Step 1: Define the IoT Problem Universe

In [204…

```
"""

            Connected Assets

                Asset                   Description
                Room                 Smart home environment
                Sensors              Temperature, Humidity, Light, CO2
                Appliances         Lights, Fan
                Gateway             Data collection unit

            Connected Operations

                • Sensor monitoring
                • Occupancy detection
                • Appliance automation
                • Energy optimization

            Business Objective

                Reduce unnecessary power consumption while maintaining user co

"""
print()
```

Step 2 :- Identify Latent Problems

In [205…

```
def iot_problem(sensor):
    problem=""
    if sensor=="Temperature":
        problem="Fan running unnecessarily"
    elif sensor=="Light":
        problem="Lights ON when room is empty"
    elif sensor=="CO2":
        problem="High CO2 when occupied"
    elif sensor=="Humidity":
        problem="False occupancy detection"
    else:
        problem="No Problem"
    return problem
```

Step 3 :- Sensor–Problem Mapping

In [206…

```
for col in df.columns[1:5]:
    print(f"[Sensor] : [{col}]  ==>  [Problem] : [{iot_problem(col)}]")
```

```
[Sensor] : [Temperature]  ==>  [Problem] : [Fan running unnecessarily]
[Sensor] : [Humidity]  ==>  [Problem] : [False occupancy detection]
[Sensor] : [Light]  ==>  [Problem] : [Lights ON when room is empty]
[Sensor] : [CO2]  ==>  [Problem] : [High CO2 when occupied]
```

Step 4 :- Design HDH Matrix

In [207…

```
hdh_data = [
                        {
                            "observation": "High C02 level",
                            "Sensor": "C02",
                            "Heuristic Rule": "C02 > 900",
                            "Hypothesis": "Room is occupied",
                            "Business Impact": "Turn ON appliances"
                        } ,

                        {
                            "observation": "Low light intensity",
                            "Sensor": "Light",
                            "Heuristic Rule": "Light < 200",
                            "Hypothesis": "Lights needed",
                            "Business Impact": "Switch ON lights"
                        } ,

                        {
                            "observation": "High temperature",
                            "Sensor": "Temperature",
                            "Heuristic Rule": "Temp > 28",
                            "Hypothesis": "Cooling required",
                            "Ousiness Impact": "Turn ON fan"
                        } ,

                        {
                            "observation": "Low C02 level",
                            "Sensor": "C02",
                            "Heuristic Rule": "C02 < 600",
                            "Hypothesis": "Room empty",
                            "Business Impact": "Turn OFF appliances"
                        }
                    ]
```

Step 5: Load and Analyze Dataset

In [208…
```
#importing modules
import numpy as np
import pandas as pd
```

In [209…
```
#Loading IOT Dataset
d1=pd.read_csv("/content/drive/MyDrive/AIOT_3rd_sem/LABS_PRACTICALS/3LAB_28_01
d2=pd.read_csv("/content/drive/MyDrive/AIOT_3rd_sem/LABS_PRACTICALS/3LAB_28_01
d3=pd.read_csv("/content/drive/MyDrive/AIOT_3rd_sem/LABS_PRACTICALS/3LAB_28_01
```

In [210…
```
#concating data
df=pd.DataFrame(pd.concat([d1,d2,d3], ignore_index=True))
```

In [211…
```
#first three data rows
df.head(3)
```

Out[211…

	date	Temperature	Humidity	Light	CO2	HumidityRatio	O
0	2015-02-02 14:19:00	23.700	26.272	585.200000	749.200000	0.004764	
1	2015-02-02 14:19:59	23.718	26.290	578.400000	760.400000	0.004773	
2	2015-02-02 14:21:00	23.730	26.230	572.666667	769.666667	0.004765	

In [212…
```
analyze_df=df.iloc[1:].copy()
analyze_df.drop(columns="HumidityRatio",inplace=True)
analyze_df.drop(columns="date",inplace=True)
analyze_df.head(3)
```

Out[212…

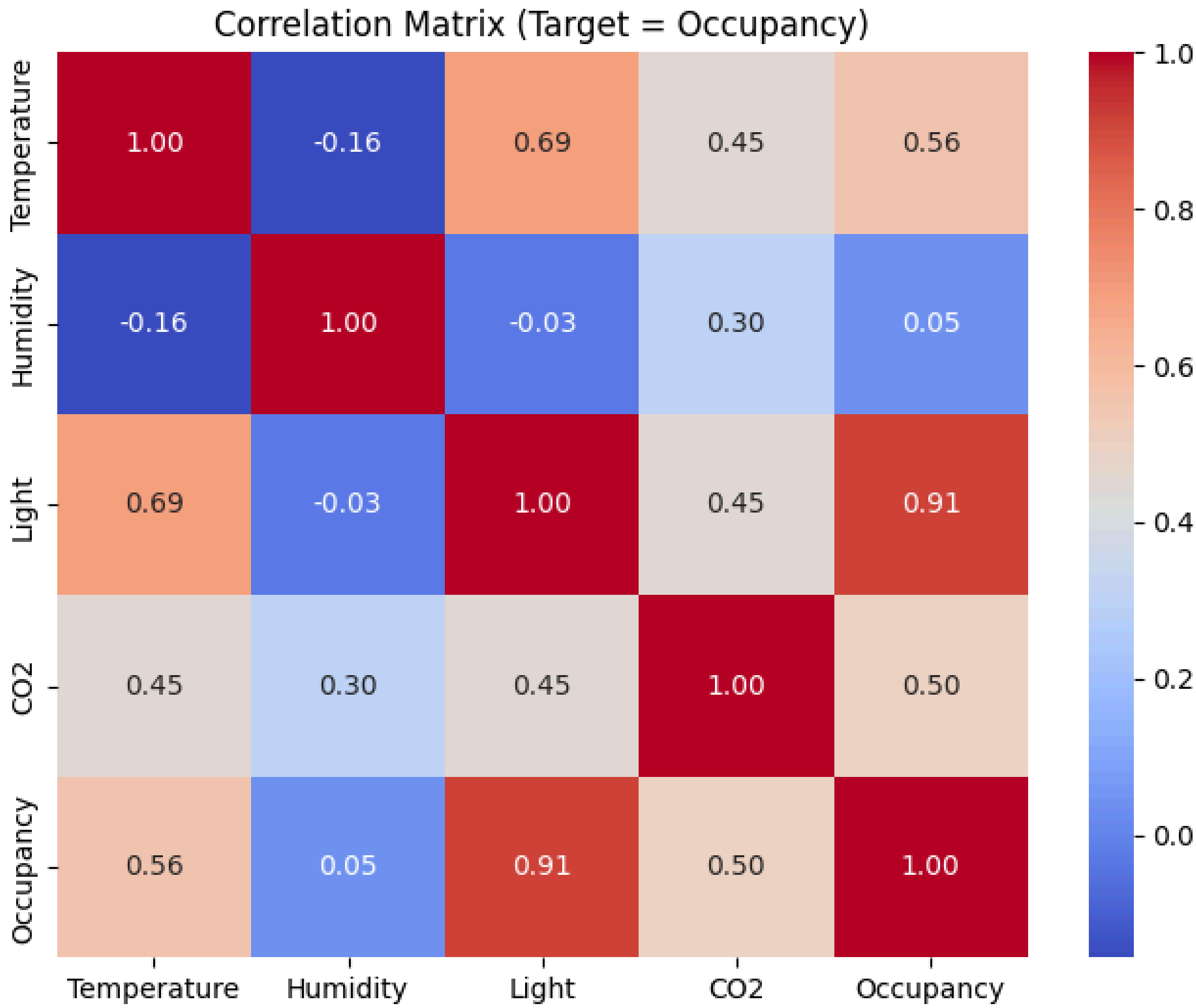
	Temperature	Humidity	Light	CO2	Occupancy
1	23.7180	26.290	578.400000	760.400000	1
2	23.7300	26.230	572.666667	769.666667	1
3	23.7225	26.125	493.750000	774.750000	1

In [213…
```
import matplotlib.pyplot as plt
import seaborn as sns

# Correlation matrix
corr =analyze_df.corr()

plt.figure(figsize=(8,6))
```

```
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Matrix (Target = Occupancy)")
plt.show()
```



Step 6: Validate Heuristics using Data

In [214…

```
high_co2_occupied =analyze_df[(analyze_df["CO2"]>900) &(analyze_df["Occupancy"
print("Samples with High CO2 & Occupied:", len(high_co2_occupied))
print(f"percentage = {float( len(high_co2_occupied))/float(len(analyze_df[anal
```

```
Samples with High CO2 & Occupied: 2620
percentage = 55.16950937039377
```

In [215…

```
high_co2_noccupied =analyze_df[(analyze_df["CO2"]>900) &(analyze_df["Occupancy
print("Samples with High CO2 & not Occupied:", len(high_co2_noccupied))
print(f"percentage = {float( len(high_co2_noccupied))/float(len(analyze_df[ana
```

```
Samples with High CO2 & not Occupied: 1292
percentage = 8.172043010752688
```

In [216…

```
low_co2_noccupied =analyze_df[(analyze_df["CO2"]<900) &(analyze_df["Occupancy"
print("Samples with low CO2 & not occupied:", len(low_co2_noccupied))
print(f"percentage = {float( len(low_co2_noccupied))/float(len(analyze_df[anal
```

```
Samples with low CO2 & not occupied: 14518
percentage = 91.82795698924731
```

In [217…

```
low_co2_occupied =analyze_df[(analyze_df["CO2"]<900) &(analyze_df["Occupancy"]
print("Samples with low CO2 & occupied:", len(low_co2_occupied))
print(f"percentage = {float( len(low_co2_occupied))/float(len(analyze_df[analy
```

```
Samples with low CO2 & occupied: 2128
percentage = 13.459835547122076
```

In [218…

```
# Counts
counts = {
    "High CO2 & Occupied": len(high_co2_occupied),
    "High CO2 & Not Occupied": len(high_co2_noccupied),
    "Low CO2 & Not Occupied": len(low_co2_noccupied),
    "Low CO2 & Occupied": len(low_co2_occupied)
}
```

CO_2 Distribution Plot with Occupancy Overlay

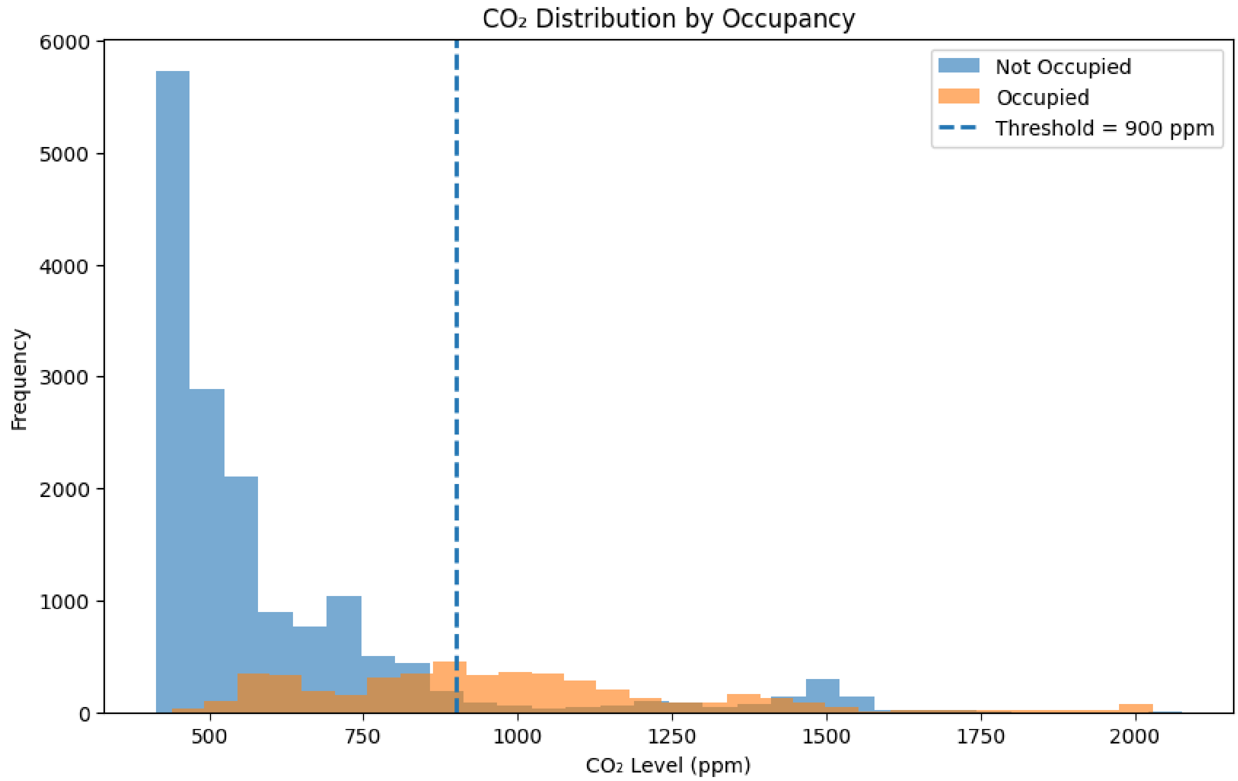
In [219…

```
plt.figure(figsize=(10,6))

plt.hist(analyze_df[analyze_df["Occupancy"]==0]["CO2"], bins=30, alpha=0.6, la
plt.hist(analyze_df[analyze_df["Occupancy"]==1]["CO2"], bins=30, alpha=0.6, la

plt.axvline(900, linestyle="--", linewidth=2, label="Threshold = 900 ppm")

plt.title("CO₂ Distribution by Occupancy")
plt.xlabel("CO₂ Level (ppm)")
plt.ylabel("Frequency")
plt.legend()
plt.show()
```

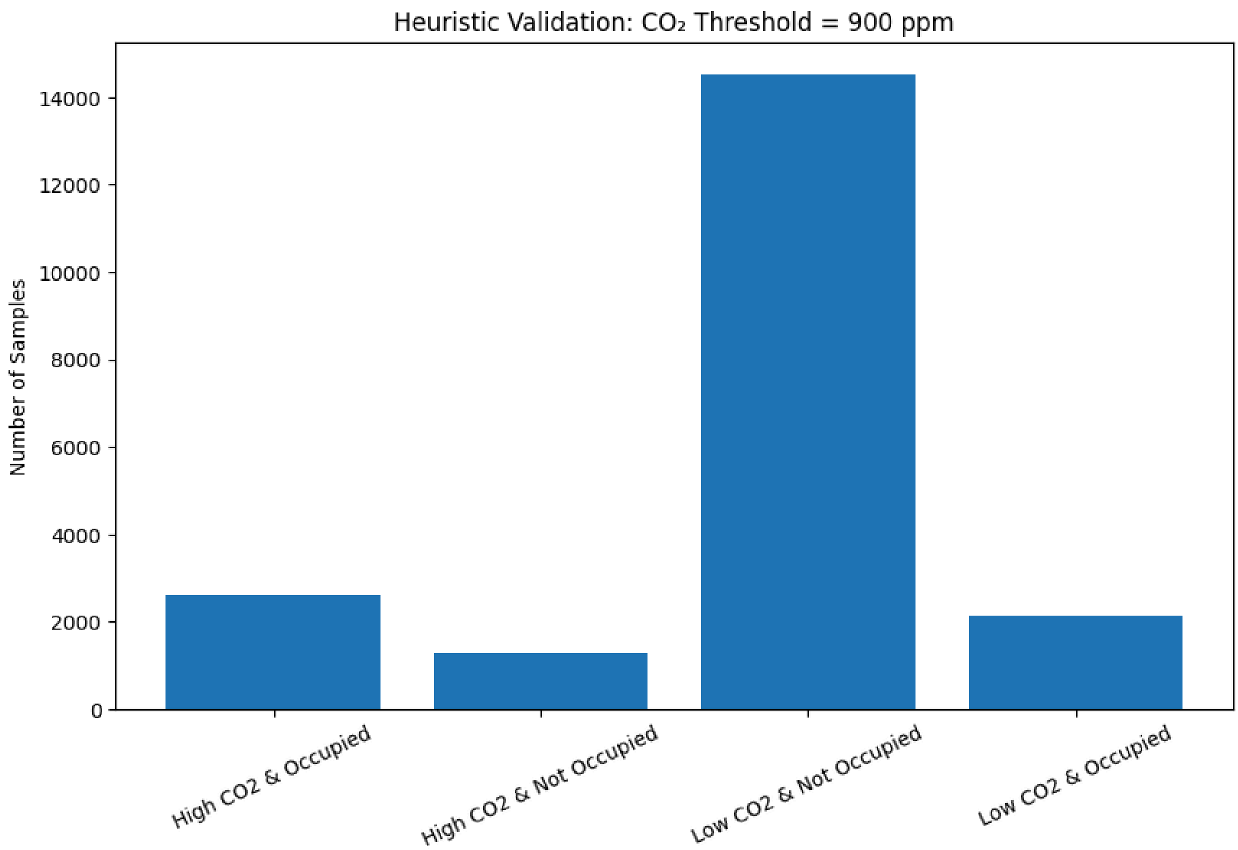


Bar Chart of the Four Heuristic Outcomes

In [220…

```
plt.figure(figsize=(10,6))
plt.bar(counts.keys(), counts.values())

plt.title("Heuristic Validation: CO₂ Threshold = 900 ppm")
plt.ylabel("Number of Samples")
plt.xticks(rotation=25)
plt.show()
```



1D Decision Tree Training

$$occupancy = \{1 \text{ if } CO_2 > threshold, 0 \text{ otherwise}\}$$

In [221…

```
import numpy as np

co2_values = []
for val in np.sort(analyze_df["CO2"].unique()):
    co2_values.extend([val-0.5, val, val+0.5])

best_thresh = None
best_acc = 0

# Try every possible breakpoint
for t in co2_values:
    preds = (analyze_df["CO2"] > t).astype(int)
    acc = (preds == analyze_df["Occupancy"]).mean()

    if acc > best_acc:
        best_acc = acc
```

```
        best_thresh = t

print("Best CO2 Breakpoint =", best_thresh)
print("Best Accuracy =", best_acc)
```

```
Best CO2 Breakpoint = 831.5
Best Accuracy = 0.8444476871443164
```

Accuracy vs CO_2 Threshold Curve (Heuristic Optimization)

In [222…

```
import numpy as np
import matplotlib.pyplot as plt
len(co2_values)
```

Out[222…

```
15498
```

In [223…

```
# Generate thresholds properly
co2_values = np.sort(analyze_df["CO2"].unique())

thresholds = []
for val in co2_values:
    thresholds.extend([val - 0.5, val, val + 0.5])

thresholds = np.array(thresholds)
print(len(thresholds))
```

```
15498
```

In [224…

```
# Compute accuracy for each threshold
accuracies = []

for t in thresholds:
    preds = (analyze_df["CO2"] > t).astype(int)
    acc = (preds == analyze_df["Occupancy"]).mean()
    accuracies.append(acc)

accuracies = np.array(accuracies)
print(len(accuracies))
```

```
15498
```

In [225…

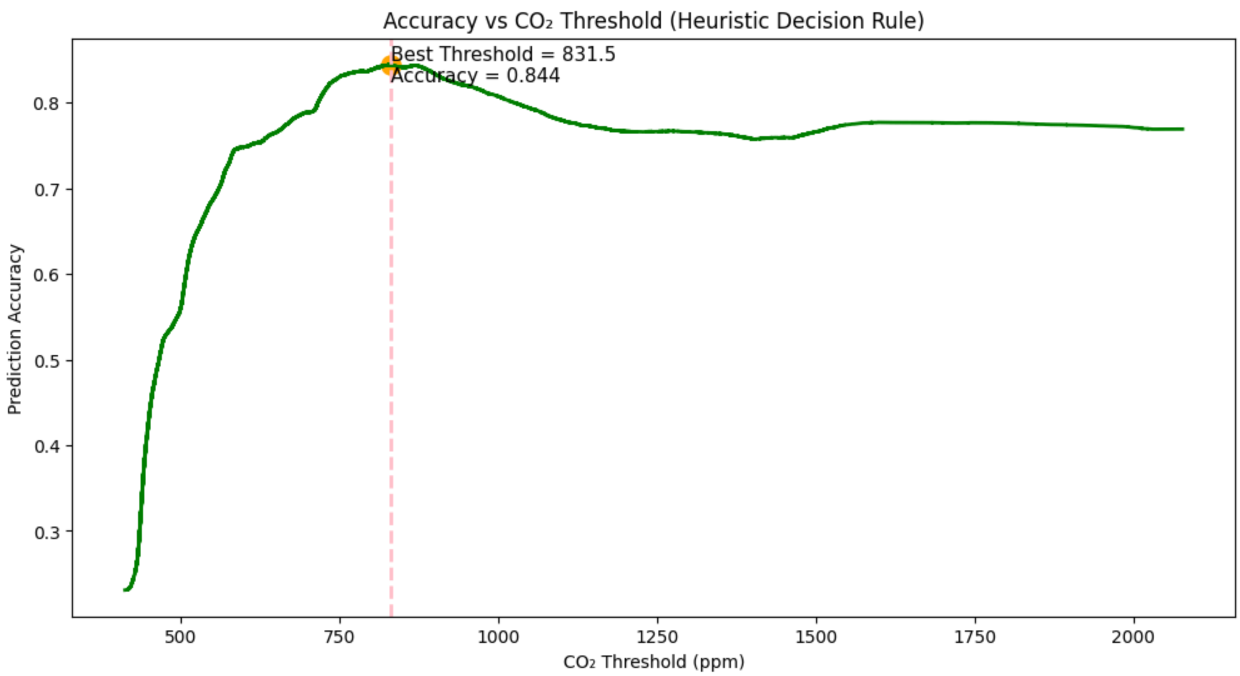
```
# Plot Accuracy Curve
plt.figure(figsize=(12,6))
plt.plot(thresholds, accuracies, color="green",linewidth=2)

# Highlight best point
plt.scatter(best_thresh, best_acc,color="orange", s=120)
plt.axvline(best_thresh, linestyle="--", color="pink",linewidth=2)
```

```
# Labels
plt.title("Accuracy vs CO₂ Threshold (Heuristic Decision Rule)")
plt.xlabel("CO₂ Threshold (ppm)")
plt.ylabel("Prediction Accuracy")

# Annotate best threshold
plt.text(
    best_thresh,
    best_acc - 0.02,
    f"Best Threshold = {best_thresh:.1f}\nAccuracy = {best_acc:.3f}",
    fontsize=11
)

plt.show()
```



Why This Matters

Instead of saying:“We chose 900 ppm because it feels right”

We can now say:“We optimized the CO_2 breakpoint and found the best threshold is 831.5 ppm, achieving 84% accuracy.”

That’s heuristic → evidence → science.

Now we can visualize the charts based on this new threshold

In [229…
```
high_co2_occupied =analyze_df[(analyze_df["CO2"]>831.5) &(analyze_df["Occupanc
print("Samples with High CO2 & Occupied:", len(high_co2_occupied))
print(f"percentage = {float( len(high_co2_occupied))/float(len(analyze_df[anal
high_co2_noccupied =analyze_df[(analyze_df["CO2"]>831.5) &(analyze_df["Occupar
print("Samples with High CO2 & not Occupied:", len(high_co2_noccupied))
print(f"percentage = {float( len(high_co2_noccupied))/float(len(analyze_df[ana
low_co2_noccupied =analyze_df[(analyze_df["CO2"]<831.5) &(analyze_df["Occupanc
print("Samples with low CO2 & not occupied:", len(low_co2_noccupied))
print(f"percentage = {float( len(low_co2_noccupied))/float(len(analyze_df[anal
low_co2_occupied =analyze_df[(analyze_df["CO2"]<831.5) &(analyze_df["Occupancy
print("Samples with low CO2 & occupied:", len(low_co2_occupied))
print(f"percentage = {float( len(low_co2_occupied))/float(len(analyze_df[analy
```

```
Samples with High CO2 & Occupied: 3142
percentage = 66.16129711518214
Samples with High CO2 & not Occupied: 1591
percentage = 10.06325110689437
Samples with low CO2 & not occupied: 14216
percentage = 89.91777356103732
Samples with low CO2 & occupied: 1607
percentage = 10.164452877925363
```

In [230…
```
# Counts
counts = {
    "High CO2 & Occupied": len(high_co2_occupied),
    "High CO2 & Not Occupied": len(high_co2_noccupied),
    "Low CO2 & Not Occupied": len(low_co2_noccupied),
    "Low CO2 & Occupied": len(low_co2_occupied)
}
```

CO_2 Distribution Plot with Occupancy Overlay

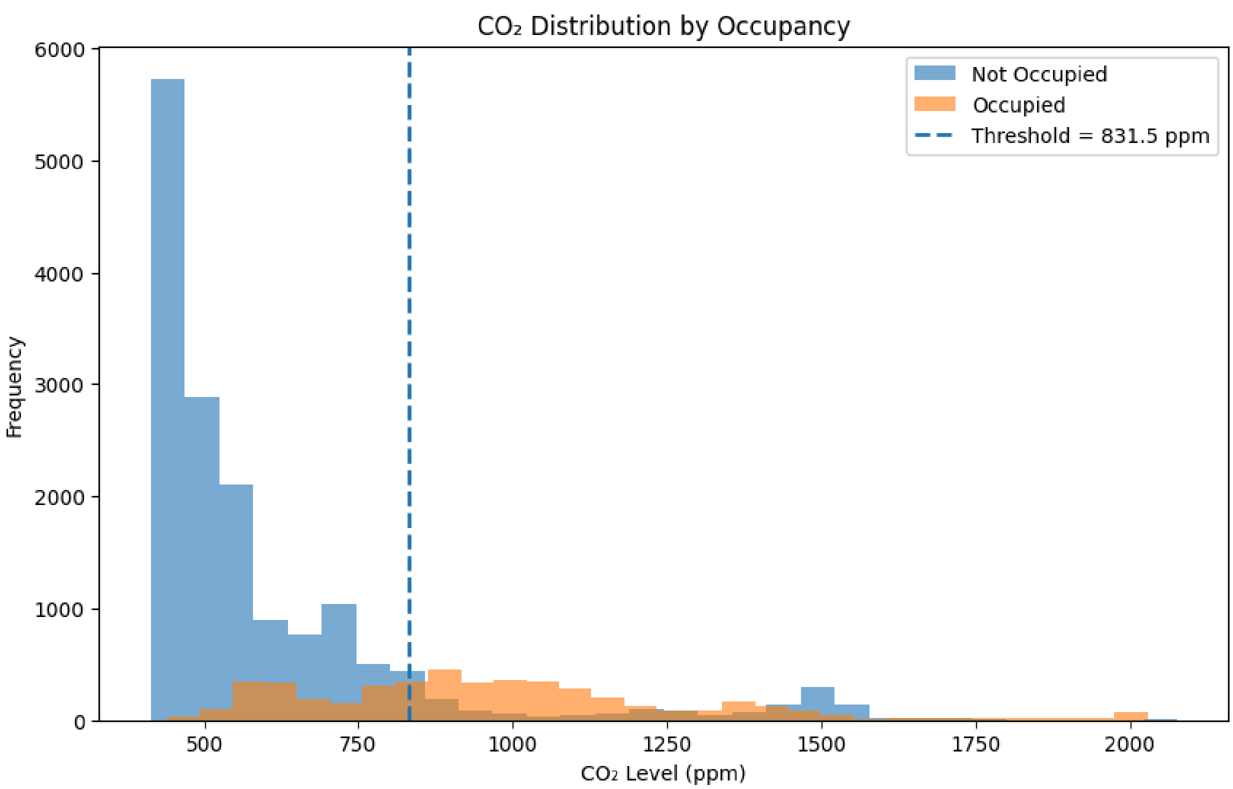
In [231…

```
plt.figure(figsize=(10,6))

plt.hist(analyze_df[analyze_df["Occupancy"]==0]["CO2"], bins=30, alpha=0.6, la
plt.hist(analyze_df[analyze_df["Occupancy"]==1]["CO2"], bins=30, alpha=0.6, la

plt.axvline(831.5, linestyle="--", linewidth=2, label="Threshold = 831.5 ppm")

plt.title("CO₂ Distribution by Occupancy")
plt.xlabel("CO₂ Level (ppm)")
plt.ylabel("Frequency")
plt.legend()
plt.show()
```

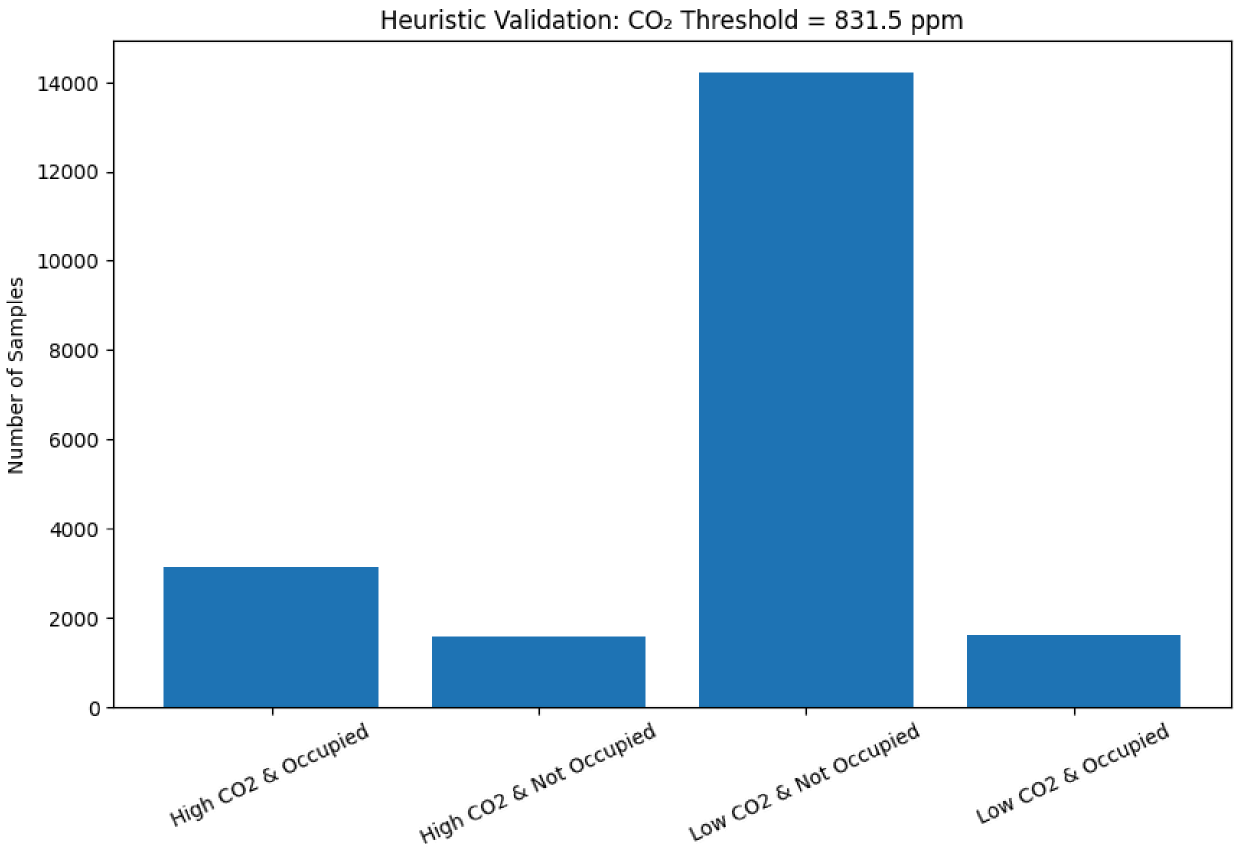


Bar Chart of the Four Heuristic Outcomes

In [232…

```
plt.figure(figsize=(10,6))
plt.bar(counts.keys(), counts.values())
```

```python
plt.title("Heuristic Validation: CO₂ Threshold = 831.5 ppm")
plt.ylabel("Number of Samples")
plt.xticks(rotation=25)
plt.show()
```



Step 7: Automation Logic Based on HDH

In [235…

```python
def hdh_decision_engine(temp, light, co2):
  decisions = []
  if co2 > 900:
    decisions.append ("Occupancy = YES")
  else:
    decisions. append ("Occupancy = NO")
  if light < 200:
    decisions.append ("Lights = ON")
  else:
    decisions. append ("Lights = OFF")
  if temp > 28:
    decisions.append ("Fan = ON")
  else:
    decisions. append ("Fan = OFF")

  return decisions
```

Step 8: Test Automation Using Dataset Samples

In [236…

```
for i in range(5):
  print(_)
  print("\nSensor Values", end=": ")
  print(f"Temp= {analyze_df.iloc[i,0]}, Light= {analyze_df.iloc[i,2]}, CO2= {a

  decisions = hdh_decision_engine(analyze_df.iloc[i,0],analyze_df.iloc[i,2],ar
  print("HDH Decisions:")

  print()
  for d in decisions:
    print(d, end="  ||  ")
```

```
15498

Sensor Values: Temp= 23.718, Light= 578.4, CO2= 760.4
HDH Decisions:

Occupancy = NO  ||  Lights = OFF  ||  Fan = OFF  ||  15498

Sensor Values: Temp= 23.73, Light= 572.666666666667, CO2= 769.666666666667
HDH Decisions:

Occupancy = NO  ||  Lights = OFF  ||  Fan = OFF  ||  15498

Sensor Values: Temp= 23.7225, Light= 493.75, CO2= 774.75
HDH Decisions:

Occupancy = NO  ||  Lights = OFF  ||  Fan = OFF  ||  15498

Sensor Values: Temp= 23.754, Light= 488.6, CO2= 779.0
HDH Decisions:

Occupancy = NO  ||  Lights = OFF  ||  Fan = OFF  ||  15498

Sensor Values: Temp= 23.76, Light= 568.666666666667, CO2= 790.0
HDH Decisions:

Occupancy = NO  ||  Lights = OFF  ||  Fan = OFF  ||
```

Observations

• CO_2 strongly correlates with occupancy

• Light values help detect artificial lighting usage

• Temperature impacts cooling requirements

• Heuristics align well with real data patterns

Result

Successfully designed and validated an HDH matrix
for smart home occupancy detection using real IoT sensor data.
