```python
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
import numpy as np
from scipy import stats
from scipy.stats import shapiro, f_oneway, skew, kurtosis, wilcoxon,
ttest_rel, chi2_contingency
import statsmodels.api as sm
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings('ignore')
```

```python
df = pd.read_csv('./data.csv')
df.head(10)
```

```
                     Timestamp  \
0   2025/06/21 5:22:28 pm EEST
1   2025/06/21 5:29:05 pm EEST
2   2025/06/21 5:59:31 pm EEST
3   2025/06/21 6:36:08 pm EEST
4   2025/06/21 7:41:10 pm EEST
5   2025/06/21 7:41:13 pm EEST
6   2025/06/21 7:43:09 pm EEST
7   2025/06/21 9:25:23 pm EEST
8  2025/06/21 10:18:19 pm EEST
9  2025/06/21 10:32:55 pm EEST

  Are you 18 years or older and willing to participate voluntarily?
\
0                                                Yes

1                                                Yes

2                                                Yes

3                                                Yes

4                                                Yes

5                                                Yes

6                                                Yes

7                                                Yes

8                                                Yes

9                                                Yes
```

```
    What is your age group?    What is your gender?    \
0                        23-27                    Male   
1                        23-27                    Male   
2                        28-50                  Female   
3                        23-27                    Male   
4                        23-27                  Female   
5                        23-27                  Female   
6                        23-27                  Female   
7                        28-50                  Female   
8                        23-27                    Male   
9                        28-50                  Female   

  What is your highest level of education?    \
0                                  Master's   
1                                  Master's   
2                                  Master's   
3                                  Master's   
4                                  Master's   
5                                Bachelor's   
6                                  Master's   
7                                  Master's   
8                                Bachelor's   
9                                Bachelor's   

   How often do you watch video ads on platforms like YouTube,
Instagram, or TikTok?    \
0                                                  5   

1                                                  5   

2                                                  5   

3                                                  4   

4                                                  1   

5                                                  3   

6                                                  3   

7                                                  5   

8                                                  3   

9                                                  2   


   How familiar are you with AI-generated content (e.g., AI-made
videos/images)?    \
0                                                  4   
```

```
1                                                   5

2                                                   5

3                                                   5

4                                                   5

5                                                   5

6                                                   5

7                                                   4

8                                                   5

9                                                   1


    Ad: A   Ad: B     The ad feels original and creative?_A  ...  \
0       3       5                                         3  ...
1       3       5                                         3  ...
2       3       3                                         3  ...
3       3       4                                         3  ...
4       3       5                                         5  ...
5       3       3                                         3  ...
6       2       4                                         2  ...
7       3       3                                         3  ...
8       4       5                                         3  ...
9       3       2                                         1  ...

   The ad presents the product in an imaginative way?_B  \
0                                                   5
1                                                   4
2                                                   4
3                                                   4
4                                                   5
5                                                   3
6                                                   3
7                                                   3
8                                                   2
9                                                   1

   The ad feels genuine and trustworthy?_B  \
0                                         5
1                                         5
2                                         4
3                                         3
4                                         5
5                                         3
```

```
6                                         3
7                                         3
8                                         2
9                                         1

   The ad aligns well with what I expect from a fashion brand?_B  \
0                                                   5
1                                                   4
2                                                   4
3                                                   5
4                                                   5
5                                                   3
6                                                   4
7                                                   3
8                                                   2
9                                                   1

   This ad appears to have been produced quickly?_B  \
0                                                 5
1                                                 2
2                                                 4
3                                                 3
4                                                 1
5                                                 4
6                                                 3
7                                                 4
8                                                 5
9                                                 4

   The visual quality suggests minimal production time?_B  \
0                                                   5
1                                                   2
2                                                   4
3                                                   4
4                                                   1
5                                                   3
6                                                   4
7                                                   4
8                                                   5
9                                                   4

   This ad seems inexpensive to produce?_B  \
0                                         5
1                                         1
2                                         4
3                                         3
4                                         1
5                                         4
6                                         3
7                                         4
```

```
8                                         5
9                                         4

   I believe less effort or budget went into making this ad?_B  \
0                                                   5
1                                                   2
2                                                   4
3                                                   2
4                                                   1
5                                                   3
6                                                   2
7                                                   4
8                                                   5
9                                                   4

   Which ad did you prefer overall?    \
0                                 Ad B
1                                 Ad B
2                                 Ad A
3                                 Ad B
4                                 Ad A
5                                 Ad B
6                                 Ad B
7                                 Ad B
8                                 Ad B
9                                 Ad A

   Which ad do you think was created using AI?    \
0                                            Ad B
1                                            Ad A
2                                            Ad B
3                                            Ad A
4                                            Ad A
5                                            Ad A
6                                            Ad A
7                                            Ad A
8                                            Ad B
9                                            Ad A

   Would you mind if ads were created using AI as long as they are
effective?
0                                                  No

1                                                  No

2                                                 Yes

3                                                  No

4                                                 Yes
```

```
5                                                   No
6                                                   No
7                                                   No
8                                                  Yes
9                                                   No

[10 rows x 28 columns]
```

```
df.columns
```

```
Index(['Timestamp',
       'Are you 18 years or older and willing to participate voluntarily?  ',
       '  What is your age group?   ', 'What is your gender?  ',
       'What is your highest level of education?  ',
       'How often do you watch video ads on platforms like YouTube, Instagram, or TikTok?  ',
       'How familiar are you with AI-generated content (e.g., AI-made videos/images)?  ',
       ' Ad: A ', 'Ad: B   ', 'The ad feels original and creative?_A',
       'The ad presents the product in an imaginative way?_A',
       'The ad feels genuine and trustworthy?_A',
       'The ad aligns well with what I expect from a fashion brand?_A',
       'This ad appears to have been produced quickly?_A',
       'The visual quality suggests minimal production time?_A',
       'This ad seems inexpensive to produce?_A',
       'I believe less effort or budget went into making this ad?_A',
       'The ad feels original and creative?_B',
       'The ad presents the product in an imaginative way?_B',
       'The ad feels genuine and trustworthy?_B',
       'The ad aligns well with what I expect from a fashion brand?_B',
       'This ad appears to have been produced quickly?_B',
       'The visual quality suggests minimal production time?_B',
       'This ad seems inexpensive to produce?_B',
       'I believe less effort or budget went into making this ad?_B',
       'Which ad did you prefer overall?  ',
       'Which ad do you think was created using AI?  ',
       'Would you mind if ads were created using AI as long as they are effective?  '],
      dtype='object')
```

```
df = df[[ '  What is your age group?   ', 'What is your gender?  ',
       'What is your highest level of education?  ',
```

```
       'How often do you watch video ads on platforms like YouTube,
Instagram, or TikTok?  ',
       'How familiar are you with AI-generated content (e.g., AI-made
videos/images)?  ','The ad feels original and creative?_A',
       'The ad presents the product in an imaginative way?_A',
       'The ad feels genuine and trustworthy?_A',
       'The ad aligns well with what I expect from a fashion brand?
_A',
       'This ad appears to have been produced quickly?_A',
       'The visual quality suggests minimal production time?_A',
       'This ad seems inexpensive to produce?_A',
       'I believe less effort or budget went into making this ad?_A',
       'The ad feels original and creative?_B',
       'The ad presents the product in an imaginative way?_B',
       'The ad feels genuine and trustworthy?_B',
       'The ad aligns well with what I expect from a fashion brand?
_B',
       'This ad appears to have been produced quickly?_B',
       'The visual quality suggests minimal production time?_B',
       'This ad seems inexpensive to produce?_B',
       'I believe less effort or budget went into making this ad?_B',
       'Which ad did you prefer overall?  ',
       'Which ad do you think was created using AI?  ']]

len(df.columns)

23

dff = pd.DataFrame({
    'age': df['  What is your age group?   '], 'gender': df['What is
your gender?  '], 'ad_exposure': df['How often do you watch video ads
on platforms like YouTube, Instagram, or TikTok?  '], 'ai_exposure':
df[ 'How familiar are you with AI-generated content (e.g., AI-made
videos/images)?  '], 'creativity_a': df[['The ad feels original and
creative?_A', 'The ad presents the product in an imaginative way?
_A']].mean(axis=1),  'creativity_b': df[['The ad feels original and
creative?_B', 'The ad presents the product in an imaginative way?
_B']].mean(axis=1), 'authenticity_a': df[['The ad feels genuine and
trustworthy?_A',  'The ad aligns well with what I expect from a
fashion brand?_A']].mean(axis=1),  'authenticity_b': df[['The ad feels
genuine and trustworthy?_B',  'The ad aligns well with what I expect
from a fashion brand?_B']].mean(axis=1), 'production_speed_a':
df[['This ad appears to have been produced quickly?_A', 'The visual
quality suggests minimal production time?_A']].mean(axis=1),
'production_speed_b': df[['This ad appears to have been produced
quickly?_B', 'The visual quality suggests minimal production time?
_B']].mean(axis=1), 'cost_eff_a': df[['This ad seems inexpensive to
produce?_A', 'I believe less effort or budget went into making this
ad?_A']].mean(axis=1),  'cost_eff_b': df[['This ad seems inexpensive
to produce?_B', 'I believe less effort or budget went into making this
```

```
ad?_B']].mean(axis=1), 'ad_preference' : df['Which ad did you prefer 
overall?  '] , 'ad_prediction': df['Which ad do you think was created 
using AI?  ']
})

dff.columns

Index(['age', 'gender', 'ad_exposure', 'ai_exposure', 'creativity_a',
       'creativity_b', 'authenticity_a', 'authenticity_b',
       'production_speed_a', 'production_speed_b', 'cost_eff_a', 
'cost_eff_b',
       'ad_preference', 'ad_prediction'],
      dtype='object')

dff.head()

     age  gender  ad_exposure  ai_exposure  creativity_a  creativity_b  
\
0  23-27    Male            5            4           4.0           5.0

1  23-27    Male            5            5           3.0           4.5

2  28-50  Female            5            5           3.0           4.0

3  23-27    Male            4            5           3.0           4.0

4  23-27  Female            1            5           5.0           5.0


   authenticity_a  authenticity_b  production_speed_a  
production_speed_b  \
0             4.0             5.0                 5.0
5.0
1             3.0             4.5                 4.5
2.0
2             4.0             4.0                 4.0
4.0
3             2.5             4.0                 4.5
3.5
4             5.0             5.0                 1.0
1.0

   cost_eff_a  cost_eff_b ad_preference ad_prediction
0         3.0         5.0          Ad B          Ad B
1         5.0         1.5          Ad B          Ad A
2         3.5         4.0          Ad A          Ad B
3         4.5         2.5          Ad B          Ad A
4         1.0         1.0          Ad A          Ad A

dff['age'].unique()
```

```
array(['23-27', '28-50', '18-22', '51 and above'], dtype=object)
```

```python
dff['gender'].unique()
```

```
array(['Male', 'Female', 'Other'], dtype=object)
```

```python
ad_mapping = {'Ad A': 1, 'Ad B': 2}

dff['ad_preference'] = dff['ad_preference'].map(ad_mapping)
dff['ad_prediction'] = dff['ad_prediction'].map(ad_mapping)

age_mapping = {'18-22': 1, '23-27': 2, '28-50': 3, '51 and above': 4}
gender_mapping = {'Male': 1, 'Female': 2, 'Other': 3}

dff['age'] = dff['age'].map(age_mapping)
dff['gender'] = dff['gender'].map(gender_mapping)

dff.head()
```

```
   age  gender  ad_exposure  ai_exposure  creativity_a
creativity_b  \
0    2       1            5            4           4.0           5.0

1    2       1            5            5           3.0           4.5

2    3       2            5            5           3.0           4.0

3    2       1            4            5           3.0           4.0

4    2       2            1            5           5.0           5.0


   authenticity_a  authenticity_b  production_speed_a
production_speed_b  \
0             4.0             5.0                 5.0
5.0
1             3.0             4.5                 4.5
2.0
2             4.0             4.0                 4.0
4.0
3             2.5             4.0                 4.5
3.5
4             5.0             5.0                 1.0
1.0

   cost_eff_a  cost_eff_b  ad_preference  ad_prediction
0         3.0         5.0              2              2
1         5.0         1.5              2              1
2         3.5         4.0              1              2
3         4.5         2.5              2              1
4         1.0         1.0              1              1
```

data mean

```
dff.mean()
```

```
age                     2.305556
gender                  1.488889
ad_exposure             4.122222
ai_exposure             4.194444
creativity_a            3.669444
creativity_b            3.730556
authenticity_a          3.541667
authenticity_b          3.647222
production_speed_a      3.333333
production_speed_b      3.172222
cost_eff_a              3.247222
cost_eff_b              2.980556
ad_preference           1.500000
ad_prediction           1.494444
dtype: float64
```

data standard deviation

```
dff.std()
```

```
age                     0.832961
gender                  0.533659
ad_exposure             0.961002
ai_exposure             1.008884
creativity_a            1.141111
creativity_b            1.093868
authenticity_a          1.040889
authenticity_b          1.047339
production_speed_a      1.160331
production_speed_b      1.087412
cost_eff_a              1.213860
cost_eff_b              1.221735
ad_preference           0.501395
ad_prediction           0.501364
dtype: float64
```

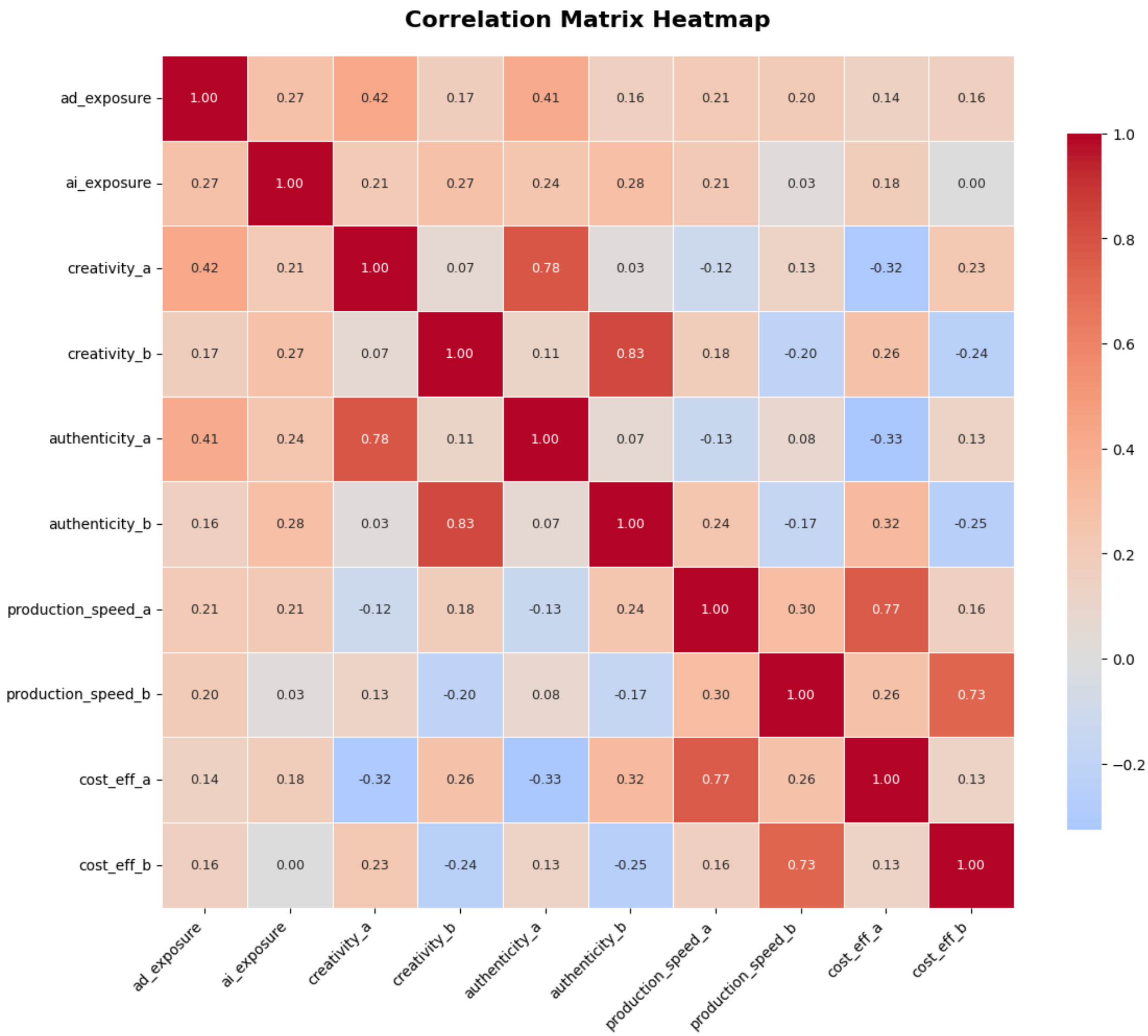
```
dff[['ad_exposure', 'ai_exposure', 'creativity_a',
       'creativity_b', 'authenticity_a', 'authenticity_b',
       'production_speed_a', 'production_speed_b', 'cost_eff_a',
       'cost_eff_b']].corr()
```

```
                    ad_exposure  ai_exposure  creativity_a
creativity_b  \
ad_exposure            1.000000     0.274981      0.421676
```

```
0.167021
ai_exposure            0.274981     1.000000      0.211427
0.265415
creativity_a           0.421676     0.211427      1.000000
0.071467
creativity_b           0.167021     0.265415      0.071467
1.000000
authenticity_a         0.410958     0.242276      0.778320
0.112953
authenticity_b         0.159640     0.282053      0.026924
0.834539
production_speed_a     0.206246     0.213956     -0.116733
0.180094
production_speed_b     0.198930     0.027866      0.130551      -
0.203821
cost_eff_a             0.136782     0.179495     -0.317778
0.263973
cost_eff_b             0.159057     0.000818      0.231789      -
0.242218

                    authenticity_a  authenticity_b  production_speed_a
\
ad_exposure                0.410958        0.159640            0.206246

ai_exposure                0.242276        0.282053            0.213956

creativity_a               0.778320        0.026924           -0.116733

creativity_b               0.112953        0.834539            0.180094

authenticity_a             1.000000        0.072491           -0.132984

authenticity_b             0.072491        1.000000            0.242110

production_speed_a        -0.132984        0.242110            1.000000

production_speed_b         0.084935       -0.167094            0.298496

cost_eff_a                -0.325444        0.320559            0.771134

cost_eff_b                 0.133530       -0.248795            0.162231


                    production_speed_b  cost_eff_a  cost_eff_b
ad_exposure                   0.198930    0.136782    0.159057
ai_exposure                   0.027866    0.179495    0.000818
creativity_a                  0.130551   -0.317778    0.231789
creativity_b                 -0.203821    0.263973   -0.242218
authenticity_a                0.084935   -0.325444    0.133530
authenticity_b               -0.167094    0.320559   -0.248795
```

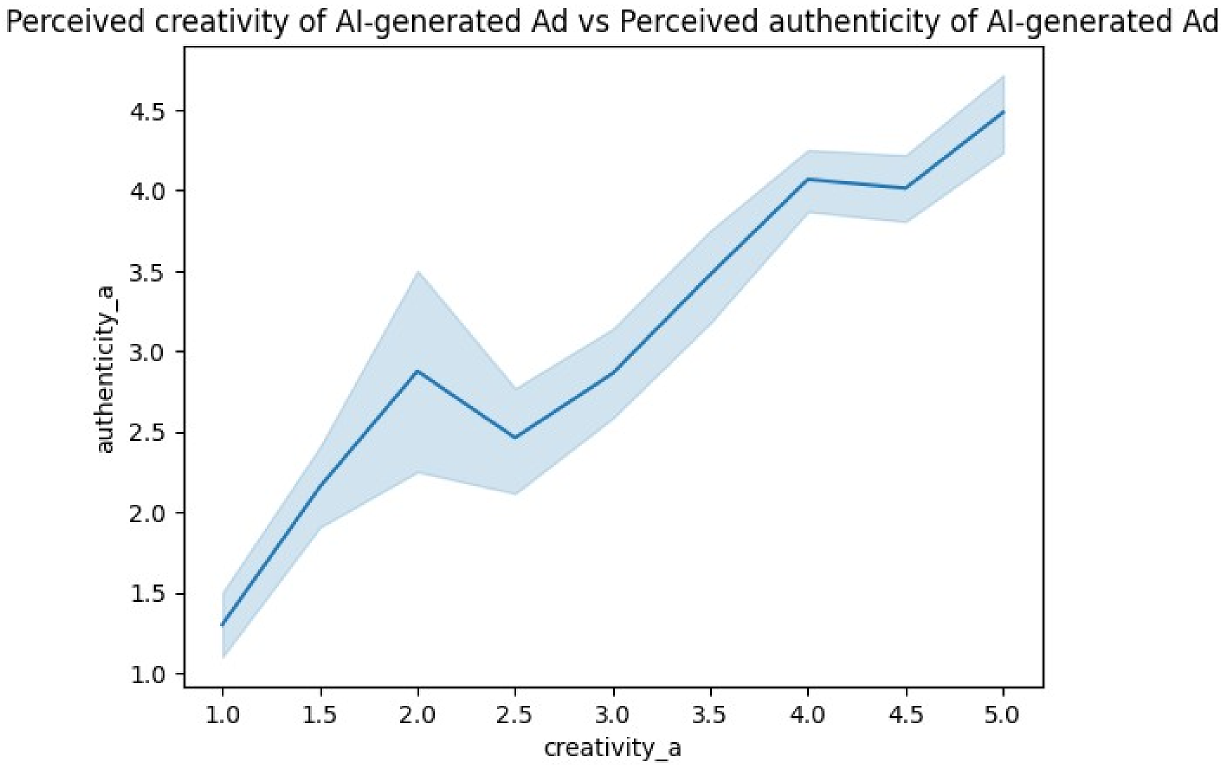
```
production_speed_a            0.298496    0.771134    0.162231
production_speed_b            1.000000    0.261714    0.727914
cost_eff_a                    0.261714    1.000000    0.134165
cost_eff_b                    0.727914    0.134165    1.000000
```

```
correlation_matrix = dff[['ad_exposure', 'ai_exposure',
'creativity_a',
                          'creativity_b', 'authenticity_a',
'authenticity_b',
                          'production_speed_a', 'production_speed_b',
'cost_eff_a',
                          'cost_eff_b']].corr()

plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix,
            annot=True,          # Show correlation values
            cmap='coolwarm',     # Color scheme (blue-white-red)
            center=0,            # Center colormap at 0
            square=True,         # Make cells square
            fmt='.2f',           # Format numbers to 2 decimal places
(better for larger matrix)
            cbar_kws={'shrink': 0.8},  # Adjust colorbar size
            linewidths=0.5,      # Add lines between cells
            annot_kws={'size': 9})  # Smaller text size for
readability

plt.title('Correlation Matrix Heatmap', fontsize=16,
fontweight='bold', pad=20)
plt.xlabel('')  # Remove x-axis label (redundant with tick labels)
plt.ylabel('')  # Remove y-axis label (redundant with tick labels)
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better
readability
plt.yticks(rotation=0)               # Keep y-axis labels horizontal

plt.tight_layout()

plt.show()

print("Correlation Matrix:")
print(correlation_matrix.round(3))
```

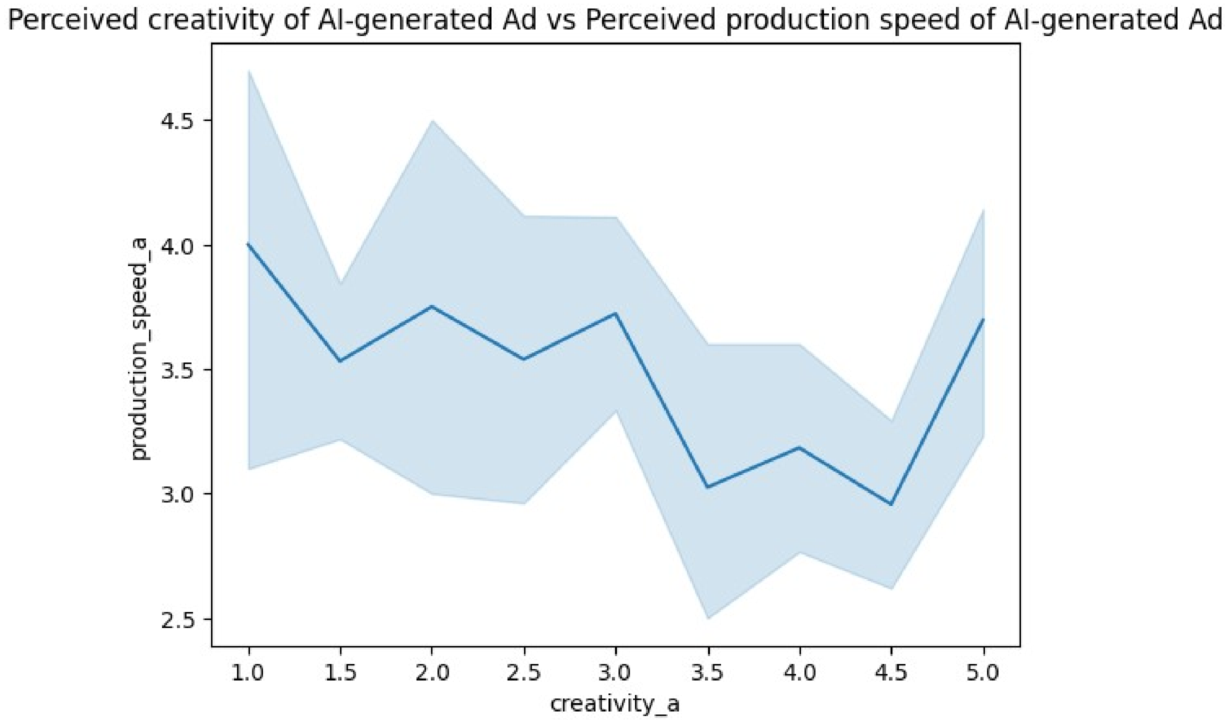



```
Correlation Matrix:
                    ad_exposure  ai_exposure  creativity_a
creativity_b  \
ad_exposure               1.000        0.275         0.422
0.167
ai_exposure               0.275        1.000         0.211
0.265
creativity_a              0.422        0.211         1.000
0.071
creativity_b              0.167        0.265         0.071
1.000
authenticity_a            0.411        0.242         0.778
0.113
authenticity_b            0.160        0.282         0.027
0.835
production_speed_a        0.206        0.214        -0.117
```

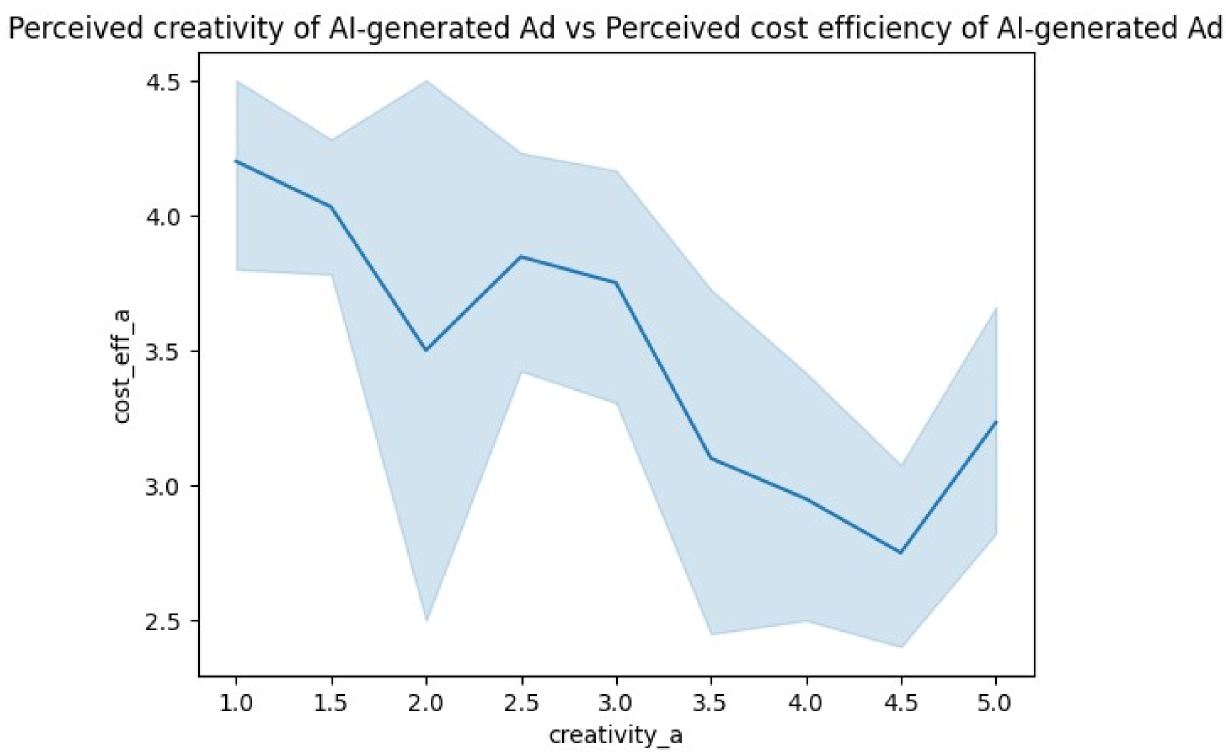
```
0.180
production_speed_b          0.199        0.028        0.131        -
0.204
cost_eff_a                  0.137        0.179       -0.318
0.264
cost_eff_b                  0.159        0.001        0.232        -
0.242

                    authenticity_a  authenticity_b  production_speed_a
\
ad_exposure                  0.411           0.160               0.206

ai_exposure                  0.242           0.282               0.214

creativity_a                 0.778           0.027              -0.117

creativity_b                 0.113           0.835               0.180

authenticity_a               1.000           0.072              -0.133

authenticity_b               0.072           1.000               0.242

production_speed_a          -0.133           0.242               1.000

production_speed_b           0.085          -0.167               0.298

cost_eff_a                  -0.325           0.321               0.771

cost_eff_b                   0.134          -0.249               0.162


                    production_speed_b  cost_eff_a  cost_eff_b
ad_exposure                      0.199       0.137       0.159
ai_exposure                      0.028       0.179       0.001
creativity_a                     0.131      -0.318       0.232
creativity_b                    -0.204       0.264      -0.242
authenticity_a                   0.085      -0.325       0.134
authenticity_b                  -0.167       0.321      -0.249
production_speed_a               0.298       0.771       0.162
production_speed_b               1.000       0.262       0.728
cost_eff_a                       0.262       1.000       0.134
cost_eff_b                       0.728       0.134       1.000

sns.lineplot(data=dff, x='creativity_a', y='authenticity_a')
plt.title('Perceived creativity of AI-generated Ad vs Perceived
authenticity of AI-generated Ad')
plt.show()
```



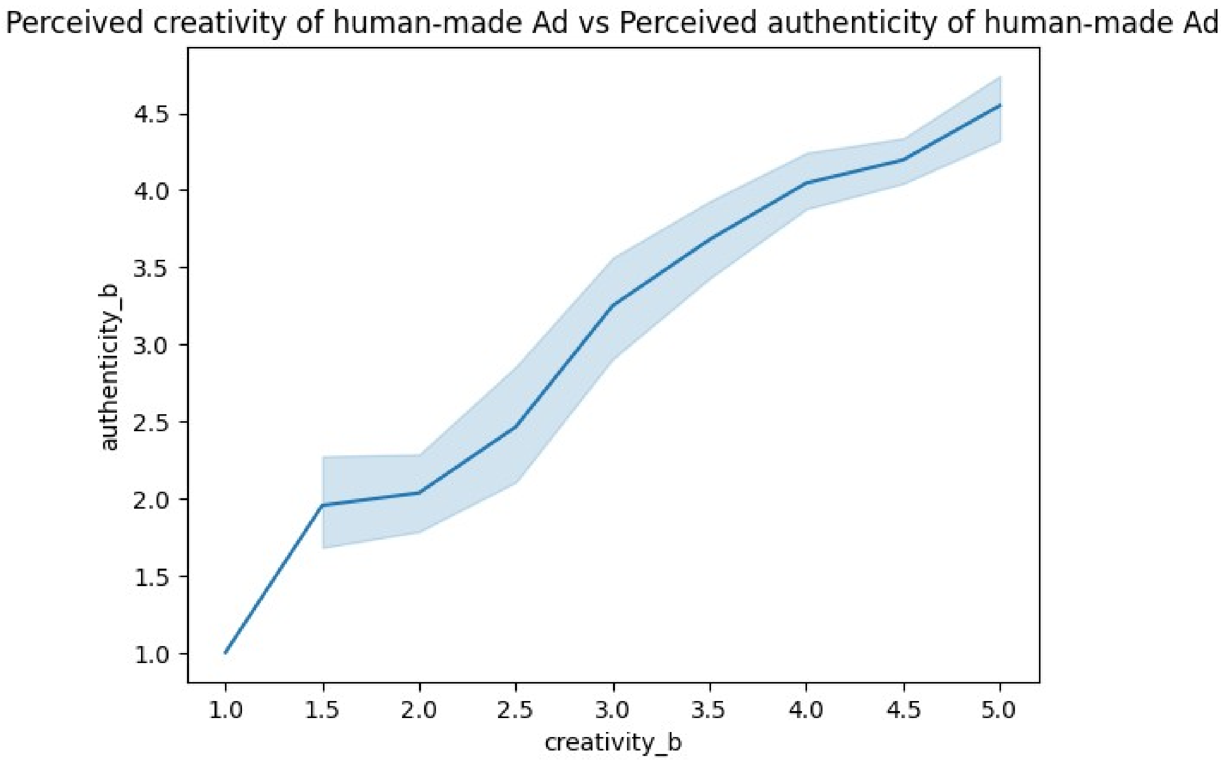

```
sns.lineplot(data=dff, x='creativity_a', y='production_speed_a')
plt.title('Perceived creativity of AI-generated Ad vs Perceived
production speed of AI-generated Ad')
plt.show()
```



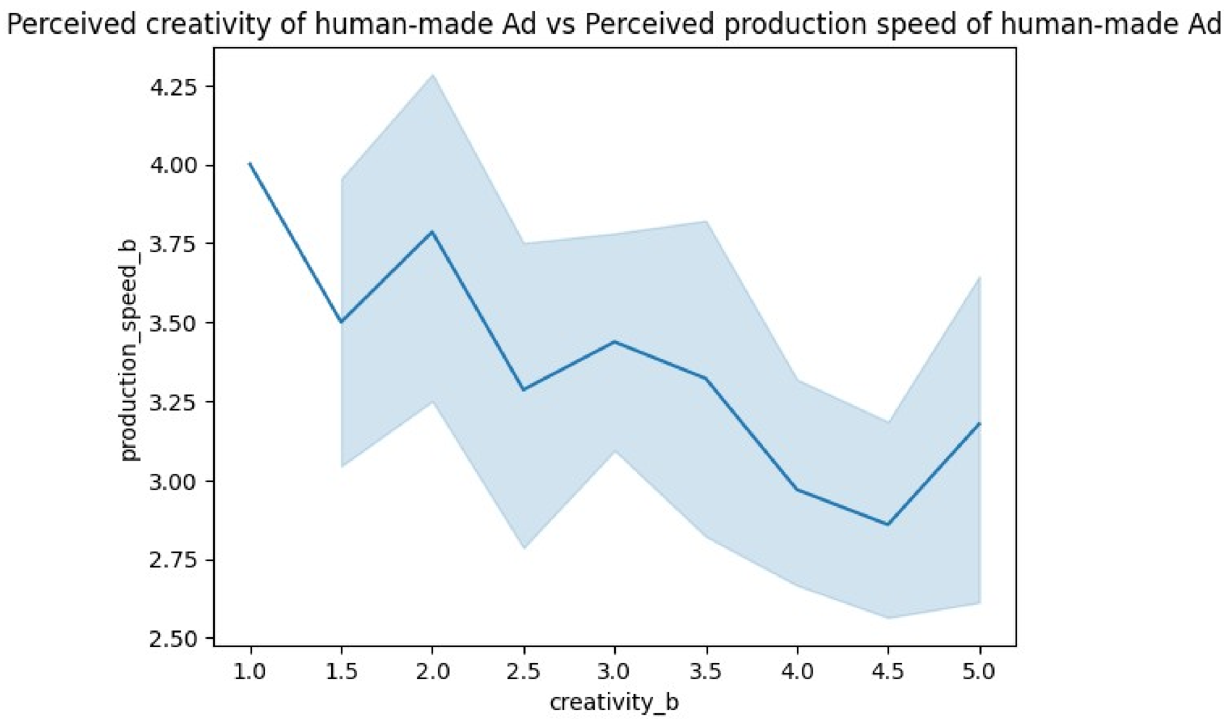

```
sns.lineplot(data=dff, x='creativity_a', y='cost_eff_a')
plt.title('Perceived creativity of AI-generated Ad vs Perceived cost
efficiency of AI-generated Ad')
plt.show()
```



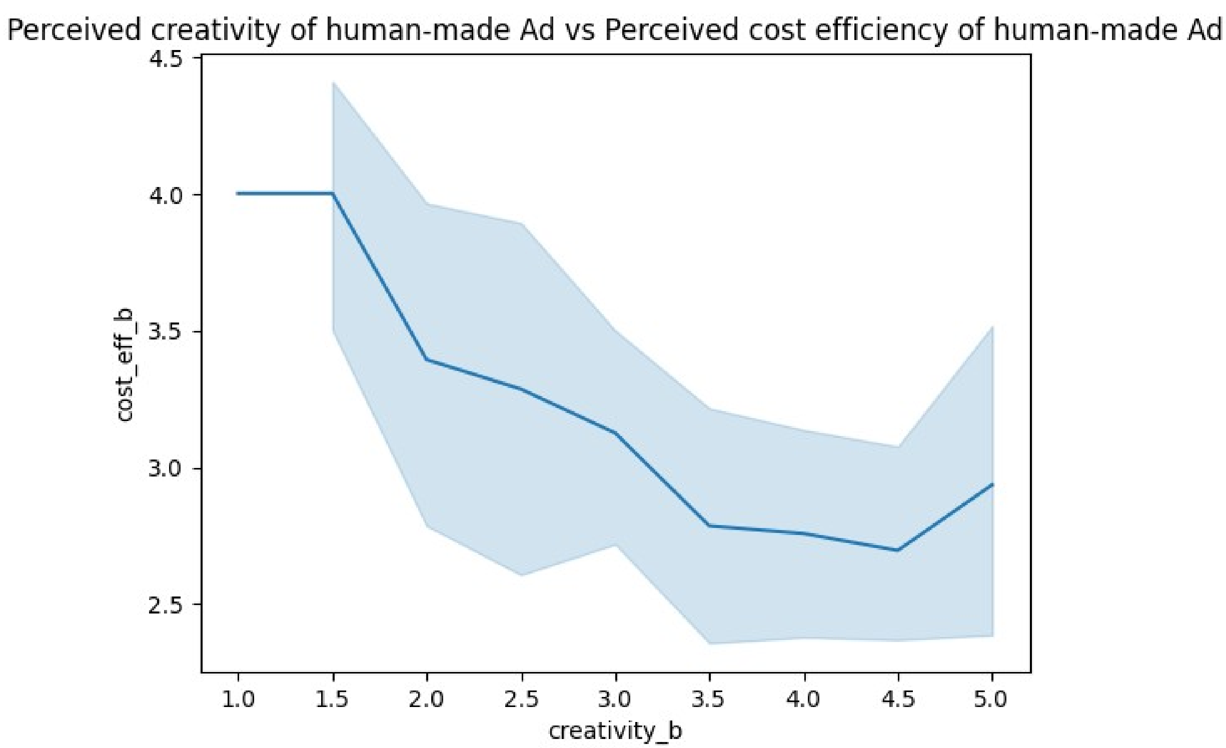
```
sns.lineplot(data=dff, x='creativity_b', y='authenticity_b')
plt.title('Perceived creativity of human-made Ad vs Perceived
authenticity of human-made Ad')
plt.show()
```




```
sns.lineplot(data=dff, x='creativity_b', y='production_speed_b')
plt.title('Perceived creativity of human-made Ad vs Perceived
production speed of human-made Ad')
plt.show()
```




```
sns.lineplot(data=dff, x='creativity_b', y='cost_eff_b')
plt.title('Perceived creativity of human-made Ad vs Perceived cost
efficiency of human-made Ad')
plt.show()
```



Overall advertisement preference and prediction breakdown

```
dff['ad_preference'].value_counts()
```

```
ad_preference
2    90
1    90
Name: count, dtype: int64
```

```
dff['ad_prediction'].value_counts()
```

```
ad_prediction
1    91
2    89
Name: count, dtype: int64
```

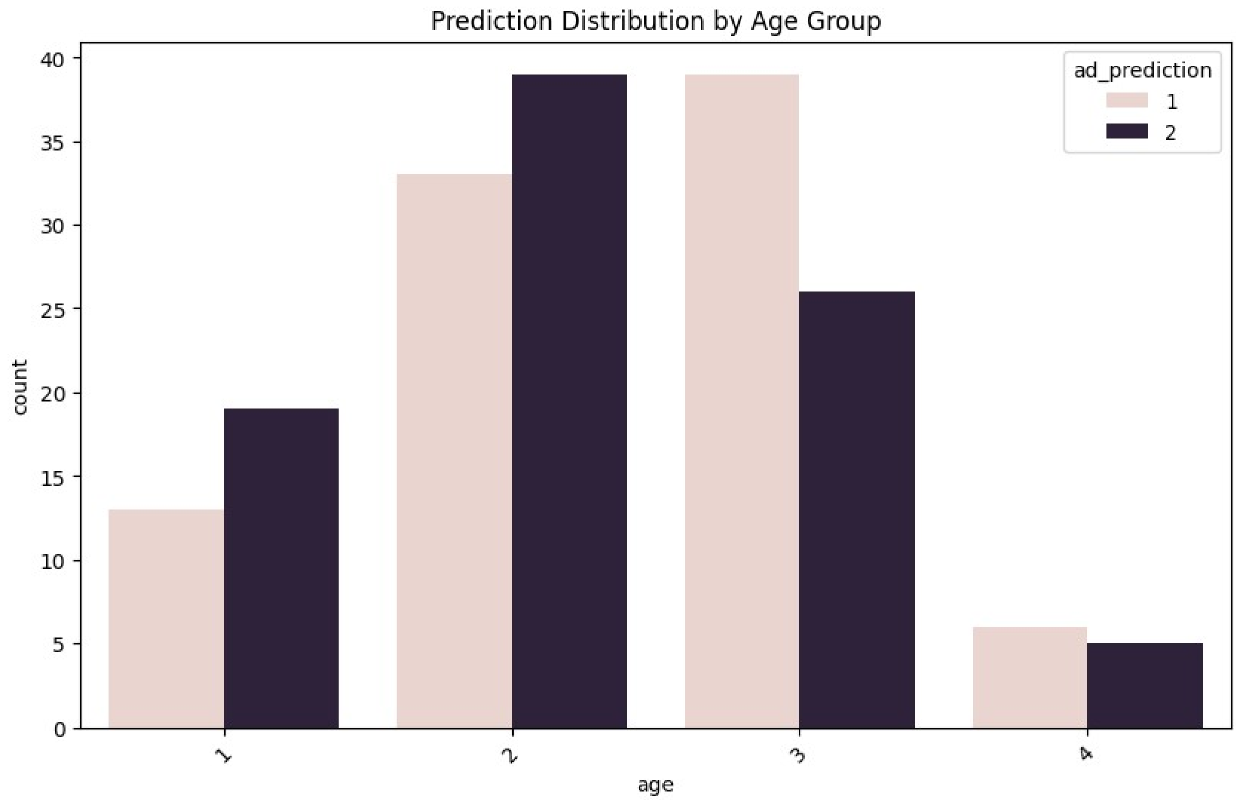
Advertisement prediction breakdown by age and ai exposure

```
dff.groupby(['age', 'ai_exposure'])['ad_prediction'].value_counts()
```

```
age  ai_exposure  ad_prediction
1    2            1                 2
                  2                 1
     3            2                 4
                  1                 2
     4            1                 5
                  2                 2
     5            2                12
                  1                 4
2    2            2                 2
     3            2                 8
                  1                 5
     4            2                10
                  1                 8
     5            1                20
                  2                19
3    1            1                 2
                  2                 1
     2            1                 1
     3            1                 4
                  2                 1
     4            1                14
                  2                 7
     5            1                18
```

```
                    2                   17
4     1             2                    1
      2             1                    2
                    2                    1
      3             1                    1
                    2                    1
      4             1                    3
                    2                    1
      5             2                    1
Name: count, dtype: int64
```

```
plt.figure(figsize=(10, 6))
sns.countplot(data=dff, x='age', hue='ad_prediction')
plt.title('Prediction Distribution by Age Group')
plt.xticks(rotation=45)
plt.show()
```

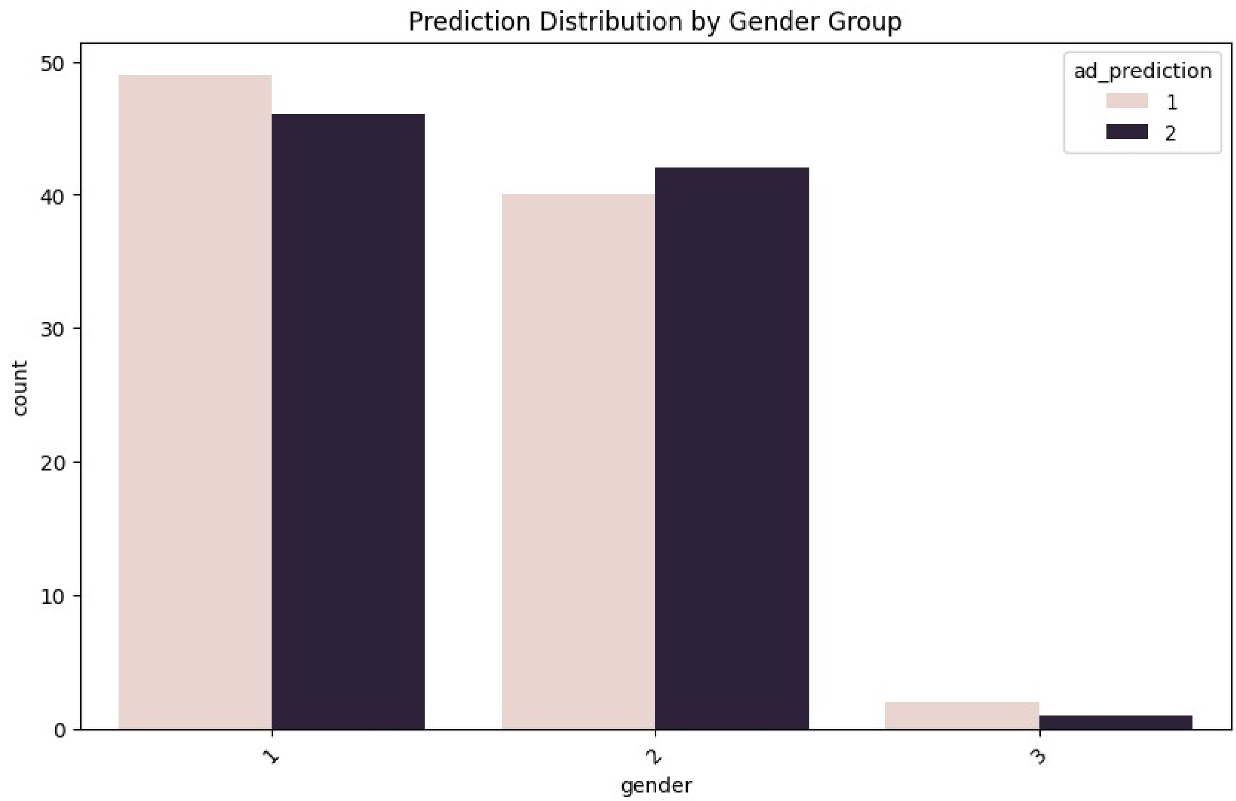


Advertisement prediction breakdown by gender and ai exposure

```
dff.groupby(['gender', 'ai_exposure'])['ad_prediction'].value_counts()
```

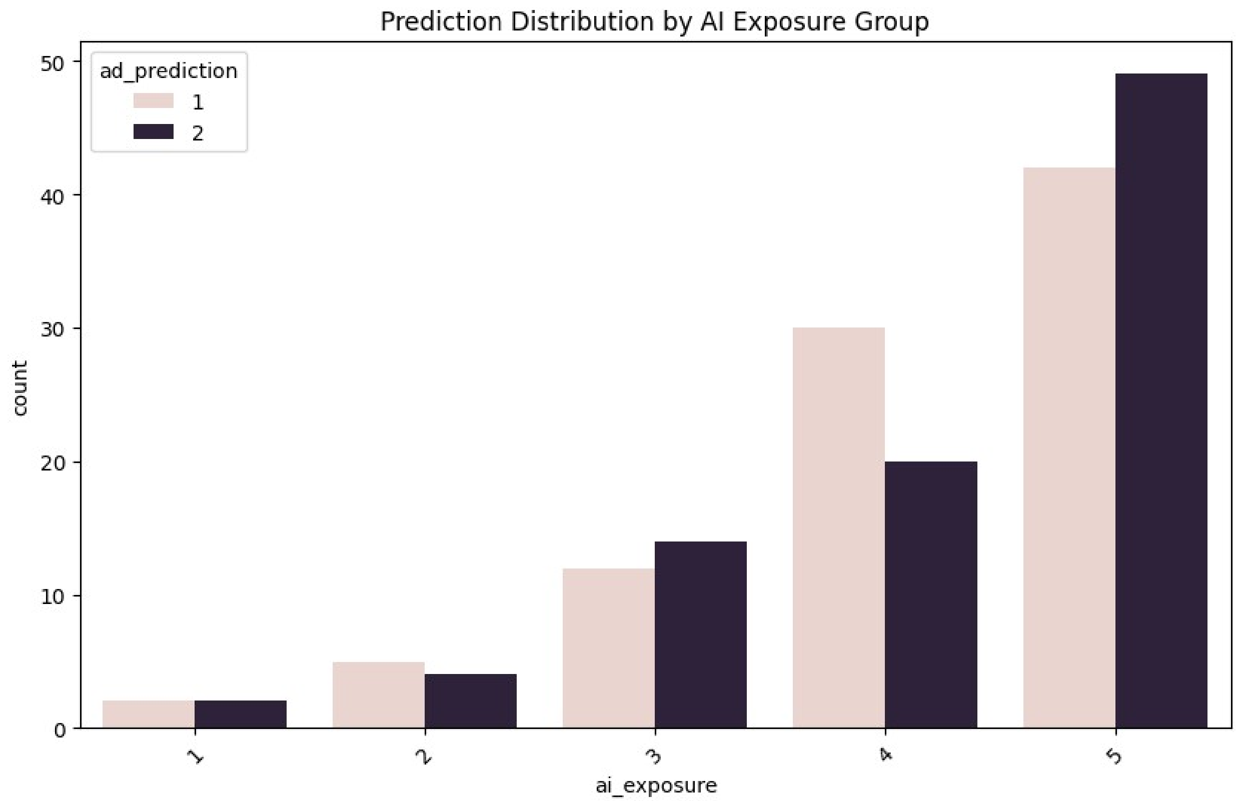
```
gender  ai_exposure  ad_prediction
1       2            1                2
                     2                2
        3            1                8
                     2                5
        4            1               13
                     2               10
        5            2               29
                     1               26
2       1            1                2
                     2                2
        2            1                3
                     2                2
        3            2                8
                     1                3
        4            1               17
                     2               10
        5            2               20
                     1               15
3       3            1                1
                     2                1
        5            1                1
Name: count, dtype: int64
```

```
plt.figure(figsize=(10, 6))
sns.countplot(data=dff, x='gender', hue='ad_prediction')
plt.title('Prediction Distribution by Gender Group')
plt.xticks(rotation=45)
plt.show()
```



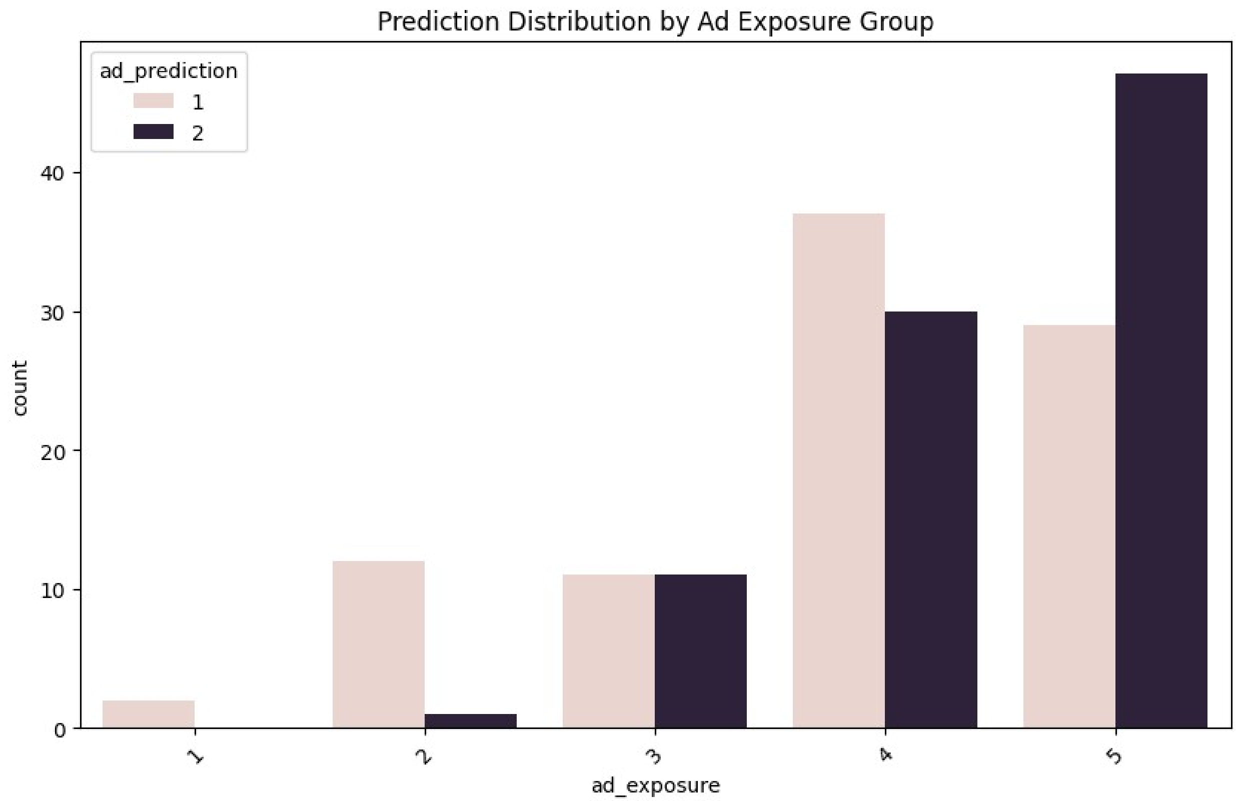
Advertisement prediction breakdown by ai exposure

```
dff.groupby('ai_exposure')['ad_prediction'].value_counts()

ai_exposure  ad_prediction
1            1                 2
             2                 2
2            1                 5
             2                 4
3            2                14
             1                12
4            1                30
             2                20
5            2                49
             1                42
Name: count, dtype: int64

plt.figure(figsize=(10, 6))
sns.countplot(data=dff, x='ai_exposure', hue='ad_prediction')
plt.title('Prediction Distribution by AI Exposure Group')
plt.xticks(rotation=45)
plt.show()
```



Advertisement prediction breakdown by ad exposure

```
dff.groupby('ad_exposure')['ad_prediction'].value_counts()

ad_exposure  ad_prediction
1            1                 2
2            1                12
             2                 1
3            1                11
             2                11
4            1                37
             2                30
5            2                47
             1                29
Name: count, dtype: int64

plt.figure(figsize=(10, 6))
sns.countplot(data=dff, x='ad_exposure', hue='ad_prediction')
plt.title('Prediction Distribution by Ad Exposure Group')
plt.xticks(rotation=45)
plt.show()
```



Quantitative Analysis

```
feature_pairs = [
    ('creativity_a', 'creativity_b'),
    ('authenticity_a', 'authenticity_b'),
    ('production_speed_a', 'production_speed_b'),
    ('cost_eff_a', 'cost_eff_b')
]

# ==================== CRONBACH'S ALPHA ====================
def cronbachs_alpha(data):
    """
    Calculate Cronbach's Alpha for internal consistency reliability

    Parameters:
    data: DataFrame or array-like with items as columns

    Returns:
    float: Cronbach's alpha coefficient
    """
    # Number of items
    k = data.shape[1]

    # Variance of each item
```

```
    item_variances = data.var(axis=0, ddof=1)

    # Variance of total scores
    total_variance = data.sum(axis=1).var(ddof=1)

    # Cronbach's alpha formula
    alpha = (k / (k - 1)) * (1 - (item_variances.sum() / 
total_variance))

    return alpha

def cronbachs_alpha_if_deleted(data):
    """Calculate Cronbach's alpha if each item is deleted"""
    results = {}
    for col in data.columns:
        subset = data.drop(columns=[col])
        alpha = cronbachs_alpha(subset)
        results[col] = alpha
    return results

print("=" * 60)
print("CRONBACH'S ALPHA ANALYSIS")
print("=" * 60)

# Calculate Cronbach's alpha for each pair
for pair_name, (col_a, col_b) in zip(['Creativity', 'Authenticity', 
'Production Speed', 'Cost Efficiency'], feature_pairs):
    pair_data = dff[[col_a, col_b]]
    alpha = cronbachs_alpha(pair_data)

    print(f"\n{pair_name} Pair:")
    print(f"  Cronbach's Alpha: {alpha:.4f}")

    # Interpretation
    if alpha >= 0.9:
        interpretation = "Excellent reliability"
    elif alpha >= 0.8:
        interpretation = "Good reliability"
    elif alpha >= 0.7:
        interpretation = "Acceptable reliability"
    elif alpha >= 0.6:
        interpretation = "Questionable reliability"
    else:
        interpretation = "Poor reliability"

    print(f"  Interpretation: {interpretation}")

    # Correlation between items
    correlation = pair_data.corr().iloc[0, 1]
    print(f"  Inter-item correlation: {correlation:.4f}")
```

```
# Extract only the feature pair columns for overall analysis
feature_columns = [col for pair in feature_pairs for col in pair]
feature_data = dff[feature_columns]

# Overall Cronbach's alpha for all feature pair items
all_alpha = cronbachs_alpha(feature_data)
print(f"\nOverall Cronbach's Alpha (all feature pair items):
{all_alpha:.4f}")

# Alpha if item deleted (only for feature pair columns)
alpha_if_deleted = cronbachs_alpha_if_deleted(feature_data)
print(f"\nCronbach's Alpha if item deleted:")
for item, alpha in alpha_if_deleted.items():
    print(f"  {item}: {alpha:.4f}")

# ==================== SHAPIRO-WILK NORMALITY TEST
====================
print("\n" + "=" * 60)
print("SHAPIRO-WILK NORMALITY TESTS")
print("=" * 60)

def perform_shapiro_test(data, column_name):
    """Perform Shapiro-Wilk test for normality"""
    statistic, p_value = shapiro(data)

    print(f"\n{column_name}:")
    print(f"  Shapiro-Wilk statistic: {statistic:.4f}")
    print(f"  p-value: {p_value:.6f}")

    if p_value > 0.05:
        print(f"  Result: Data appears normally distributed (p >
0.05)")
    else:
        print(f"  Result: Data does NOT appear normally distributed (p
≤ 0.05)")

    return statistic, p_value

# Test normality for each feature pair variable only
shapiro_results = {}
for col in feature_columns:
    stat, p_val = perform_shapiro_test(dff[col], col)
    shapiro_results[col] = {'statistic': stat, 'p_value': p_val}

# Test normality for differences between pairs (col_b - col_a order)
print(f"\nNormality tests for paired differences:")
difference_normality = {}
for pair_name, (col_a, col_b) in zip(['Creativity', 'Authenticity',
'Production Speed', 'Cost Efficiency'], feature_pairs):
```

```
    diff = dff[col_b] - dff[col_a]  # col_b - col_a order
    stat, p_val = perform_shapiro_test(diff, f"{pair_name} difference
({col_b} - {col_a})")
    difference_normality[pair_name] = {'statistic': stat, 'p_value':
p_val, 'normal': p_val > 0.05}

# ==================== PAIRED COMPARISONS ====================
print("\n" + "=" * 60)
print("PAIRED STATISTICAL TESTS")
print("=" * 60)

def perform_paired_tests(data_b, data_a, pair_name):
    """Perform both paired t-test and Wilcoxon signed-rank test with
col_b - col_a order"""

    print(f"\n{pair_name} Comparison:")
    print(f"  Sample size: {len(data_a)}")
    print(f"  Mean A: {data_a.mean():.3f} (SD: {data_a.std():.3f})")
    print(f"  Mean B: {data_b.mean():.3f} (SD: {data_b.std():.3f})")
    print(f"  Mean difference (B - A): {(data_b -
data_a).mean():.3f}")

    # Paired t-test (comparing B to A, so B - A)
    t_stat, t_p = ttest_rel(data_b, data_a)
    print(f"\n  Paired t-test:")
    print(f"    t-statistic: {t_stat:.4f}")
    print(f"    p-value: {t_p:.6f}")

    # Wilcoxon signed-rank test
    try:
        w_stat, w_p = wilcoxon(data_b, data_a, alternative='two-
sided')
        print(f"\n  Wilcoxon signed-rank test:")
        print(f"    W-statistic: {w_stat:.4f}")
        print(f"    p-value: {w_p:.6f}")
    except ValueError as e:
        print(f"\n  Wilcoxon test error: {e}")
        w_stat, w_p = None, None

    # Effect size (Cohen's d for paired samples) - using B - A
difference
    diff = data_b - data_a
    cohens_d = diff.mean() / diff.std()
    print(f"\n  Effect size (Cohen's d): {cohens_d:.4f}")

    if abs(cohens_d) < 0.2:
        effect_interpretation = "negligible"
    elif abs(cohens_d) < 0.5:
        effect_interpretation = "small"
```

```python
    elif abs(cohens_d) < 0.8:
        effect_interpretation = "medium"
    else:
        effect_interpretation = "large"

    print(f"  Effect size interpretation: {effect_interpretation}")

    # Interpretation
    alpha_level = 0.05
    if t_p < alpha_level:
        print(f"  Conclusion: Significant difference found (p <
{alpha_level})")
    else:
        print(f"  Conclusion: No significant difference found (p ≥
{alpha_level})")

    return {
        't_stat': t_stat, 't_p': t_p,
        'w_stat': w_stat, 'w_p': w_p,
        'cohens_d': cohens_d,
        'mean_diff': diff.mean()
    }

# Perform paired tests with col_b - col_a order
paired_results = {}
for pair_name, (col_a, col_b) in zip(['Creativity', 'Authenticity',
'Production Speed', 'Cost Efficiency'], feature_pairs):
    results = perform_paired_tests(dff[col_b], dff[col_a], pair_name)
    paired_results[pair_name] = results

# ==================== CHI-SQUARE TEST ====================
print("\n" + "=" * 60)
print("CHI-SQUARE TESTS")
print("=" * 60)

def categorize_scores(data, thresholds=[2, 3, 4, 5]):
    """Categorize continuous scores into ordinal categories"""
    categories = []
    for score in data:
        if score <= thresholds[0]:
            categories.append('Very Low')
        elif score <= thresholds[1]:
            categories.append('Low')
        elif score <= thresholds[2]:
            categories.append('Medium')
        elif score <= thresholds[3]:
            categories.append('High')
        else:
            categories.append('Very High')
    return categories
```

```
def perform_chi_square_test(data_b, data_a, pair_name):
    """Perform chi-square test of independence on categorized data"""

    # Categorize the continuous data
    cat_a = categorize_scores(data_a)
    cat_b = categorize_scores(data_b)

    # Create contingency table
    contingency_df = pd.DataFrame({'A': cat_a, 'B': cat_b})
    contingency_table = pd.crosstab(contingency_df['A'],
contingency_df['B'])

    print(f"\n{pair_name} Chi-square test:")
    print("Contingency Table:")
    print(contingency_table)

    # Perform chi-square test
    chi2_stat, p_value, dof, expected =
chi2_contingency(contingency_table)

    print(f"\nChi-square statistic: {chi2_stat:.4f}")
    print(f"Degrees of freedom: {dof}")
    print(f"p-value: {p_value:.6f}")

    # Cramer's V (effect size for chi-square)
    n = contingency_table.sum().sum()
    cramers_v = np.sqrt(chi2_stat / (n * (min(contingency_table.shape)
- 1)))
    print(f"Cramer's V (effect size): {cramers_v:.4f}")

    if p_value < 0.05:
        print("Result: Significant association between categories (p <
0.05)")
    else:
        print("Result: No significant association between categories
(p ≥ 0.05)")

    return {
        'chi2_stat': chi2_stat,
        'p_value': p_value,
        'dof': dof,
        'cramers_v': cramers_v,
        'contingency_table': contingency_table
    }

# Perform chi-square tests with col_b - col_a order
chi_square_results = {}
for pair_name, (col_a, col_b) in zip(['Creativity', 'Authenticity',
```

```
'Production Speed', 'Cost Efficiency'], feature_pairs):
    results = perform_chi_square_test(dff[col_b], dff[col_a],
pair_name)
    chi_square_results[pair_name] = results

# ==================== SUMMARY AND RECOMMENDATIONS
====================
print("\n" + "=" * 60)
print("SUMMARY AND RECOMMENDATIONS")
print("=" * 60)

print("\n1. RELIABILITY ASSESSMENT:")
for pair_name, (col_a, col_b) in zip(['Creativity', 'Authenticity',
'Production Speed', 'Cost Efficiency'], feature_pairs):
    pair_data = dff[[col_a, col_b]]
    alpha = cronbachs_alpha(pair_data)
    if alpha >= 0.7:
        print(f"   ✓ {pair_name}: Reliable (α = {alpha:.3f})")
    else:
        print(f"   ⚠ {pair_name}: Low reliability (α = {alpha:.3f})")

print("\n2. NORMALITY ASSUMPTIONS:")
normal_pairs = []
for pair_name in ['Creativity', 'Authenticity', 'Production Speed',
'Cost Efficiency']:
    if difference_normality[pair_name]['normal']:
        print(f"   ✓ {pair_name} differences: Normally distributed")
        normal_pairs.append(pair_name)
    else:
        print(f"   ⚠ {pair_name} differences: Not normally
distributed")

print("\n3. STATISTICAL TEST RECOMMENDATIONS:")
for pair_name in ['Creativity', 'Authenticity', 'Production Speed',
'Cost Efficiency']:
    if difference_normality[pair_name]['normal']:
        print(f"   {pair_name}: Use paired t-test (normality
assumption met)")
    else:
        print(f"   {pair_name}: Use Wilcoxon signed-rank test
(normality violated)")

print("\n4. SIGNIFICANT DIFFERENCES FOUND:")
significant_pairs = []
for pair_name in ['Creativity', 'Authenticity', 'Production Speed',
'Cost Efficiency']:
    t_p = paired_results[pair_name]['t_p']
    effect_size = abs(paired_results[pair_name]['cohens_d'])
    mean_diff = paired_results[pair_name]['mean_diff']
    if t_p < 0.05:
```

```
        direction = "B > A" if mean_diff > 0 else "B < A"
        print(f"   ✓ {pair_name}: Significant difference (p =
{t_p:.4f}, d = {effect_size:.3f}, {direction})")
        significant_pairs.append(pair_name)
    else:
        print(f"   - {pair_name}: No significant difference (p =
{t_p:.4f})")

print(f"\nAnalysis completed for {len(feature_pairs)} feature pairs
with {len(dff)} observations.")
print("\nNote: All difference calculations use the order (B - A)
where:")
for pair_name, (col_a, col_b) in zip(['Creativity', 'Authenticity',
'Production Speed', 'Cost Efficiency'], feature_pairs):
    print(f"  {pair_name}: {col_b} - {col_a}")
```

```
============================================================
CRONBACH'S ALPHA ANALYSIS
============================================================

Creativity Pair:
  Cronbach's Alpha: 0.1333
  Interpretation: Poor reliability
  Inter-item correlation: 0.0715

Authenticity Pair:
  Cronbach's Alpha: 0.1352
  Interpretation: Poor reliability
  Inter-item correlation: 0.0725

Production Speed Pair:
  Cronbach's Alpha: 0.4590
  Interpretation: Poor reliability
  Inter-item correlation: 0.2985

Cost Efficiency Pair:
  Cronbach's Alpha: 0.2366
  Interpretation: Poor reliability
  Inter-item correlation: 0.1342

Overall Cronbach's Alpha (all feature pair items): 0.5779

Cronbach's Alpha if item deleted:
  creativity_a: 0.5721
  creativity_b: 0.5510
  authenticity_a: 0.5724
  authenticity_b: 0.5424
  production_speed_a: 0.4995
  production_speed_b: 0.5259
  cost_eff_a: 0.5336
```

```
  cost_eff_b: 0.5564

============================================================
SHAPIRO-WILK NORMALITY TESTS
============================================================

creativity_a:
  Shapiro-Wilk statistic: 0.8863
  p-value: 0.000000
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

creativity_b:
  Shapiro-Wilk statistic: 0.8869
  p-value: 0.000000
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

authenticity_a:
  Shapiro-Wilk statistic: 0.9400
  p-value: 0.000001
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

authenticity_b:
  Shapiro-Wilk statistic: 0.9102
  p-value: 0.000000
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

production_speed_a:
  Shapiro-Wilk statistic: 0.9321
  p-value: 0.000000
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

production_speed_b:
  Shapiro-Wilk statistic: 0.9477
  p-value: 0.000004
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

cost_eff_a:
  Shapiro-Wilk statistic: 0.9241
  p-value: 0.000000
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

cost_eff_b:
  Shapiro-Wilk statistic: 0.9289
  p-value: 0.000000
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

Normality tests for paired differences:

Creativity difference (creativity_b - creativity_a):
  Shapiro-Wilk statistic: 0.9735
```

```
  p-value: 0.001660
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

Authenticity difference (authenticity_b - authenticity_a):
  Shapiro-Wilk statistic: 0.9809
  p-value: 0.014479
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

Production Speed difference (production_speed_b - production_speed_a):
  Shapiro-Wilk statistic: 0.9708
  p-value: 0.000793
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

Cost Efficiency difference (cost_eff_b - cost_eff_a):
  Shapiro-Wilk statistic: 0.9664
  p-value: 0.000251
  Result: Data does NOT appear normally distributed (p ≤ 0.05)

============================================================
PAIRED STATISTICAL TESTS
============================================================

Creativity Comparison:
  Sample size: 180
  Mean A: 3.669 (SD: 1.141)
  Mean B: 3.731 (SD: 1.094)
  Mean difference (B - A): 0.061

  Paired t-test:
    t-statistic: 0.5383
    p-value: 0.591070

  Wilcoxon signed-rank test:
    W-statistic: 4308.0000
    p-value: 0.739210

  Effect size (Cohen's d): 0.0401
  Effect size interpretation: negligible
  Conclusion: No significant difference found (p ≥ 0.05)

Authenticity Comparison:
  Sample size: 180
  Mean A: 3.542 (SD: 1.041)
  Mean B: 3.647 (SD: 1.047)
  Mean difference (B - A): 0.106

  Paired t-test:
    t-statistic: 0.9958
    p-value: 0.320668
```

```
  Wilcoxon signed-rank test:
    W-statistic: 4734.0000
    p-value: 0.329680

  Effect size (Cohen's d): 0.0742
  Effect size interpretation: negligible
  Conclusion: No significant difference found (p ≥ 0.05)

Production Speed Comparison:
  Sample size: 180
  Mean A: 3.333 (SD: 1.160)
  Mean B: 3.172 (SD: 1.087)
  Mean difference (B - A): -0.161

  Paired t-test:
    t-statistic: -1.6222
    p-value: 0.106530

  Wilcoxon signed-rank test:
    W-statistic: 3961.5000
    p-value: 0.074464

  Effect size (Cohen's d): -0.1209
  Effect size interpretation: negligible
  Conclusion: No significant difference found (p ≥ 0.05)

Cost Efficiency Comparison:
  Sample size: 180
  Mean A: 3.247 (SD: 1.214)
  Mean B: 2.981 (SD: 1.222)
  Mean difference (B - A): -0.267

  Paired t-test:
    t-statistic: -2.2325
    p-value: 0.026821

  Wilcoxon signed-rank test:
    W-statistic: 3618.5000
    p-value: 0.032043

  Effect size (Cohen's d): -0.1664
  Effect size interpretation: negligible
  Conclusion: Significant difference found (p < 0.05)

============================================================
CHI-SQUARE TESTS
============================================================

Creativity Chi-square test:
Contingency Table:
```

```
B          High  Low  Medium  Very Low
A
High         35   14      16         9
Low          13    5      10         3
Medium       18    7      15        10
Very Low     11    4       6         4

Chi-square statistic: 4.5717
Degrees of freedom: 9
p-value: 0.869938
Cramer's V (effect size): 0.0920
Result: No significant association between categories (p ≥ 0.05)

Authenticity Chi-square test:
Contingency Table:
B          High  Low  Medium  Very Low
A
High         23    8      15         5
Low          15    5      25         4
Medium       16   14      15        15
Very Low      7    2       8         3

Chi-square statistic: 18.8001
Degrees of freedom: 9
p-value: 0.026947
Cramer's V (effect size): 0.1866
Result: Significant association between categories (p < 0.05)

Production Speed Chi-square test:
Contingency Table:
B          High  Low  Medium  Very Low
A
High         14   11      17         7
Low           7   16      11        10
Medium        6   16      14         8
Very Low     10    6       4        23

Chi-square statistic: 31.6513
Degrees of freedom: 9
p-value: 0.000229
Cramer's V (effect size): 0.2421
Result: Significant association between categories (p < 0.05)

Cost Efficiency Chi-square test:
Contingency Table:
B          High  Low  Medium  Very Low
A
High         14   10       7        11
Low           5   11       6         8
Medium        5    7      19        22
```

```
Very Low    10    4      14        27

Chi-square statistic: 26.5481
Degrees of freedom: 9
p-value: 0.001661
Cramer's V (effect size): 0.2217
Result: Significant association between categories (p < 0.05)

============================================================
SUMMARY AND RECOMMENDATIONS
============================================================

1. RELIABILITY ASSESSMENT:
   ⚠ Creativity: Low reliability (α = 0.133)
   ⚠ Authenticity: Low reliability (α = 0.135)
   ⚠ Production Speed: Low reliability (α = 0.459)
   ⚠ Cost Efficiency: Low reliability (α = 0.237)

2. NORMALITY ASSUMPTIONS:
   ⚠ Creativity differences: Not normally distributed
   ⚠ Authenticity differences: Not normally distributed
   ⚠ Production Speed differences: Not normally distributed
   ⚠ Cost Efficiency differences: Not normally distributed

3. STATISTICAL TEST RECOMMENDATIONS:
   Creativity: Use Wilcoxon signed-rank test (normality violated)
   Authenticity: Use Wilcoxon signed-rank test (normality violated)
   Production Speed: Use Wilcoxon signed-rank test (normality
violated)
   Cost Efficiency: Use Wilcoxon signed-rank test (normality violated)

4. SIGNIFICANT DIFFERENCES FOUND:
   - Creativity: No significant difference (p = 0.5911)
   - Authenticity: No significant difference (p = 0.3207)
   - Production Speed: No significant difference (p = 0.1065)
   ✓ Cost Efficiency: Significant difference (p = 0.0268, d = 0.166, B
< A)

Analysis completed for 4 feature pairs with 180 observations.

Note: All difference calculations use the order (B - A) where:
  Creativity: creativity_b - creativity_a
  Authenticity: authenticity_b - authenticity_a
  Production Speed: production_speed_b - production_speed_a
  Cost Efficiency: cost_eff_b - cost_eff_a
```

Using all independent features

```
# Step 1: Define the features and target
features = ['age', 'gender', 'ad_exposure', 'ai_exposure',
'creativity_a', 'authenticity_a', 'production_speed_a', 'cost_eff_a',
'creativity_b', 'authenticity_b', 'production_speed_b', 'cost_eff_b',
'ad_preference']
target_col = 'ad_prediction'  # Replace with your actual target column
name

# Step 2: Clean and filter the data
df_model = dff[features + [target_col]].dropna()

# Ensure target is binary (0/1)
df_model = df_model[df_model[target_col].isin([1, 2])]
df_model['target_bin'] = df_model[target_col].apply(lambda x: 1 if x
== 2 else 0)

# Step 3: Add constant for intercept
X = sm.add_constant(df_model[features])
y = df_model['target_bin']

# Step 4: Fit the logistic regression model
logit_model = sm.Logit(y, X).fit()

# Step 5: Display the summary
print(logit_model.summary())

# Step 6: Predict and evaluate
y_pred = (logit_model.predict(X) > 0.5).astype(int)

print("\nConfusion Matrix:")
print(confusion_matrix(y, y_pred))

print("\nClassification Report:")
print(classification_report(y, y_pred, target_names=['Class 1', 'Class
2']))
```

```
Optimization terminated successfully.
         Current function value: 0.225806
         Iterations 8
                           Logit Regression Results

======================================================================
========
Dep. Variable:             target_bin   No. Observations:
180
Model:                          Logit   Df Residuals:
166
Method:                           MLE   Df Model:
```

```
13
Date:                     Sat, 09 Aug 2025   Pseudo R-squ.:
0.6742
Time:                             11:06:12   Log-Likelihood:
-40.645
converged:                            True   LL-Null:
-124.76
Covariance Type:             nonrobust   LLR p-value:
4.244e-29
==============================================================================
================
                         coef    std err          z      P>|z|
[0.025      0.975]
------------------------------------------------------------------------------
----------------
const                  1.4015      2.693      0.520      0.603      -
3.876       6.679
age                   -0.7911      0.404     -1.956      0.050      -
1.584       0.001
gender                 0.6429      0.584      1.101      0.271      -
0.501       1.787
ad_exposure            0.6072      0.367      1.657      0.098      -
0.111       1.326
ai_exposure            0.2783      0.350      0.796      0.426      -
0.407       0.964
creativity_a           0.4775      0.453      1.054      0.292      -
0.410       1.365
authenticity_a         0.0956      0.467      0.205      0.838      -
0.820       1.011
production_speed_a    -0.0392      0.490     -0.080      0.936      -
0.999       0.921
cost_eff_a            -0.6654      0.543     -1.226      0.220      -
1.729       0.398
creativity_b           0.6057      0.581      1.042      0.297      -
0.534       1.745
authenticity_b        -0.9566      0.633     -1.510      0.131      -
2.198       0.285
production_speed_b     0.8864      0.455      1.948      0.051      -
0.005       1.778
cost_eff_b             0.3782      0.368      1.027      0.304      -
0.343       1.100
ad_preference         -4.5739      0.812     -5.636      0.000      -
6.165      -2.983
==============================================================================
================

Confusion Matrix:
[[84  7]
 [ 8 81]]
```

```
Classification Report:
              precision    recall  f1-score   support

     Class 1       0.91      0.92      0.92        91
     Class 2       0.92      0.91      0.92        89

    accuracy                           0.92       180
   macro avg       0.92      0.92      0.92       180
weighted avg       0.92      0.92      0.92       180
```

Feature selection for model building

```
dff.corr()
```

```
                         age    gender  ad_exposure  ai_exposure  \
age                 1.000000  0.089371    -0.060873    -0.104334
gender              0.089371  1.000000    -0.062697    -0.177550
ad_exposure        -0.060873 -0.062697     1.000000     0.274981
ai_exposure        -0.104334 -0.177550     0.274981     1.000000
creativity_a       -0.095918 -0.077163     0.421676     0.211427
creativity_b        0.020353  0.006805     0.167021     0.265415
authenticity_a     -0.127526  0.033524     0.410958     0.242276
authenticity_b     -0.000623  0.045423     0.159640     0.282053
production_speed_a  0.035644 -0.210512     0.206246     0.213956
production_speed_b  0.111191 -0.107394     0.198930     0.027866
cost_eff_a          0.098918 -0.161750     0.136782     0.179495
cost_eff_b          0.118409 -0.058171     0.159057     0.000818
ad_preference       0.073571 -0.020879    -0.173914     0.060742
ad_prediction      -0.136374  0.010208     0.268101     0.040804

                    creativity_a  creativity_b  authenticity_a  \
age                    -0.095918      0.020353       -0.127526
gender                 -0.077163      0.006805        0.033524
ad_exposure             0.421676      0.167021        0.410958
ai_exposure             0.211427      0.265415        0.242276
creativity_a            1.000000      0.071467        0.778320
creativity_b            0.071467      1.000000        0.112953
authenticity_a          0.778320      0.112953        1.000000
authenticity_b          0.026924      0.834539        0.072491
production_speed_a     -0.116733      0.180094       -0.132984
production_speed_b      0.130551     -0.203821        0.084935
cost_eff_a             -0.317778      0.263973       -0.325444
cost_eff_b              0.231789     -0.242218        0.133530
ad_preference          -0.417422      0.399799       -0.371978
ad_prediction           0.502104     -0.300703        0.436678
```

```
                    authenticity_b  production_speed_a
production_speed_b  \
age                      -0.000623            0.035644
0.111191
gender                    0.045423           -0.210512            -
0.107394
ad_exposure               0.159640            0.206246
0.198930
ai_exposure               0.282053            0.213956
0.027866
creativity_a              0.026924           -0.116733
0.130551
creativity_b              0.834539            0.180094            -
0.203821
authenticity_a            0.072491           -0.132984
0.084935
authenticity_b            1.000000            0.242110            -
0.167094
production_speed_a        0.242110            1.000000
0.298496
production_speed_b       -0.167094            0.298496
1.000000
cost_eff_a                0.320559            0.771134
0.261714
cost_eff_b               -0.248795            0.162231
0.727914
ad_preference             0.444157            0.187249            -
0.071725
ad_prediction            -0.357505           -0.155250
0.222077

                    cost_eff_a  cost_eff_b  ad_preference
ad_prediction
age                   0.098918    0.118409       0.073571       -
0.136374
gender               -0.161750   -0.058171      -0.020879
0.010208
ad_exposure           0.136782    0.159057      -0.173914
0.268101
ai_exposure           0.179495    0.000818       0.060742
0.040804
creativity_a         -0.317778    0.231789      -0.417422
0.502104
creativity_b          0.263973   -0.242218       0.399799       -
0.300703
authenticity_a       -0.325444    0.133530      -0.371978
0.436678
authenticity_b        0.320559   -0.248795       0.444157       -
0.357505
```

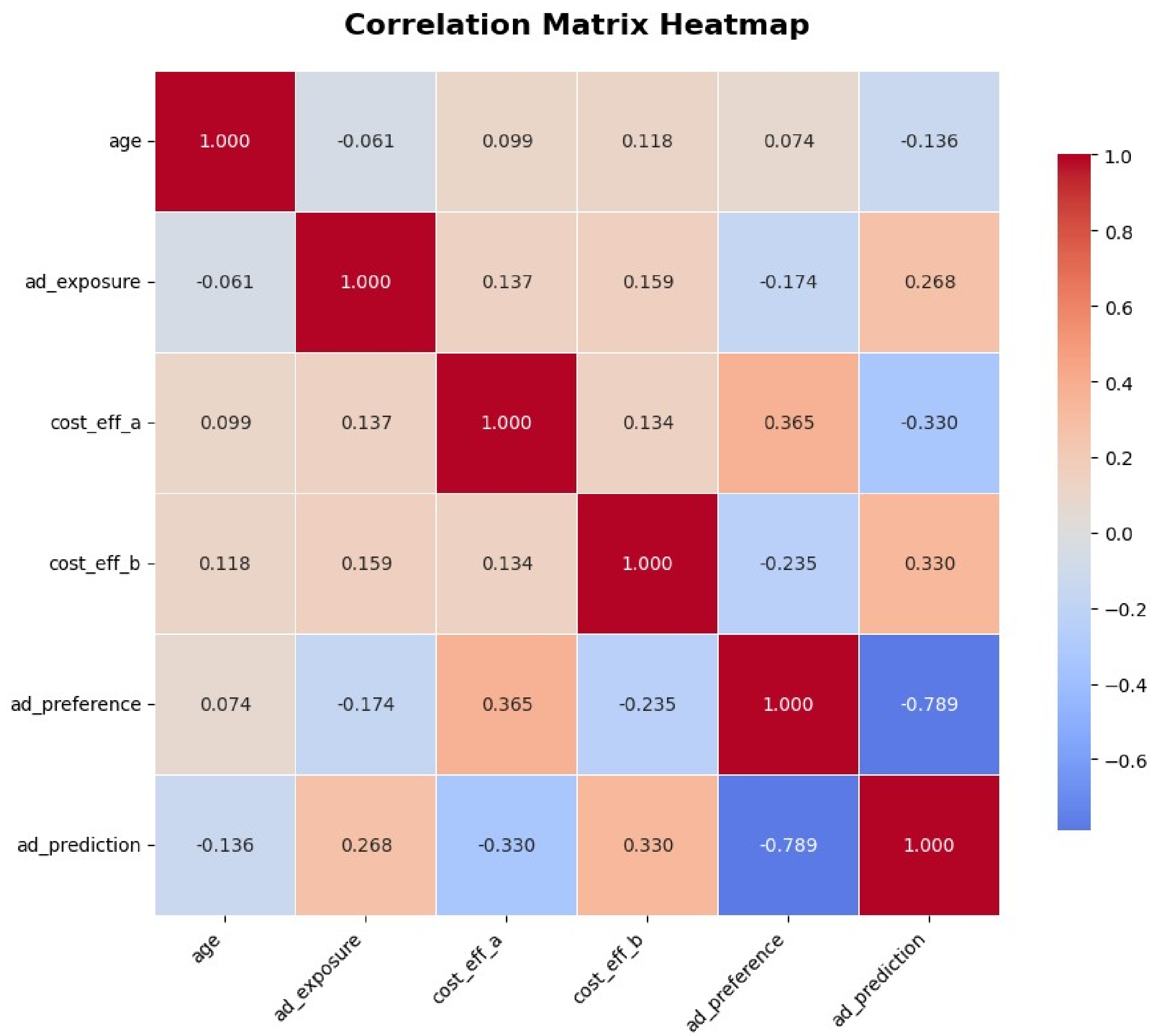
```
production_speed_a    0.771134    0.162231       0.187249      -
0.155250
production_speed_b    0.261714    0.727914      -0.071725
0.222077
cost_eff_a            1.000000    0.134165       0.364868      -
0.330492
cost_eff_b            0.134165    1.000000      -0.234837
0.330440
ad_preference         0.364868   -0.234837       1.000000      -
0.788938
ad_prediction        -0.330492    0.330440      -0.788938
1.000000
```

```
dff[['age', 'ad_exposure', 'cost_eff_a', 'cost_eff_b',
'ad_preference', 'ad_prediction']].corr()
```

```
                    age  ad_exposure  cost_eff_a  cost_eff_b
ad_preference  \
age            1.000000    -0.060873    0.098918    0.118409
0.073571
ad_exposure   -0.060873     1.000000    0.136782    0.159057       -
0.173914
cost_eff_a     0.098918     0.136782    1.000000    0.134165
0.364868
cost_eff_b     0.118409     0.159057    0.134165    1.000000       -
0.234837
ad_preference  0.073571    -0.173914    0.364868   -0.234837
1.000000
ad_prediction -0.136374     0.268101   -0.330492    0.330440       -
0.788938

               ad_prediction
age                -0.136374
ad_exposure         0.268101
cost_eff_a         -0.330492
cost_eff_b          0.330440
ad_preference      -0.788938
ad_prediction       1.000000
```

```
correlation_matrix = dff[['age', 'ad_exposure', 'cost_eff_a',
'cost_eff_b', 'ad_preference', 'ad_prediction']].corr()

# Create the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix,
            annot=True,              # Show correlation values
            cmap='coolwarm',         # Color scheme (blue-white-red)
            center=0,                # Center colormap at 0
            square=True,             # Make cells square
            fmt='.3f',               # Format numbers to 3 decimal places
```

```
            cbar_kws={'shrink': 0.8},  # Adjust colorbar size
            linewidths=0.5)       # Add lines between cells

plt.title('Correlation Matrix Heatmap', fontsize=16,
fontweight='bold', pad=20)
plt.xlabel('')  # Remove x-axis label (redundant with tick labels)
plt.ylabel('')  # Remove y-axis label (redundant with tick labels)
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better
readability
plt.yticks(rotation=0)               # Keep y-axis labels horizontal

plt.tight_layout()

plt.show()

# Optional: Print the correlation matrix values
print("Correlation Matrix:")
print(correlation_matrix.round(3))
```




```
Correlation Matrix:
                  age  ad_exposure  cost_eff_a  cost_eff_b
ad_preference  \
age             1.000       -0.061       0.099       0.118
0.074
ad_exposure    -0.061        1.000       0.137       0.159          -
0.174
cost_eff_a      0.099        0.137       1.000       0.134
0.365
cost_eff_b      0.118        0.159       0.134       1.000          -
0.235
ad_preference   0.074       -0.174       0.365      -0.235
1.000
ad_prediction -0.136        0.268      -0.330       0.330          -
0.789
```

```
                 ad_prediction
age                     -0.136
ad_exposure              0.268
cost_eff_a              -0.330
cost_eff_b               0.330
ad_preference           -0.789
ad_prediction            1.000
```

Using only age, ad_exposure, cost-efficiency and ad preference feature

```python
# Step 1: Define the features and target
# features = ['age', 'gender', 'ad_exposure', 'ai_exposure',
'cost_eff_a', 'cost_eff_b', 'ad_preference']
features = ['age', 'ad_exposure', 'cost_eff_a', 'cost_eff_b',
'ad_preference']
target_col = 'ad_prediction'  # Replace with your actual target column
name

# Step 2: Clean and filter the data
df_model = dff[features + [target_col]].dropna()

# Ensure target is binary (0/1)
df_model = df_model[df_model[target_col].isin([1, 2])]
df_model['target_bin'] = df_model[target_col].apply(lambda x: 1 if x
== 2 else 0)

# Step 3: Add constant for intercept
X = sm.add_constant(df_model[features])
y = df_model['target_bin']

# Step 4: Fit the logistic regression model
logit_model = sm.Logit(y, X).fit()

# Step 5: Display the summary
print(logit_model.summary())

# Step 6: Predict and evaluate
y_pred = (logit_model.predict(X) > 0.5).astype(int)

print("\nConfusion Matrix:")
print(confusion_matrix(y, y_pred))

print("\nClassification Report:")
print(classification_report(y, y_pred, target_names=['Class 1', 'Class
2']))
```

```
Optimization terminated successfully.
         Current function value: 0.258454
         Iterations 8
                           Logit Regression Results

======================================================================
========
Dep. Variable:             target_bin   No. Observations:
180
Model:                          Logit   Df Residuals:
174
Method:                           MLE   Df Model:
5
Date:                Sat, 09 Aug 2025   Pseudo R-squ.:
0.6271
Time:                        11:06:12   Log-Likelihood:
-46.522
converged:                       True   LL-Null:
-124.76
Covariance Type:            nonrobust   LLR p-value:
5.602e-32
======================================================================
===========
                    coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
-----------
const             4.4950      1.686      2.666      0.008       1.190
7.800
age              -0.8019      0.359     -2.231      0.026      -1.506
-0.097
ad_exposure       0.8185      0.309      2.645      0.008       0.212
1.425
cost_eff_a       -0.7243      0.284     -2.547      0.011      -1.282
-0.167
cost_eff_b        0.8966      0.261      3.440      0.001       0.386
1.407
ad_preference    -4.2598      0.614     -6.935      0.000      -5.464
-3.056
======================================================================
===========

Confusion Matrix:
[[84  7]
 [ 9 80]]

Classification Report:
              precision    recall  f1-score   support

     Class 1       0.90      0.92      0.91        91
```

```
     Class 2       0.92      0.90      0.91        89

    accuracy                           0.91       180
   macro avg       0.91      0.91      0.91       180
weighted avg       0.91      0.91      0.91       180
```

Key metrics:

True Negatives (TN): 84 - correctly predicted as class 0 False Positives (FP): 7 - incorrectly predicted as class 1 (Type I error) False Negatives (FN): 9 - incorrectly predicted as class 0 (Type II error) True Positives (TP): 80 - correctly predicted as class 1

Performance summary:

Total samples: 180 Correct predictions: 164 (84 + 80) Accuracy: 91.1% (164/180) Precision for class 1: 92.0% (80/87) - of predicted positives, how many were correct Recall for class 1: 89.9% (80/89) - of actual positives, how many were caught Precision for class 0: 90.3% (84/93) Recall for class 0: 92.3% (84/91)

Hypothesis analysis

H1: AI-generated Ads are perceived to be as creative as human-made Ads

Not accepted due to non-significance (No)

H2: AI-generated Ads are perceived to be more authentic than Human-made Ads

Not accepted due to non-significance (No)

H3: AI-generated Ads are perceived to be faster to produce than human-made Ads

Not accepted due to non-significance (No)

H4: AI-generated Ads are perceived to be more cost efficient than human-made Ads

Accepted due to significance (Yes)