```
!pip install duckdb
!pip install matplotlib
!pip install seaborn
```

```
Collecting duckdb
  Downloading duckdb-1.2.2-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (966 bytes)
Downloading duckdb-1.2.2-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (20.2 MB)
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atplotlib
  Downloading matplotlib-3.10.3-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (11 kB)
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  Downloading contourpy-1.3.2-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (5.5 kB)
Collecting cycler>=0.10 (from matplotlib)
  Downloading cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
Collecting fonttools>=4.22.0 (from matplotlib)
  Downloading fonttools-4.57.0-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (102 kB)
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 matplotlib)
  Downloading kiwisolver-1.4.8-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (6.2 kB)
Requirement already satisfied: numpy>=1.23 in
/opt/conda/lib/python3.11/site-packages (from matplotlib) (2.2.5)
Requirement already satisfied: packaging>=20.0 in
/opt/conda/lib/python3.11/site-packages (from matplotlib) (23.2)
Collecting pillow>=8 (from matplotlib)
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Requirement already satisfied: python-dateutil>=2.7 in
/opt/conda/lib/python3.11/site-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in
/opt/conda/lib/python3.11/site-packages (from python-dateutil>=2.7-
>matplotlib) (1.16.0)
Downloading matplotlib-3.10.3-cp311-cp311-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (8.6 MB)
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atplotlib
Successfully installed contourpy-1.3.2 cycler-0.12.1 fonttools-4.57.0
kiwisolver-1.4.8 matplotlib-3.10.3 pillow-11.2.1 pyparsing-3.2.3
Collecting seaborn
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Requirement already satisfied: numpy!=1.24.0,>=1.20 in
/opt/conda/lib/python3.11/site-packages (from seaborn) (2.2.5)
Requirement already satisfied: pandas>=1.2 in
/opt/conda/lib/python3.11/site-packages (from seaborn) (2.2.3)
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/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (23.2)
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/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in
/opt/conda/lib/python3.11/site-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/opt/conda/lib/python3.11/site-packages (from pandas>=1.2->seaborn)
(2023.3.post1)
Requirement already satisfied: tzdata>=2022.7 in
/opt/conda/lib/python3.11/site-packages (from pandas>=1.2->seaborn)
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Requirement already satisfied: six>=1.5 in
/opt/conda/lib/python3.11/site-packages (from python-dateutil>=2.7-
>matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
Downloading seaborn-0.13.2-py3-none-any.whl (294 kB)
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```

```
import duckdb
import pandas as pd

# Connect to DuckDB in memory
con = duckdb.connect(database=':memory:')

# Load all required CSVs as DuckDB tables
con.execute("CREATE TABLE prescriptions AS SELECT * FROM
read_csv_auto('PRESCRIPTIONS.csv');")
con.execute("CREATE TABLE patients AS SELECT * FROM
read_csv_auto('PATIENTS.csv');")
con.execute("CREATE TABLE icustays AS SELECT * FROM
read_csv_auto('ICUSTAYS.csv');")
con.execute("CREATE TABLE procedures_icd AS SELECT * FROM
read_csv_auto('PROCEDURES_ICD.csv');")
con.execute("CREATE TABLE d_icd_procedures AS SELECT * FROM
read_csv_auto('D_ICD_PROCEDURES.csv');")
con.execute("CREATE TABLE drgcodes AS SELECT * FROM
read_csv_auto('DRGCODES.csv');")
con.execute("CREATE TABLE admissions AS SELECT * FROM
read_csv_auto('ADMISSIONS.csv');")
```

```
<duckdb.duckdb.DuckDBPyConnection at 0x7fa4237e60b0>
```

```
con.execute("SHOW TABLES").df()
```

```
               name
0        admissions
1  d_icd_procedures
2          drgcodes
3          icustays
4          patients
5     prescriptions
6    procedures_icd
```

```
con.execute("""
SELECT
    a.ethnicity,
    pr.drug,
    COUNT(*) AS times_prescribed
FROM prescriptions pr
JOIN admissions a ON pr.subject_id = a.subject_id
GROUP BY a.ethnicity, pr.drug
```

```
ORDER BY a.ethnicity, times_prescribed DESC;
""").df()

                                                 ethnicity  \
0     AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGN...
1     AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGN...
2     AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGN...
3     AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGN...
4     AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGN...
...                                                ...
1255                                             WHITE
1256                                             WHITE
1257                                             WHITE
1258                                             WHITE
1259                                             WHITE

                              drug  times_prescribed
0                      5% Dextrose                54
1             0.9% Sodium Chloride                44
2               Potassium Chloride                42
3                        Lactulose                26
4       Albumin 25% (12.5g / 50mL)                22
...                            ...               ...
1255                       Namenda                 1
1256                            Ny                 1
1257  Theophylline (Oral Solution)                 1
1258                         Soln.                 1
1259                  Mannitol 20%                 1

[1260 rows x 3 columns]

# Question 1
con.execute("""
SELECT ethnicity, drug, COUNT(*) AS times_prescribed
FROM (
    SELECT DISTINCT
        a.subject_id,
        a.ethnicity,
        pr.drug
    FROM prescriptions pr
    JOIN admissions a ON pr.subject_id = a.subject_id
    WHERE pr.drug IS NOT NULL AND a.ethnicity IS NOT NULL
)
GROUP BY ethnicity, drug
QUALIFY ROW_NUMBER() OVER (PARTITION BY ethnicity ORDER BY COUNT(*)
DESC) = 1;
""").df()

                                              ethnicity  \
0                      HISPANIC/LATINO - PUERTO RICAN
```

```
1                                          WHITE
2                              UNABLE TO OBTAIN
3  AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGN...
4                                          OTHER
5                        BLACK/AFRICAN AMERICAN
6                            HISPANIC OR LATINO
7                                          ASIAN
8                         UNKNOWN/NOT SPECIFIED
```

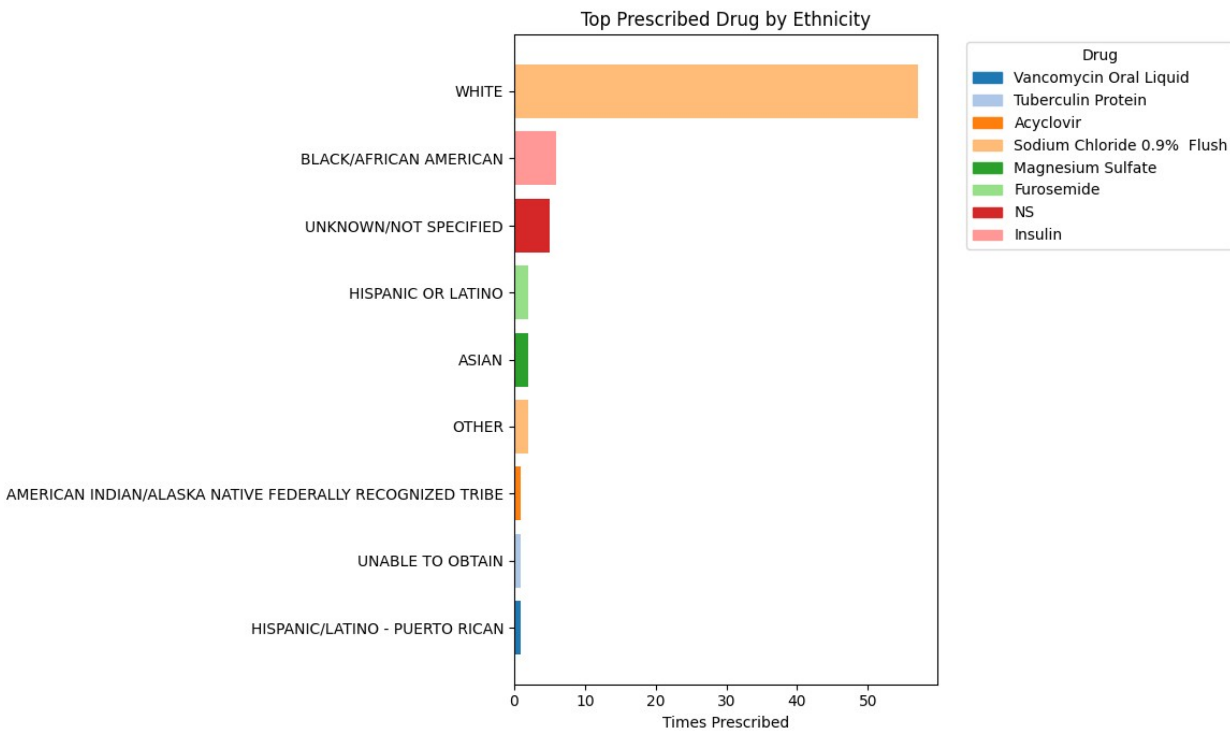
```
                         drug  times_prescribed
0       Vancomycin Oral Liquid                 1
1  Sodium Chloride 0.9%  Flush                57
2          Tuberculin Protein                  1
3                   Acyclovir                  1
4  Sodium Chloride 0.9%  Flush                 2
5                     Insulin                  6
6                  Furosemide                  2
7            Magnesium Sulfate                 2
8                          NS                  5
```

```
'''
I joined prescriptions and admissions on subject_id to associate each
prescription with a patient's ethnicity.
Then, the results were grouped by ethnicity and drug name, and how
often each drug was prescribed was counted.
A window function extracted only the top drug per ethnicity group.
'''
```

```
"\nI joined prescriptions and admissions on subject_id to associate
each prescription with a patient's ethnicity. \nThen, the results were
grouped by ethnicity and drug name, and how often each drug was
prescribed was counted. \nA window function extracted only the top
drug per ethnicity group.\n"
```

```
import matplotlib.pyplot as plt

# Run query again
top_drugs_df = con.execute("""
SELECT ethnicity, drug, COUNT(*) AS times_prescribed
FROM (
    SELECT DISTINCT
        a.subject_id,
        a.ethnicity,
        pr.drug
    FROM prescriptions pr
    JOIN admissions a ON pr.subject_id = a.subject_id
    WHERE pr.drug IS NOT NULL AND a.ethnicity IS NOT NULL
)
GROUP BY ethnicity, drug
QUALIFY ROW_NUMBER() OVER (PARTITION BY ethnicity ORDER BY COUNT(*)
```

```
DESC) = 1;
""").df()

# Sort for clean visuals
top_drugs_df = top_drugs_df.sort_values("times_prescribed",
ascending=True)

# Assign color per drug
unique_drugs = top_drugs_df['drug'].unique()
color_map = {drug: plt.cm.tab20(i) for i, drug in
enumerate(unique_drugs)}
colors = top_drugs_df['drug'].map(color_map)

# Plot without text labels
plt.figure(figsize=(12, 7))
plt.barh(top_drugs_df['ethnicity'], top_drugs_df['times_prescribed'],
color=colors)

# Add legend
handles = [plt.Rectangle((0,0),1,1, color=color_map[drug]) for drug in
unique_drugs]
plt.legend(handles, unique_drugs, title="Drug", bbox_to_anchor=(1.05,
1), loc='upper left')

plt.xlabel("Times Prescribed")
plt.title("Top Prescribed Drug by Ethnicity")
plt.tight_layout()
plt.show()
```




```
'''
Findings Explained:
Most of the top-prescribed drugs are intravenous fluids used to treat dehydration or maintain fluid balance,
such as normal saline (NS), D5W, and 5% dextrose. Potassium chloride is commonly given to correct low potassium levels,
which is vital for heart and muscle function. Insulin is prescribed to manage high blood sugar, especially in patients
with diabetes. The most commonly prescribed drugs skew towards the most common illnesses, which makes a lot of sense.
Despite ethnic diversity, the treatment patterns are strikingly similar. This could indicate that these drugs are first-line
Interventions for common hospital conditions like dehydration, shock, or medication infusion. This could be showing us the
baseline standard of care. I also noticed Black/African American patients had insulin as their top prescribed drug.
This reflects well-documented disparities in diabetes prevalence and management needs in this population, emphasizing the
intersection of chronic disease trends with prescription patterns. This, to me, was an important stand out in the data.
The presence of categories like “UNKNOWN/NOT SPECIFIED” and “UNABLE TO OBTAIN” may point to gaps in demographic recording and
this could theoretically limit the reliability of our findings.
'''

# Question 2
```

```
con.execute("""
SELECT
  CASE
    WHEN DATE_DIFF('year', p.dob, a.admittime) <= 19 THEN '<=19'
    WHEN DATE_DIFF('year', p.dob, a.admittime) <= 49 THEN '20-49'
    WHEN DATE_DIFF('year', p.dob, a.admittime) <= 79 THEN '50-79'
    ELSE '80+'
  END AS age_group,
  d.short_title AS procedure_name,
  COUNT(*) AS procedure_count
FROM procedures_icd picd
JOIN admissions a ON picd.hadm_id = a.hadm_id
JOIN patients p ON a.subject_id = p.subject_id
JOIN d_icd_procedures d ON picd.icd9_code = d.icd9_code
GROUP BY age_group, procedure_name
QUALIFY ROW_NUMBER() OVER (PARTITION BY age_group ORDER BY COUNT(*)
DESC) <= 3
""").df()
```

	age_group	procedure_name	procedure_count
0	<=19	Venous cath NEC	2
1	<=19	Vertebral fx repair	1
2	<=19	Interruption vena cava	1
3	50-79	Venous cath NEC	25
4	50-79	Entral infus nutrit sub	22
5	50-79	Packed cell transfusion	13
6	80+	Venous cath NEC	20
7	80+	Packed cell transfusion	13
8	80+	Insert endotracheal tube	8
9	20-49	Venous cath NEC	9
10	20-49	Entral infus nutrit sub	7
11	20-49	Insert endotracheal tube	6

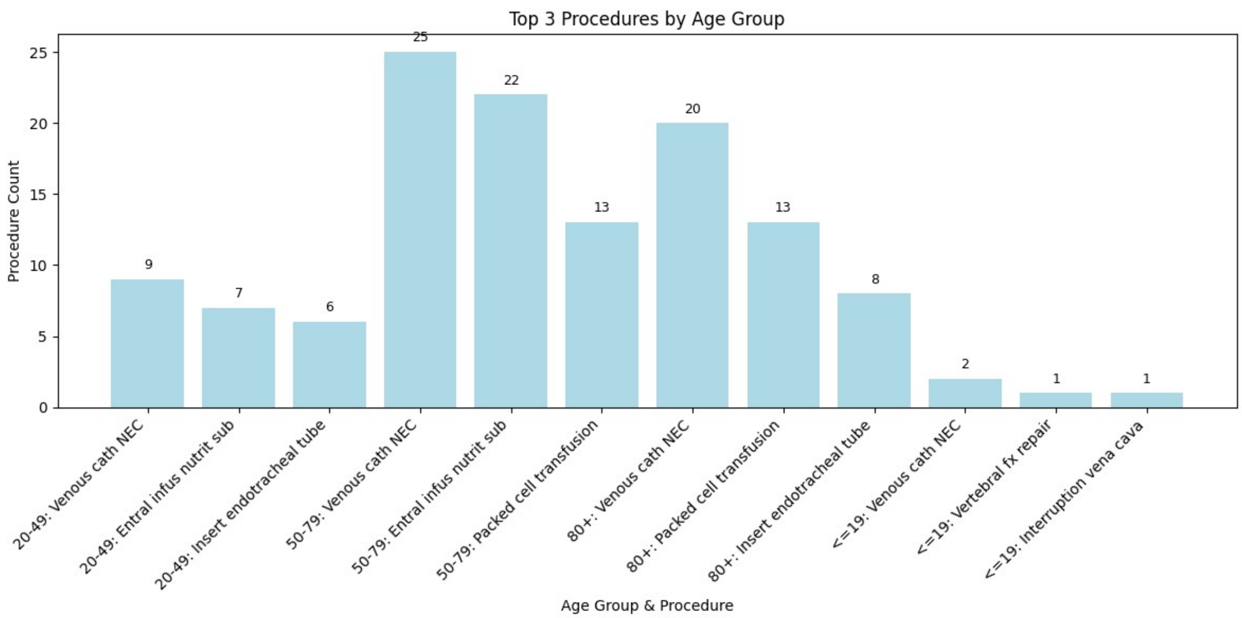
```
'''
Query Explanation:
This query identifies the top 3 most common medical procedures
performed within each age group of patients.
Age is calculated at the time of hospital admission using the
DATE_DIFF function on the patient's date of birth
and the admission time. Patients are grouped into four bins: <=19, 20–
49, 50–79, and 80+. The query joins clinical
procedure records with demographic and procedural description tables
to retrieve the readable names. It then
counts how often each procedure was performed per group and uses
ROW_NUMBER with QUALIFY to return only the top 3
procedures for each age group.
'''
```

```
"\nQuery Explanation:\nThis query identifies the top 3 most common
medical procedures performed within each age group of patients. \nAge
```

```
is calculated at the time of hospital admission using the DATE_DIFF
function on the patient's date of birth \nand the admission time.
Patients are grouped into four bins: <=19, 20–49, 50–79, and 80+. The
query joins clinical \nprocedure records with demographic and
procedural description tables to retrieve the readable names. It
then \ncounts how often each procedure was performed per group and
uses ROW_NUMBER with QUALIFY to return only the top 3 \nprocedures for
each age group.\n"
```

```
import matplotlib.pyplot as plt

# Run your query
df = con.execute("""
SELECT
  CASE
    WHEN DATE_DIFF('year', p.dob, a.admittime) <= 19 THEN '<=19'
    WHEN DATE_DIFF('year', p.dob, a.admittime) <= 49 THEN '20-49'
    WHEN DATE_DIFF('year', p.dob, a.admittime) <= 79 THEN '50-79'
    ELSE '80+'
  END AS age_group,
  d.short_title AS procedure_name,
  COUNT(*) AS procedure_count
FROM procedures_icd picd
JOIN admissions a ON picd.hadm_id = a.hadm_id
JOIN patients p ON a.subject_id = p.subject_id
JOIN d_icd_procedures d ON picd.icd9_code = d.icd9_code
GROUP BY age_group, procedure_name
QUALIFY ROW_NUMBER() OVER (PARTITION BY age_group ORDER BY COUNT(*)
DESC) <= 3
""").df()

# Sort for consistent bar order
df = df.sort_values(by=["age_group", "procedure_count"],
ascending=[True, False])

# Create labels with age group and procedure
df["label"] = df["age_group"] + ": " + df["procedure_name"]

# Plot
plt.figure(figsize=(12, 6))
bars = plt.bar(df["label"], df["procedure_count"], color="lightblue")

# Add bar labels
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, height + 0.5,
int(height), ha='center', va='bottom', fontsize=9)

plt.xticks(rotation=45, ha='right')
plt.xlabel("Age Group & Procedure")
```

```python
plt.ylabel("Procedure Count")
plt.title("Top 3 Procedures by Age Group")
plt.tight_layout()
plt.show()
```




```python
'''
Findings Summarized:
The chart shows the top three most common procedures performed for
each age group. Across the 50–79 and 80+ age
ranges, procedures like venous catheter placement, enteral nutrition
infusion, and packed cell transfusion dominate,
indicating a higher need for vascular access and nutritional or blood
support in older patients. In contrast, younger
patients (<=19) have far fewer recorded procedures overall, with a
steep drop in counts, suggesting they undergo
fewer invasive interventions. The 20–49 age group shows some overlap
with older groups in terms of procedure types but
at lower frequencies. These trends reflect the increasing medical
complexity and support needs that come with age.
'''
```

```
'\nFindings Summarized:\nThe chart shows the top three most common
procedures performed for each age group. Across the 50–79 and 80+
age \nranges, procedures like venous catheter placement, enteral
nutrition infusion, and packed cell transfusion dominate, \nindicating
a higher need for vascular access and nutritional or blood support in
older patients. In contrast, younger \npatients (<=19) have far fewer
recorded procedures overall, with a steep drop in counts, suggesting
they undergo \nfewer invasive interventions. The 20–49 age group shows
some overlap with older groups in terms of procedure types but \nat
```

```
lower frequencies. These trends reflect the increasing medical
complexity and support needs that come with age.\n'
```

```
# Question 3
con.execute("""
SELECT
  a.admission_type,
  ROUND(AVG(i.los), 2) AS avg_icu_los_days
FROM icustays i
JOIN admissions a ON i.hadm_id = a.hadm_id
WHERE i.los IS NOT NULL
GROUP BY a.admission_type
ORDER BY avg_icu_los_days DESC
""").df()
```

```
  admission_type  avg_icu_los_days
0         URGENT              5.21
1      EMERGENCY              4.53
2       ELECTIVE              3.01
```

```
con.execute("""
SELECT
  p.gender,
  ROUND(AVG(i.los), 2) AS avg_icu_los_days,
  COUNT(*) AS num_cases
FROM icustays i
JOIN admissions a ON i.hadm_id = a.hadm_id
JOIN patients p ON a.subject_id = p.subject_id
WHERE i.intime IS NOT NULL AND i.outtime IS NOT NULL
GROUP BY p.gender
ORDER BY avg_icu_los_days DESC
""").df()
```

```
  gender  avg_icu_los_days  num_cases
0      F              5.54         63
1      M              3.51         73
```

```
con.execute("""
SELECT
  a.ethnicity,
  ROUND(AVG(i.los), 2) AS avg_icu_los_days,
  COUNT(*) AS num_cases
FROM icustays i
JOIN admissions a ON i.hadm_id = a.hadm_id
WHERE i.intime IS NOT NULL AND i.outtime IS NOT NULL
GROUP BY a.ethnicity
ORDER BY avg_icu_los_days DESC
""").df()
```

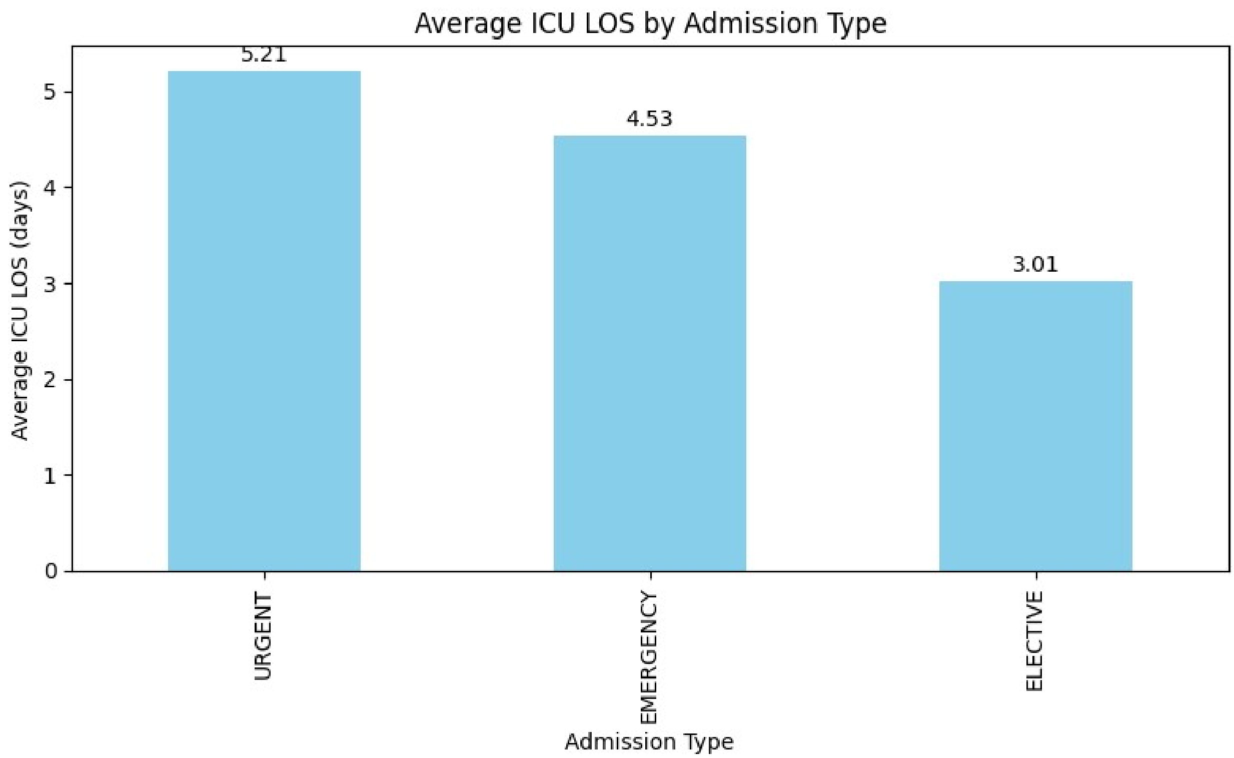
```
                                           ethnicity  avg_icu_los_days  \
```

0	UNABLE TO OBTAIN	13.36
1	AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGN...	11.34
2	BLACK/AFRICAN AMERICAN	7.68
3	HISPANIC OR LATINO	7.46
4	UNKNOWN/NOT SPECIFIED	4.93
5	WHITE	4.13
6	ASIAN	3.89
7	HISPANIC/LATINO - PUERTO RICAN	3.24
8	OTHER	0.93

	num_cases
0	1
1	2
2	7
3	3
4	11
5	92
6	2
7	15
8	3

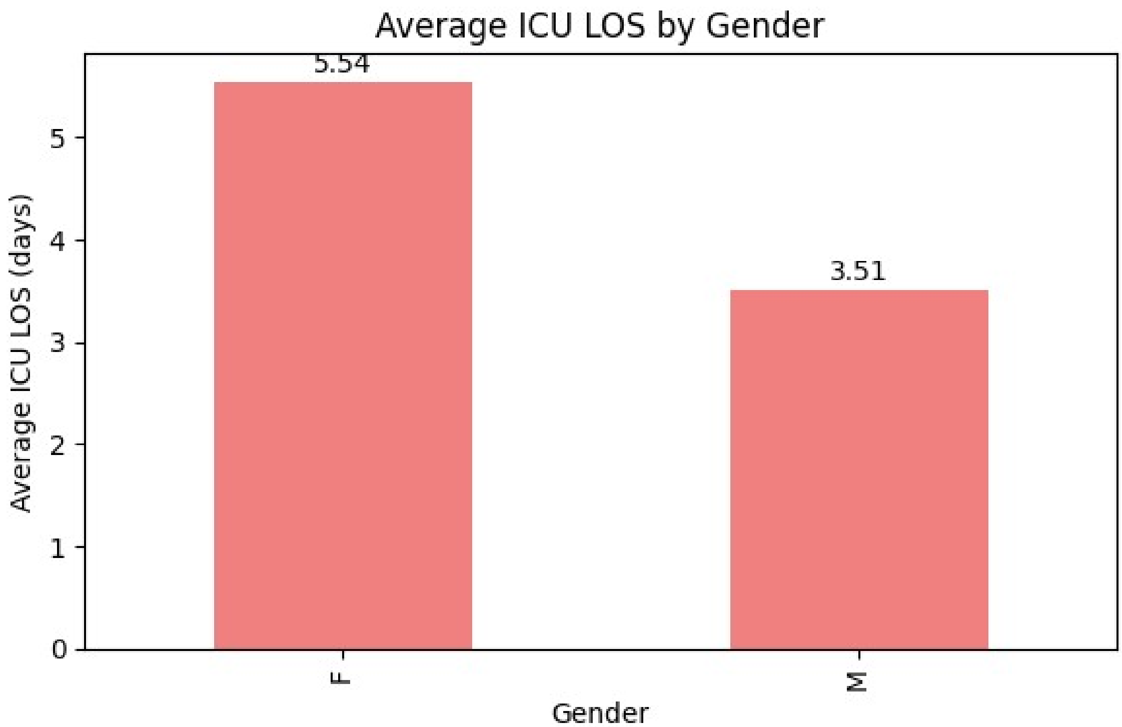
```
'''
Queries explained:
Query 1: This query calculates the average ICU length of stay (LOS) in days for each hospital admission type
(EMERGENCY, URGENT, ELECTIVE). It uses the los (length of stay) column from the icustays table and joins it with
the admissions table to group by admission_type. It also includes a count of how many cases fall into each group.

Query 2: This query computes the average ICU LOS by gender (M or F). It joins icustays, admissions, and patients
tables and filters for non-null intime and outtime values. The result shows both the average stay duration and the
total number of ICU cases per gender.

Query 3: This query finds the average ICU LOS grouped by patient ethnicity (from the admissions table). It also
counts the number of cases per ethnicity. This helps identify disparities in ICU stay durations across different
ethnic groups.
```

```python
df_admission = con.execute("""
SELECT
  a.admission_type,
  ROUND(AVG(i.los), 2) AS avg_icu_los_days
FROM icustays i
JOIN admissions a ON i.hadm_id = a.hadm_id
WHERE i.los IS NOT NULL
GROUP BY a.admission_type
ORDER BY avg_icu_los_days DESC
""").df()

# Assuming df_admission is your DataFrame from the first query
df_admission.plot.bar(
    x='admission_type',
    y='avg_icu_los_days',
    legend=False,
    color='skyblue',
    figsize=(8, 5)
)
plt.title("Average ICU LOS by Admission Type")
plt.xlabel("Admission Type")
plt.ylabel("Average ICU LOS (days)")

# Add value labels
for idx, val in enumerate(df_admission['avg_icu_los_days']):
    plt.text(idx, val + 0.1, str(val), ha='center')

plt.tight_layout()
plt.show()
```



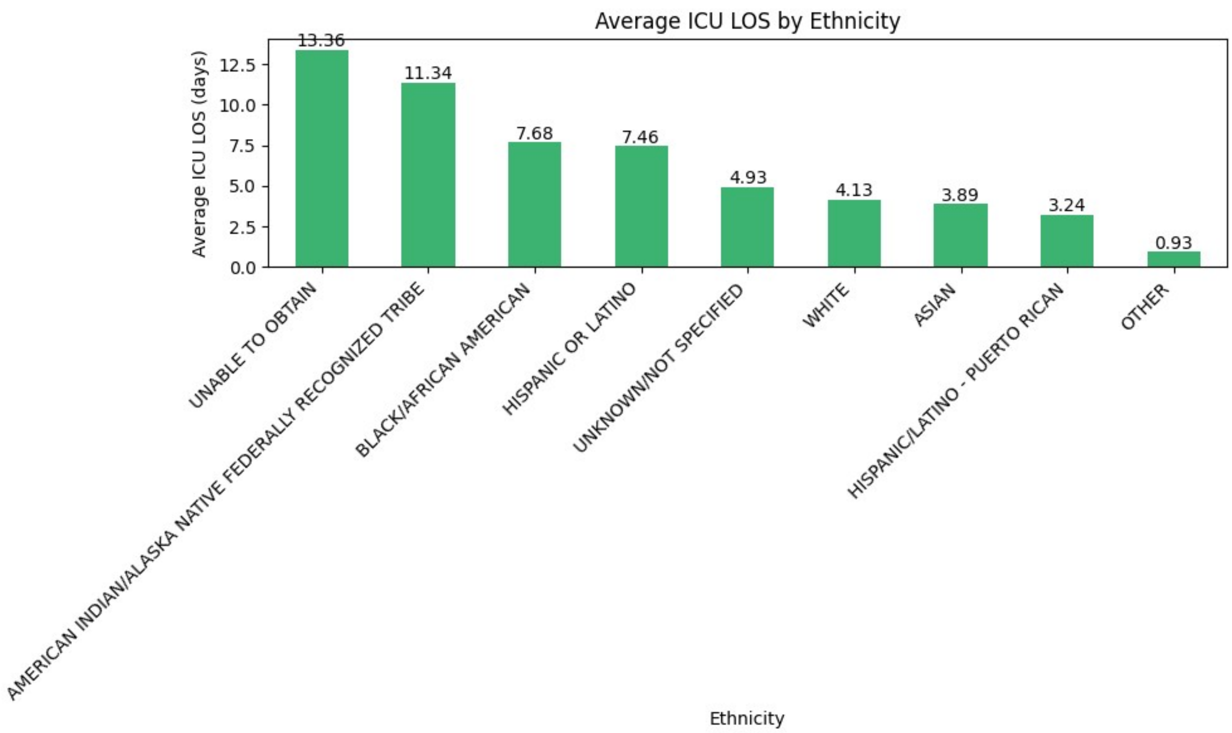

```
df_gender = con.execute("""
SELECT
  p.gender,
  ROUND(AVG(i.los), 2) AS avg_icu_los_days,
  COUNT(*) AS num_cases
FROM icustays i
JOIN admissions a ON i.hadm_id = a.hadm_id
JOIN patients p ON a.subject_id = p.subject_id
WHERE i.intime IS NOT NULL AND i.outtime IS NOT NULL
GROUP BY p.gender
ORDER BY avg_icu_los_days DESC
""").df()

df_gender.plot.bar(
    x='gender',
    y='avg_icu_los_days',
    legend=False,
    color='lightcoral',
    figsize=(6, 4)
)
plt.title("Average ICU LOS by Gender")
plt.xlabel("Gender")
plt.ylabel("Average ICU LOS (days)")

for idx, val in enumerate(df_gender['avg_icu_los_days']):
    plt.text(idx, val + 0.1, str(val), ha='center')
```

```
plt.tight_layout()
plt.show()
```




```
df_ethnicity = con.execute("""
SELECT
  a.ethnicity,
  ROUND(AVG(i.los), 2) AS avg_icu_los_days,
  COUNT(*) AS num_cases
FROM icustays i
JOIN admissions a ON i.hadm_id = a.hadm_id
WHERE i.intime IS NOT NULL AND i.outtime IS NOT NULL
GROUP BY a.ethnicity
ORDER BY avg_icu_los_days DESC
""").df()

df_ethnicity.plot.bar(
    x='ethnicity',
    y='avg_icu_los_days',
    legend=False,
    color='mediumseagreen',
    figsize=(10, 6)
)
plt.title("Average ICU LOS by Ethnicity")
plt.xlabel("Ethnicity")
plt.ylabel("Average ICU LOS (days)")
```

```python
# Rotate x labels for readability
plt.xticks(rotation=45, ha='right')

for idx, val in enumerate(df_ethnicity['avg_icu_los_days']):
    plt.text(idx, val + 0.2, str(val), ha='center')

plt.tight_layout()
plt.show()
```




```python
'''
Findings Analyzed:
Query 1: The chart shows that ICU patients admitted under urgent
conditions have the longest average length of stay
(5.21 days), followed by those admitted under emergency conditions
(4.53 days), and lastly elective admissions
(3.01 days). This trend aligns with clinical expectations: urgent
cases often involve more complex, time-sensitive health
issues requiring prolonged care, while elective admissions are
typically scheduled procedures with more predictable recovery
paths, resulting in shorter ICU stays.

Query 2: The chart reveals that female patients have a notably longer
average ICU length of stay (5.54 days) compared to
male patients (3.51 days). One plausible factor could be the inclusion
of pregnancy-related or labor-related ICU admissions,
which are specific to females and can involve complex, high-risk
```

```
scenarios requiring extended monitoring and care. Additionally,
it may reflect differences in baseline health status, treatment
response, or care pathways between genders. However, further
investigation would be needed to confirm the specific causes behind
this disparity.

Query 3: This chart shows variation in average ICU length of stay
(LOS) across different ethnic groups, but it's important
to interpret these results with caution due to the small sample sizes
in many categories. For example, the highest average
LOS values—like 13.36 days for "UNABLE TO OBTAIN" and 11.34 days for
"AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGNIZED TRIBE"
—are based on only one or two cases, which limits their reliability.
In contrast, groups like "WHITE" and "HISPANIC/LATINO -
PUERTO RICAN" have much larger sample sizes (e.g., 92 and 15 cases),
making their average LOS figures more representative.
These disparities highlight the importance of considering both
magnitude and statistical weight when analyzing healthcare outcomes.
I would say it is important to take all these results with a grain of
salt, because besides the category with 92 samples, I am not
convinced that any of the other sizes are large enough to draw any
thoughtful concluions.
'''

!pip install cassandra-driver
!pip install cassandra-sigv4 boto3
```

```
Requirement already satisfied: cassandra-driver in
/opt/conda/lib/python3.11/site-packages (3.29.2)
Requirement already satisfied: geomet<0.3,>=0.1 in
/opt/conda/lib/python3.11/site-packages (from cassandra-driver)
(0.2.1.post1)
Requirement already satisfied: click in
/opt/conda/lib/python3.11/site-packages (from geomet<0.3,>=0.1-
>cassandra-driver) (8.1.8)
Requirement already satisfied: six in /opt/conda/lib/python3.11/site-
packages (from geomet<0.3,>=0.1->cassandra-driver) (1.16.0)
Requirement already satisfied: cassandra-sigv4 in
/opt/conda/lib/python3.11/site-packages (4.0.2)
Requirement already satisfied: boto3 in
/opt/conda/lib/python3.11/site-packages (1.38.12)
Requirement already satisfied: cassandra-driver in
/opt/conda/lib/python3.11/site-packages (from cassandra-sigv4)
(3.29.2)
Requirement already satisfied: six in /opt/conda/lib/python3.11/site-
packages (from cassandra-sigv4) (1.16.0)
Requirement already satisfied: botocore<1.39.0,>=1.38.12 in
/opt/conda/lib/python3.11/site-packages (from boto3) (1.38.12)
Requirement already satisfied: jmespath<2.0.0,>=0.7.1 in
/opt/conda/lib/python3.11/site-packages (from boto3) (1.0.1)
```

```
Requirement already satisfied: s3transfer<0.13.0,>=0.12.0 in
/opt/conda/lib/python3.11/site-packages (from boto3) (0.12.0)
Requirement already satisfied: python-dateutil<3.0.0,>=2.1 in
/opt/conda/lib/python3.11/site-packages (from
botocore<1.39.0,>=1.38.12->boto3) (2.8.2)
Requirement already satisfied: urllib3!=2.2.0,<3,>=1.25.4 in
/opt/conda/lib/python3.11/site-packages (from
botocore<1.39.0,>=1.38.12->boto3) (2.0.7)
Requirement already satisfied: geomet<0.3,>=0.1 in
/opt/conda/lib/python3.11/site-packages (from cassandra-driver-
>cassandra-sigv4) (0.2.1.post1)
Requirement already satisfied: click in
/opt/conda/lib/python3.11/site-packages (from geomet<0.3,>=0.1-
>cassandra-driver->cassandra-sigv4) (8.1.8)
```

```python
# Part 2
'''
Due to a consistent access key error in Jupyter Notebook, I was only
able to run my cassandra functions in my terminal;
however, you can access all my functions here and I will be giving a
report on all of their performances.
'''
```

```
'\nDue to a consistent access key error in Jupyter Notebook, I was
only able to run my cassandra functions in my terminal; \nhowever, you
can access all my functions here and I will be giving a report on all
of their performances. An interesting \nhurdle that exists is that I
cannot use the same JOIN functions that made these queries more simple
in the attempts above.\n'
```

```python
# Question 1
'''
CREATE TABLE IF NOT EXISTS ethnicity_drug_prescriptions (
    subject_id TEXT,
    ethnicity TEXT,
    drug TEXT,
    PRIMARY KEY (ethnicity, subject_id, drug)
);

Thoughts on design:
partition key is ethnicity to allow for grouping by ethnicity
culstering columns of subject_id and drug ensures uniqueness and
supports efficient range queries per ethnicity
'''
```

```
'\nCREATE TABLE IF NOT EXISTS ethnicity_drug_prescriptions (\n
subject_id TEXT,\n    ethnicity TEXT,\n    drug TEXT,\n    PRIMARY KEY
(ethnicity, subject_id, drug)\n);\n\nThoughts on design:\npartition
key is ethnicity to allow for grouping by ethnicity\nculstering
```

```
columns of subject_id and drug ensures uniqueness and supports
efficient range queries per ethnicity\n'
```

```
'''
Data upload code:
ethnicity_lookup = {}
with open("ADMISSIONS.csv", newline='') as f:
    reader = csv.DictReader(f)
    for row in reader:
        ethnicity_lookup[row["subject_id"]] = row["ethnicity"]

inserted = 0
skipped = 0

with open("PRESCRIPTIONS.csv", newline='') as f:
    reader = csv.DictReader(f)
    for row in reader:
        sid = row["subject_id"]
        drug = row["drug"]
        ethnicity = ethnicity_lookup.get(sid)
        if ethnicity and drug:
            try:
                session.execute("""
                    INSERT INTO ethnicity_drug_prescriptions
(subject_id, ethnicity, drug)
                    VALUES (%s, %s, %s)
                """, (sid, ethnicity, drug))
                inserted += 1
            except Exception:
                skipped += 1
        else:
            skipped += 1

print(f"Inserted {inserted} rows. Skipped {skipped}.")

# We did not have to skip any rows
'''
```

```
'\nData upload code:\nethnicity_lookup = {}\nwith
open("ADMISSIONS.csv", newline=\'\') as f:\n    reader =
csv.DictReader(f)\n    for row in reader:\n
ethnicity_lookup[row["subject_id"]] = row["ethnicity"]\n\ninserted =
0\nskipped = 0\n\nwith open("PRESCRIPTIONS.csv", newline=\'\') as f:\n
reader = csv.DictReader(f)\n    for row in reader:\n        sid =
row["subject_id"]\n        drug = row["drug"]\n        ethnicity =
ethnicity_lookup.get(sid)\n        if ethnicity and drug:\n
try:\n                session.execute("""\n                    INSERT
INTO ethnicity_drug_prescriptions (subject_id, ethnicity, drug)\n
VALUES (%s, %s, %s)\n                """, (sid, ethnicity, drug))\n
inserted += 1\n            except Exception:\n               skipped
```

```
+= 1\n        else:\n            skipped += 1\n\nprint(f"Inserted {inserted} rows. Skipped {skipped}.")\n\n# We did not have to skip any rows\n'
```

```
'''
Cassandra Query:
SELECT ethnicity, drug FROM ethnicity_drug_prescriptions;

Then since cassandra does not support a count function, I had to use python:
from collections import defaultdict, Counter

rows = session.execute("SELECT ethnicity, drug FROM ethnicity_drug_prescriptions")
ethnicity_drug_counts = defaultdict(Counter)

for row in rows:
    ethnicity_drug_counts[row.ethnicity][row.drug] += 1

for ethnicity, drug_counts in ethnicity_drug_counts.items():
    top_drug, count = drug_counts.most_common(1)[0]
    print(f"{ethnicity}: {top_drug} ({count} prescriptions)")
'''
```

```
'\nCassandra Query:\nSELECT ethnicity, drug FROM ethnicity_drug_prescriptions;\n\nThen since cassandra does not support a count function, I had to use python:\nfrom collections import defaultdict, Counter\n\nrows = session.execute("SELECT ethnicity, drug FROM ethnicity_drug_prescriptions")\nethnicity_drug_counts = defaultdict(Counter)\n\nfor row in rows:\n    ethnicity_drug_counts[row.ethnicity][row.drug] += 1\n\nfor ethnicity, drug_counts in ethnicity_drug_counts.items():\n    top_drug, count = drug_counts.most_common(1)[0]\n    print(f"{ethnicity}: {top_drug} ({count} prescriptions)")\n'
```

```
'''
I confirmed results by visually matching the top drug per ethnicity with those seen in SQL outputs. The script prints the
most prescribed drug and count per ethnicity. There were no unexpected results.
'''

# Question 2
'''
CREATE TABLE procedures_by_age (
    age_group TEXT,
    procedure_name TEXT,
    PRIMARY KEY (age_group, procedure_name)
);

age_group is the parition key to segment data by demographic
```

```
procedure_name is the clustering key in order to make the read and
deduplication within groups
'''

'\nCREATE TABLE procedures_by_age (\n    age_group TEXT,\n
procedure_name TEXT,\n    PRIMARY KEY (age_group, procedure_name)\n);\
n\n'

'''
for age_group, counter in age_proc_count.items():
    for proc_name, _ in counter.most_common(3):
        session.execute("""
            INSERT INTO procedures_by_age (age_group, procedure_name)
            VALUES (%s, %s)
        """, (age_group, proc_name))

This Python snippet parses and filters from four CSV files to insert
top 3 procedures per age group into the table. I was able to
join PROCEDURES_ICD.csv with ADMISSIONS.csv, PATIENTS.csv, and
D_ICD_PROCEDURES.csv via lookups. Age is calculated based on dob
and admittime from two tables (the difference between the two). The
use of most_common(3) ensures only the top 3 per group
are inserted.

'''

'''
The query I used to get the final answer was:
SELECT age_group, procedure_name FROM procedures_by_age;

Because Cassandra does not support aggregation (meaning we cannot use
COUNT), this was done in Python before insert.
'''

'\nThe query I used to get the final answer was:\nSELECT age_group,
procedure_name FROM procedures_by_age;\n\nBecause Cassandra does not
support aggregation (meaning we cannot use COUNT), this was done in
Python before insert.\n'

'''
The Cassandra strategy I used could allow for some of the
discrepencies we see here. Cassandra script only
inserts the top 3 per group after local aggregation, so discrepancies
can arise based on preprocessing filters,
timestamp formatting, or ICD descriptions. SQL on the other hand
grouped and counted using all records.

'''

# Question 3
'''
```

```
CREATE TABLE IF NOT EXISTS stays_by_gender (
    patient_id TEXT,
    gender TEXT,
    icustay_id TEXT,
    intime TIMESTAMP,
    outtime TIMESTAMP,
    PRIMARY KEY (gender, patient_id, icustay_id)
);

This table uses a composite primary key of (gender, patient_id,
icustay_id) to enable the retrieval
of all ICU stays by gender. Storing intime and outtime allows
computation of length of stay.

'''

'''
# Load gender lookup from PATIENTS.csv
gender_lookup = {}
with open("PATIENTS.csv", newline='') as f:
    reader = csv.DictReader(f)
    for row in reader:
        gender_lookup[row["subject_id"]] = row["gender"]

# Merge with ICU stays
with open("ICUSTAYS.csv", newline='') as f:
    reader = csv.DictReader(f)
    for row in reader:
        sid = row["subject_id"]
        gender = gender_lookup.get(sid)
        if gender:
            session.execute("""
                INSERT INTO stays_by_gender (patient_id, gender,
icustay_id, intime, outtime)
                VALUES (%s, %s, %s, %s, %s)
            """, (
                sid, gender, row["icustay_id"], row["intime"],
row["outtime"]
            ))

Data is loaded by merging PATIENTS.csv with ICUSTAYS.csv using the
subject_id. Only records with valid gender,
intime, and outtime are inserted in order to keep the data clean.

'''

'''
rows = session.execute("SELECT gender, intime, outtime FROM
stays_by_gender;")
```

```
for row in rows:
    if row.intime and row.outtime:
        delta = row.outtime - row.intime
        days = delta.total_seconds() / (3600.0 * 24)
        durations[row.gender] += days
        counts[row.gender] += 1


I needed to include post data extraction logic to calculate the
duration. Cassandra does not support aggregation like AVG()
natively, so we compute durations in Python using timestamps.
'''

'''
The extracted data from Cassandra was verified by comparing the
computed average ICU stay duration by gender
to the results obtained from the SQL-based analysis. This consistency
demonstrates that the non-relational (Cassandra)
approach yields correct and reliable results for this type of
analysis, despite requiring external logic due to
Cassandra's constraints.
'''
```