Importing libraries and loading dataset

In [1]:
```
# Importing necessary libraries
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, RandomizedSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
import shap

# Loading dataset
df = pd.read_csv("customer_shopping_data.csv")

# Showing first rows
df.head()
```

Out[1]:

	invoice_no	customer_id	gender	age	category	quantity	price	payment_method	i
0	I138884	C241288	Female	28	Clothing	5	1500.40	Credit Card	
1	I317333	C111565	Male	21	Shoes	3	1800.51	Debit Card	
2	I127801	C266599	Male	20	Clothing	1	300.08	Cash	
3	I173702	C988172	Female	66	Shoes	5	3000.85	Credit Card	
4	I337046	C189076	Female	53	Books	4	60.60	Cash	

Data Cleaning

In [2]:
```
# Removing duplicate rows
df = df.drop_duplicates()

# Handling missing values by filling or dropping
df = df.dropna(subset=['price', 'quantity'])
df['age'] = df['age'].fillna(df['age'].median())

# Converting invoice_date into datetime
df['invoice_date'] = pd.to_datetime(df['invoice_date'], format='%d/%m/%Y')

# Creating target variable "total_sales"
df['total_sales'] = df['price'] * df['quantity']

df.head()
```

Out[2]:

	invoice_no	customer_id	gender	age	category	quantity	price	payment_method	i
0	I138884	C241288	Female	28	Clothing	5	1500.40	Credit Card	
1	I317333	C111565	Male	21	Shoes	3	1800.51	Debit Card	
2	I127801	C266599	Male	20	Clothing	1	300.08	Cash	
3	I173702	C988172	Female	66	Shoes	5	3000.85	Credit Card	
4	I337046	C189076	Female	53	Books	4	60.60	Cash	

Feature engineering

In [3]:

```
# Extracting time features
df['year'] = df['invoice_date'].dt.year
df['month'] = df['invoice_date'].dt.month
df['day'] = df['invoice_date'].dt.day
df['weekday'] = df['invoice_date'].dt.weekday

# Aggregating customer-level behavior
customer_avg_price = df.groupby('customer_id')['price'].mean().rename("customer_avg
df = df.merge(customer_avg_price, on='customer_id', how='left')

# Creating encoded categorical and numeric lists
categorical_features = ['gender', 'category', 'payment_method', 'shopping_mall']
numeric_features = ['age', 'quantity', 'price', 'customer_avg_price', 'year', 'mont

df.head()
```

Out[3]:

	invoice_no	customer_id	gender	age	category	quantity	price	payment_method	i
0	I138884	C241288	Female	28	Clothing	5	1500.40	Credit Card	
1	I317333	C111565	Male	21	Shoes	3	1800.51	Debit Card	
2	I127801	C266599	Male	20	Clothing	1	300.08	Cash	
3	I173702	C988172	Female	66	Shoes	5	3000.85	Credit Card	
4	I337046	C189076	Female	53	Books	4	60.60	Cash	

EDA & Visualizations

In [4]:

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

# Ensuring style
sns.set(style="whitegrid")

# Creating backup cleaned dataset
df_clean = df.copy()

# Creating additional segments (age bins)
df_clean['age_segment'] = pd.cut(
```

```
    df_clean['age'],
    bins=[0, 18, 30, 45, 60, 100],
    labels=['Teen', 'Young Adult', 'Adult', 'Middle Age', 'Senior']
)

# Creating day_of_week names for sharp visuals
df_clean['day_of_week'] = df_clean['invoice_date'].dt.day_name()
```

SETTING UP 3×3 VISUALIZATION GRID

In [5]:
```
fig, axes = plt.subplots(3, 3, figsize=(22, 18))

# 1. Total Sales Distribution
axes[0,0].hist(df_clean['total_sales'], bins=50, edgecolor='black', alpha=0.7)
axes[0,0].set_title('Distribution of Total Sales Amount', fontsize=14, fontweight='
axes[0,0].set_xlabel('Total Sales (TL)')
axes[0,0].set_ylabel('Frequency')

# 2. Monthly Sales Trend
monthly_sales = df_clean.groupby('month')['total_sales'].sum()
axes[0,1].plot(monthly_sales.index, monthly_sales.values, marker='o', linewidth=2)
axes[0,1].set_title('Monthly Sales Trend', fontsize=14, fontweight='bold')
axes[0,1].set_xlabel('Month')
axes[0,1].set_ylabel('Total Sales (TL)')
axes[0,1].grid(True, alpha=0.3)

# 3. Sales by Product Category
category_sales = df_clean.groupby('category')['total_sales'].sum().sort_values(asce
axes[0,2].bar(category_sales.index, category_sales.values, color='skyblue')
axes[0,2].set_title('Total Sales by Product Category', fontsize=14, fontweight='bol
axes[0,2].tick_params(axis='x', rotation=45)

# 4. Sales by Shopping Mall
mall_sales = df_clean.groupby('shopping_mall')['total_sales'].sum().sort_values(asc
axes[1,0].bar(mall_sales.index, mall_sales.values, color='lightgreen')
axes[1,0].set_title('Sales by Shopping Mall', fontsize=14, fontweight='bold')
axes[1,0].tick_params(axis='x', rotation=45)

# 5. Sales by Payment Method
payment_sales = df_clean.groupby('payment_method')['total_sales'].sum()
axes[1,1].pie(
    payment_sales.values,
    labels=payment_sales.index,
    autopct='%1.1f%%',
    colors=['gold', 'lightcoral', 'lightblue']
)
axes[1,1].set_title('Sales Distribution by Payment Method', fontsize=14, fontweight

# 6. Sales by Age Segment
age_sales = df_clean.groupby('age_segment')['total_sales'].sum()
axes[1,2].bar(age_sales.index, age_sales.values, color='orange')
axes[1,2].set_title('Sales by Age Segment', fontsize=14, fontweight='bold')
axes[1,2].tick_params(axis='x', rotation=45)

# 7. Sales by Day of Week
```

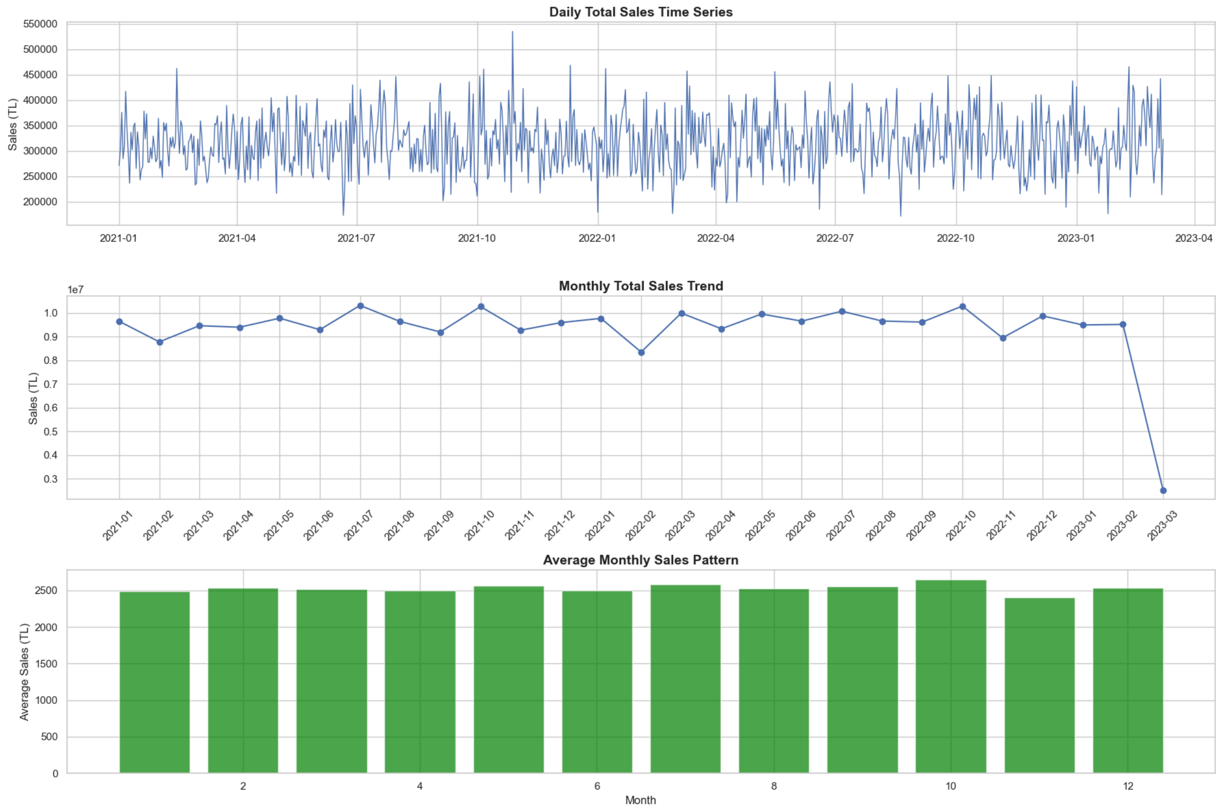
```
daily_sales = df_clean.groupby('day_of_week')['total_sales'].sum()
days = ['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday']
axes[2,0].bar(days, [daily_sales.get(day, 0) for day in days], color='purple')
axes[2,0].set_title('Sales by Day of Week', fontsize=14, fontweight='bold')
axes[2,0].tick_params(axis='x', rotation=45)

# 8. Quantity vs Price Scatter
axes[2,1].scatter(df_clean['quantity'], df_clean['price'], alpha=0.5, color='red')
axes[2,1].set_title('Quantity vs Price Relationship', fontsize=14, fontweight='bold
axes[2,1].set_xlabel('Quantity')
axes[2,1].set_ylabel('Price (TL)')

# 9. Gender-wise Sales Comparison
gender_sales = df_clean.groupby('gender')['total_sales'].sum()
axes[2,2].bar(gender_sales.index, gender_sales.values, color=['pink', 'lightblue'])
axes[2,2].set_title('Total Sales by Gender', fontsize=14, fontweight='bold')
axes[2,2].set_ylabel('Total Sales (TL)')

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

```
C:\Users\oumat\AppData\Local\Temp\ipykernel_10328\1007118356.py:40: FutureWarning: T
he default of observed=False is deprecated and will be changed to True in a future v
ersion of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  age_sales = df_clean.groupby('age_segment')['total_sales'].sum()
```

TIME SERIES & SEASONAL PATTERNS

In [6]:
```
print("Performing time series analysis...")

daily_total_sales = df_clean.groupby('invoice_date')['total_sales'].sum()

plt.figure(figsize=(18, 12))

# 1. Daily Series
plt.subplot(3, 1, 1)
plt.plot(daily_total_sales.index, daily_total_sales.values, linewidth=1)
plt.title('Daily Total Sales Time Series', fontsize=14, fontweight='bold')
plt.ylabel('Sales (TL)')

# 2. Monthly Aggregate
monthly_total_sales = df_clean.groupby(df_clean['invoice_date'].dt.to_period('M'))[
plt.subplot(3, 1, 2)
plt.plot(monthly_total_sales.index.astype(str), monthly_total_sales.values, marker=
plt.title('Monthly Total Sales Trend', fontsize=14, fontweight='bold')
plt.ylabel('Sales (TL)')
plt.xticks(rotation=45)

# 3. Seasonal Monthly Pattern
monthly_avg_sales = df_clean.groupby('month')['total_sales'].mean()
plt.subplot(3, 1, 3)
plt.bar(monthly_avg_sales.index, monthly_avg_sales.values, color='green', alpha=0.7
plt.title('Average Monthly Sales Pattern', fontsize=14, fontweight='bold')
plt.xlabel('Month')
plt.ylabel('Average Sales (TL)')

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

```
Performing time series analysis...
```



Preparing ML pipeline

In [7]:

```
# Creating transformers
numeric_transformer = Pipeline(steps=[
    ('scaling', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combining transformations
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ]
)

# Splitting data
X = df[numeric_features + categorical_features]
y = df['total_sales']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

PCA dimensionality reduction

In [8]:

```
# Adding PCA for dimensionality reduction
pca = PCA(n_components=0.95)  # keeping 95% variance
```

Building models

1. **Random Forest Pipeline**

In [9]:
```
rf_pipeline = Pipeline(steps=[
    ('preprocess', preprocessor),
    ('pca', pca),
    ('model', RandomForestRegressor(random_state=42))
])
```

2. **XGBoost Pipeline**

In [10]:
```
xgb_pipeline = Pipeline(steps=[
    ('preprocess', preprocessor),
    ('pca', pca),
    ('model', xgb.XGBRegressor(
        objective='reg:squarederror',
        random_state=42,
        n_estimators=300
    ))
])
```

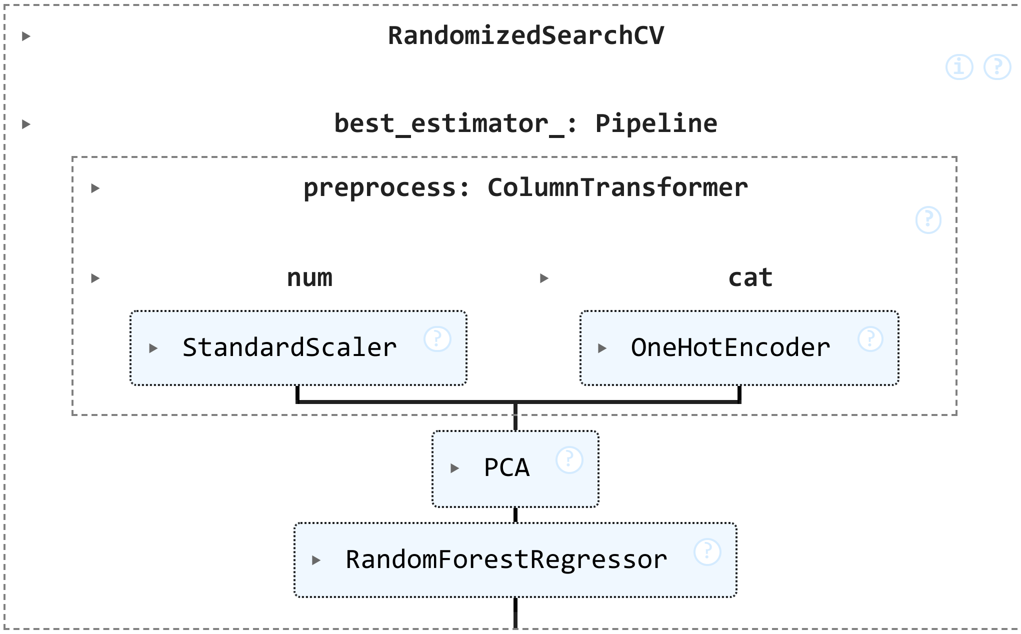
Hyperparameter tuning

Random Forest tuning

In [11]:
```
rf_params = {
    'model__n_estimators': [100, 150, 200],
    'model__max_depth': [6, 10],
    'model__min_samples_split': [2, 5],
    'model__max_features': ['sqrt']
}

rf_tuned = RandomizedSearchCV(
    rf_pipeline,
    rf_params,
    cv=2,
    n_iter=4,
    n_jobs=-1,
    verbose=1
)

rf_tuned.fit(X_train, y_train)
```

```
Fitting 2 folds for each of 4 candidates, totalling 8 fits
```

Out[11]:



XGBoost tuning

In [21]:

```python
from sklearn.model_selection import RandomizedSearchCV, train_test_split
import numpy as np # Import numpy for np.sqrt

# 1. Spliting a small validation set for early stopping (will be used to train the
X_tr, X_val, y_tr, y_val = train_test_split(
    X_train, y_train, test_size=0.15, random_state=42
)

# 2. Using the already defined xgb_pipeline as the estimator


# 3. Fast hyperparameter search space for the pipeline's XGBoost model

xgb_params = {
    'model__max_depth': [4, 6],          # reduced
    'model__learning_rate': [0.05, 0.1],
    'model__subsample': [0.8, 1],
    'model__min_child_weight': [1, 3],
    'model__gamma': [0, 1],
    'model__n_estimators': [100, 150, 200] # Adding n_estimators to tune
}

# 4. Randomized Search (without early stopping during CV)
xgb_tuned = RandomizedSearchCV(
    estimator=xgb_pipeline,
    param_distributions=xgb_params,
    n_iter=5,
    cv=3,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=1
)
```

```python
xgb_tuned.fit(
    X_tr, y_tr
)

# 5. Best estimator
best_xgb = xgb_tuned.best_estimator_
print("Best params:", xgb_tuned.best_params_)
# The best_score_ will be negative for 'neg_mean_squared_error', so negate it and t
print("Best CV RMSE:", np.sqrt(-xgb_tuned.best_score_))

# Retraining the best model with early stopping on X_train and X_val
print("\nRetraining best XGBoost model with early stopping...")

X_train_transformed = best_xgb.named_steps['preprocess'].transform(X_train)
X_train_transformed = best_xgb.named_steps['pca'].transform(X_train_transformed)

X_val_transformed = best_xgb.named_steps['preprocess'].transform(X_val)
X_val_transformed = best_xgb.named_steps['pca'].transform(X_val_transformed)

# Extracting best XGBoost model parameters from xgb_tuned.best_params_
best_xgb_model_params = {k.replace('model__', ''): v for k, v in xgb_tuned.best_par

# Creating a new XGBoost Regressor with the best parameters
xgb_model_final = xgb.XGBRegressor(
    **best_xgb_model_params,
    objective='reg:squarederror',
    random_state=42 # Ensure reproducibility
)

# Fitting the new XGBoost model directly with the transformed data and early stoppi
xgb_model_final.fit(
    X_train_transformed, y_train,
    eval_set=[(X_val_transformed, y_val)]
)
print("Retraining complete.")

# Updating best_xgb to be the retrained model for subsequent evaluation and SHAP
best_xgb.named_steps['model'] = xgb_model_final
```

```
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Best params: {'model__subsample': 1, 'model__n_estimators': 200, 'model__min_child_w
eight': 1, 'model__max_depth': 6, 'model__learning_rate': 0.1, 'model__gamma': 0}
Best CV RMSE: 55.49829903478258

Retraining best XGBoost model with early stopping...
[0]	validation_0-rmse:3846.89689
[1]	validation_0-rmse:3462.85236
[2]	validation_0-rmse:3117.12688
[3]	validation_0-rmse:2805.93513
[4]	validation_0-rmse:2525.83656
[5]	validation_0-rmse:2273.69718
[6]	validation_0-rmse:2046.66582
[7]	validation_0-rmse:1842.31791
[8]	validation_0-rmse:1658.38269
[9]	validation_0-rmse:1492.68840
[10]	validation_0-rmse:1343.68586
[11]	validation_0-rmse:1209.43765
[12]	validation_0-rmse:1088.70727
[13]	validation_0-rmse:980.03689
[14]	validation_0-rmse:882.13210
[15]	validation_0-rmse:794.08549
[16]	validation_0-rmse:714.75337
[17]	validation_0-rmse:643.41348
[18]	validation_0-rmse:579.19368
[19]	validation_0-rmse:521.33726
[20]	validation_0-rmse:469.31339
[21]	validation_0-rmse:422.44126
[22]	validation_0-rmse:380.29280
[23]	validation_0-rmse:342.32243
[24]	validation_0-rmse:308.17695
[25]	validation_0-rmse:277.44688
[26]	validation_0-rmse:249.79242
[27]	validation_0-rmse:224.90573
[28]	validation_0-rmse:202.48875
[29]	validation_0-rmse:182.34128
[30]	validation_0-rmse:164.21958
[31]	validation_0-rmse:147.89711
[32]	validation_0-rmse:133.21160
[33]	validation_0-rmse:119.99197
[34]	validation_0-rmse:108.10281
[35]	validation_0-rmse:97.37343
[36]	validation_0-rmse:87.77187
[37]	validation_0-rmse:79.13821
[38]	validation_0-rmse:71.33695
[39]	validation_0-rmse:64.37579
[40]	validation_0-rmse:58.13401
[41]	validation_0-rmse:52.46851
[42]	validation_0-rmse:47.38191
[43]	validation_0-rmse:42.82753
[44]	validation_0-rmse:38.74207
[45]	validation_0-rmse:35.06283
[46]	validation_0-rmse:31.77446
[47]	validation_0-rmse:28.84083
[48]	validation_0-rmse:26.21566
[49]	validation_0-rmse:23.87006
```

```
[50]	validation_0-rmse:21.75195
[51]	validation_0-rmse:19.88223
[52]	validation_0-rmse:18.24124
[53]	validation_0-rmse:16.77862
[54]	validation_0-rmse:15.46361
[55]	validation_0-rmse:14.30096
[56]	validation_0-rmse:13.32021
[57]	validation_0-rmse:12.41118
[58]	validation_0-rmse:11.63495
[59]	validation_0-rmse:10.95807
[60]	validation_0-rmse:10.34586
[61]	validation_0-rmse:9.83088
[62]	validation_0-rmse:9.34217
[63]	validation_0-rmse:8.93534
[64]	validation_0-rmse:8.55586
[65]	validation_0-rmse:8.27451
[66]	validation_0-rmse:8.01256
[67]	validation_0-rmse:7.78945
[68]	validation_0-rmse:7.53652
[69]	validation_0-rmse:7.37796
[70]	validation_0-rmse:7.19069
[71]	validation_0-rmse:7.07188
[72]	validation_0-rmse:6.97598
[73]	validation_0-rmse:6.84664
[74]	validation_0-rmse:6.78167
[75]	validation_0-rmse:6.69719
[76]	validation_0-rmse:6.63546
[77]	validation_0-rmse:6.41844
[78]	validation_0-rmse:6.24490
[79]	validation_0-rmse:6.11939
[80]	validation_0-rmse:5.94639
[81]	validation_0-rmse:5.83368
[82]	validation_0-rmse:5.75340
[83]	validation_0-rmse:5.64433
[84]	validation_0-rmse:5.56940
[85]	validation_0-rmse:5.47549
[86]	validation_0-rmse:5.38841
[87]	validation_0-rmse:5.27167
[88]	validation_0-rmse:5.18953
[89]	validation_0-rmse:5.09435
[90]	validation_0-rmse:5.03826
[91]	validation_0-rmse:4.98059
[92]	validation_0-rmse:4.94579
[93]	validation_0-rmse:4.92600
[94]	validation_0-rmse:4.75694
[95]	validation_0-rmse:4.67920
[96]	validation_0-rmse:4.62956
[97]	validation_0-rmse:4.48841
[98]	validation_0-rmse:4.36140
[99]	validation_0-rmse:4.28828
[100]	validation_0-rmse:4.16701
[101]	validation_0-rmse:4.11068
[102]	validation_0-rmse:4.06773
[103]	validation_0-rmse:4.01005
[104]	validation_0-rmse:3.95614
[105]	validation_0-rmse:3.90968
```

```
[106]	validation_0-rmse:3.85926
[107]	validation_0-rmse:3.78422
[108]	validation_0-rmse:3.74681
[109]	validation_0-rmse:3.71407
[110]	validation_0-rmse:3.67834
[111]	validation_0-rmse:3.63972
[112]	validation_0-rmse:3.61488
[113]	validation_0-rmse:3.58938
[114]	validation_0-rmse:3.54847
[115]	validation_0-rmse:3.50451
[116]	validation_0-rmse:3.46722
[117]	validation_0-rmse:3.42410
[118]	validation_0-rmse:3.39343
[119]	validation_0-rmse:3.37562
[120]	validation_0-rmse:3.35755
[121]	validation_0-rmse:3.32130
[122]	validation_0-rmse:3.29039
[123]	validation_0-rmse:3.24689
[124]	validation_0-rmse:3.22573
[125]	validation_0-rmse:3.14204
[126]	validation_0-rmse:3.10371
[127]	validation_0-rmse:3.06681
[128]	validation_0-rmse:3.02835
[129]	validation_0-rmse:3.00806
[130]	validation_0-rmse:2.98778
[131]	validation_0-rmse:2.96571
[132]	validation_0-rmse:2.94068
[133]	validation_0-rmse:2.92670
[134]	validation_0-rmse:2.90776
[135]	validation_0-rmse:2.89493
[136]	validation_0-rmse:2.87763
[137]	validation_0-rmse:2.85578
[138]	validation_0-rmse:2.82895
[139]	validation_0-rmse:2.81975
[140]	validation_0-rmse:2.79233
[141]	validation_0-rmse:2.77597
[142]	validation_0-rmse:2.74958
[143]	validation_0-rmse:2.72278
[144]	validation_0-rmse:2.70175
[145]	validation_0-rmse:2.68985
[146]	validation_0-rmse:2.66852
[147]	validation_0-rmse:2.64479
[148]	validation_0-rmse:2.63760
[149]	validation_0-rmse:2.62599
[150]	validation_0-rmse:2.60944
[151]	validation_0-rmse:2.59741
[152]	validation_0-rmse:2.58768
[153]	validation_0-rmse:2.56635
[154]	validation_0-rmse:2.56184
[155]	validation_0-rmse:2.55935
[156]	validation_0-rmse:2.54884
[157]	validation_0-rmse:2.53883
[158]	validation_0-rmse:2.53117
[159]	validation_0-rmse:2.51287
[160]	validation_0-rmse:2.50018
[161]	validation_0-rmse:2.49111
```

```
[162]	validation_0-rmse:2.48536
[163]	validation_0-rmse:2.46896
[164]	validation_0-rmse:2.45962
[165]	validation_0-rmse:2.44926
[166]	validation_0-rmse:2.44331
[167]	validation_0-rmse:2.41380
[168]	validation_0-rmse:2.40708
[169]	validation_0-rmse:2.40008
[170]	validation_0-rmse:2.39187
[171]	validation_0-rmse:2.38796
[172]	validation_0-rmse:2.37317
[173]	validation_0-rmse:2.33940
[174]	validation_0-rmse:2.32078
[175]	validation_0-rmse:2.30225
[176]	validation_0-rmse:2.29239
[177]	validation_0-rmse:2.27760
[178]	validation_0-rmse:2.23774
[179]	validation_0-rmse:2.22514
[180]	validation_0-rmse:2.21557
[181]	validation_0-rmse:2.21165
[182]	validation_0-rmse:2.20166
[183]	validation_0-rmse:2.17105
[184]	validation_0-rmse:2.16604
[185]	validation_0-rmse:2.15537
[186]	validation_0-rmse:2.14085
[187]	validation_0-rmse:2.12759
[188]	validation_0-rmse:2.11152
[189]	validation_0-rmse:2.10310
[190]	validation_0-rmse:2.09679
[191]	validation_0-rmse:2.09063
[192]	validation_0-rmse:2.08684
[193]	validation_0-rmse:2.07888
[194]	validation_0-rmse:2.07645
[195]	validation_0-rmse:2.06397
[196]	validation_0-rmse:2.05993
[197]	validation_0-rmse:2.05303
[198]	validation_0-rmse:2.04889
[199]	validation_0-rmse:2.03297
Retraining complete.
```

Evaluation function

In [13]:

```python
def evaluate_model(model, X_test, y_test):
    predictions = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, predictions))
    mae = mean_absolute_error(y_test, predictions)
    r2 = r2_score(y_test, predictions)
    adj_r2 = 1 - (1 - r2) * (len(y_test) - 1) / (len(y_test) - X_test.shape[1] - 1)

    return rmse, mae, r2, adj_r2
```

Comparing model performance

In [14]:

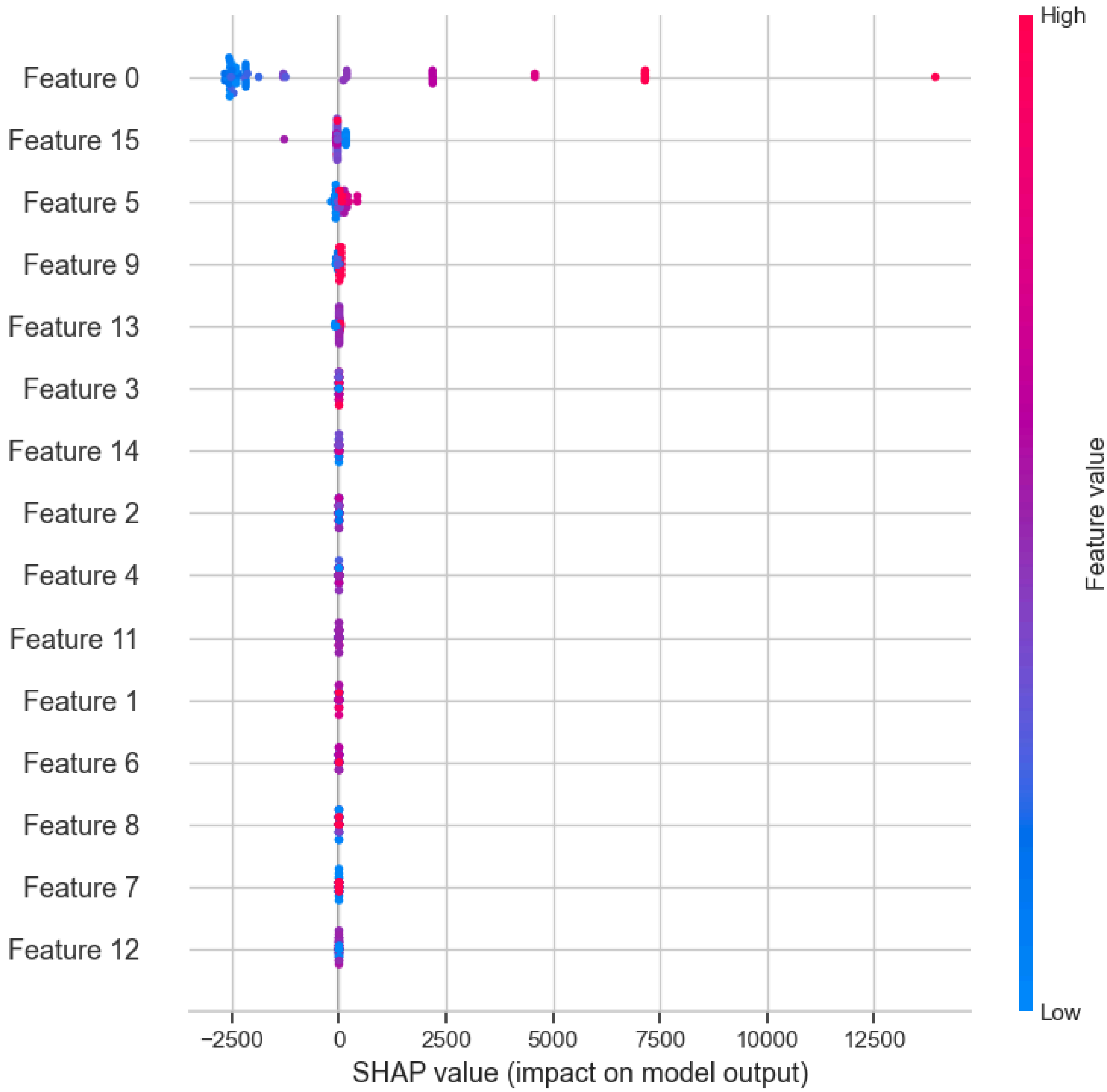
```python
rf_scores = evaluate_model(rf_tuned, X_test, y_test)
xgb_scores = evaluate_model(xgb_tuned, X_test, y_test)
```

```
print("Random Forest:", rf_scores)
print("XGBoost:", xgb_scores)
```

```
Random Forest: (np.float64(76.77882561762327), 52.13785288190788, 0.999678153658253
9, 0.9996779593750353)
XGBoost: (np.float64(37.790186958972065), 3.1784182237682206, 0.9999220306833233, 0.
9999219836169819)
```

SHAP Explainability (XGBoost recommended)

In [22]:
```
explainer = shap.TreeExplainer(
    xgb_tuned.best_estimator_['model'],
    feature_perturbation="tree_path_dependent",
    model_output="raw"
)

X_small = X_test.sample(50, random_state=0)
# The preprocessor expects a DataFrame, so we transform X_small first
X_small_t_raw = xgb_tuned.best_estimator_['preprocess'].transform(X_small)

X_small_t = xgb_tuned.best_estimator_.named_steps['preprocess'].transform(X_small)
X_small_t = xgb_tuned.best_estimator_.named_steps['pca'].transform(X_small_t)

shap_values = explainer.shap_values(X_small_t)
shap.summary_plot(shap_values, X_small_t, max_display=15)
```



MODEL PERFORMANCE COMPARISON

In [27]:

```
print("--- Random Forest Model Metrics ---")
print(f"RMSE: {rf_rmse:.4f}")
print(f"MAE: {rf_mae:.4f}")
print(f"R²: {rf_r2:.4f}")
print(f"Adjusted R²: {rf_adj:.4f}")
print("\n--- XGBoost Model Metrics ---")
print(f"RMSE: {xgb_rmse:.4f}")
print(f"MAE: {xgb_mae:.4f}")
print(f"R²: {xgb_r2:.4f}")
print(f"Adjusted R²: {xgb_adj:.4f}")
```

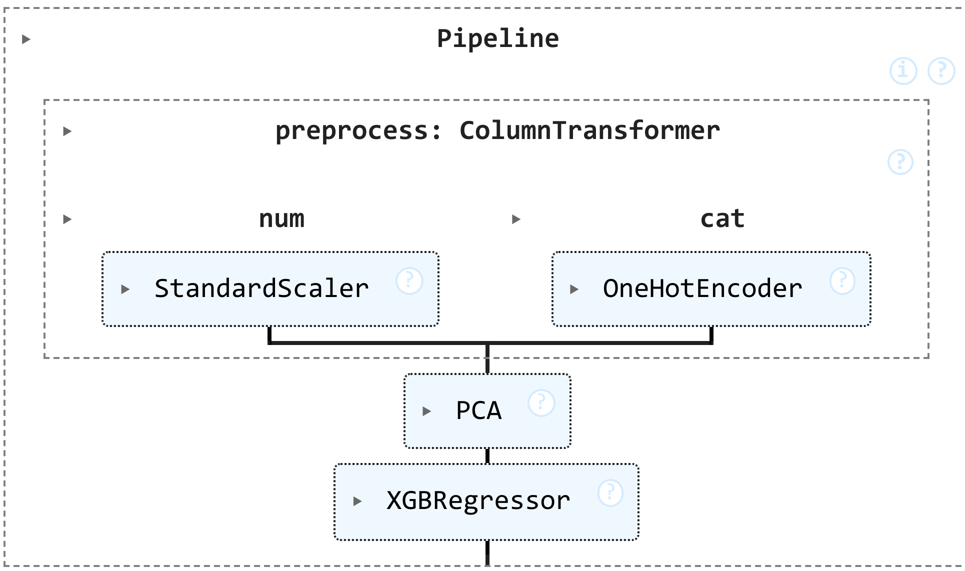
```
--- Random Forest Model Metrics ---
RMSE: 76.7788
MAE: 52.1379
R²: 0.9997
Adjusted R²: 0.9997

--- XGBoost Model Metrics ---
RMSE: 37.7902
MAE: 3.1784
R²: 0.9999
Adjusted R²: 0.9999
```

Printing system architecture & pipeline diagrams

In [24]:

```python
from sklearn import set_config
set_config(display='diagram')

xgb_tuned.best_estimator_
```

Out[24]:



In [25]:

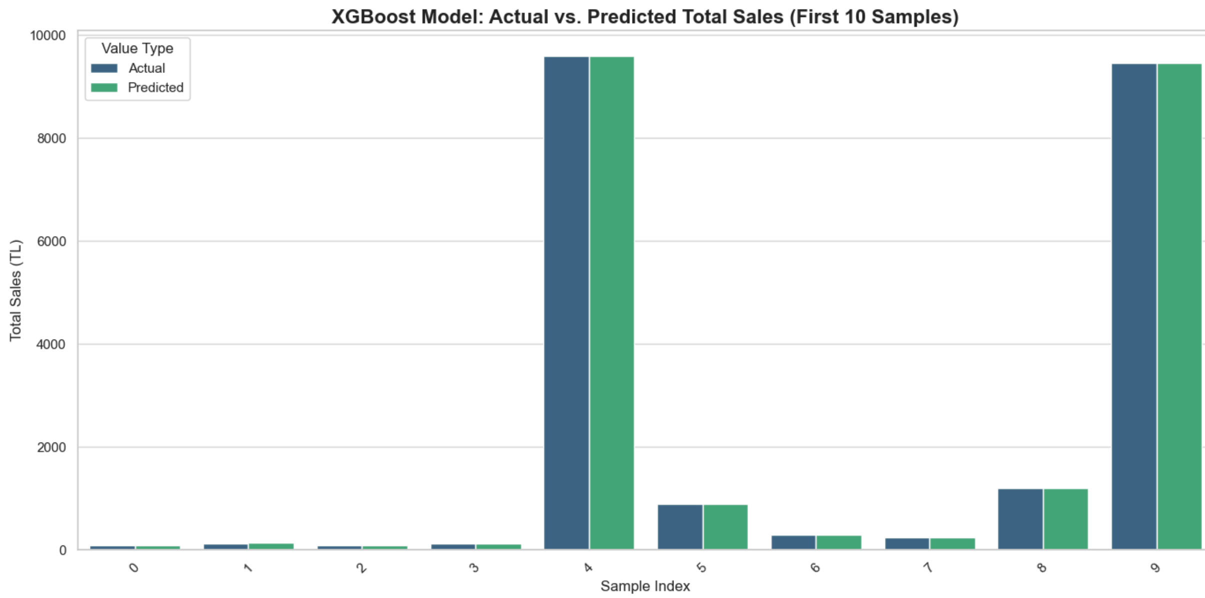
```python
y_pred_xgb = best_xgb.predict(X_test)

# Creating a DataFrame to display actual vs. predicted values
predictions_df = pd.DataFrame({
    'Actual': y_test.values,
    'Predicted': y_pred_xgb
})

print("First 10 Actual vs. Predicted values from XGBoost model:")
display(predictions_df.head(10))
```

```
First 10 Actual vs. Predicted values from XGBoost model:
```

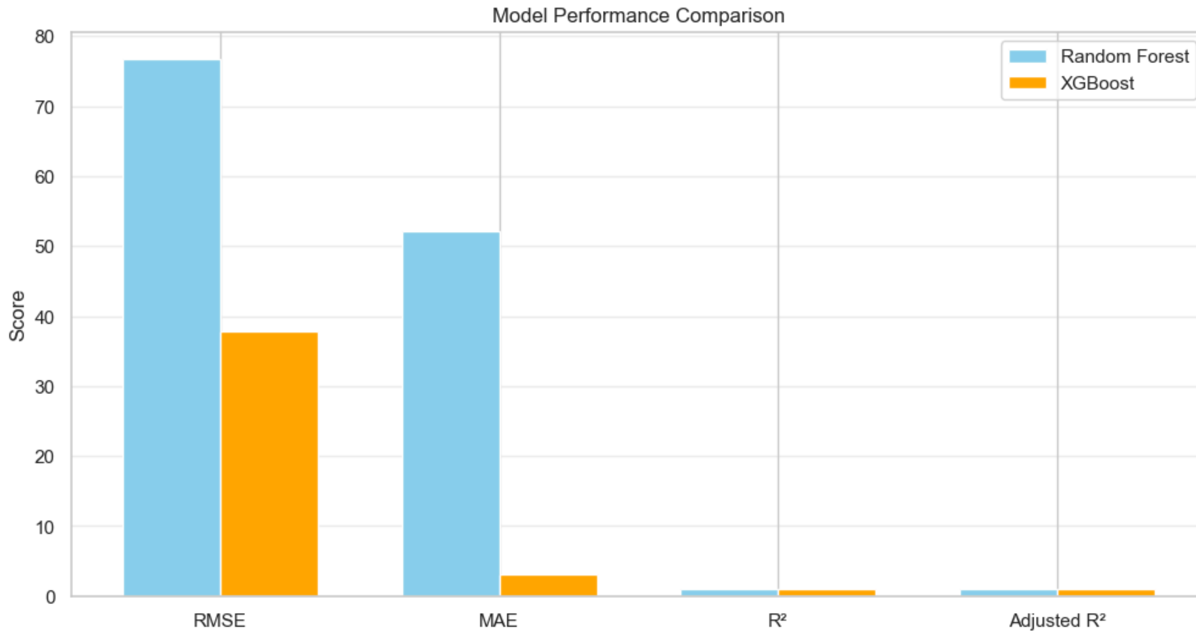
	Actual	Predicted
0	83.68	83.899185
1	130.75	133.850357
2	83.68	81.559914
3	130.75	131.126892
4	9602.72	9602.690430
5	896.00	895.225647
6	300.08	294.046387
7	242.40	244.286575
8	1200.32	1200.334717
9	9450.00	9450.093750

In [26]:

```
n_samples = 10 # Number of samples to display

# Get the first 'n_samples' from the predictions_df
subset_predictions_df = predictions_df.head(n_samples)

# Melt the DataFrame to prepare for seaborn bar plot
plot_df = subset_predictions_df.reset_index().melt(id_vars='index', var_name='Type'

plt.figure(figsize=(14, 7))
sns.barplot(x='index', y='Total Sales', hue='Type', data=plot_df, palette='viridis'
plt.title(f'XGBoost Model: Actual vs. Predicted Total Sales (First {n_samples} Samp
plt.xlabel('Sample Index', fontsize=12)
plt.ylabel('Total Sales (TL)', fontsize=12)
plt.xticks(rotation=45)
plt.grid(axis='y', alpha=0.75)
plt.legend(title='Value Type')
plt.tight_layout()
plt.show()
```



In [19]:
```
metrics = ['RMSE', 'MAE', 'R²', 'Adjusted R²']

# Unpack the scores from the tuples
rf_rmse, rf_mae, rf_r2, rf_adj = rf_scores
xgb_rmse, xgb_mae, xgb_r2, xgb_adj = xgb_scores

rf_values = [rf_rmse, rf_mae, rf_r2, rf_adj]
xgb_values = [xgb_rmse, xgb_mae, xgb_r2, xgb_adj]

x = np.arange(len(metrics))
width = 0.35

plt.figure(figsize=(12, 6))
plt.bar(x - width/2, rf_values, width, label='Random Forest', color='skyblue')
plt.bar(x + width/2, xgb_values, width, label='XGBoost', color='orange')

plt.ylabel("Score")
plt.title("Model Performance Comparison")
plt.xticks(x, metrics)
plt.legend()
plt.grid(axis='y', alpha=0.3)
plt.show()
```



In [20]:
```
plt.figure(figsize=(10, 6))
sns.histplot(df['age'], bins=20, kde=True, color='skyblue')
plt.title('Distribution of Customer Age', fontsize=16, fontweight='bold')
plt.xlabel('Age', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.grid(axis='y', alpha=0.75)
plt.show()
```