Healthcare Patient Analytics & ETL Star Schema Report

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1. Generating and Loading CSV Data

I started by generating synthetic data for six main entities:

- **Patients** (patient demographics)
- **Doctors** (doctor details)
- **Admissions** (patient admissions)
- **Vitals** (patient vitals during hospital stays)
- **Treatments** (treatments and medications)
- Readmission_Risk (predicted readmission risk)

To ensure adequate variety, I created **at least 10 rows** per table. For example, in the **Patients** table, I randomly generated first names, last names, dates of birth, and phone numbers. In the **Doctors** table, I randomly generated specialties and contact numbers. Here is a **Python code snippet** showing how I generated some of the sample data:

```
import names
```

```
def random_date(start_year=2020, end_year=2025):
    """Generate a random date between start year and end year."""
    start date = datetime(start_year, 1, 1)
    end date = datetime(end year, 12, 31)
    delta = end_date - start_date
    random days = random.randrange(delta.days)
    return start_date + timedelta(days=random_days)
def random_phone():
    """Generate a random 10-digit phone number as a string."""
    return str(random.randint(10**9, 10**10 - 1))
def random diagnosis():
    return random.choice(["Pneumonia", "Hypertension", "Asthma Attack", "Diabetes
Complications", "Heart Failure", "Sepsis", "Kidney Stones", "Migraine", "COVID-19",
"Fracture"])
def random_specialization():
    return random.choice(["Cardiologist", "Pulmonologist", "General Physician",
"Neurologist", "Orthopedic", "Endocrinologist", "Gastroenterologist"])
def random_chronic_condition():
    return random.choice(["None", "Hypertension", "Asthma", "Diabetes", "Heart Disease",
"None", "None"])
# 1.1 Patients (>= 10 rows)
num patients = 10
patient_ids = list(range(101, 101 + num_patients))
patients data = []
for pid in patient ids:
    patients_data.append([
        pid,
        names.get first name(),
        names.get_last_name(),
```

```
random_date(1950, 2000).date(), # dob
        random.choice(["Male", "Female"]),
        random phone(),
        f"{random.randint(100,999)} Main St",
        random_chronic_condition()
    ])
patients df = pd.DataFrame(patients data, columns=[
    "patient_id", "first_name", "last_name", "dob", "gender", "contact_no", "address",
"chronic conditions"
1)
# 1.2 Doctors (>= 10 rows)
num doctors = 10
doctor_ids = list(range(301, 301 + num_doctors))
doctors_data = []
for did in doctor ids:
    doctors_data.append([
        did.
        names.get_first_name(),
        names.get_last_name(),
        random specialization(),
        random_phone()
    ])
doctors_df = pd.DataFrame(doctors_data, columns=[
    "doctor id", "first name", "last name", "specialization", "contact no"
])
# 1.3 Admissions (>= 10 rows)
# We will ensure each admission references an existing patient & doctor
num admissions = 10
admission ids = list(range(2001, 2001 + num admissions))
admissions data = []
for aid in admission ids:
    patient id = random.choice(patient ids)
    doctor_id = random.choice(doctor_ids)
    admission date = random date(2024, 2025)
    # Some admissions have not been discharged yet
    discharge_date = admission_date + timedelta(days=random.randint(1, 10)) if
random.random() > 0.3 else None
    diagnosis = random diagnosis()
    room no =
random.choice(["A101","A102","B210","C305","B405","ICU1","ICU2","D110","D120","E201"])
    admissions data.append([
        aid, patient_id, admission_date.date(),
        discharge_date.date() if discharge_date else None,
        diagnosis, doctor_id, room_no
    1)
admissions_df = pd.DataFrame(admissions_data, columns=[
    "admission_id", "patient_id", "admission_date", "discharge_date",
    "diagnosis", "doctor_id", "room_no"
])
```

```
# 1.4 Vitals (>= 10 rows)
# Each vitals row references an existing admission
num_vitals = 10
vital ids = list(range(5001, 5001 + num vitals))
vitals_data = []
for vid in vital ids:
   admission id = random.choice(admission ids)
   # Just pick a random time near the admission date
   base_date = admissions_df.loc[admissions_df['admission_id'] == admission_id,
'admission_date'].values[0]
   # Convert base date to datetime
   base datetime = pd.to datetime(base date)
   recorded time = base datetime + timedelta(hours=random.randint(0, 100))
   heart rate = random.randint(60, 120)
   bp systolic = random.randint(100, 160)
   bp_diastolic = random.randint(70, 100)
   blood_pressure = f"{bp_systolic}/{bp_diastolic}"
   oxygen level = random.randint(88, 100)
   temperature = round(random.uniform(97.0, 103.0), 1)
   vitals data.append([
       vid, admission_id, recorded_time, heart_rate, blood_pressure, oxygen_level,
temperature
   1)
vitals df = pd.DataFrame(vitals data, columns=[
    "vital id", "admission id", "recorded time", "heart rate",
   "blood_pressure", "oxygen_level", "temperature"
1)
# 1.5 Treatments (>= 10 rows)
num treatments = 10
treatment_ids = list(range(7001, 7001 + num_treatments))
treatments_data = []
possible_meds = ["Amoxicillin 500mg", "Prednisone 10mg", "Metoprolol 50mg", "Ibuprofen
400mg",
                "Acetaminophen 500mg", "Atorvastatin 20mg", "Insulin 10units"]
for tid in treatment ids:
   admission id = random.choice(admission ids)
   # approximate date of treatment around admission_date
   base date = admissions df.loc[admissions df['admission id'] == admission id,
'admission_date'].values[0]
   base datetime = pd.to_datetime(base_date)
   treat date = base datetime + timedelta(days=random.randint(∅, 5))
   procedure = random.choice(possible procedures)
   medication = random.choice(possible meds)
   dosage = random.choice(["1x daily", "2x daily", "3x daily", "As needed"])
   treatments data.append([
       tid, admission_id, treat_date.date(), procedure, medication, dosage
   1)
treatments df = pd.DataFrame(treatments data, columns=[
    "treatment_id", "admission_id", "treatment_date", "procedure", "medication", "dosage"
])
```

```
# 1.6 Readmission Risk (>= 10 rows)
# We'll keep a 1-to-1 relationship with admissions for demonstration
risk ids = list(range(9001, 9001 + num admissions))
risk data = []
for i, aid in enumerate(admission ids):
    pred_date = admissions_df.loc[admissions_df['admission_id'] == aid,
'admission date'].values[0]
    pred date = pd.to datetime(pred date) + timedelta(days=random.randint(0,2))
    risk score = round(random.uniform(0.2, 0.9), 2)
    if risk score < 0.4:</pre>
        risk_level = "Low"
    elif risk_score < 0.7:</pre>
        risk_level = "Medium"
    else:
        risk level = "High"
    risk data.append([
        risk_ids[i], aid, pred_date.date(), risk_score, risk_level
    1)
risk_df = pd.DataFrame(risk_data, columns=[
    "risk id", "admission id", "prediction date", "risk score", "risk level"
])
Each DataFrame was then written out to a CSV file:
patients_df.to_csv("patients.csv", index=False)
doctors_df.to_csv("doctors.csv", index=False)
admissions_df.to_csv("admissions.csv", index=False)
vitals_df.to_csv("vitals.csv", index=False)
treatments df.to csv("treatments.csv", index=False)
risk_df.to_csv("readmission_risk.csv", index=False)
print("Sample CSV files created with >= 10 rows each.")
```

2. Reading the CSV Files into Pandas

After generating the CSV files, I **extracted** the data into Pandas DataFrames. I used the following code to read each CSV:

```
patients = pd.read_csv("patients.csv", parse_dates=["dob"])
doctors = pd.read_csv("doctors.csv")
admissions = pd.read_csv("admissions.csv", parse_dates=["admission_date",
    "discharge_date"])
vitals = pd.read_csv("vitals.csv", parse_dates=["recorded_time"])
treatments = pd.read_csv("treatments.csv", parse_dates=["treatment_date"])
readmission_risk = pd.read_csv("readmission_risk.csv", parse_dates=["prediction_date"])
```

I parsed date columns such as dob, admission_date, discharge_date, and recorded_time to ensure they were stored in proper date/datetime formats.

3. Data Cleaning and Quality Checks

3.1 Primary Key Uniqueness

I verified that the **primary keys** (e.g., patient_id, doctor_id, admission_id) were unique within their respective DataFrames. If duplicates existed, I dropped them:

```
def check_and_drop_duplicates(df, pk_col, table_name):
    dup_count = df.duplicated(subset=[pk_col]).sum()
    if dup_count > 0:
        print(f"{table_name}: Dropping {dup_count} duplicate rows based on primary key
{pk_col}.")
        df = df.drop_duplicates(subset=[pk_col])
        return df

patients = check_and_drop_duplicates(patients, "patient_id", "Patients")
doctors = check_and_drop_duplicates(doctors, "doctor_id", "Doctors")
admissions = check_and_drop_duplicates(admissions, "admission_id", "Admissions")
vitals = check_and_drop_duplicates(vitals, "vital_id", "Vitals")
treatments = check_and_drop_duplicates(treatments, "treatment_id", "Treatments")
readmission_risk = check_and_drop_duplicates(readmission_risk, "risk_id",
"Readmission_Risk")
```

3.2 Not-Null Checks

Certain columns, such as first_name, last_name, admission_date, diagnosis, etc., are **NOT NULL** in the conceptual design. I dropped rows that had missing values in these columns:

```
def drop_missing_required(df, required_cols, table_name):
    missing mask = df[required cols].isnull().any(axis=1)
    missing count = missing mask.sum()
    if missing count > 0:
        print(f"{table name}: Dropping {missing count} rows with missing data in required
columns {required_cols}.")
        df = df[~missing mask]
    return df
patients = drop_missing_required(patients, ["patient_id", "first_name", "last_name",
"dob", "gender", "contact_no"], "Patients")
doctors = drop_missing_required(doctors, ["doctor_id", "first_name", "last_name",
"specialization", "contact_no"], "Doctors")
admissions = drop_missing_required(admissions, ["admission_id", "patient_id",
"admission_date", "diagnosis", "doctor_id"], "Admissions")
vitals = drop_missing_required(vitals, ["vital_id", "admission_id", "recorded_time",
"heart_rate", "blood_pressure", "oxygen_level", "temperature"], "Vitals")
treatments = drop_missing_required(treatments, ["treatment_id", "admission id",
"treatment_date", "medication"], "Treatments")
readmission_risk = drop_missing_required(readmission_risk, ["risk_id", "admission_id",
"prediction_date", "risk_score", "risk_level"], "Readmission_Risk")
```

3.3 Foreign Key Validation

I also enforced **foreign key constraints** to ensure that, for instance, every admission referenced a valid patient_id and doctor_id. Rows with invalid references were dropped:

```
# Admissions -> Patients
invalid pat fk = ~admissions['patient id'].isin(patients['patient id'])
if invalid pat fk.sum() > 0:
    print(f"Admissions: Dropping {invalid pat fk.sum()} rows with invalid patient id.")
    admissions = admissions[~invalid pat fk]
# Admissions -> Doctors
invalid doc fk = ~admissions['doctor id'].isin(doctors['doctor id'])
if invalid doc fk.sum() > 0:
    print(f"Admissions: Dropping {invalid_doc_fk.sum()} rows with invalid doctor_id.")
    admissions = admissions[~invalid doc fk]
# Vitals -> Admissions
invalid adm fk v = ~vitals['admission id'].isin(admissions['admission id'])
if invalid adm fk v.sum() > 0:
    print(f"Vitals: Dropping {invalid_adm_fk_v.sum()} rows with invalid admission id.")
    vitals = vitals[~invalid adm fk v]
# Treatments -> Admissions
invalid_adm_fk_t = ~treatments['admission_id'].isin(admissions['admission_id'])
if invalid adm fk t.sum() > 0:
    print(f"Treatments: Dropping {invalid adm fk t.sum()} rows with invalid
admission id.")
    treatments = treatments[~invalid adm fk t]
# Readmission Risk -> Admissions
invalid adm fk r = ~readmission risk['admission id'].isin(admissions['admission id'])
if invalid adm fk r.sum() > 0:
    print(f"Readmission_Risk: Dropping {invalid_adm_fk r.sum()} rows with invalid
admission id.")
    readmission_risk = readmission_risk[~invalid_adm_fk_r]
print("Data cleaning & validation complete.")
4. Star Schema Construction
4.1 Dimension Tables with Surrogate Keys
I created two dimension tables: dim_patients and dim_doctors. Rather than using the natural IDs
```

I created two dimension tables: **dim_patients** and **dim_doctors**. Rather than using the natural IDs (patient_id, doctor_id) as the primary keys, I introduced **surrogate keys** (patient_key, doctor_key). This approach is beneficial for slowly changing dimensions and ensures consistent referencing over time.

4.2 Fact Tables

1. **FactAdmissions**: I merged the **Admissions** table with the **Readmission_Risk** table. This single table contains columns such as admission_date, discharge_date, diagnosis, plus risk_score and risk_level. I then replaced patient_id and doctor_id with the new surrogate keys from dim_patients and dim_doctors.

- 2. **FactVitals**: Stores vitals for each admission (heart_rate, blood_pressure, etc.), keyed by admission id.
- 3. **FactTreatments**: Stores treatment and medication data for each admission, also keyed by admission id.

5. Loading the Data into MySQL

Finally, I **loaded** the dimension and fact tables into MySQL using **SQLAlchemy**. Below is an example of how I wrote each table to the database:

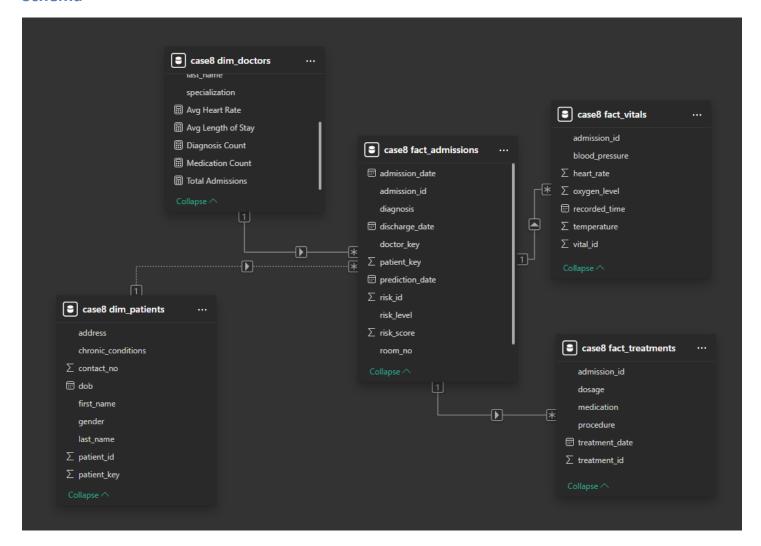
```
username = 'root'
password = '12345'
host = 'localhost'
port = '3306'
database = 'case8'
engine = create_engine(f"mysql+pymysql://{username}:{password}@{host}:{port}/{database}")

dim_patients.to_sql('dim_patients', engine, if_exists='replace', index=False)
dim_doctors.to_sql('dim_doctors', engine, if_exists='replace', index=False)
fact_admissions.to_sql('fact_admissions', engine, if_exists='replace', index=False)
fact_vitals.to_sql('fact_vitals', engine, if_exists='replace', index=False)
fact_treatments.to_sql('fact_treatments', engine, if_exists='replace', index=False)

print("Data successfully loaded to MySQL with improved star schema.")
```

This finalizes the **ETL pipeline**. At this point, I can connect **Power BI** (or any other BI tool) to the case8 MySQL database and begin constructing dashboards and analytics.

Schema



6. PowerBI Report

All Data is self generated so creating report is unnessesary

7. Example SQL Queries for Analytics

Once the data is in MySQL, I can run queries such as:

```
Admissions by Day
SELECT

DATE(admission_date) AS admission_day,
COUNT(*) AS total_admissions
FROM fact_admissions
GROUP BY DATE(admission_date)
ORDER BY admission_day;
```

	admission_day	total_admissions
•	2024-01-14	1
	2024-01-15	1
	2024-05-30	1
	2024-06-28	2
	2024-11-06	1
	2025-03-10	1
	2025-04-09	1
	2025-06-16	1
	2025-10-09	1

Average Risk Score by Diagnosis

SELECT

diagnosis,
 AVG(risk_score) AS avg_risk
FROM fact_admissions
WHERE risk_score IS NOT NULL
GROUP BY diagnosis
ORDER BY avg_risk DESC;

		_
	diagnosis	avg_risk
•	Asthma Attack	0.855
	Pneumonia	0.68
	Heart Failure	0.585
	Diabetes Complications	0.54
	Hypertension	0.505
	Kidney Stones	0.48
	COVID-19	0.27

Most Common Diagnoses

SELECT

diagnosis,
 COUNT(*) AS diagnosis_count
FROM fact_admissions
GROUP BY diagnosis
ORDER BY diagnosis_count DESC
LIMIT 5;

	diagnosis	diagnosis_count
•	Hypertension	2
	Asthma Attack	2
	Heart Failure	2
	Kidney Stones	1
	Diabetes Complications	1

Average Length of Stay by Diagnosis

SELECT

```
diagnosis,
   AVG(DATEDIFF(discharge_date, admission_date)) AS avg_length_of_stay
FROM fact_admissions
WHERE discharge_date IS NOT NULL
GROUP BY diagnosis
ORDER BY avg_length_of_stay DESC;
```

	diagnosis	avg_length_of_stay
•	Pneumonia	8.0000
	Hypertension	5.5000
	Asthma Attack	4.5000
	COVID-19	2.0000
	Kidney Stones	1.0000
	Heart Failure	1.0000

Most Frequently Prescribed Medications

SELECT

medication,
 COUNT(*) AS usage_count
FROM fact_treatments
GROUP BY medication
ORDER BY usage_count DESC
LIMIT 5;

	medication	usage_count
•	Prednisone 10mg	2
	Metoprolol 50mg	2
	Amoxicillin 500mg	2
	Ibuprofen 400mg	2
	Atorvastatin 20mg	1

Average Heart Rate by Diagnosis

SELECT

fa.diagnosis,
 AVG(fv.heart_rate) AS avg_heart_rate
FROM fact_admissions AS fa
JOIN fact_vitals AS fv
 ON fa.admission_id = fv.admission_id
GROUP BY fa.diagnosis
ORDER BY avg_heart_rate DESC;

	diagnosis	avg_heart_rate
•	COVID-19	111.0000
	Heart Failure	111.0000
	Pneumonia	94.0000
	Diabetes Complications	90.0000
	Hypertension	84.5000
	Asthma Attack	74.5000
	Kidney Stones	72.0000

Conclusion

No conclusion because data is all self generated.