Loading and Preparing Data

Purpose: Load predictions from different meta-learners and prepare the data for analysis.

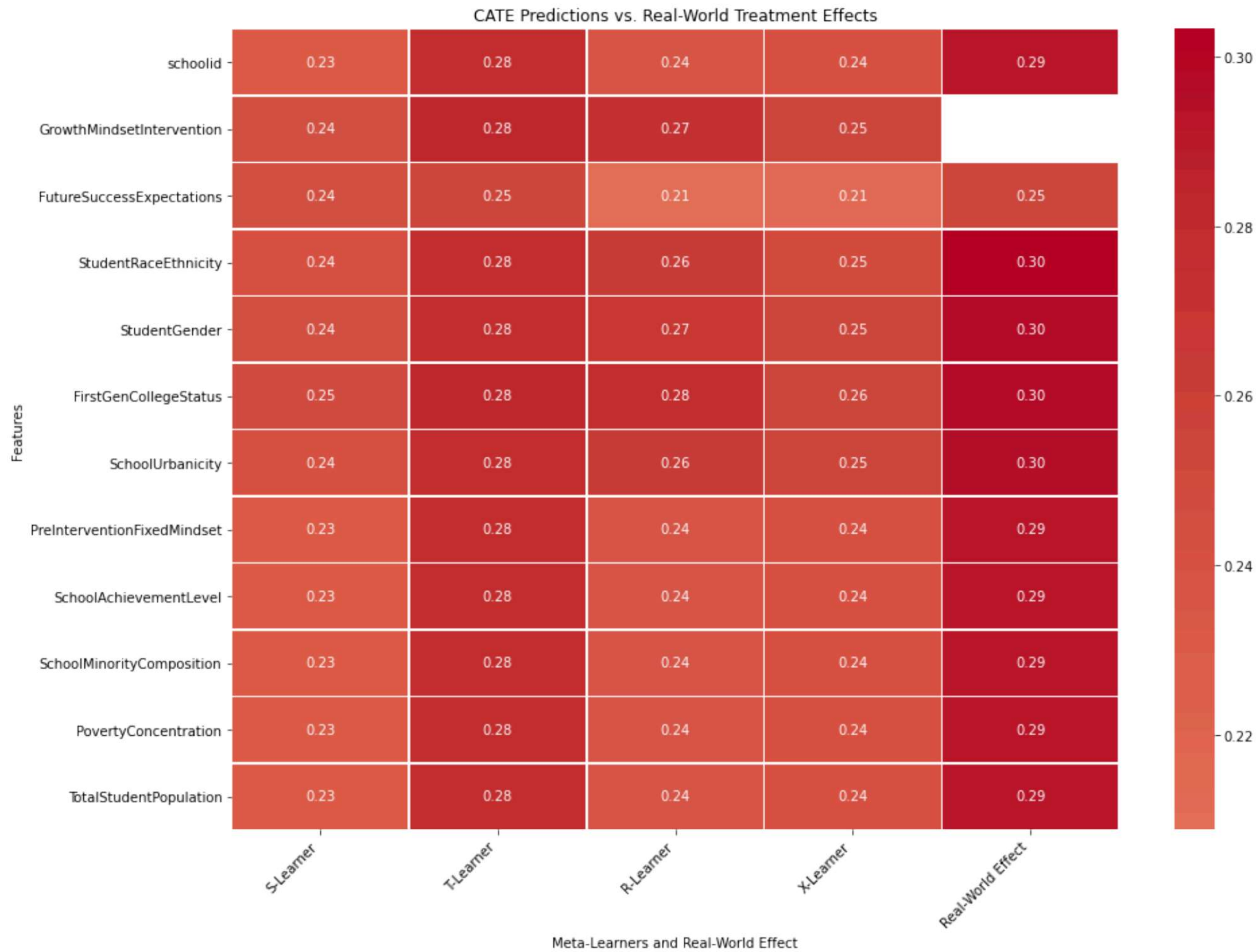
In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error

# Load the CSV files
slearner_data = pd.read_csv('../results/s_predictions.csv')
tlearner_data = pd.read_csv('../results/t_predictions.csv')
xlearner_data = pd.read_csv('../results/x_predictions.csv')
rlearner_data = pd.read_csv('../results/r_predictions.csv')

# Add a learner identifier column
slearner_data['Learner'] = 'S-Learner'
tlearner_data['Learner'] = 'T-Learner'
rlearner_data['Learner'] = 'R-Learner'
xlearner_data['Learner'] = 'X-Learner'

# Combine all data into one DataFrame
combined_data = pd.concat([slearner_data, tlearner_data, rlearner_data, xlearner_data], ignore_index=True)
```

Calculating CATE for Each Feature

Purpose: Calculate the average CATE for each feature using the predictions from each meta-learner.

In [2]:
```python
# List of features to calculate CATE for
features = [
    'schoolid', 'GrowthMindsetIntervention', 'FutureSuccessExpectations',
    'StudentRaceEthnicity', 'StudentGender', 'FirstGenCollegeStatus', 'SchoolUrbanicity',
    'PreInterventionFixedMindset', 'SchoolAchievementLevel', 'SchoolMinorityComposition',
    'PovertyConcentration', 'TotalStudentPopulation'
]

# Initialize a dictionary to hold CATE results
cate_results = {}

# Function to calculate CATE for a given feature
def calculate_cate(feature):
    grouped_data = combined_data.groupby(['Learner', feature]).agg({'CATE': 'mean'}).reset_index()
    grouped_data.columns = ['Learner', feature, 'CATE']
    return grouped_data

# Calculate CATE for each feature and store the results
for feature in features:
    cate_results[feature] = calculate_cate(feature)
```

```
                             S-Learner T-Learner R-Learner X-Learner  \
schoolid                      0.230647  0.278851  0.238911  0.240691
GrowthMindsetIntervention     0.244798  0.279892  0.270576  0.253454
FutureSuccessExpectations     0.243297  0.252234  0.208768  0.212314
StudentRaceEthnicity          0.240382  0.278262    0.2606  0.248819
StudentGender                 0.243489  0.279347  0.267875  0.251988
FirstGenCollegeStatus         0.246866  0.280338  0.277363  0.255865
SchoolUrbanicity              0.240176  0.278914  0.263373  0.251655
PreInterventionFixedMindset   0.230647  0.278851  0.238911  0.240691
SchoolAchievementLevel        0.230647  0.278851  0.238911  0.240691
SchoolMinorityComposition     0.230647  0.278851  0.238911  0.240691
PovertyConcentration          0.230647  0.278851  0.238911  0.240691
TotalStudentPopulation        0.230647  0.278851  0.238911  0.240691

                             Real-World Effect
schoolid                              0.292974
GrowthMindsetIntervention                  NaN
FutureSuccessExpectations             0.252985
StudentRaceEthnicity                  0.303306
StudentGender                         0.298372
FirstGenCollegeStatus                 0.297111
SchoolUrbanicity                      0.295658
PreInterventionFixedMindset           0.292974
SchoolAchievementLevel                0.292974
SchoolMinorityComposition             0.292974
PovertyConcentration                  0.292974
TotalStudentPopulation                0.292974
```



Calculating Real-World Treatment Effects

Purpose: Compute the actual difference in student achievement scores between treated and control groups for each feature, representing the real-world effect.

In [ ]:
```
# Calculate Real-World Treatment Effects
real_world_effects = {}

for feature in features:
    # Group by the feature and treatment
    grouped_data = combined_data.groupby([feature, 'GrowthMindsetIntervention'])['StudentAchievementScore'].mean()

    # Calculate the real-world treatment effect as the difference between treated and control
    real_world_effect = grouped_data[1] - grouped_data[0]

    # Store the result
    real_world_effects[feature] = real_world_effect
```

Creating and Displaying the Comparison Matrix

Purpose: Compare the predicted CATE values from each meta-learner with the real-world treatment effects

In [ ]:
```
# Create a new DataFrame to compare the predicted CATE with real-world treatment effects
comparison_matrix_with_real = pd.DataFrame(index=features, columns=['S-Learner', 'T-Learner', 'R-Learner', 'X-Lear

# Fill the matrix with the predicted CATE values and real-world treatment effects
for feature in features:
    for learner in ['S-Learner', 'T-Learner', 'R-Learner', 'X-Learner']:
        learner_data = cate_results[feature]
        mean_cate = learner_data[learner_data['Learner'] == learner]['CATE'].mean()
        comparison_matrix_with_real.loc[feature, learner] = mean_cate

    # Fill in the real-world effect for the feature
    comparison_matrix_with_real.loc[feature, 'Real-World Effect'] = real_world_effects[feature].mean()

# Display the updated comparison matrix
print(comparison_matrix_with_real)

# Visualize the Comparison
plt.figure(figsize=(14, 10))

# Heatmap showing both CATE predictions and real-world effects
sns.heatmap(comparison_matrix_with_real.astype(float), annot=True, cmap="coolwarm", center=0, cbar=True, fmt=".2f"

plt.title('CATE Predictions vs. Real-World Treatment Effects')
plt.xlabel('Meta-Learners and Real-World Effect')
plt.ylabel('Features')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.tight_layout()

plt.show()
```

Handling NaN Values and Recalculating Real-World Effects

Purpose: Resolve NaN values in the real-world effects by manually recalculating the mean scores for treated and control groups.

In [3]:
```
# Step 1: Check for missing values in the relevant columns
missing_values = combined_data[['GrowthMindsetIntervention', 'StudentAchievementScore']].isnull().sum()
print("Missing values:\n", missing_values)
```

```
Missing values:
 GrowthMindsetIntervention    0
StudentAchievementScore      0
dtype: int64
```

In [4]:
```
# Step 2: Inspect data for GrowthMindsetIntervention to see if treated or control group has insufficient data
print("\nData distribution for GrowthMindsetIntervention:")
print(combined_data['GrowthMindsetIntervention'].value_counts())
```

```

Data distribution for GrowthMindsetIntervention:
0    28028
1    13536
Name: GrowthMindsetIntervention, dtype: int64
```

In [6]:
```
# Step 3: Investigate the distribution of StudentAchievementScore for treated and control groups
treated_scores = combined_data[combined_data['GrowthMindsetIntervention'] == 1]['StudentAchievementScore']
control_scores = combined_data[combined_data['GrowthMindsetIntervention'] == 0]['StudentAchievementScore']
```

In [7]:
```
print("\nTreated group scores (first few rows):")
print(treated_scores.head())

print("\nControl group scores (first few rows):")
print(control_scores.head())
```

```
Treated group scores (first few rows):
0    0.081602
1   -0.385869
2    0.398184
3   -0.175037
4    0.884583
Name: StudentAchievementScore, dtype: float64

Control group scores (first few rows):
3384   -1.434893
3385    0.999290
3386    0.197742
3387   -0.059160
3388   -0.041489
Name: StudentAchievementScore, dtype: float64
```

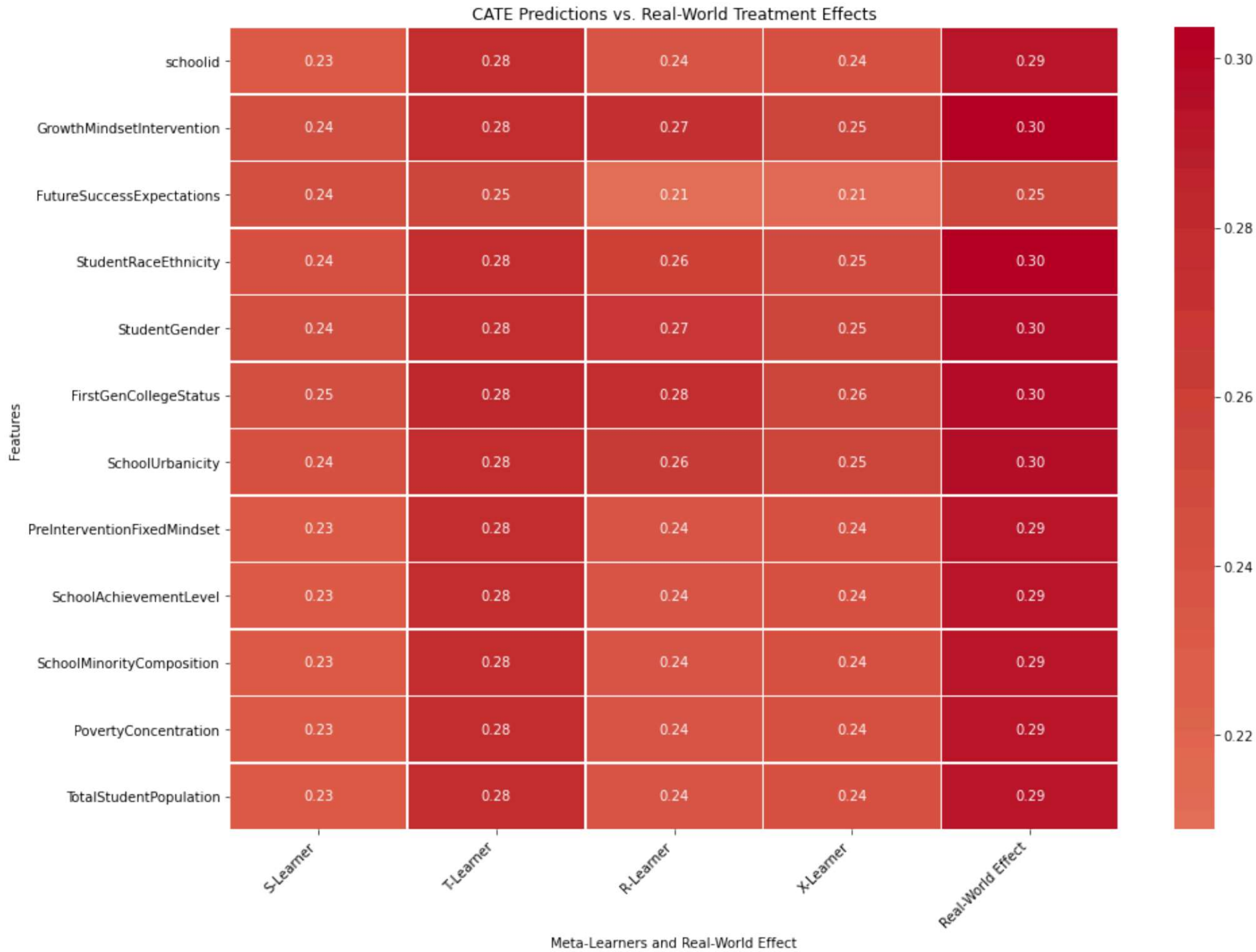
In [8]:
```
# Manually calculate the mean scores for treated and control groups
mean_treated_score = treated_scores.mean()
mean_control_score = control_scores.mean()

# Calculate the real-world effect
real_world_effect_growth_mindset = mean_treated_score - mean_control_score
print("\nManually Recalculated Real-World Effect for GrowthMindsetIntervention:", real_world_effect_growth_mindset
```

```
Manually Recalculated Real-World Effect for GrowthMindsetIntervention: 0.3036748422490185
```

In [9]:
```
# Update the comparison matrix with the manually recalculated real-world effect
comparison_matrix_with_real.loc['GrowthMindsetIntervention', 'Real-World Effect'] = real_world_effect_growth_minds

# Display the updated comparison matrix
print("\nUpdated comparison matrix with recalculated Real-World Effect:")
print(comparison_matrix_with_real)
```

```
Updated comparison matrix with recalculated Real-World Effect:
                            S-Learner T-Learner R-Learner X-Learner  \
schoolid                     0.230647  0.278851  0.238911  0.240691
GrowthMindsetIntervention    0.244798  0.279892  0.270576  0.253454
FutureSuccessExpectations    0.243297  0.252234  0.208768  0.212314
StudentRaceEthnicity         0.240382  0.278262    0.2606  0.248819
StudentGender                0.243489  0.279347  0.267875  0.251988
FirstGenCollegeStatus        0.246866  0.280338  0.277363  0.255865
SchoolUrbanicity             0.240176  0.278914  0.263373  0.251655
PreInterventionFixedMindset  0.230647  0.278851  0.238911  0.240691
SchoolAchievementLevel       0.230647  0.278851  0.238911  0.240691
SchoolMinorityComposition    0.230647  0.278851  0.238911  0.240691
PovertyConcentration         0.230647  0.278851  0.238911  0.240691
TotalStudentPopulation       0.230647  0.278851  0.238911  0.240691

                            Real-World Effect
schoolid                             0.292974
GrowthMindsetIntervention            0.303675
FutureSuccessExpectations            0.252985
StudentRaceEthnicity                 0.303306
StudentGender                        0.298372
FirstGenCollegeStatus                0.297111
SchoolUrbanicity                     0.295658
PreInterventionFixedMindset          0.292974
SchoolAchievementLevel               0.292974
SchoolMinorityComposition            0.292974
PovertyConcentration                 0.292974
TotalStudentPopulation               0.292974
```

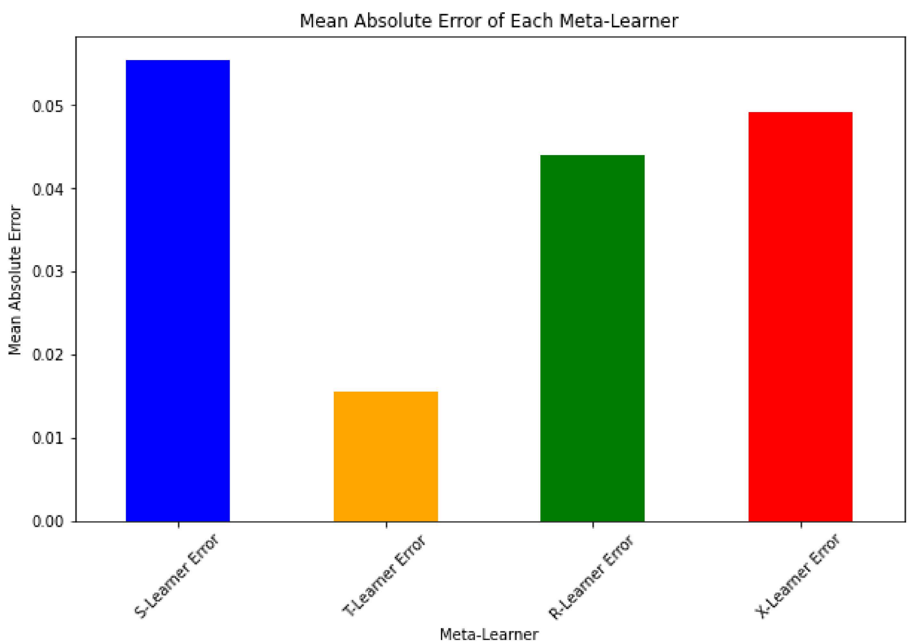
In [10]:
```
# Visualize the Comparison
plt.figure(figsize=(14, 10))

# Heatmap showing both CATE predictions and real-world effects
sns.heatmap(comparison_matrix_with_real.astype(float), annot=True, cmap="coolwarm", center=0, cbar=True, fmt=".2f"

plt.title('CATE Predictions vs. Real-World Treatment Effects')
plt.xlabel('Meta-Learners and Real-World Effect')
plt.ylabel('Features')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.tight_layout()

plt.show()
```



Comparative Analysis of Meta-Learners

Purpose: Evaluate the accuracy of each meta-learner by comparing their predicted CATE values with the real-world effects, and identify the best-performing learner for each feature.

In [19]:
```
import numpy as np

# Ensure all errors are numeric and handle NaN values by filling them with a large number (infinity)
comparison_matrix_with_real['S-Learner Error'] = pd.to_numeric(comparison_matrix_with_real['S-Learner Error'], err
comparison_matrix_with_real['T-Learner Error'] = pd.to_numeric(comparison_matrix_with_real['T-Learner Error'], err
comparison_matrix_with_real['R-Learner Error'] = pd.to_numeric(comparison_matrix_with_real['R-Learner Error'], err
comparison_matrix_with_real['X-Learner Error'] = pd.to_numeric(comparison_matrix_with_real['X-Learner Error'], err

# Identify the best learner for each feature by finding the minimum error
comparison_matrix_with_real['Best Learner'] = comparison_matrix_with_real[['S-Learner Error', 'T-Learner Error', '

#print("\nBest Learner for each feature:")
#print(comparison_matrix_with_real[['S-Learner', 'T-Learner', 'R-Learner', 'X-Learner', 'Real-World Effect', 'Best

# Visualize the mean absolute errors using a bar plot
plt.figure(figsize=(10, 6))
mean_errors = comparison_matrix_with_real[['S-Learner Error', 'T-Learner Error', 'R-Learner Error', 'X-Learner Err
mean_errors.plot(kind='bar', color=['blue', 'orange', 'green', 'red'])
plt.title('Mean Absolute Error of Each Meta-Learner')
plt.ylabel('Mean Absolute Error')
plt.xlabel('Meta-Learner')
plt.xticks(rotation=45)
plt.show()

# Display the updated comparison matrix with error calculations
#print("\nUpdated comparison matrix with error calculations:")
print(comparison_matrix_with_real)
```



	S-Learner	T-Learner	R-Learner	X-Learner
schoolid	0.230647	0.278851	0.238911	0.240691
GrowthMindsetIntervention	0.244798	0.279892	0.270576	0.253454
FutureSuccessExpectations	0.243297	0.252234	0.208768	0.212314
StudentRaceEthnicity	0.240382	0.278262	0.2606	0.248819
StudentGender	0.243489	0.279347	0.267875	0.251988
FirstGenCollegeStatus	0.246866	0.280338	0.277363	0.255865
SchoolUrbanicity	0.240176	0.278914	0.263373	0.251655
PreInterventionFixedMindset	0.230647	0.278851	0.238911	0.240691
SchoolAchievementLevel	0.230647	0.278851	0.238911	0.240691
SchoolMinorityComposition	0.230647	0.278851	0.238911	0.240691
PovertyConcentration	0.230647	0.278851	0.238911	0.240691
TotalStudentPopulation	0.230647	0.278851	0.238911	0.240691

	Real-World Effect	S-Learner Error
schoolid	0.292974	0.062327
GrowthMindsetIntervention	0.303675	0.058877
FutureSuccessExpectations	0.252985	0.009688
StudentRaceEthnicity	0.303306	0.062923
StudentGender	0.298372	0.054884
FirstGenCollegeStatus	0.297111	0.050245
SchoolUrbanicity	0.295658	0.055483
PreInterventionFixedMindset	0.292974	0.062327
SchoolAchievementLevel	0.292974	0.062327
SchoolMinorityComposition	0.292974	0.062327
PovertyConcentration	0.292974	0.062327
TotalStudentPopulation	0.292974	0.062327

	T-Learner Error	R-Learner Error
schoolid	0.014123	0.054063
GrowthMindsetIntervention	0.023783	0.033099
FutureSuccessExpectations	0.000751	0.044217
StudentRaceEthnicity	0.025044	0.042706
StudentGender	0.019025	0.030497
FirstGenCollegeStatus	0.016773	0.019748
SchoolUrbanicity	0.016744	0.032285
PreInterventionFixedMindset	0.014123	0.054063
SchoolAchievementLevel	0.014123	0.054063
SchoolMinorityComposition	0.014123	0.054063
PovertyConcentration	0.014123	0.054063
TotalStudentPopulation	0.014123	0.054063

	X-Learner Error	Best Learner
schoolid	0.052283	T-Learner Error
GrowthMindsetIntervention	0.050221	T-Learner Error
FutureSuccessExpectations	0.040671	T-Learner Error
StudentRaceEthnicity	0.054487	T-Learner Error
StudentGender	0.046384	T-Learner Error
FirstGenCollegeStatus	0.041246	T-Learner Error
SchoolUrbanicity	0.044004	T-Learner Error
PreInterventionFixedMindset	0.052283	T-Learner Error
SchoolAchievementLevel	0.052283	T-Learner Error
SchoolMinorityComposition	0.052283	T-Learner Error
PovertyConcentration	0.052283	T-Learner Error
TotalStudentPopulation	0.052283	T-Learner Error

Summary of the Results:

Best Learner Identification: The Best Learner column in the final matrix shows which meta-learner most accurately predicted the real-world effects for each feature based on the smallest absolute error. T-Learner Performance: The T-Learner consistently appears as the best performer across multiple features, indicating it may be the most accurate model in this scenario.