which includes the asset retail_customers_202405100903.csv.
- This data then flows into RETAIL_CUSTOMERS and proceeds towards the target resource cpg_snowflake_retail, which contains the asset RETAIL_CUSTOMERS.





show me the impact analysis of adding a column to @RETAIL_CUSTOMERS



Showing the impact analysis of adding a column to retail_customers

Impact Analysis of Changing RETAIL_CUSTOMERS:

• Upstream Impact:

- Changes to RETAIL_CUSTOMERS could necessitate modifications in how data is ingested from the source catalog: cpg_adlsg2_retail.
- The single asset, retail_customers_202405100903.csv, might require adjustments in its format, structure, or data type to ensure compatibility with the new RETAIL_CUSTOMERS structure.

Downstream Impact:

- Any changes in RETAIL_CUSTOMERS would directly influence the data being supplied to the downstream target: cpg_snowflake_retail.
- o The single target asset, RETAIL_CUSTOMERS, might need updates to accommodate changes in the data's format, granularity, or semantics. This could impact the accuracy, timeliness, and relevance of insights derived from this data.

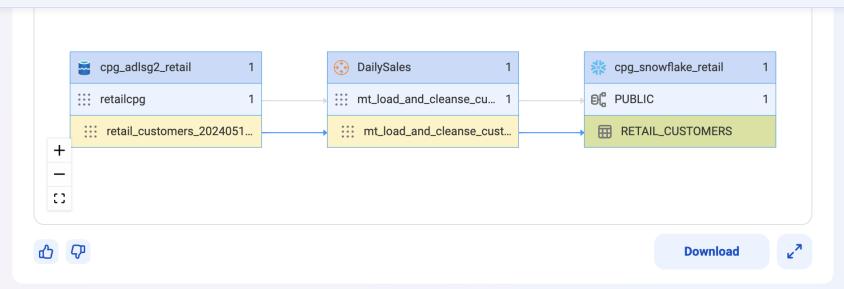
Overall Ecosystem Impact:

- The coherence and efficiency of the entire data flow, from the initial data source through RETAIL_CUSTOMERS to the eventual data target, might be impacted. This necessitates a thorough review and potentially a redesign of the data processing, transformation, and analysis pipelines to align with the new RETAIL_CUSTOMERS configuration.
- o Stakeholders relying on the insights generated from these data flows, such as retail analysts and customer relationship managers, may experience changes in the decision-making process due to the adjusted data inputs and outputs.

Lineage of RETAIL_CUSTOMERS Table <a>□









Show me tables that can be joined with @RETAIL_CUSTOMERS



Searching for tables that can be joined with retail_customers

Here are the tables that can be joined with **RETAIL_CUSTOMERS**. They are part of the **cpg_snowflake_retail** resource in Snowflake, situated under the RETAIL_CPG database in the PUBLIC schema.

1. **RETAIL_ORDERS**: This table is related to the **RETAIL_CUSTOMERS** table.





Find me dataset with data lineage to RETAIL_ORDERS

Show an overview of RETAIL_ORDERS

Show me data preview for RETAIL_ORDERS





Show me information about @RETAIL_ORDERS



Showing information about retail_orders

The RETAIL_ORDERS is a table stored in the cpg_snowflake_retail resource. Here's a summary of its key characteristics:

Name: RETAIL_ORDERS Resource Name: cpg_snowflake_retail Type: Table Profiled: Yes

Data Profiling

• Profiled: Yes

• Last Profiled State: Complete

• Class Type: com.infa.odin.models.relational.Table

• Name: RETAIL_ORDERS

Data Quality

• Data Quality: Not Available

Stakeholdership

• Created By: Scott Ligocki

• Modified By: Errick Coughlin

Get tables that can be joined with RETAIL_ORDE...

• Certified: No

• Asset Lifecycle: Published

Show me data preview for RETAIL_ORDE...

Get dataset with data lineage to RETAIL_ORDE...

Ask CLAIRE...



•







Show me information about @RETAIL_ORDERS



Showing information about retail_orders

The RETAIL_ORDERS is a table stored in the cpg_snowflake_retail resource. Here's a summary of its key characteristics:

Name: RETAIL_ORDERS Resource Name: cpg_snowflake_retail Type: Table Profiled: Yes

Data Profiling

• Profiled: Yes

• Last Profiled State: Complete

• Class Type: com.infa.odin.models.relational.Table

• Name: RETAIL_ORDERS

Data Quality

• Data Quality: Not Available

Stakeholdership

• Created By: Scott Ligocki

• Modified By: Errick Coughlin

• Certified: No

• Asset Lifecycle: Published

Get tables that can be joined with RETAIL_ORDE...

Show me data preview for RETAIL_ORDE...

Get dataset with data lineage to RETAIL_ORDE...









Show me a data preview of @RETAIL_CUSTOMERS



Showing a data preview of retail_customers

TABLE | RETAIL_CUSTOMERS

cpg_snowflake_retail / RETAIL_CPG / PUBLIC Columns: 16

1 Privacy guidelines prevent us from storing sample data, but you can download the data for your reference.

×

| A AREA | A City | A Country | □ Date_Of_Birth | A EMAIL | A First_Name |
|--------|----------|-------------|-----------------|-----------------|---------------|
| Main | Catania | Italy | 21 Dec 1985 | bgretham5y@g | Maite |
| Main | Venlo | Netherlands | 08 Jul 1949 | gkarle52@csm | Adelie |
| North | Paris | France | 25 Feb 1948 | cburganemn@b | Maelyss |
| Main | Best | Netherlands | 18 Oct 1954 | lcowlesk4@ute | Frederique |
| Main | Padova | Italy | 09 Jan 1965 | mlampskb@joo | Clea |
| Main | Den Haag | Netherlands | 21 Jul 1970 | rthurlbornnx@fl | Publicite |
| Main | Mestre | Italy | 22 Jan 1985 | goneilna@amaz | Marta |
| North | Paris | France | 24 Jan 2000 | bmartyntsevlz | Yu |
| North | Paris | France | 23 Sept 1954 | ccarletonei@ac | Ма |
| North | Paris | France | 04 Feb 2001 | rskinner5d@im | Personnalisee |
| | | | | | |

Viewing sample data: 100 rows and 4 data types

Combine RETAIL_CUSTOMERS with RETAIL_ORDERS

Create a mapping for the above





Combine @RETAIL_CUSTOMERS with RETAIL_ORDERS



Combining retail_customers with retail_orders

TABLE | RETAIL_CUSTOMERS

cpg_snowflake_retail / RETAIL_CPG / PUBLIC Columns: 25

1 Privacy guidelines prevent us from storing sample data, but you can download the data for your reference.

X

| A AREA | A City | A Country | □ Date_Of_Birth | A EMAIL | A First_Name |
|--------|---------------|-----------|-----------------|-----------------|--------------|
| Main | Barcelona | Spain | 22 Aug 1995 | hkarsh0@fema | Yao |
| Main | Barcelona | Spain | 22 Aug 1995 | hkarsh0@fema | Yao |
| Main | Barcelona | Spain | 22 Aug 1995 | hkarsh0@fema | Yao |
| Main | Washington | Sweden | 10 Mar 1955 | cyaakov2@reve | Ye |
| Main | Washington | Sweden | 10 Mar 1955 | cyaakov2@reve | Ye |
| Main | Springfield | Sweden | 30 Mar 1950 | eswaine3@peo | Penelope |
| North | Sannois | France | 28 Jun 1952 | lmatiashvili5@d | Yenora |
| Main | New York City | Sweden | 31 Mar 1965 | mhabens6@spr | Marylene |
| Main | Sparks | Sweden | 21 Dec 1997 | gboddis9@tech | Aurelie |
| Main | Sparks | Sweden | 21 Dec 1997 | gboddis9@tech | Aurelie |
| | - | | | | |

Viewing sample data: 100 rows and 5 data types

Combine RETAIL_CUSTOMERS with RETAIL_ORDERS

Create a mapping for the above





How many customers we have per country?



Finding out how many customers we have per country in RETAIL_CUSTOMERS

TABLE | RETAIL_CUSTOMERS

cpg_snowflake_retail / RETAIL_CPG / PUBLIC Columns: 2

1 Privacy guidelines prevent us from storing sample data, but you can download the data for your reference.

×

| A Country | # COUNT(*) |
|----------------|------------|
| Italy | 21 |
| Netherlands | 51 |
| France | 457 |
| Germany | 44 |
| Spain | 42 |
| United Kingdom | 22 |
| Sweden | 332 |
| Switzerland | 8 |
| Singapore | 1 |
| NULL | 2 |

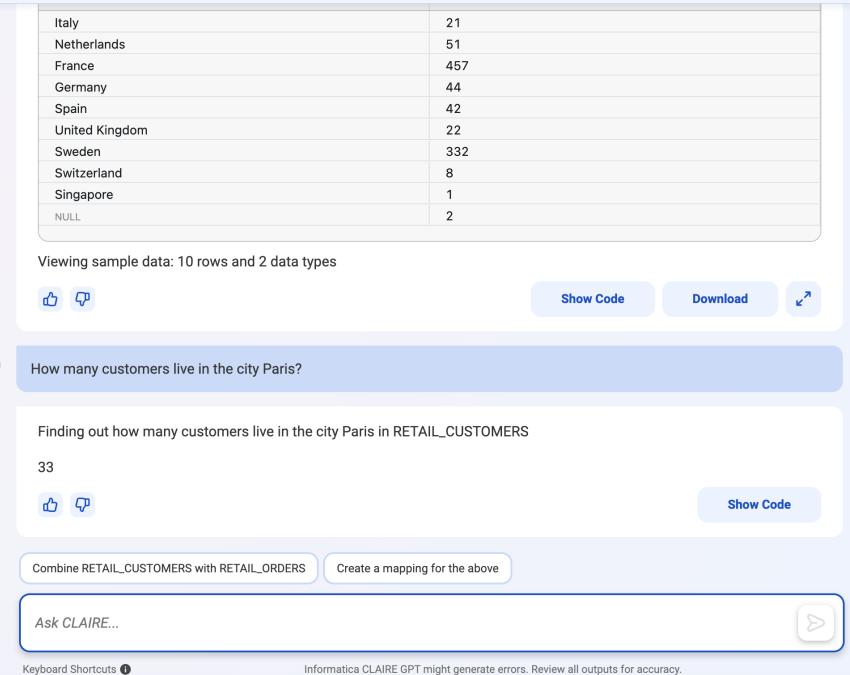
Viewing sample data: 10 rows and 2 data types

Combine RETAIL_CUSTOMERS with RETAIL_ORDERS

Create a mapping for the above



CG



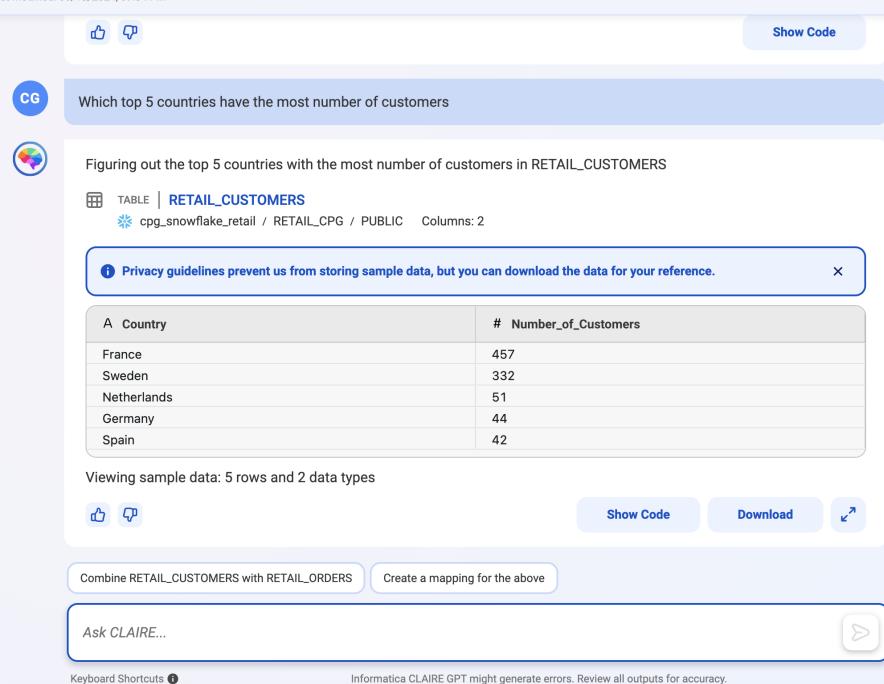






TABLE | RETAIL_CUSTOMERS

cpg_snowflake_retail / RETAIL_CPG / PUBLIC Columns: 2

1 Privacy guidelines prevent us from storing sample data, but you can download the data for your reference.

A Country # total_orders France 457 Sweden 332 Netherlands 51 Germany 44 Spain 42 United Kingdom 22 Italy 21 Switzerland NULL Singapore

Viewing sample data: 10 rows and 2 data types





Show Code

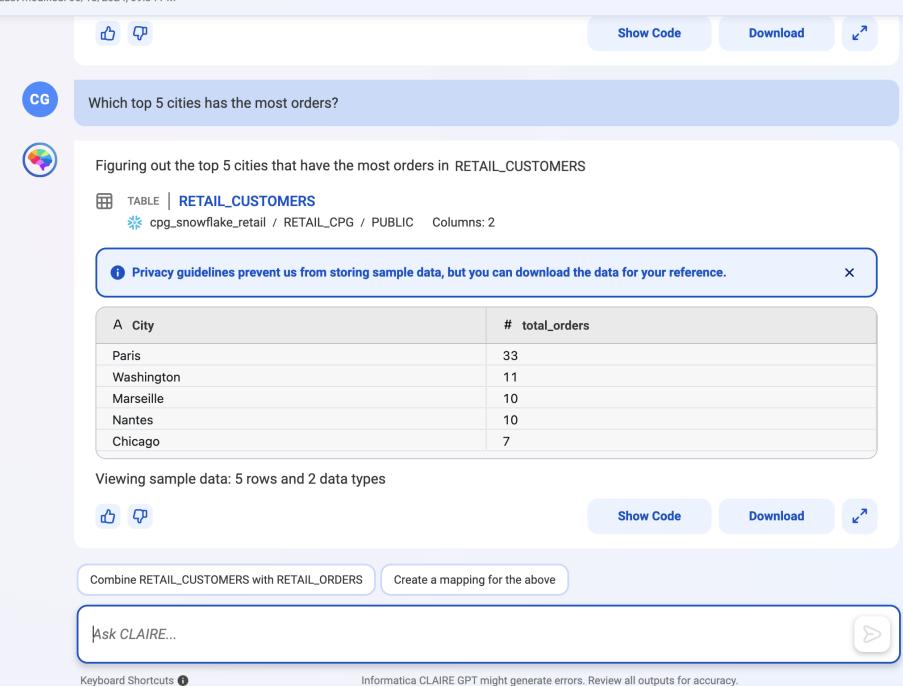
Download

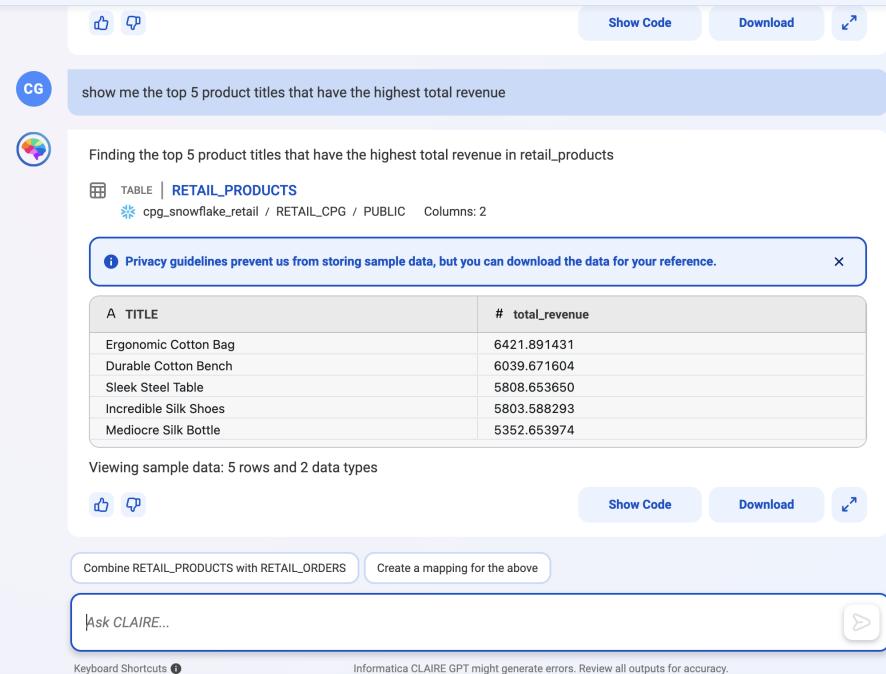
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Combine RETAIL_CUSTOMERS with RETAIL_ORDERS

Create a mapping for the above









show customers that live in the country France or Italy with the number of orders, average order amount, and number of products, and product title purchased with the revenue generated in for each product



Showing customers that live in the countryfrance or italy with the number of orders, average order amount, and number of products, and product title purchased with the revenue generated in for each product in retail_products



TABLE | RETAIL_PRODUCTS

cpg_snowflake_retail / RETAIL_CPG / PUBLIC Columns: 5



×

| A TITLE | # Number_of_orde | # Average_order | # Number_of_prod | # Revenue |
|-----------------------|------------------|------------------|------------------|-------------|
| Incredible Silk Shoes | 26 | 122.910031692308 | 26 | 3195.660824 |
| Intelligent Granite | 18 | 139.376185277778 | 18 | 2508.771335 |
| Small Cotton Chair | 29 | 63.459520793103 | 29 | 1840.326103 |
| Synergistic Marble | 25 | 104.860768200000 | 25 | 2621.519205 |
| Ergonomic Cotton | 25 | 131.736799160000 | 25 | 3293.419979 |
| Lightweight Linen | 24 | 40.885450416667 | 24 | 981.250810 |
| Lightweight Paper | 18 | 74.820339500000 | 18 | 1346.766111 |
| Ergonomic Silk Table | 18 | 66.658319888889 | 18 | 1199.849758 |
| Synergistic Rubber | 15 | 47.899319933333 | 15 | 718.489799 |
| Incredible Aluminu | 12 | 137.206993750000 | 12 | 1646.483925 |



Combine RETAIL_PRODUCTS with RETAIL_ORDERS

Create a mapping for the above





Showing customers that live in the countryfrance or italy with the number of orders, average order amount, and number of products, and product title purchased with the revenue generated in for each product in retail_products



TABLE | RETAIL_PRODUCTS

cpg_snowflake_retail / RETAIL_CPG / PUBLIC Columns: 5

1 Privacy guidelines prevent us from storing sample data, but you can download the data for your reference.

×

| A TITLE | # Number_of_orde | # Average_order | # Number_of_prod | # Revenue |
|-----------------------|------------------|------------------|------------------|-------------|
| Enormous Steel Wa | 18 | 107.105990944444 | 18 | 1927.907837 |
| Mediocre Cotton T | 17 | 43.729770705882 | 17 | 743.406102 |
| Small Granite Gloves | 22 | 112.191645454545 | 22 | 2468.216200 |
| Aerodynamic Grani | 25 | 42.465341640000 | 25 | 1061.633541 |
| Fantastic Steel Knife | 16 | 54.840186687500 | 16 | 877.442987 |
| Aerodynamic Linen | 14 | 144.119922785714 | 14 | 2017.678919 |
| Heavy-Duty Steel | 11 | 54.255236818182 | 11 | 596.807605 |
| Incredible Concret | 14 | 116.435405500000 | 14 | 1630.095677 |
| Intelligent Paper Car | 13 | 107.110623384615 | 13 | 1392.438104 |
| Ergonomic Silk Key | 17 | 105.208409647059 | 17 | 1788.542964 |
| Enormous Marble | 19 | 55.667306947368 | 19 | 1057.678832 |

Viewing sample data: 100 rows and 3 data types





Show Code

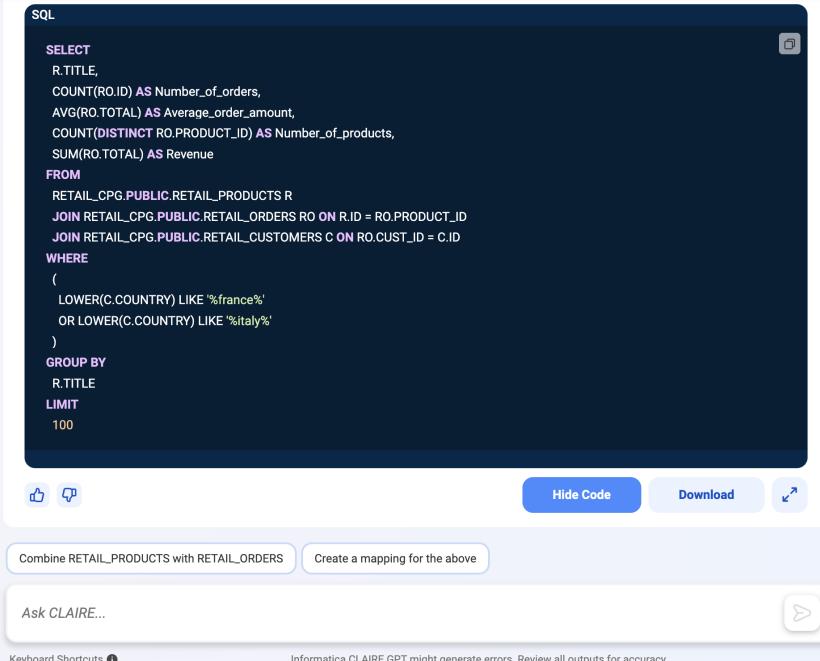
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Combine RETAIL_PRODUCTS with RETAIL_ORDERS

Create a mapping for the above







Showing customers that live in the countryfrance or italy with the number of orders, average order amount, and number of products, and product title purchased with the revenue generated in for each product in retail_products



cpg_snowflake_retail / RETAIL_CPG / PUBLIC Columns: 5

1 Privacy guidelines prevent us from storing sample data, but you can download the data for your reference.

X

| A TITLE | # Number_of_orde | # Average_order | # Number_of_prod | # Revenue |
|-----------------------|------------------|------------------|------------------|-------------|
| Enormous Steel Wa | 18 | 107.105990944444 | 18 | 1927.907837 |
| Mediocre Cotton T | 17 | 43.729770705882 | 17 | 743.406102 |
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| Aerodynamic Linen | 14 | 144.119922785714 | 14 | 2017.678919 |
| Heavy-Duty Steel | 11 | 54.255236818182 | 11 | 596.807605 |
| Incredible Concret | 14 | 116.435405500000 | 14 | 1630.095677 |
| Intelligent Paper Car | 13 | 107.110623384615 | 13 | 1392.438104 |
| Ergonomic Silk Key | 17 | 105.208409647059 | 17 | 1788.542964 |
| Enormous Marble | 19 | 55.667306947368 | 19 | 1057.678832 |

Viewing sample data: 100 rows and 3 data types





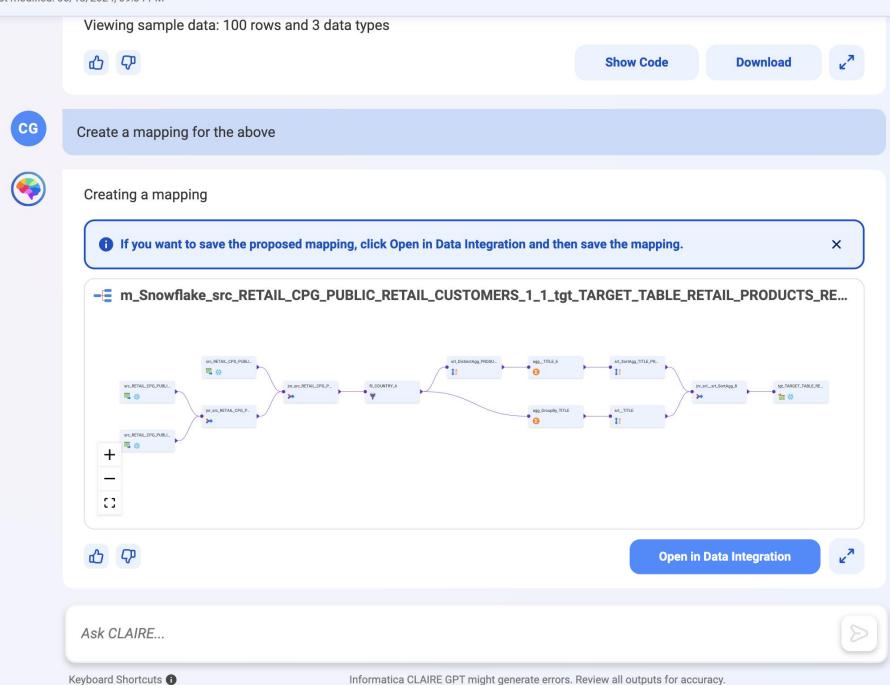
Show Code

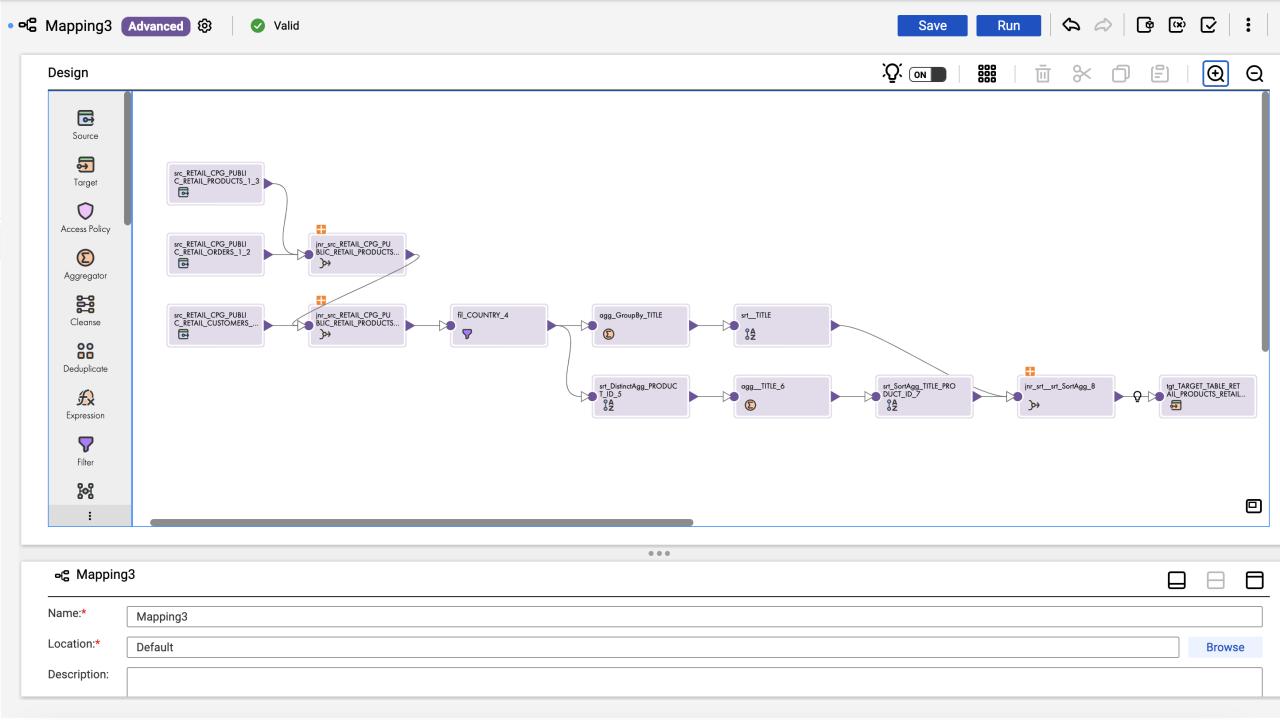
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Combine RETAIL_PRODUCTS with RETAIL_ORDERS

Create a mapping for the above







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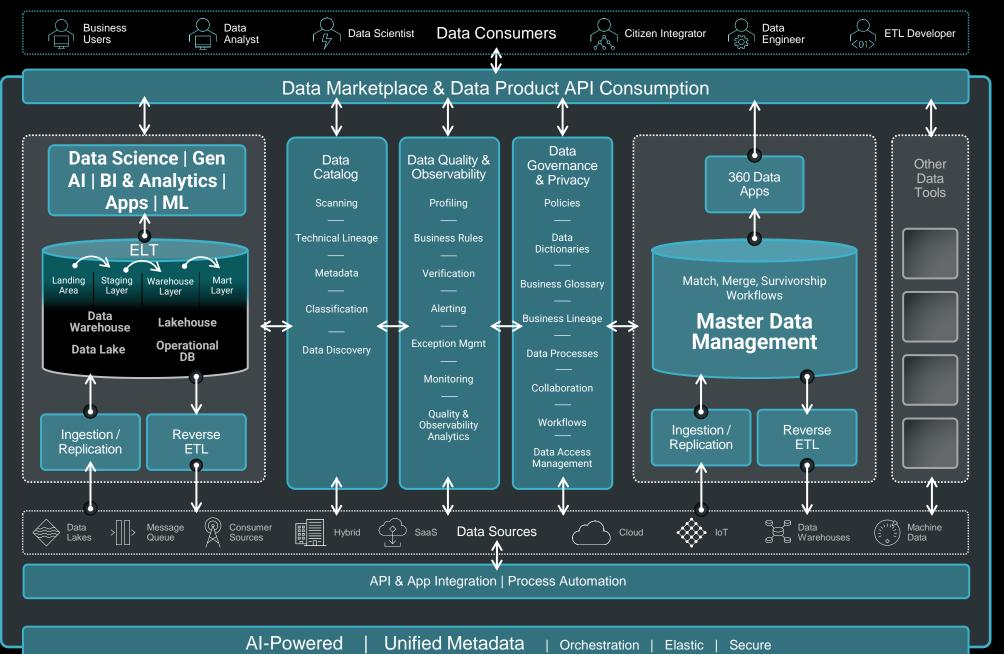
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Wrap up:

Al Needs a Modern Data Architecture & Data Management Needs Al

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dhein@informatica.com



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Thank you

