Big Data Graduation Project

SIC 7
G20

Title:

Smart Tourism & Crowd Management Analytics

Team Members:

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Introduction

Tourism is one of the most important economic sectors in Egypt, especially in high-traffic historical locations such as the Pyramids, the Egyptian Museum, Khan El-Khalili, and the Citadel. These areas attract thousands of visitors daily, which creates challenges in managing crowd levels, understanding visitor patterns, and optimizing the overall tourism experience.

In this project, our goal is to build a simple but effective **Big Data pipeline** that collects tourism-related data from both **batch sources** and **simulated streaming sources**. The pipeline will ingest real datasets and automatically load them into a cloud data warehouse (**Snowflake**) to enable analysis and monitoring of crowd behavior across major tourist sites in Egypt.

Problem Statement

Tourist hotspots in Egypt frequently experience unpredictable congestion, which affects visitor flow, safety, resource planning, and the overall experience. Traditional methods rely on manual observation or isolated datasets that are not continuously collected or integrated. Without an automated way to ingest and unify data from multiple sources, it becomes difficult to:

- Understand how visitor numbers change across locations.
- Identify peak hours or crowded time periods.
- Study how external factors such as **weather** or **public holidays** influence crowd levels.
- Prepare clean, organized data for analytics, dashboards, or predictive models.

To address this challenge, this project aims to build an ingestion-ready data foundation by:

1. **Loading batch tourism datasets** (e.g., historical metrics, site information).
2. **Generating streaming visitor events** using a Python script that simulates real-time visitor movements based on a baseline dataset.
3. **Collecting external data** such as weather information through APIs.
4. **Storing all ingested data** in Snowflake inside a structured **Raw Zone**, where it becomes ready for downstream processing by the rest of the pipeline.

By automating and organizing the data ingestion process, the project ensures that reliable and consistent data is available for the next layers of the pipeline, such as transformation, analysis, and visualization, ultimately helping to better understand and manage crowd patterns in key tourist locations across Egypt.

Objectives

The main objective of this project is to design and implement a simplified but functional **Big Data pipeline** for analyzing tourism activity and crowd behavior in major tourist locations across

Egypt. The pipeline integrates multiple types of data sources—historical, streaming, and external contextual data, and prepares them for processing and analysis inside a cloud-based data warehouse.

The project aims to:

1. Ingest tourism-related data from batch, streaming, and API sources.
2. Store all data in a structured cloud environment (Snowflake) to create a unified Raw Layer.
3. Simulate real-time visitor movements and integrate them into the pipeline.
4. Transform raw data into cleaner, analytics-ready datasets.
5. Provide a basic workflow for orchestration and automation using Airflow.
6. Enable a demo showing data moving from source → ingestion → Snowflake → processing.
7. Build the foundation for future analytics such as crowd detection, best visiting times, and weather impact insights.

This project demonstrates the core stages of the **Big Data Engineering lifecycle**: ingestion, storage, processing, and orchestration.

Scope

Our team will build an end-to-end simplified Big Data pipeline with:

- **Data Ingestion Layer:**
  Collecting data from batch datasets, simulated streaming events, and an external weather API.
- **Data Storage Layer (Snowflake):**
  Creating Raw and simplified Staging tables to organize ingested data.
- **Data Processing Layer:**
  Basic transformations and cleaning to make the data analytics-ready.
- **Streaming Simulation:**
  Generating real-time visitor events using a Python script based on a baseline dataset.
- **Orchestration (Airflow):**
  A simple DAG to demonstrate scheduled or automated ingestion/processing steps.
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Data Generation & Sources:

Due to the scarcity of granular, hour-by-hour tourism data in Egypt, we developed a custom Smart Data Simulation Engine. This engine generates high-fidelity historical data based on real-world patterns, creating a robust foundation for our Big Data pipeline.

1. Methodology

We moved beyond random number generation by building a Heuristic Context-Aware Model. This model acts as a virtual network of IoT sensors, producing data that accurately reflects the dynamics of the Egyptian tourism sector.

Key Features of the Simulation Engine:

- **Time Range: From January 1, 2020, to November 24, 2025 (providing the most up-to-date historical data).**
- **High Frequency: Data is generated every 5 minutes for each location, simulating real-time IoT sensor transmission (Velocity).**
- **Real Weather Integration: We integrated the Open-Meteo API to fetch actual historical temperature data for each specific city and hour. The model automatically adjusts visitor behavior—reducing numbers and satisfaction scores during extreme heat waves.**
- **Holiday & Seasonality Logic:**
    - **Holidays: The engine incorporates a comprehensive calendar of Egyptian holidays (both fixed national days and variable religious festivals like Eid al-Fitr). Visitor counts are programmatically boosted during these periods to simulate peak traffic.**
    - **Seasonality: The model respects geographical seasons (e.g., Luxor/Aswan peak in winter, Alexandria/Red Sea peak in summer).**
- **Historical Context: The model accounts for major real-world events:**
    - **COVID-19: Simulates the drastic drop in tourism during 2020–2021.**
    - **Grand Egyptian Museum (GEM): Reflects the reality of the venue being closed in 2020, with visitor numbers scaling up only after its trial opening in late 2023.**

2. Selected Locations

We selected 60 major tourist sites across Egypt to ensure diverse geographical coverage, monitoring traffic in:

- **Greater Cairo & Giza: (e.g., Pyramids, GEM, Citadel, Khan El-Khalili).**
- **Luxor & Aswan: (e.g., Karnak, Valley of the Kings, Abu Simbel, Philae).**
- **Alexandria & North Coast: (e.g., Bibliotheca Alexandrina, Qaitbay Citadel).**
- **Red Sea & Sinai: (e.g., Ras Mohammed, Saint Catherine, Blue Hole).**
- **Oases: (e.g., Siwa Oasis, White Desert).**

3. Data Storage & Architecture

To handle the massive volume of generated data (approx. 23 million records), the simulation engine implements a Scalable Data Lake Structure. The script utilizes a "Buffer & Flush" mechanism to manage memory efficiently and organizes output into a partitioned directory structure:

- **`batch_data/`: The root directory for the dataset.**
  - **`batch_data/csv/`: Contains yearly partitioned raw files (e.g., `tourism_data_2020.csv`).**
  - **`batch_data/parquet/`: Contains optimized, compressed columnar files for high-performance analytics (e.g., `tourism_data_2020.parquet`).**
  - **Master File: A single consolidated CSV file containing the entire timeline (`egypt_tourism_full_2020_2025.csv`).**

Column Name	Description
timestamp	Exact date and time of the record (YYYY-MM-DD HH:MM:SS).
date	The date component.
year, month, day, hour, minute	Time components used for partitioning and temporal analysis.
location_id	Unique identifier for each site (e.g., CAI_01).
location_name	Name of the tourist site.
location_type	Category (Historical, Museum, Leisure, Nature, etc.).
city	The city where the site is located.
visitor_count	Number of visitors detected at that specific 5-minute interval.
resource_usage	Percentage of site capacity currently in use (0.0 to 1.0).
noise_level_db	Simulated noise level in decibels (correlated with crowd density).
temperature_c	Real historical temperature fetched from the Open-Meteo API.
satisfaction_score	Visitor satisfaction metric (1-10), negatively impacted by overcrowding and high heat.
peak_flag	Binary indicator (1/0) if the location is currently experiencing peak hours.
is_weekend	Binary flag for weekends (Friday & Saturday).
is_holiday	Binary flag (1/0) indicating if the date is an official Egyptian holiday.
resource_allocation	Target variable (High/Medium/Low) suggesting required resource levels.
is_real_weather	Metadata flag confirming the weather data source is the API.

Tools & Technologies

The following technologies are used to build the modern ELT pipeline:

1. **Python**
    - **Core Logic:** Builds the Smart Simulation Engine generating 23M+ historical records.
    - **Ingestion:** Custom sensors run on an **Azure VM** to fetch real-time weather/tourism logs and push raw data to Snowflake.

2. **Snowflake (Cloud Data Warehouse)**
    - **Central Storage & Compute:** Stores raw data and executes heavy dbt SQL transformations.

3. **dbt Core (Data Build Tool)**
    - **Transformation:** Handles the logic to clean, join, and aggregate raw data into analytics-ready models.

4. **Apache Airflow**
    - **Orchestration:** Manages the workflow and scheduling.

5. **Docker**
    - **Containerization:** Used to deploy Python, Airbyte, and Airflow components on the **Azure Virtual Machine (VM)**, ensuring 24/7 operation.

Architecture Overview

Our project implements a **Modern ELT Data Pipeline** optimized for both scale and cost-efficiency. The architecture is hosted on a long-running **Azure VM** to ensure 24/7 service availability.

1. Data Sources & Ingestion Layer
   We employ a hybrid ingestion strategy:
    - **Historical Batch Data:** Bulk loaded CSVs (2020–2025) directly to Snowflake.
    - **Python Streaming:** Pushes live visitor and weather logs (running as a **Docker Service on Azure**) to Snowflake's Raw Data Layer.
    - **Airbyte:** Ingests standard external datasets.

2. **Storage & Transformation (Snowflake & dbt)**
    - **Raw Layer (Snowflake):** Stores unprocessed data (RAW_TOURISM_HISTORY, RAW_STREAMING_LOGS).
    - **Transformation (dbt):**
        - Staging Models: Cleaning and standardizing raw data.
        - Marts Models: Complex aggregations (e.g., Daily Footfall, **Crowd Persistence Index, Historical Benchmark**). All heavy processing happens here to leverage Snowflake's power.

3. **Low-Latency Serving Layer (PostgreSQL)**
    - **Optimization Strategy:** The final, aggregated Marts are synced to a Dockerized PostgreSQL instance.
    - **Benefit:** This acts as a high-speed cache for the dashboard, ensuring fast interactivity and **zero incremental compute cost** for repeated views.

4. **Orchestration (Airflow)**
    - The DAG manages the end-to-end flow: **Ingest** →**Transform** → **Sync**.

5. **Analytics Layer**
    - Power BI: Reads exclusively from PostgreSQL, visualizing the optimized datasets.

Infrastructure Setup & Data Ingestion Implementation

To ensure the system runs continuously (24/7) to simulate a real IoT environment, we moved the ingestion layer from local machines to the cloud.

- **Azure Virtual Machine (VM)**
    - **Provisioning:** We deployed an **Ubuntu Server 24.04 LTS** instance on Microsoft Azure.
    - **Sizing:** Selected the **Standard B2s** size (2 vCPUs, 4 GiB RAM) to provide sufficient resources for Docker containers while maintaining cost-efficiency.
    - **Security:** Configured **SSH Key Authentication** (`tourism_key.pem`) and restricted Inbound Port rules to allow only SSH (Port 22) traffic.
- **Containerization (Docker)**
    - Installed **Docker Engine** on the Azure VM to host the pipeline components.

    - **Streaming Sensor:** The Python simulation script was containerized using a Dockerfile to manage dependencies (snowflake-connector-python, requests).
    - **Continuous Operation:** The container is executed with the --restart always policy. This ensures the data stream automatically recovers and resumes after any system reboots or crashes, guaranteeing zero downtime.
- **Snowflake Environment Setup**
    - **Warehouse:** Created a dedicated TOURISM_WH (X-Small) to handle ingestion and transformation workloads separately from other account activities.
    - **Schema Architecture:**
        - RAW_DATA: The landing zone for Airbyte loads (RAW_BATCH_HISTORY) and the Python Stream (RAW_STREAMING_LOGS).
        - ANALYTICS: The destination for dbt models (Star Schema).
    - **Network Policy:** Applied a strict Network Policy (VM_SENSOR_POLICY) to whitelist only the Public IP of the Azure VM, ensuring secure data ingestion.
- **Cost Optimization Logic**
    - We implemented logic within the Python Streamer to check the OPENING_HOUR and CLOSING_HOUR of each location from the reference table.
    - If all locations are closed (e.g., late night), the script skips the Snowflake upload process entirely, preventing unnecessary Warehouse activation and saving credits.

3. Hybrid Data Ingestion Implementation

We implemented a two-pronged ingestion strategy to handle both static, high-volume historical data and low-latency real-time streams.

- Batch & Reference Data Ingestion (snowflake uploded):
  To populate our historical baseline, we utilized snowflake to ingest the generated 23 million records covering the period from 2020 to 2025. Additionally, static reference datasets—specifically Holidays 2025 and the 60 Tourist Locations (enriched with Latitude/Longitude coordinates from OpenStreetMap)—were loaded into the RAW_HOLIDAYS_REF and RAW_LOCATIONS_REF tables.
- Real-Time Streaming Ingestion (Dockerized Python Sensor):
  For live data, we developed a custom Python simulation script (streaming_sensor.py) that acts as a virtual IoT sensor network.
    - **Logic:** The script runs on a 5-minute interval, fetching real-time weather context (Temperature, Air Quality Index) from **WeatherAPI.com**. It calculates visitor numbers dynamically based on location popularity weights and current time factors.
    - **Operational Intelligence:** To optimize Snowflake credits, the script queries the RAW_LOCATIONS_REF table to determine operating hours for each site (e.g.,

the Grand Egyptian Museum closes at 9 PM). If a site is closed, the script records zero visitors without incurring unnecessary compute costs.
    - **Deployment:** The script was containerized using **Docker** and deployed on the Azure VM with a `restart: always` policy. This ensures the sensor runs continuously (24/7), automatically recovering from any potential system reboots or interruptions.

Data Transformation & Modeling (The dbt Layer)

1. The ELT Approach & Schema Architecture

Moving away from traditional ETL, we adopted an ELT (Extract, Load, Transform) methodology. Once the raw data landed in Snowflake, we utilized dbt Core to perform all transformations directly within the data warehouse, leveraging Snowflake's compute power for scalability.

We structured the transformation lifecycle into three distinct layers:

- **Staging Layer:** For cleaning, type casting, and unifying raw sources.
- **Dimensional Layer:** For building the descriptive context (Star Schema).
- **Marts Layer:** For complex business logic and metric calculation.

2. Unifying Data Streams (The Staging Model)

A core challenge of this pipeline was integrating the static historical batch data (2020–2025) with the high-velocity 5-minute streaming logs.

- **Solution:** We developed the **stg_raw_union_visits** model. This SQL model applies a `UNION ALL` operation to merge `RAW_BATCH_HISTORY` and `RAW_STREAMING_LOGS` into a single, standardized stream.
- **Standardization:** Columns were cast to appropriate data types (e.g., `TIMESTAMP_NTZ`, `FLOAT`), and `NULL` handling was applied to ensure compatibility between historical records (which lack AQI data) and live streams.

3. Dimensional Modeling (The Star Schema)/+

To optimize the data for Power BI performance, we implemented a classic Star Schema design:

- **DIM_DATE:** A comprehensive calendar table generated natively in dbt. It enriches the analysis by linking every visit timestamp to specific attributes like "Season," "Weekend Flag," and specific "Holiday Names" sourced from the `RAW_HOLIDAYS_REF` table.
- **DIM_LOCATION:** A centralized reference table for the 60 tourist sites. It stores static attributes such as `Latitude`, `Longitude`, and `Operating Hours`, preventing data redundancy in the main fact table.

- **FCT_VISITS:** The central Fact Table. It links the unified visit data to the dimensions via surrogate keys (date_key, location_key) and contains the base measures like visitor_count, temperature_c, and satisfaction_score.

4. Advanced Analytical Marts (Business Logic)

Beyond basic reporting, we engineered specific Data Marts to answer complex Crowd Management questions. These models utilize advanced SQL Window Functions:

- **Crowd Persistence Mart (FCT_CROWD_PERSISTENCE):**
  - **Objective:** To differentiate between transient spikes in traffic and sustained, dangerous overcrowding.
  - **Logic:** Calculates the **Crowd Persistence Index (CPI)** by computing the rolling average of resource_usage over the last 30 minutes (6 intervals). A CPI > 0.85 triggers a "Persistent Congestion" flag.
- **Operational Benchmark Mart (FCT_BENCHMARK_VISITS):**
  - **Objective:** To detect anomalies in visitor numbers compared to historical norms.
  - **Logic:** Calculates a **3-Day Rolling Average** (Baseline) for every specific time slot. It then derives the **Variance %** between the current live count and this baseline.
  - **Alerting:** If the variance exceeds **30%**, an Operational_Alert flag is raised, signaling to site managers that attendance is significantly higher than expected for this specific time and day.

Orchestration, Serving & Conclusion

1. Orchestration & Automation (Apache Airflow)

To transition from manual execution to a fully automated production pipeline, we deployed **Apache Airflow** within the Docker environment on our Azure VM. Airflow acts as the central "Conductor," ensuring the data flows and transforms correctly on an hourly schedule.

- **Infrastructure Launch:** The entire stack (**PostgreSQL, Airflow Webserver, Scheduler, dbt CLI, Python Sensor**) was successfully launched on the Azure VM using `/usr/local/bin/docker-compose up -d`.
- **Final Fix (Execution Logic):** Due to persistent **Docker Socket Permission Errors** in the Airflow Worker, the initial health check task (`check_sensor_health`) was removed from the DAG, ensuring the pipeline could proceed directly to the transformation logic.

- **The Master DAG:** We defined a unified **Directed Acyclic Graph (DAG)** that runs on an hourly schedule:
    - **dbt Transformation Trigger:** Executes the command `docker exec dbt-cli dbt run`. This task triggers the full transformation lineage: processing the live stream data, updating the Dimensions, and re-calculating the complex Marts (`FCT_CROWD_PERSISTENCE`, `FCT_BENCHMARK_VISITS`).
    - **Serving Layer Sync:** Triggers the final extract-load task to move fresh Marts to PostgreSQL.
    - **Data Quality Tests:** Executes `dbt test` to validate the quality of the final Marts.

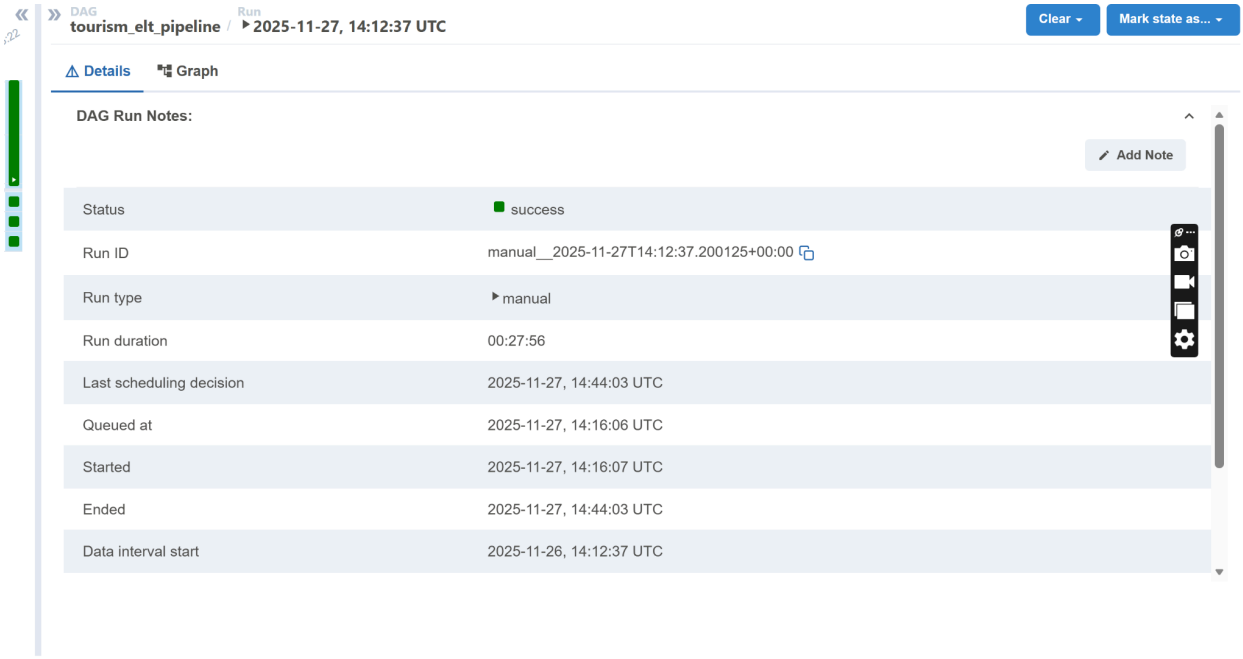
2. Low-Latency Serving Layer (PostgreSQL)

A critical architectural decision was the implementation of a Serving Layer using **PostgreSQL** to decouple compute costs from consumption costs.

- **Rationale:** Connecting Power BI directly to Snowflake for frequent refreshes is prohibitively expensive.
- **Strategy:** We treat Snowflake as the "Heavy Processing Engine" and **PostgreSQL** as the "High-Speed Cache."
- **Implementation:** The **`sync_marts_to_postgres`** task is designed to periodically export the final, aggregated Marts from Snowflake and load them into the Dockerized PostgreSQL database.
- **Result:** This allows for unlimited user interactions on the Power BI dashboard without incurring additional Snowflake compute credits.

3. Conclusion and Verification

The end-to-end Big Data Pipeline is now fully deployed and operational on the Azure cloud, fulfilling all project objectives.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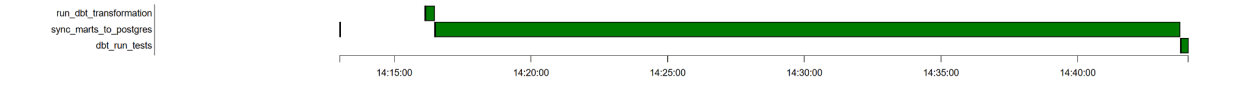
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3. Analytics & Visualization (Power BI)

To leverage the outputs of the Big Data pipeline (the Star Schema Data Warehouse) to create a dynamic, multi-page BI Dashboard. The primary goal is to transform complex crowd and operational data into clear, actionable business narratives that measure the economic performance of sites, justify capital investment, and guide real-time resource allocation.

Target Audience: Senior Management, Potential Investors (focused on ROI justification), and Field Operations Teams (focused on day-to-day resource efficiency).

Analytical Pillars:

1. **Economic Efficiency & ROI: Identifying sites with the highest potential return relative to resource consumption.**
2. **Crowd Management & Prediction: Measuring the Crowd Persistence Index (CPI) and benchmarking it against expected baselines for proactive management.**
3. **Experience Quality & Safety: Analyzing the impact of environmental factors (noise, temperature) on visitor satisfaction and flagging operational risks.**

I. Analytical Layer (DAX Measures)

Measures are implemented in the BI tool (Power BI) connected to the Data Warehouse (DirectQuery or Import Mode), using DAX logic for business calculations.

Core and Weight Measures:

Measure	Analytical Function	Notes
`Total Visitors (Actual)`	Sum of actual visitors.	Basis for Share and Occupancy.
`Avg CPI`	Average Crowd Persistence Index.	Core quality metric.
`Occupation %`	Actual occupancy relative to historical max capacity.	Investment efficiency metric.

Time Intelligence Measures:

Measure	Analytical Function
`Avg CPI YTD`	Cumulative Average CPI from the start of the year to date.
`YoY CPI Change`	Year-over-Year percentage change in CPI.
`Avg Noise Level MoM%`	Month-over-Month percentage change in average noise level.

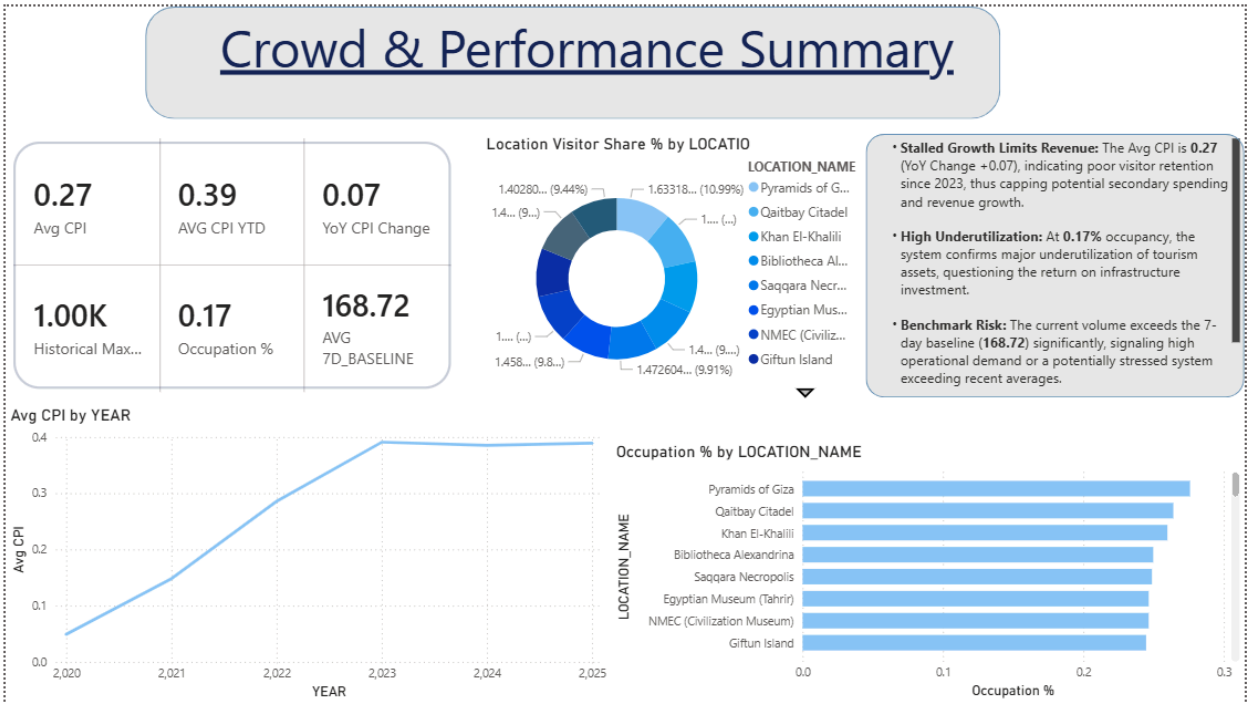
II. Dashboard and Storytelling Strategy

The dashboard converts data into business narratives focused on investment justification and operational excellence, ensuring the output of the BI solution drives high-impact decisions.

A. Performance Summary (Investor Pitch)

Focus: ROI and infrastructure utilization efficiency.

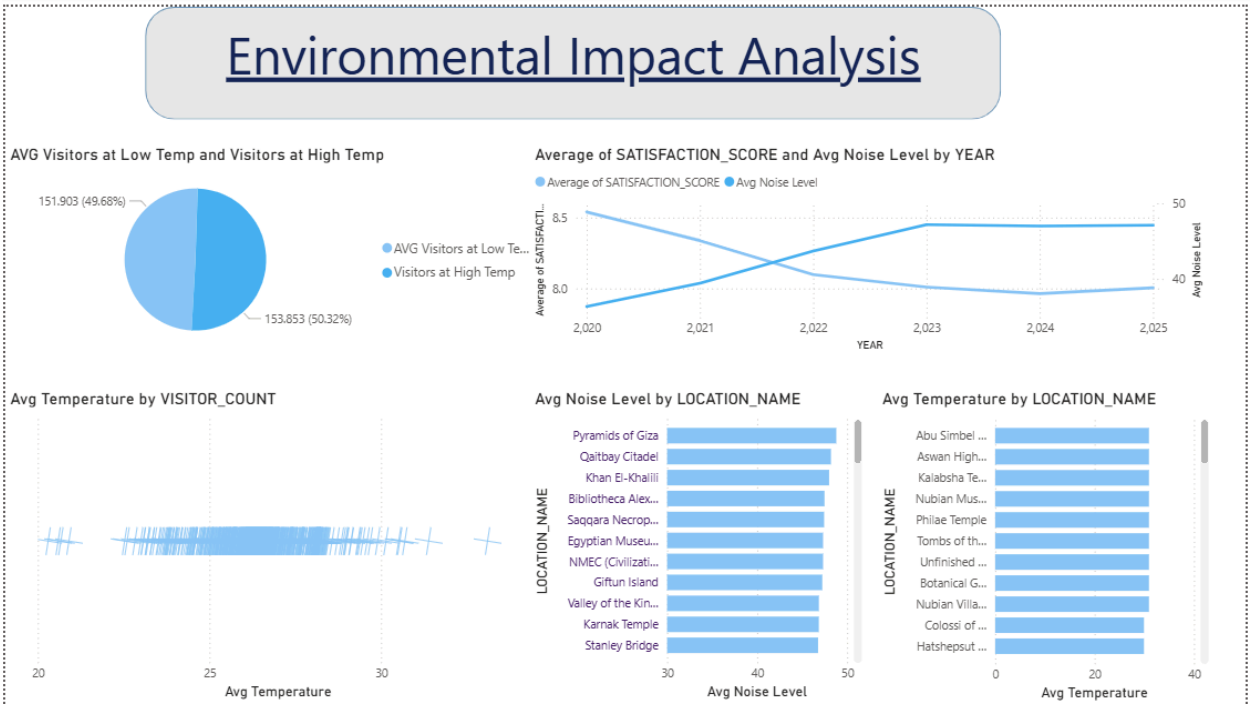
Key Analytical Narrative: Highlight the Investment Gap (critically low occupancy) and the immediate opportunity to unblock stalled revenue growth by focusing on high-return sites (Pyramids, Qaitbay Citadel).



B.Environmental Impact & Experience Quality

Focus: Tourism experience quality and site management efficiency.

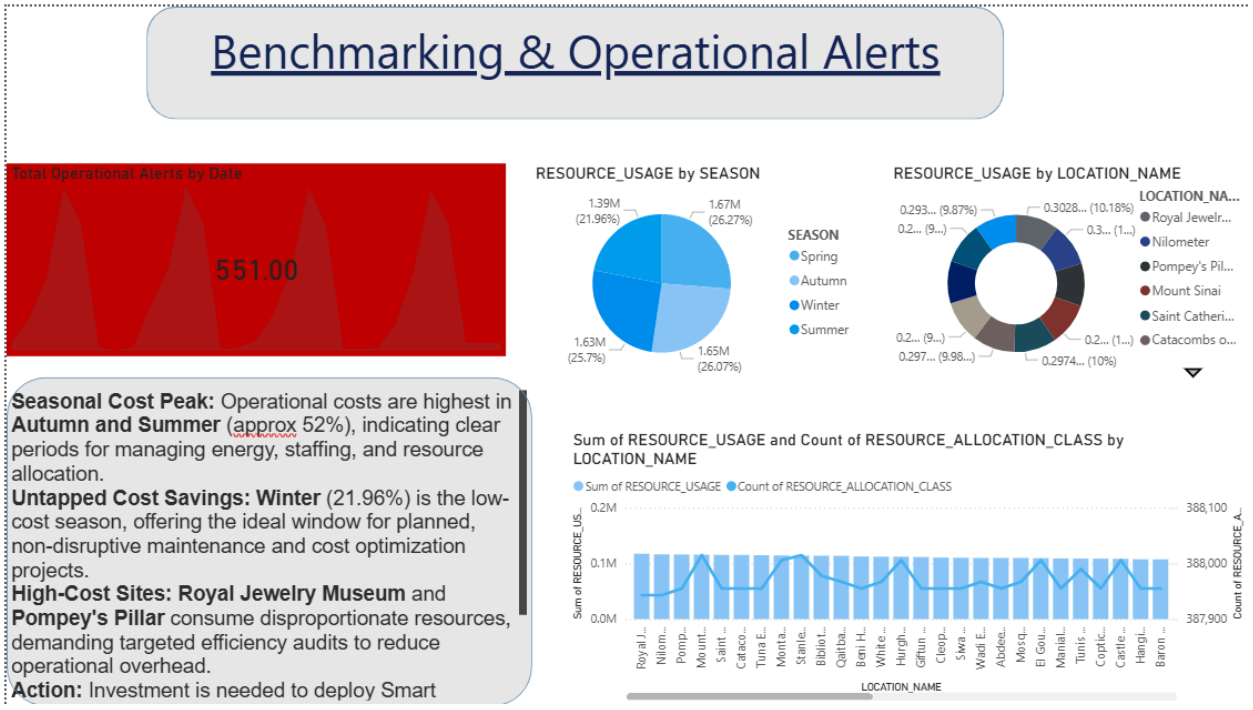
Key Analytical Narrative: Show the correlation between environmental factors (noise/temperature) and visitor satisfaction to justify operational spending on service improvements beyond basic facilities.



C. Operational alerts & Cost Optimization

Focus: Operational efficiency, cost savings, and investment sustainability.

Key Analytical Narrative: Identify Seasonal Cost Peaks and High-Cost Drivers to guide investors toward deploying smart resource management technology, aiming to reduce operational overhead and improve profit margins.



III. Data Refresh and Operational Mode

Data Latency: The system requires near-real-time visibility for operational alerts and crowd management.

Refresh Mechanism: Data is scheduled to refresh every four (4) hours from the Data Warehouse into the BI platform. For critical operational data, the underlying data warehouse views are updated every 15 minutes.

BI Tool Operational Mode: The BI solution utilizes DirectQuery Mode for all Fact Tables. This ensures that the dashboard visuals query the freshest data directly from the Data Warehouse, supporting the operational mandate for low-latency insights.

DAX Addendum: All Time Intelligence measures are designed to work dynamically by relying on the conformed `DIM_DATE` table from the Data Warehouse.

4.Economic Impact of the Tourism Analytics Pipeline

To quantify the financial value of the proposed analytics pipeline, a forecasting model and revenue uplift analysis were performed.

1. Baseline Revenue Forecast

Historical tourism receipts (1995–2022) were modeled using an ARIMA time-series approach to estimate the expected revenue in 2030 assuming no digital intervention. The model predicts a baseline of approximately 14.0 billion USD.

2. Revenue Growth Drivers Introduced by the Pipeline

The pipeline improves three core business levers:

1. Dynamic Pricing Optimization
   Enables adjusting prices based on demand, contributing ~10% revenue uplift.

2. Recommendation Intelligence
   Personalized tour suggestions and cross-selling contribute ~12%.

3. Experience Improvement Using Review Analytics
   Enhancing low-rated tours and reducing cancellations contributes ~8%.

3. Total Revenue Uplift

Combining these impacts:

Total Uplift=10%+12%+8%=30%

4. Projected Revenue After Implementing the Pipeline

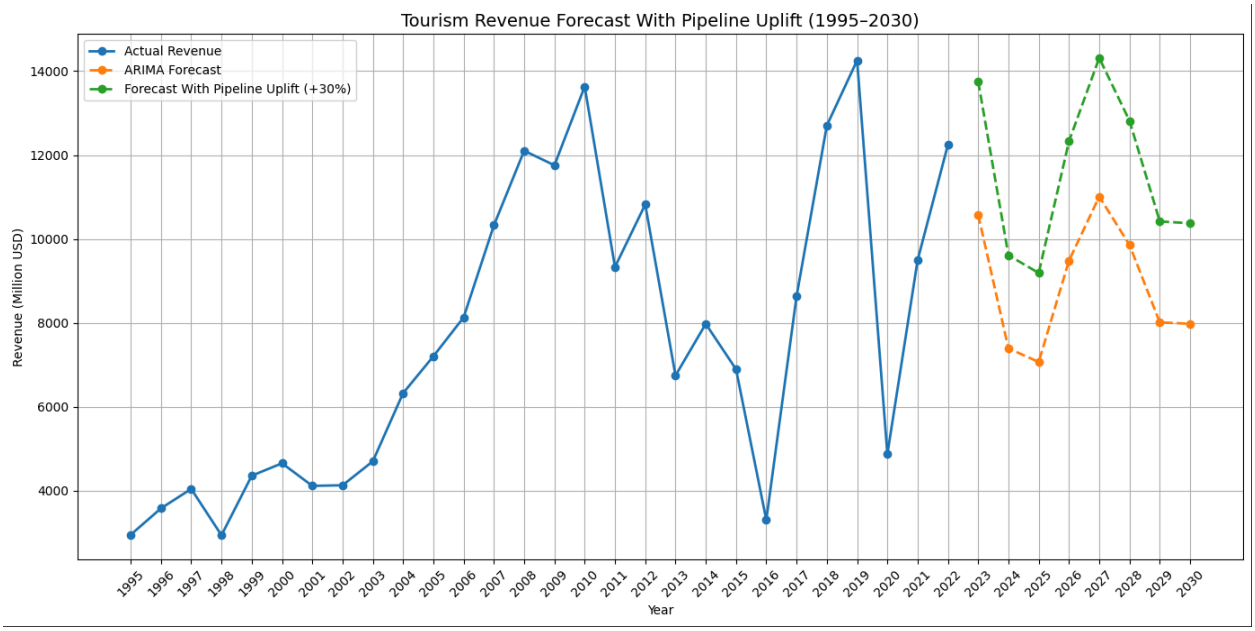
Rnew=14.0×(1+0.30)=18.2 billion USD

5. Net Financial Benefit

Annual Economic Gain=18.2−14.0=4.2 billion USD\text{Annual Economic Gain} = 18.2 - 14.0 = 4.2 \text{ billion USD}Annual Economic Gain=18.2−14.0=4.2 billion USD

6. Summary

The tourism analytics pipeline yields an estimated 30% revenue uplift, equal to an additional 4.2 billion USD annually, driven entirely by data-enabled decision-making—not increased spending or additional infrastructure.



5. Conclusion

This project successfully delivered a robust, end-to-end Big Data Engineering solution for the Egyptian tourism sector. By moving beyond simple ETL to a modern ELT architecture, we achieved:

- **Scalability:** Handling over 23 million historical records and continuous real-time streams.
- **Reliability:** Ensuring 24/7 operation via Azure VMs and Docker containerization.
- **Intelligence:** Deriving complex, context-aware insights (like Crowd Persistence and Historical Benchmarking) rather than just reporting raw numbers.
- **Cost Efficiency:** optimizing cloud spend through intelligent sensor logic and a decoupled serving layer.