In [262]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import RandomizedSearchCV
```

In [263]:

```
filepath = "/content/drive/MyDrive/synthetic_ecommerce_data.csv"
```

In [264]:

```
df = pd.read_csv(filepath, parse_dates=['Transaction_Date'])
```

##EDA

In [265]:

```
df.head()
```

Out[265]:

	Transaction_ID	Customer_ID	Product_ID	Transaction_Date
0	8b460852-7c64-46fa-998b-b0976879d082	Customer_65	Product_224	2024-10-06
1	418612e7-8744-4ba3-bb0c-105b47e2a968	Customer_1910	Product_584	2024-10-29
2	5bc3b98f-cb0c-4b12-947c-df8bbb35a73e	Customer_2306	Product_374	2024-04-04
3	28fb67c8-e8c0-447a-841c-f760730de0eb	Customer_17206	Product_220	2024-08-25
4	8bee087a-a8a9-45bb-89d7-04d1710f1b00	Customer_16033	Product_358	2024-05-05

In [266]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 15 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Transaction_ID    100000 non-null  object
 1   Customer_ID       100000 non-null  object
 2   Product_ID        100000 non-null  object
 3   Transaction_Date  100000 non-null  datetime64[ns]
 4   Units_Sold        100000 non-null  int64
 5   Discount_Applied  100000 non-null  float64
 6   Revenue           100000 non-null  float64
 7   Clicks            100000 non-null  int64
 8   Impressions       100000 non-null  int64
 9   Conversion_Rate   100000 non-null  float64
 10  Category          100000 non-null  object
 11  Region            100000 non-null  object
 12  Ad_CTR            100000 non-null  float64
 13  Ad_CPC            100000 non-null  float64
 14  Ad_Spend          100000 non-null  float64
dtypes: datetime64[ns](1), float64(6), int64(3), object(5)
memory usage: 11.4+ MB
```

In [267]:

```
# nothing's missing lowkey, some cols are objects (categories to handle before training on)
```

In [268]:

```
df.isnull().sum()
# cinfirmed
```

Out[268]:

	0
Transaction_ID	0
Customer_ID	0
Product_ID	0
Transaction_Date	0
Units_Sold	0
Discount_Applied	0
Revenue	0
Clicks	0
Impressions	0
Conversion_Rate	0
Category	0
Region	0
Ad_CTR	0
Ad_CPC	0
Ad_Spend	0

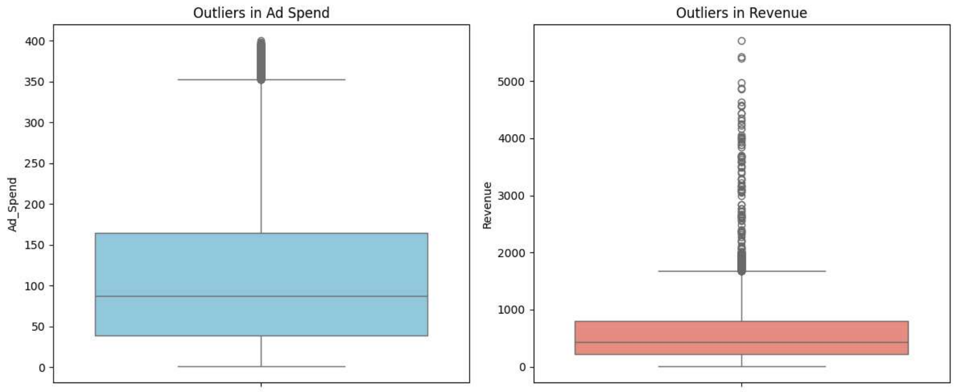
dtype: int64

Outlier detection

if they're outliers or justifiable data points

In [269]:

```
plt.figure(figsize=(12, 5))

# Plotting Ad Spend and Revenue outliers
plt.subplot(1, 2, 1)
sns.boxplot(y=df['Ad_Spend'], color='skyblue')
plt.title('Outliers in Ad Spend')

plt.subplot(1, 2, 2)
sns.boxplot(y=df['Revenue'], color='salmon')
plt.title('Outliers in Revenue')

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



Several high-revenue data points are "outliers", think of a model that's robust to this situation

Feature engineering

In [270]:

```
df['Month'] = df['Transaction_Date'].dt.month
df['DayOfWeek'] = df['Transaction_Date'].dt.dayofweek
```

In [271]:

```
# engineering the campaigns out of date, cat, region
data = df.groupby(['Transaction_Date', 'Category', 'Region', 'Month',
'DayOfWeek']).agg({
    'Ad_Spend': 'sum',
    'Clicks': 'sum',
    'Impressions': 'sum',
    'Revenue': 'sum',
    'Units_Sold': 'sum',
    'Ad_CTR': 'sum',
    'Ad_CPC': 'sum'
}).reset_index()
```

In [272]:

```
data['Spend_Efficiency'] = data['Ad_Spend'] * data['Clicks']
```

In [273]:

```
# features and y : target column
X = data[['Ad_Spend', 'Clicks', 'Impressions', 'Month', 'DayOfWeek',
'Category', 'Region', 'Spend_Efficiency', 'Ad_CTR', 'Ad_CPC']]
y = data['Revenue']
```

In [274]:

```
X
```

Out[274]:

	Ad_Spend	Clicks	Impressions	Month	DayOfWeek	Categ
0	1837.26	389	3365	12	3	Books
1	2385.95	405	4477	12	3	Books
2	2910.23	517	6199	12	3	Books
3	2498.42	403	4692	12	3	Clothir
4	1845.82	309	4542	12	3	Clothir
...	...	...	...	...	...	...
5485	2093.20	256	3343	12	4	Home Appliar
5486	2224.22	409	4165	12	4	Home Appliar
5487	1797.73	430	5375	12	4	Toys
5488	1581.18	409	3015	12	4	Toys
5489	1087.23	339	2919	12	4	Toys

5490 rows × 10 columns

In [275]:

```
# Encoding categories (transforming the Xs that are categories to
numericals)
X = pd.get_dummies(X, columns=['Category', 'Region'], drop_first=True)
# X : as expected
```

In [276]:

```
X_train_full, X_test, y_train_full, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train_full,
y_train_full, test_size=0.2, random_state=42)

print(f"Train size: {X_train.shape[0]}, Val size: {X_val.shape[0]}, Test
size: {X_test.shape[0]}")
```

```
Train size: 3513, Val size: 879, Test size: 1098
```

Further preprocessing

normalization, standardization

In [277]:

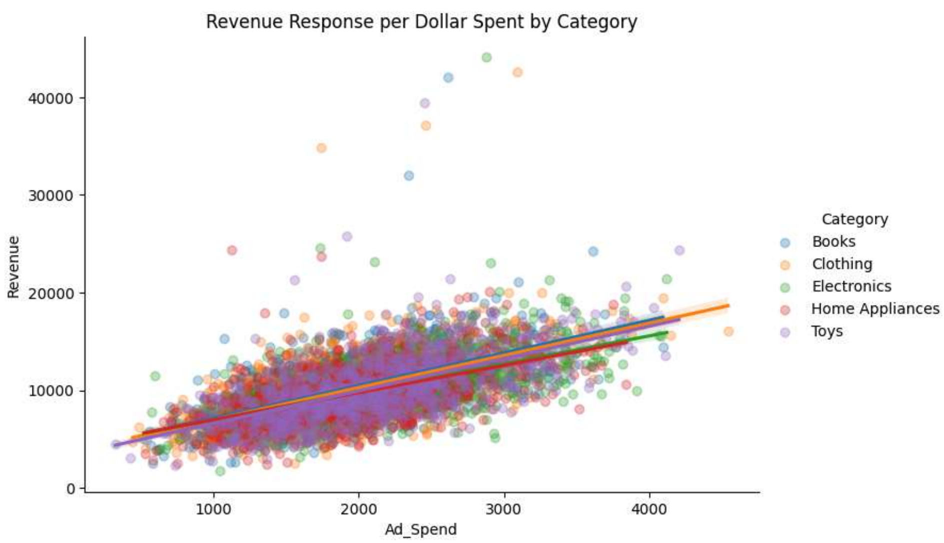
```
num_features = ['Ad_Spend', 'Clicks', 'Impressions', 'Month',
'DayOfWeek']

# scaler at work
scaler = StandardScaler()
# init the new X_train , y_train
X_train_scaled = X_train.copy()
X_val_scaled = X_val.copy()
X_test_scaled = X_test.copy()

X_train_scaled[num_features] =
scaler.fit_transform(X_train[num_features])
X_val_scaled[num_features] = scaler.transform(X_val[num_features])
X_test_scaled[num_features] = scaler.transform(X_test[num_features])
```

Marketing dynamics analysis

In [278]:

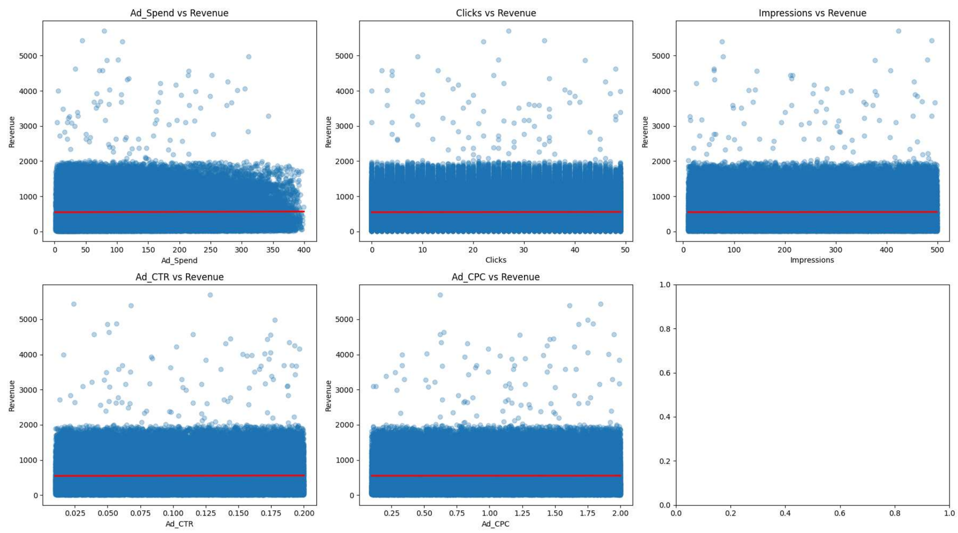
```
# correlation ? between category budget and revenue
for cat in data['Category'].unique():
    subset = data[data['Category'] == cat]
    correlation = subset['Ad_Spend'].corr(subset['Revenue'])
    print(f"Correlation for {cat}: {correlation:.2f}")



plt.figure(figsize=(10, 6))
sns.lmplot(x='Ad_Spend', y='Revenue', hue='Category', data=data,
aspect=1.5, scatter_kws={'alpha':0.3})
plt.title('Revenue Response per Dollar Spent by Category')
plt.show()
```

```
Correlation for Books: 0.59
Correlation for Clothing: 0.58
Correlation for Electronics: 0.58
Correlation for Home Appliances: 0.56
Correlation for Toys: 0.63

<Figure size 1000x600 with 0 Axes>
```



In [279]:

```
# List of numeric features to test
features_to_plot = ['Ad_Spend', 'Clicks', 'Impressions', 'Ad_CTR',
'Ad_CPC']

fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(18, 10))
axes = axes.flatten()

for i, col in enumerate(features_to_plot):
    sns.regplot(data=df, x=col, y='Revenue', ax=axes[i],
                scatter_kws={'alpha':0.3}, line_kws={'color':'red'})
    axes[i].set_title(f'{col} vs Revenue')

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



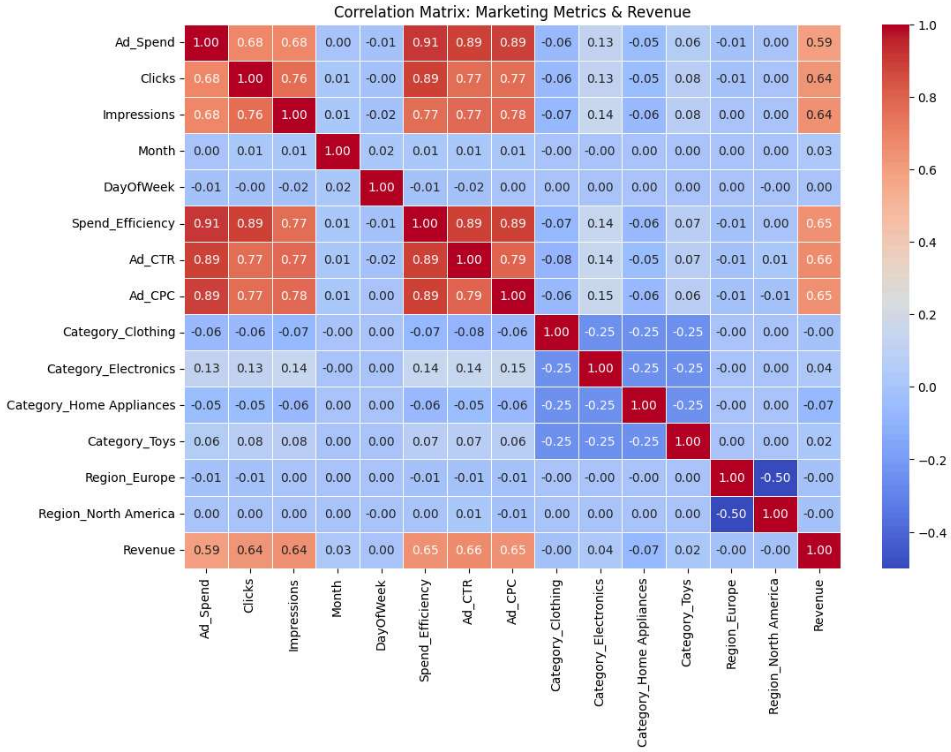
In [280]:

```
# df.dtypes
```

Global correlations

In [281]:

```
# cols_excluded_heat_map = ['Transaction_ID', 'Customer_ID',
'Transaction_Date', 'Product_ID']
# only numerics are left
data_HM = pd.concat([X, y], axis=1)

plt.figure(figsize=(12, 8))
sns.heatmap(pd.concat([X, y], axis=1).corr(), annot=True,
cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Correlation Matrix: Marketing Metrics & Revenue")
plt.show()
```



##Model training

In [284]:

```
from xgboost import XGBRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor

# grid params to try
param_grid = {
    'n_estimators': [100, 300, 500],
    'learning_rate': [0.01, 0.05, 0.1],
    'max_depth': [3, 7, 12],
    'subsample': [0.8]
}

# Grid Search on XGBoost
grid_xgb = GridSearchCV(XGBRegressor(random_state=42), param_grid, cv=4,
scoring='r2')
grid_xgb.fit(X_train_scaled, y_train)

best_xgb = grid_xgb.best_estimator_
best_xgb.score(X_val_scaled, y_val)
```

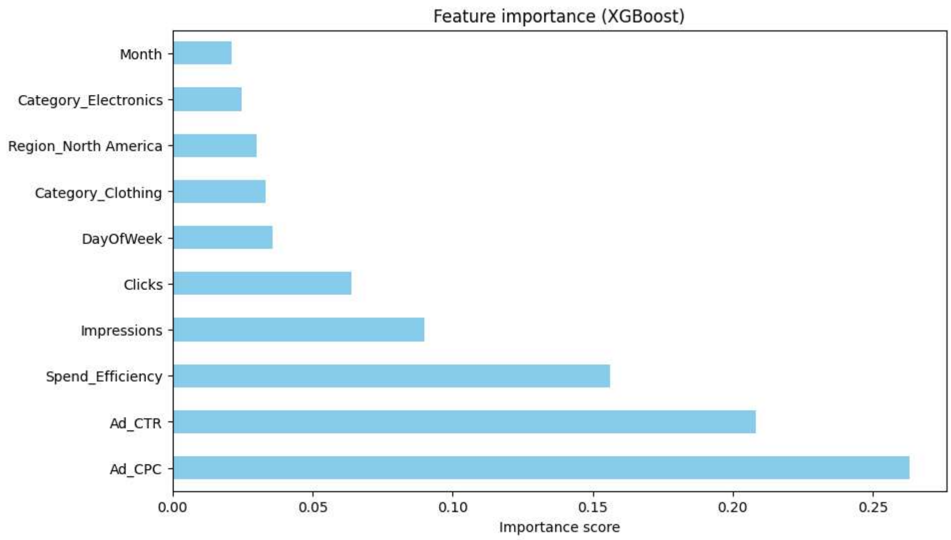
Out[284]: 0.5304849480000307

In [285]:

```
bag_rf = BaggingRegressor(
    estimator=RandomForestRegressor(n_estimators=100),
    n_estimators=10,
    random_state=42
)

# Fit the model on the same scaled training data used for XGBoost
bag_rf.fit(X_train_scaled, y_train)

bag_test_preds = bag_rf.predict(X_test_scaled)
```

In [286]:

```
import matplotlib.pyplot as plt

importances = best_xgb.feature_importances_
feat_importances = pd.Series(importances, index=X.columns)

plt.figure(figsize=(10,6))
feat_importances.nlargest(10).plot(kind='barh', color='skyblue')
plt.title("Feature importance (XGBoost)")
plt.xlabel("Importance score")
plt.show()
```



In [287]:

```
from sklearn.metrics import r2_score, mean_absolute_error,
mean_squared_error

# Final prediction on the tst set (which the model NEVER saw)
final_test_preds = best_xgb.predict(X_test_scaled)

test_r2 = r2_score(y_test, final_test_preds)
test_mae = mean_absolute_error(y_test, final_test_preds)
test_rmse = np.sqrt(mean_squared_error(y_test, final_test_preds))

print(f"--- FINAL TEST SET RESULTS ---")
print(f"R2 Score: {test_r2:.4f}")
print(f"MAE: ${test_mae:.2f}")
print(f"RMSE: ${test_rmse:.2f}")
```

```
--- FINAL TEST SET RESULTS ---
R2 Score: 0.5244
MAE: $1634.29
RMSE: $2273.93
```

In [288]:

```
bag_test_r2 = r2_score(y_test, bag_test_preds)
bag_test_mae = mean_absolute_error(y_test, bag_test_preds)
bag_test_rmse = np.sqrt(mean_squared_error(y_test, bag_test_preds))

print(f"--- BAGGING RF TEST SET RESULTS ---")
print(f"R2 Score: {bag_test_r2:.4f}")
print(f"MAE: ${bag_test_mae:.2f}")
print(f"RMSE: ${bag_test_rmse:.2f}")
```

```
--- BAGGING RF TEST SET RESULTS ---
R2 Score: 0.5037
MAE: $1678.93
RMSE: $2322.93
```

XGBoost is better

In [290]:

```
import numpy as np

# Train on log values
y_train_log = np.log1p(y_train)
best_xgb.fit(X_train_scaled, y_train_log)

# Predict and transform back to dollars
log_preds = best_xgb.predict(X_test_scaled)
final_preds = np.expm1(log_preds) # inverser log using exp

print(f"New R2: {r2_score(y_test, final_preds)}")
print(f"MAE: ${mean_absolute_error(y_test, final_test_preds)}")
```

```
New R2: 0.5103692168572471
MAE: $1634.2862791901468
```

Changed nothing significant

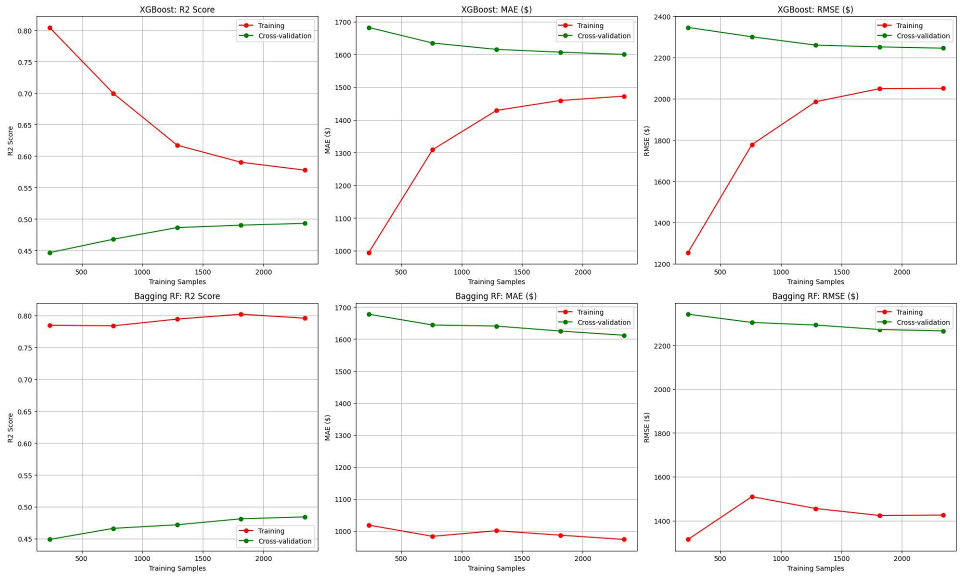
In [291]:

```
from sklearn.metrics import mean_absolute_error,
mean_absolute_percentage_error

# core Eval metrics
mae = mean_absolute_error(y_test, final_test_preds)
mape = mean_absolute_percentage_error(y_test, final_test_preds)

# Calculate 'accuracy' as 1 - MAPE
accuracy_pct = (1 - mape) * 100

# Calculate the 'Relative Error' against the Mean
mean_revenue = y_test.mean()
relative_error = (mae / mean_revenue) * 100

print(f"--- Objective Performance Metrics ---")
print(f"Mean Revenue in Test Set: ${mean_revenue:.2f}")
print(f"Mean Absolute Error (MAE): ${mae:.2f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape*100:.2f}%")
print(f"--- Report Ready Statistics ---")
print(f"Predictive Accuracy (1-MAPE): {accuracy_pct:.2f}%")
print(f"Error as % of Mean Revenue: {relative_error:.2f}%")
```

```
--- Objective Performance Metrics ---
Mean Revenue in Test Set: $10161.77
Mean Absolute Error (MAE): $1634.29
Mean Absolute Percentage Error (MAPE): 17.64%
--- Report Ready Statistics ---
Predictive Accuracy (1-MAPE): 82.36%
Error as % of Mean Revenue: 16.08%
```

In [292]:

```
from sklearn.model_selection import learning_curve
from sklearn.metrics import make_scorer, mean_squared_error
import matplotlib.pyplot as plt
import numpy as np

def plot_comprehensive_learning_curves(models, X, y):
    # Define RMSE scorer since it's not a default string option
    rmse_scorer = make_scorer(lambda y_true, y_pred:
np.sqrt(mean_squared_error(y_true, y_pred)), greater_is_better=False)

    metrics = [
        ('r2', 'R2 Score', False),
        ('neg_mean_absolute_error', 'MAE ($)', True),
        (rmse_scorer, 'RMSE ($)', True)
    ]

    fig, axes = plt.subplots(len(models), len(metrics), figsize=(20,
12))

    for i, (name, model) in enumerate(models.items()):
        for j, (scorer, label, is_error_metric) in enumerate(metrics):
            train_sizes, train_scores, test_scores = learning_curve(
                model, X, y, cv=3, n_jobs=-1,
                train_sizes=np.linspace(0.1, 1.0, 5), scoring=scorer
            )

            # Convert negative scores back to positive for MAE and RMSE
            if is_error_metric:
                train_mean = -np.mean(train_scores, axis=1)
                test_mean = -np.mean(test_scores, axis=1)
            else:
                train_mean = np.mean(train_scores, axis=1)
                test_mean = np.mean(test_scores, axis=1)

            axes[i, j].plot(train_sizes, train_mean, 'o-', color="r",
label="Training")
            axes[i, j].plot(train_sizes, test_mean, 'o-', color="g",
label="Cross-validation")
            axes[i, j].set_title(f"{name}: {label}")
            axes[i, j].set_xlabel("Training Samples")
            axes[i, j].set_ylabel(label)
            axes[i, j].legend(loc="best")
            axes[i, j].grid(True)

    plt.tight_layout()
    plt.show()

# Run the function (Uses the 3513 training rows)
plot_comprehensive_learning_curves({"XGBoost": best_xgb, "Bagging RF":
bag_rf}, X_train_scaled, y_train)
```


XGBoost: R2 Score
R2 Score
Training Samples
Training
Cross-validation
XGBoost: MAE ($)
MAE ($)
Training Samples
Training
Cross-validation
XGBoost: RMSE ($)
RMSE ($)
Training Samples
Training
Cross-validation
Bagging RF: R2 Score
R2 Score
Training Samples
Training
Cross-validation
Bagging RF: MAE ($)
MAE ($)
Training Samples
Training
Cross-validation
Bagging RF: RMSE ($)
RMSE ($)
Training Samples
Training
Cross-validation

In [293]:

```
import seaborn as sns
import matplotlib.pyplot as plt

def plot_error_histograms(models, X_test, y_test):
    """
    Generates histograms of the prediction errors (residuals) for both
models.
    """
    fig, axes = plt.subplots(1, len(models), figsize=(15, 6))

    for i, (name, model) in enumerate(models.items()):
        preds = model.predict(X_test)
        residuals = y_test - preds

        sns.histplot(residuals, kde=True, ax=axes[i], color='teal' if
"XGB" in name else 'orange')
        axes[i].set_title(f"Error Distribution: {name}")
        axes[i].set_xlabel("Dollar Error (Actual - Predicted)")
        axes[i].set_ylabel("Frequency")

        # Add a vertical line at 0 (Perfect Prediction)
        axes[i].axvline(0, color='red', linestyle='--')

    plt.tight_layout()
    plt.show()

# Run for your models
plot_error_histograms({"XGBoost": best_xgb, "Bagging RF": bag_rf},
X_test_scaled, y_test)
```