

You are analyzing the impact of product placement on monthly sales performance. Specifically, you are comparing the sales of a product displayed in two different store locations:

Special Up-Front Display

In-Aisle Placement

## Hypothesis Formulation

Null Hypothesis ( $H_0$ ): There is no significant difference in monthly sales between the special up-front display and the in-aisle placement.

Alternative Hypothesis ( $H_1$ ): There is a significant difference in monthly sales between the special up-front display and the in-aisle placement.

Significance level of 0.05 (Confidence level of 95%) Independent T Test

```
In [1]: import pandas as pd
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [6]: # Construct the raw GitHub URLs
url_independent = "https://raw.githubusercontent.com/Kartavya-Jharwal/Kartavya_Busi
url_paired = "https://raw.githubusercontent.com/Kartavya-Jharwal/Kartavya_Business_

# Load the data into pandas DataFrames directly from the URLs
df_independent = pd.read_excel(url_independent)
df_paired = pd.read_excel(url_paired)
```

```
In [7]: # Display shape, head, describe, and info for df_independent
print("Shape of df_independent:")
display(df_independent.shape)

print("\nHead of df_independent:")
display(df_independent.head())

print("\nDescription of df_independent:")
display(df_independent.describe())

print("\nInfo of df_independent:")
display(df_independent.info())
```

Shape of df\_independent:

(10, 2)

Head of df\_independent:

	Special Front	In-Aisle
0	224	192
1	189	236
2	248	164
3	285	154
4	273	189

Description of df\_independent:

	Special Front	In-Aisle
count	10.000000	10.000000
mean	246.400000	202.300000
std	42.542005	32.527083
min	189.000000	154.000000
25%	217.250000	186.750000
50%	245.500000	197.000000
75%	278.250000	219.750000
max	317.000000	261.000000

Info of df\_independent:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 2 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Special Front    10 non-null     int64
1   In-Aisle         10 non-null     int64
dtypes: int64(2)
memory usage: 292.0 bytes
None
```

```
In [9]: # Normality check with seaborn plots
plt.figure(figsize=(8, 6))

sns.histplot(data=df_independent, x='Special Front', kde=True, color='skyblue', label='Special Front')
sns.histplot(data=df_independent, x='In-Aisle', kde=True, color='salmon', label='In-Aisle')

plt.title('Normality check and comparison of Special Front and In-Aisle Sales')
plt.xlabel('Monthly Sales')
plt.ylabel('Frequency')
plt.legend()
plt.show()

# Shapiro-Wilk test for normality
shapiro_special_front = stats.shapiro(df_independent['Special Front'])
```

```

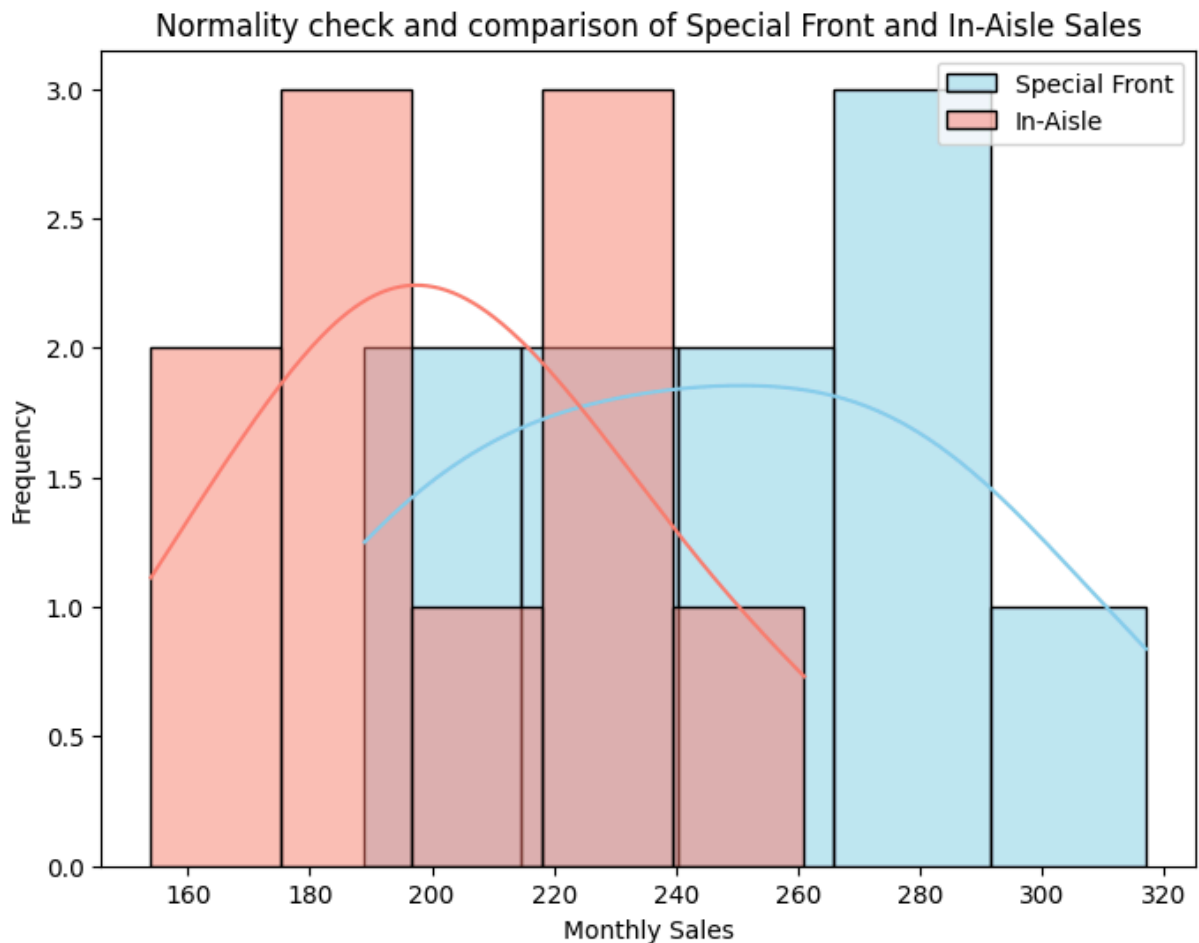
shapiro_in_aisle = stats.shapiro(df_independent['In-Aisle'])

print("\nShapiro-Wilk test results:")
print(f"Special Front: Statistic={shapiro_special_front.statistic:.4f}, P-value={shapiro_special_front.pvalue:.4f}")
print(f"In-Aisle: Statistic={shapiro_in_aisle.statistic:.4f}, P-value={shapiro_in_aisle.pvalue:.4f}")

# Interpret the Shapiro-Wilk test results
alpha = 0.05
print("\nInterpretation:")
if shapiro_special_front.pvalue < alpha:
    print("Special Front: Data is likely not normally distributed (Reject H0)")
else:
    print("Special Front: Data is likely normally distributed (Fail to reject H0)")

if shapiro_in_aisle.pvalue < alpha:
    print("In-Aisle: Data is likely normally distributed (Fail to reject H0)")
else:
    print("In-Aisle: Data is likely normally distributed (Fail to reject H0)")

```



Shapiro-Wilk test results:  
Special Front: Statistic=0.9568, P-value=0.7486  
In-Aisle: Statistic=0.9769, P-value=0.9462

Interpretation:  
Special Front: Data is likely normally distributed (Fail to reject H0)  
In-Aisle: Data is likely normally distributed (Fail to reject H0)

```
In [4]: # Perform independent samples t-test
t_statistic, p_value = stats.ttest_ind(df_independent['Special Front'], df_independent['In-aisle'])

# Print the results
print(f"Independent t-test results:")
print(f"T-statistic: {t_statistic}")
print(f"P-value: {p_value}")

# Interpret the results
alpha = 0.05
if p_value < alpha:
    print("\nResult: Reject the null hypothesis.")
    print("Conclusion: There is a significant difference in monthly sales between the special up-front display and the in-aisle placement.")
else:
    print("\nResult: Fail to reject the null hypothesis.")
    print("Conclusion: There is no significant difference in monthly sales between the special up-front display and the in-aisle placement.")
```

Independent t-test results:  
T-statistic: 2.604123851375045  
P-value: 0.01794309835110639

Result: Reject the null hypothesis.  
Conclusion: There is a significant difference in monthly sales between the special up-front display and the in-aisle placement.

Based on the independent t-test results (P-value: 0.0179), which is less than the significance level of 0.05, we reject the null hypothesis. This indicates there is a statistically significant difference in monthly sales between the special up-front display and the in-aisle placement.

This confirms that where you place a product can materially affect how much you sell. If up-front displays consistently outperform, a small business can boost sales simply by rethinking shelf strategy

## Paired T Test

A researcher wants to determine if there is any difference between the mean price at Costco and Walmart of a market basket containing  $n = 7$  different items.

Null hypothesis  $H_0$ : There is no difference in monthly sales between the special up-front display and the in-aisle placement.

Alternative hypothesis  $H_1$  (two-sided): There is a difference in monthly sales between the special up-front display and the in-aisle placement.

Primary Significance Level:  $\alpha = 0.05$

```
In [10]: # Display shape, head, describe, and info for df_paired
print("Shape of df_paired:")
display(df_paired.shape)
```

```

print("\nHead of df_paired:")
display(df_paired.head())

print("\nDescription of df_paired:")
display(df_paired.describe())

print("\nInfo of df_paired:")
display(df_paired.info())

```

Shape of df\_paired:

(7, 3)

Head of df\_paired:

	Item	Costco	Walmart
0	Chicken Broth	5.98	5.88
1	Ice Cream	8.59	7.19
2	Dishwasher Detergent	9.00	17.00
3	Laundry Detergent	11.00	12.00
4	Paper Towels	1.47	2.09

Description of df\_paired:

	Costco	Walmart
count	7.000000	7.000000
mean	7.038571	10.325714
std	4.328816	9.197376
min	1.230000	1.120000
25%	3.725000	3.985000
50%	8.590000	7.190000
75%	10.000000	14.500000
max	12.000000	27.000000

Info of df\_paired:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 7 entries, 0 to 6

Data columns (total 3 columns):

#	Column	Non-Null Count	Dtype
0	Item	7 non-null	object
1	Costco	7 non-null	float64
2	Walmart	7 non-null	float64

dtypes: float64(2), object(1)

memory usage: 300.0+ bytes

None

```
In [14]: df_paired['Price Difference'] = df_paired['Costco'] - df_paired['Walmart']
display(df_paired.head())
```

	Item	Costco	Walmart	Price Difference
0	Chicken Broth	5.98	5.88	0.10
1	Ice Cream	8.59	7.19	1.40
2	Dishwasher Detergent	9.00	17.00	-8.00
3	Laundry Detergent	11.00	12.00	-1.00
4	Paper Towels	1.47	2.09	-0.62

## Paired data normality check

```
In [15]: # Normality check with seaborn plots for price difference
plt.figure(figsize=(8, 6))

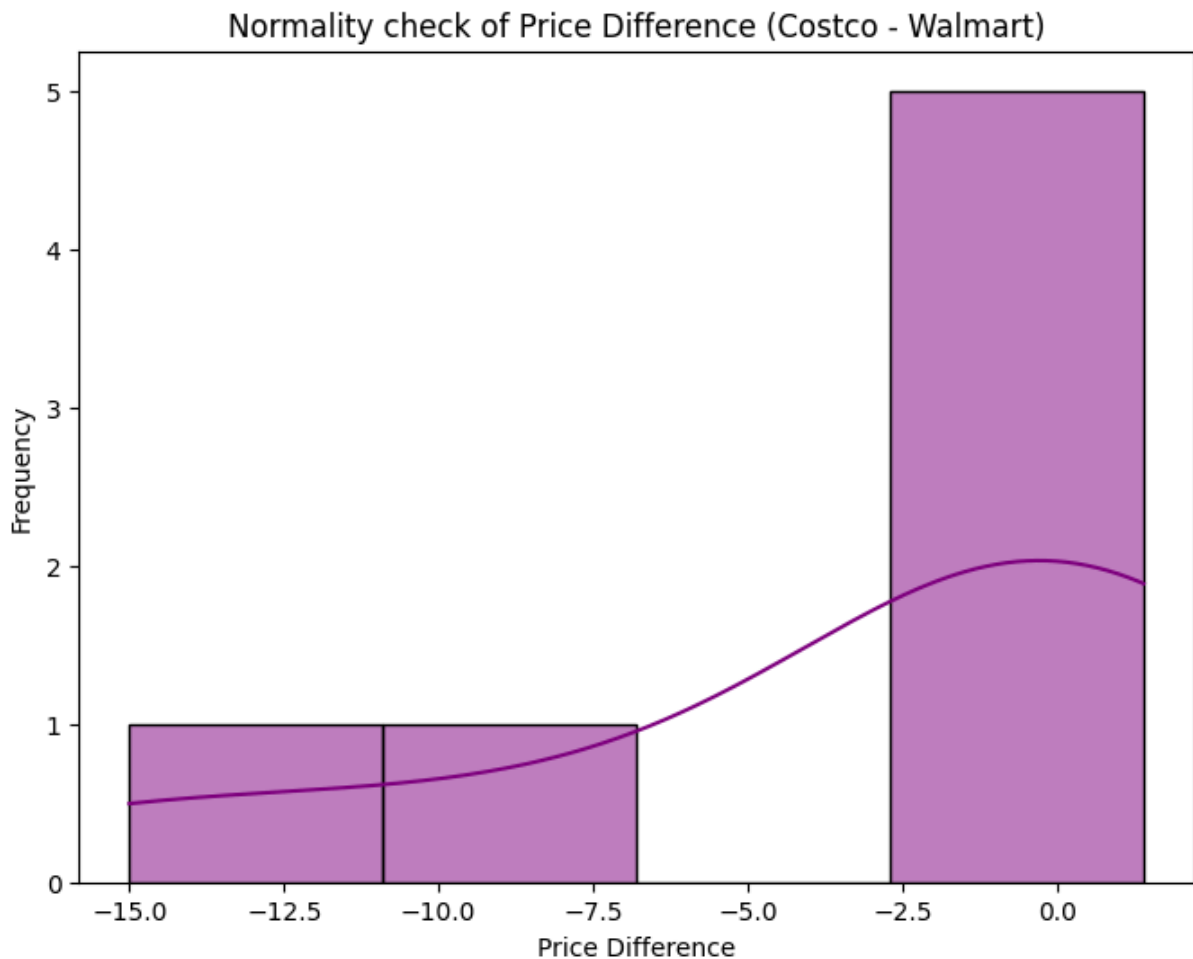
sns.histplot(data=df_paired, x='Price Difference', kde=True, color='purple')

plt.title('Normality check of Price Difference (Costco - Walmart)')
plt.xlabel('Price Difference')
plt.ylabel('Frequency')
plt.show()

# Shapiro-Wilk test for normality on price difference
shapiro_diff = stats.shapiro(df_paired['Price Difference'])

print("\nShapiro-Wilk test results for Price Difference:")
print(f"Statistic={shapiro_diff.statistic:.4f}, P-value={shapiro_diff.pvalue:.4f}")

# Interpret the Shapiro-Wilk test results
alpha = 0.05
print("\nInterpretation:")
if shapiro_diff.pvalue < alpha:
    print("Price Difference: Data is likely not normally distributed (Reject H0)")
else:
    print("Price Difference: Data is likely normally distributed (Fail to reject H0)")
```



Shapiro-Wilk test results for Price Difference:  
Statistic=0.7597, P-value=0.0160

Interpretation:

Price Difference: Data is likely not normally distributed (Reject  $H_0$ )

## Paired t-test

```
In [12]: # Perform paired samples t-test
t_statistic_paired, p_value_paired = stats.ttest_rel(df_paired['Costco'], df_paired['Walmart'])

# Print the results
print(f"Paired t-test results:")
print(f"T-statistic: {t_statistic_paired}")
print(f"P-value: {p_value_paired}")

# Interpret the results
alpha = 0.05
if p_value_paired < alpha:
    print("\nResult: Reject the null hypothesis.")
    print("Conclusion: There is a significant difference in the mean price between Costco and Walmart.")
else:
    print("\nResult: Fail to reject the null hypothesis.")
    print("Conclusion: There is no significant difference in the mean price between Costco and Walmart.")
```

Paired t-test results:  
T-statistic: -1.4470527628170282  
P-value: 0.19803202683637366

Result: Fail to reject the null hypothesis.

Conclusion: There is no significant difference in the mean price between Costco and Walmart for the market basket items.

## Summary:

### Data Analysis Key Findings

- The paired t-test resulted in a t-statistic of -1.447 and a p-value of 0.198.
- Based on the paired t-test p-value ( $0.198 > 0.05$ ), there is no statistically significant difference in the mean prices between Costco and Walmart for the market basket items in this dataset.

Based on the caveat of the small and not normally distributed sample

## Implications

Price-sensitive sourcing decisions should be cautious: Small businesses should not assume consistent savings by switching supplier or retailer based solely on these results

Treat Costco and Walmart as roughly equivalent for this basket until further evidence emerges