### **EXECUTABLE INFO DOCUMENT**

# DATA WAREHOUSING INTEGRATION

### 1. INTRODUCTION

This document provides execution evidence and project results for the **Data Warehousing Integration** solution built using Azure Data Factory (ADF), Azure Databricks, Azure Data Lake Storage (ADLS), and Azure Synapse Analytics.

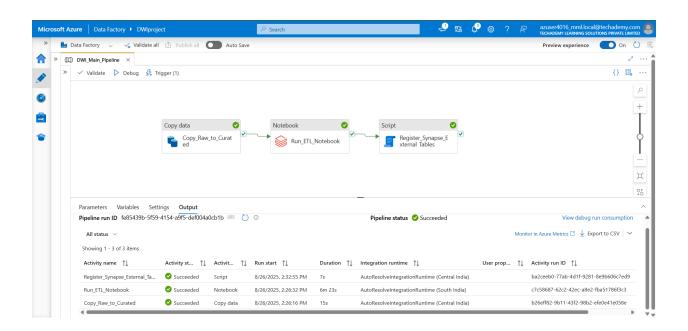
The purpose of this document is to:

- Demonstrate the successful end-to-end execution of the ETL pipeline.
- Showcase validation outputs and query results proving schema consistency and data correctness.
- Present analytical insights derived from curated warehouse tables.

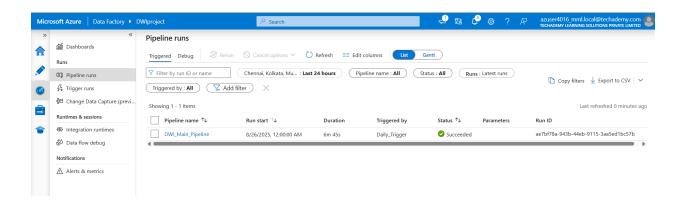
# 2. PIPELINE EXECUTION PROOF

# 2.1 AZURE DATA FACTORY (ADF)

• Pipeline Design View



• Pipeline Monitoring



### 2.2 AZURE DATABRICKS

• Databricks Notebook Transformation Output

```
✓ Yesterday (<1s)
    df = df.toDF(*[c.replace(" ", "_") for c in df.columns])
    df.printSchema()
▶ ■ df: pyspark.sql.dataframe.DataFrame = [Transaction_ID: string, Date: string ... 7 more fields]
|-- Transaction_ID: string (nullable = true)
|-- Date: string (nullable = true)
|-- Customer_ID: string (nullable = true)
-- Gender: string (nullable = true)
|-- Age: string (nullable = true)
|-- Product_Category: string (nullable = true)
|-- Quantity: string (nullable = true)
|-- Price_per_Unit: string (nullable = true)
|-- Total_Amount: string (nullable = true)
 Yesterday (3s)
    print("Total rows:", df.count())
 ▶ (2) Spark Jobs
Total rows: 1000
```

# 3. Transform – Create Dimension Tables 3.1 Customer Dimension Vesterday (<1s) # Dim Customer dim\_customer = df.select( "Customer\_ID", "Gender", "Age" ).dropDuplicates(["Customer\_ID"]) dim\_customer: pyspark.sql.dataframe.DataFrame = [Customer\_ID: string, Gender: string ... 1 more field]

```
# Create Fact Table

V V Vesterday(<1s) 19

from pyspark.sql.functions import col, to_date

# Ensure Date is proper type

df = df.withColumn("Date", to_date("Date"))

# Join with dim_product (to get Product_ID)

# Join with dim_product (to get Product_ID)

# Join with dim_date (to get Date_ID)

fact_sales = (

df.join(dim_product, on="Product_Category", how="left")

.join(dim_date, on="Date", how="left")

.select(

col("Transaction_ID"),
 col("Date_ID"), # now exists after join with dim_date

col("Customer_ID"),
 col("Product_ID"), # surrogate key from dim_product

col("Quantity"),
 col("Price_pen_Unit"),
 (col("Price_pen_Unit")).alias("Total_Amount")

) 

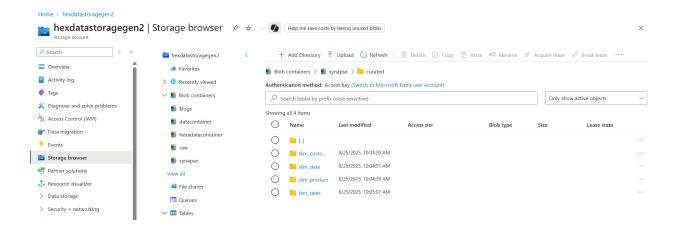
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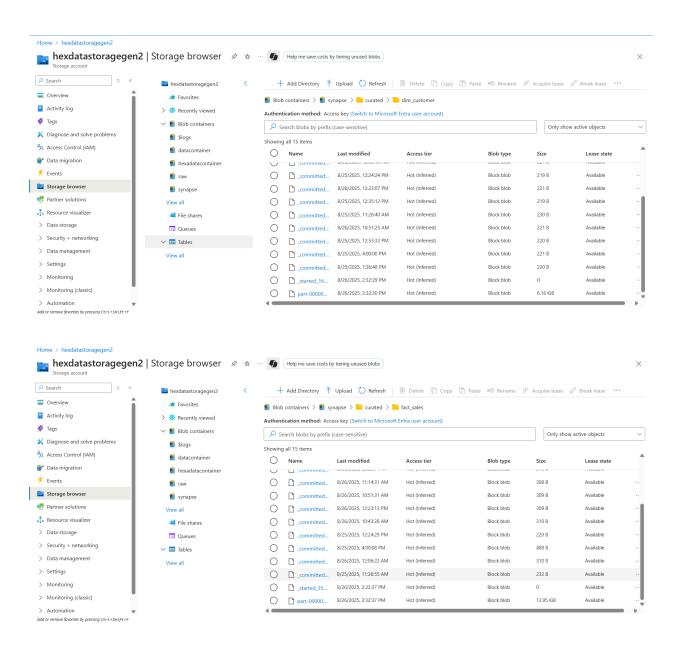
df: pyspark.sql.dataframe.DataFrame = [Transaction_ID: integer, Date: date ... 7 more fields]

I 

fact_sales: pyspark.sql.dataframe.DataFrame = [Transaction_ID: integer, Date_ID: long ... 5 more fields]
```

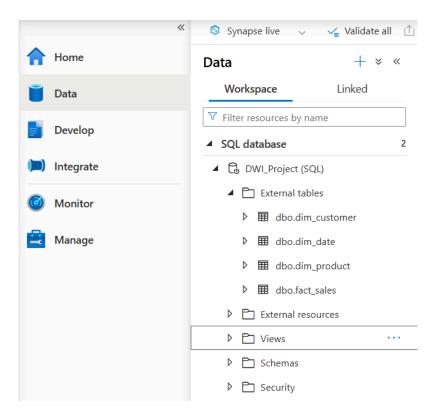
# • Curated Data Stored in ADLS





# 2.3 AZURE SYNAPSE ANALYTICS

# • External Tables Registered



# • Data Source & Credential Setup

```
-- STEP 3: Create External Data Source

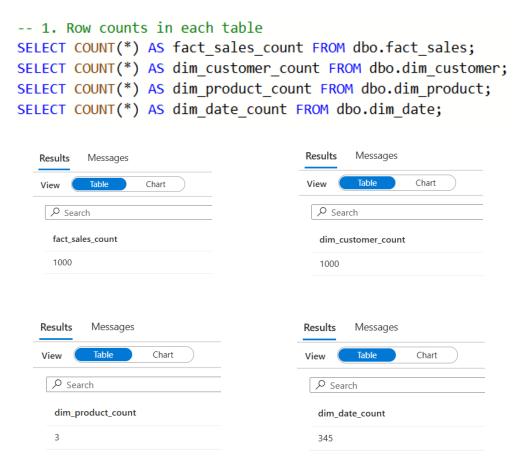
IF EXISTS (SELECT * FROM sys.external_data_sources WHERE name = 'dwi_curated')
        DROP EXTERNAL DATA SOURCE dwi_curated;

CREATE EXTERNAL DATA SOURCE dwi_curated
WITH (
        LOCATION = 'https://hexdatastoragegen2.blob.core.windows.net/synapse',
        CREDENTIAL = BlobsAS
);
```

### 3. VALIDATION OUTPUTS

Validation was carried out in Synapse Studio using SQL queries to confirm row counts, schema correctness, and referential integrity.

### • Row Count Validation



# • Referential Integrity Checks

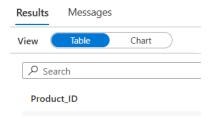
```
-- 2. Check for orphaned Product_IDs in fact

SELECT DISTINCT f.Product_ID

FROM dbo.fact_sales f

LEFT JOIN dbo.dim_product p ON f.Product_ID = p.Product_ID

WHERE p.Product_ID IS NULL;
```



```
-- 3. Check for orphaned Date_IDs in fact
SELECT DISTINCT f.Date_ID
FROM dbo.fact_sales f
LEFT JOIN dbo.dim_date d ON f.Date_ID = d.Date_ID
WHERE d.Date_ID IS NULL;
```



# • Sales by Product Category

```
-- 4. Sales by product category

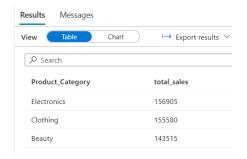
SELECT p.Product_Category, SUM(f.Total_Amount) AS total_sales

FROM dbo.fact_sales f

JOIN dbo.dim_product p ON f.Product_ID = p.Product_ID

GROUP BY p.Product_Category

ORDER BY total_sales DESC;
```



# • Monthly Sales Trends

```
-- 6. Sales trend by month (quick time sanity check)

SELECT d.Year, d.Month, SUM(f.Total_Amount) AS monthly_sales

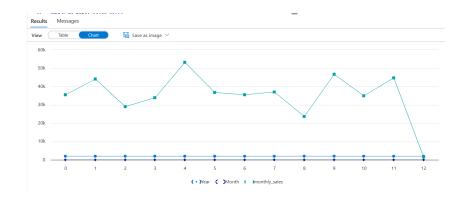
FROM dbo.fact_sales f

JOIN dbo.dim_date d ON f.Date_ID = d.Date_ID

GROUP BY d.Year, d.Month

ORDER BY d.Year, d.Month;
```

Year	Month	monthly_sales
2023	1	35450
2023	2	44060
2023	3	28990
2023	4	33870
2023	5	53150



# • Top 10 Customers by Spend

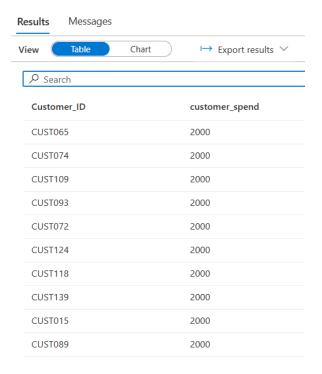
```
-- 8. Top 10 customers by spend

SELECT TOP 10 f.Customer_ID, SUM(f.Total_Amount) AS customer_spend

FROM dbo.fact_sales f

GROUP BY f.Customer_ID

ORDER BY customer_spend DESC;
```



# 4. ANALYSIS & INSIGHTS

The validated star schema enables rich analytical queries. Some business insights observed:

• **Product Category Contribution**: Certain categories dominate sales.

```
-- 4. Sales by product category

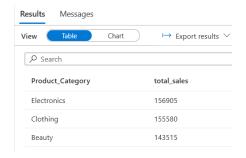
SELECT p.Product_Category, SUM(f.Total_Amount) AS total_sales

FROM dbo.fact_sales f

JOIN dbo.dim_product p ON f.Product_ID = p.Product_ID

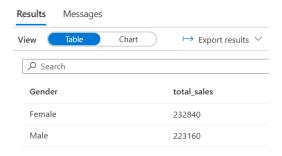
GROUP BY p.Product_Category

ORDER BY total_sales DESC;
```

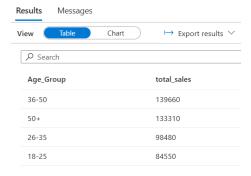


• Customer Segmentation: Spending patterns vary across gender and age groups.

```
-- 5. Sales by gender
SELECT c.Gender, SUM(f.Total_Amount) AS total_sales
FROM dbo.fact_sales f
JOIN dbo.dim_customer c ON f.Customer_ID = c.Customer_ID
GROUP BY c.Gender;
```



```
-- 7. Age group sales contribution
SELECT
    CASE
        WHEN c.Age BETWEEN 18 AND 25 THEN '18-25'
        WHEN c.Age BETWEEN 26 AND 35 THEN '26-35'
        WHEN c.Age BETWEEN 36 AND 50 THEN '36-50'
        ELSE '50+'
    END AS Age Group,
    SUM(f.Total_Amount) AS total_sales
FROM dbo.fact sales f
JOIN dbo.dim_customer c ON f.Customer_ID = c.Customer_ID
GROUP BY CASE
        WHEN c.Age BETWEEN 18 AND 25 THEN '18-25'
        WHEN c.Age BETWEEN 26 AND 35 THEN '26-35'
        WHEN c.Age BETWEEN 36 AND 50 THEN '36-50'
        ELSE '50+'
    END
ORDER BY total_sales DESC;
```



• **Revenue Trends Over Time**: Sales volume shows monthly variations, enabling time-series analysis.

```
-- 6. Sales trend by month (quick time sanity check)

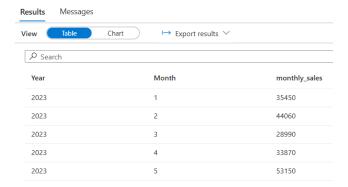
SELECT d.Year, d.Month, SUM(f.Total_Amount) AS monthly_sales

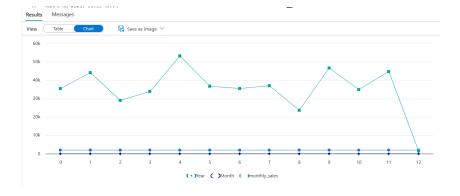
FROM dbo.fact_sales f

JOIN dbo.dim_date d ON f.Date_ID = d.Date_ID

GROUP BY d.Year, d.Month

ORDER BY d.Year, d.Month;
```





# **5. CONCLUSION**

The project successfully delivered:

- Automated ETL pipelines (ADF orchestrated).
- Scalable data transformations (Databricks PySpark).
- Optimized loading into a **Synapse star schema** (fact + dimensions).
- Validation queries confirming data integrity and usability for analytics.

This system is now **analytics-ready**, with potential for Power BI integration to deliver dashboards and business reporting.