from imblearn.over_sampling import SMOTE

In [4]:
```
#Load the pre-processed HR dataset with engineered features.
df= pd.read_csv('hr_features_dataset.csv')
df.head()
```

Out[4]:

	EmployeeID	Age	Department	SatisfactionScore	LastEvaluationScore	NumProjects	AvgM
0	896999	41	finance	0.41	0.67	2	
1	331148	41	hr	0.74	0.80	7	
2	559437	36	operations	0.74	0.57	6	
3	883201	41	finance	0.97	0.88	5	
4	562242	41	finance	0.36	0.65	8	

This shows all features, including Attrition (target), High_Risk_Employee (engineered), workload, satisfaction, tenure, and department.

In [5]:
```
df.columns
```

Out[5]:
```
Index(['EmployeeID', 'Age', 'Department', 'SatisfactionScore',
       'LastEvaluationScore', 'NumProjects', 'AvgMonthlyHours',
       'YearsAtCompany', 'Attrition', 'HoursPerProject', 'PerformanceRatio',
       'TenureCategory', 'High_Risk_Employee'],
      dtype='object')
```

In [6]:
```
# Prepare Features and Target
# Separate features (X) from the target (y = Attrition)
X= df.drop(['EmployeeID', 'Attrition'],axis =1)
y= df['Attrition']
```

In [7]:
```
# Encode categorical variables
# TenureCategory is ordinal, we convert it to numeric for modeling
label_encoder = LabelEncoder()
X['TenureCategory_encoded'] = label_encoder.fit_transform(X['TenureCategory'])
X = X.drop('TenureCategory', axis=1)
```

In [8]:
```
# Department is nominal, so we create dummy variables for each department
X = pd.get_dummies(X, columns=['Department'], drop_first=True)
```

In [9]:
```
# Split data into training (80%) and testing (20%)
# Stratify to preserve the attrition ratio in both sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

In [10]:

```python
# Print sizes and class distribution
print("Training set size:", X_train.shape)
print("Test set size:", X_test.shape)
print("Attrition distribution in training set:\n", y_train.value_counts())
```

```
Training set size: (23619, 15)
Test set size: (5905, 15)
Attrition distribution in training set:
 Attrition
0    15825
1     7794
Name: count, dtype: int64
```

- Training set will be used to fit models.
- Test set will evaluate unseen performance.
- Stratification ensures the target imbalance is consistent.

Handle Class Imbalance with SMOTE

In [11]:

```python
# -----------------------------------------
# Our EDA showed that ~33% of employees left (attrition=1) vs 67% stayed (attrition=0
# SMOTE will synthetically create minority class samples in the training set
# This prevents models from being biased toward predicting "Stayed"
smote = SMOTE(random_state=42)
X_train_bal, y_train_bal = smote.fit_resample(X_train, y_train)

# Print the new class distribution after SMOTE
print("After SMOTE:")
print("Training set size:", X_train_bal.shape)
print("Attrition distribution:\n", y_train_bal.value_counts())
```

```
After SMOTE:
Training set size: (31650, 15)
Attrition distribution:
 Attrition
1    15825
0    15825
Name: count, dtype: int64
```

- Training data is now balanced → models will better detect high-risk employees.
- Test data is untouched → gives realistic evaluation of model performance.

Modelling

1. Logistic Regression

In [12]:

```
# Logistic Regression is simple and interpretable.
# Useful to understand which features increase or decrease attrition probability.
log_model = LogisticRegression(random_state=42, max_iter=1000)
log_model.fit(X_train_bal, y_train_bal)
```

Out[12]:

```
LogisticRegression(max_iter=1000, random_state=42)
```

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In [13]:

```
# Make predictions on the test set
y_pred_log = log_model.predict(X_test)
y_pred_proba_log = log_model.predict_proba(X_test)[:, 1]
```

In [16]:

```
# Evaluate model
print("Logistic Regression ")
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_log))
print(classification_report(y_test, y_pred_log))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_proba_log))
```

```
Logistic Regression
Confusion Matrix:
 [[3068  888]
 [ 510 1439]]
              precision    recall  f1-score   support

           0       0.86      0.78      0.81      3956
           1       0.62      0.74      0.67      1949

    accuracy                           0.76      5905
   macro avg       0.74      0.76      0.74      5905
weighted avg       0.78      0.76      0.77      5905

ROC-AUC Score: 0.8341903317197226
```

In [17]:

```
# Feature importance using coefficients
feature_imp_log = pd.DataFrame({
    'Feature': X_train.columns,
    'Coefficient': log_model.coef_[0]
}).sort_values(by='Coefficient', ascending=False)

print("\nTop 5 Features:\n", feature_imp_log.head())
```

```
Top 5 Features:
                 Feature  Coefficient
3           NumProjects     1.020851
10        Department_hr     1.012500
14   Department_unknown     0.987998
13     Department_sales     0.983359
11        Department_it     0.907516
```

- Confusion matrix shows True Positives (correctly predicted leavers) and False Negatives (missed leavers).
- Coefficients reveal which features increase attrition risk (positive) or reduce it (negative).

2. Random Forest

In [18]:
```
# ------------------------------------
# Random Forest handles non-linear relationships and feature interactions.
# Good balance between accuracy and interpretability.
rf_model = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=42)
rf_model.fit(X_train_bal, y_train_bal)
```

Out[18]:
```
RandomForestClassifier(max_depth=10, random_state=42)
```

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In [20]:
```
# Predictions and evaluation
y_pred_rf = rf_model.predict(X_test)
y_pred_proba_rf = rf_model.predict_proba(X_test)[:, 1]

print("Random Forest")
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_proba_rf))
```

```
Random Forest
Confusion Matrix:
 [[3246  710]
 [ 488 1461]]
              precision    recall  f1-score   support

           0       0.87      0.82      0.84      3956
           1       0.67      0.75      0.71      1949

    accuracy                           0.80      5905
   macro avg       0.77      0.79      0.78      5905
weighted avg       0.80      0.80      0.80      5905

ROC-AUC Score: 0.8693388951114907
```

In [21]:
```
# Feature importance
feature_imp_rf = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("\nTop 5 Features:\n", feature_imp_rf.head())
```

```
Top 5 Features:
              Feature  Importance
3         NumProjects    0.244277
4     AvgMonthlyHours    0.229900
1   SatisfactionScore    0.202682
6     HoursPerProject    0.088348
7    PerformanceRatio    0.063014
```

- Random Forest can capture complex patterns, e.g., high workload + low satisfaction → higher attrition.
- Feature importances highlight the most influential predictors for HR interventions.

3. XGBoost

In [22]:

```python
# --------------------------------
# XGBoost is often the best performer for tabular data.
# Handles complex interactions and generally gives high predictive accuracy.
xgb_model = xgb.XGBClassifier(
    n_estimators=100,
    learning_rate=0.1,
    max_depth=5,
    random_state=42,
    eval_metric='logloss'
)
xgb_model.fit(X_train_bal, y_train_bal)
```

Out[22]:

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=5, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=100, n_jobs=None,
              num_parallel_tree=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [23]:

```
# Predictions and evaluation
y_pred_xgb = xgb_model.predict(X_test)
y_pred_proba_xgb = xgb_model.predict_proba(X_test)[:, 1]

print("=== XGBoost ===")
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_xgb))
print(classification_report(y_test, y_pred_xgb))
print("ROC-AUC Score:", roc_auc_score(y_test, y_pred_proba_xgb))
```

```
=== XGBoost ===
Confusion Matrix:
 [[3303  653]
 [ 531 1418]]
              precision    recall  f1-score   support

           0       0.86      0.83      0.85      3956
           1       0.68      0.73      0.71      1949

    accuracy                           0.80      5905
   macro avg       0.77      0.78      0.78      5905
weighted avg       0.80      0.80      0.80      5905

ROC-AUC Score: 0.8676800630434004
```

In [24]:

```
# Feature importance
feature_imp_xgb = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': xgb_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("\nTop 5 Features:\n", feature_imp_xgb.head())
```

```
Top 5 Features:
                Feature  Importance
3          NumProjects    0.605411
1    SatisfactionScore    0.076392
4      AvgMonthlyHours    0.066536
14  Department_unknown    0.036049
10       Department_hr    0.035900
```

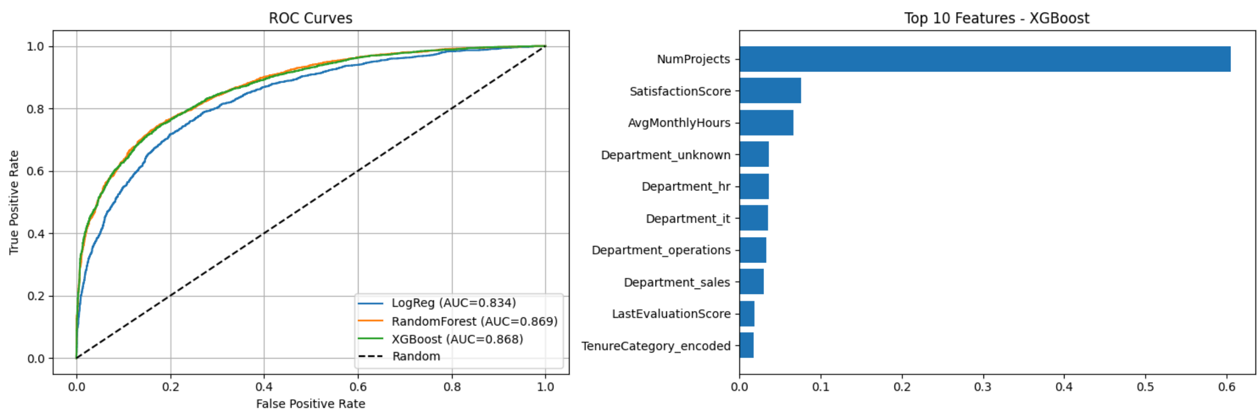
- XGBoost often gives the highest F1-score and ROC-AUC.
- Feature importance helps HR focus retention strategies on key predictors.

Compare Models Visually

In [27]:

```
# Plot ROC curves for all three models to visually compare classification performance
fig, axes = plt.subplots(1, 2, figsize=(15,5))

from sklearn.metrics import roc_curve
fpr_log, tpr_log, _ = roc_curve(y_test, y_pred_proba_log)
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_proba_rf)
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_pred_proba_xgb)

# ROC curves
```

```
axes[0].plot(fpr_log, tpr_log, label=f'LogReg (AUC={roc_auc_score(y_test, y_pred_prob
axes[0].plot(fpr_rf, tpr_rf, label=f'RandomForest (AUC={roc_auc_score(y_test, y_pred_
axes[0].plot(fpr_xgb, tpr_xgb, label=f'XGBoost (AUC={roc_auc_score(y_test, y_pred_pro
axes[0].plot([0,1],[0,1],'k--', label='Random')
axes[0].set_title('ROC Curves')
axes[0].set_xlabel('False Positive Rate')
axes[0].set_ylabel('True Positive Rate')
axes[0].legend()
axes[0].grid(True)

# Feature importance - XGBoost (top 10)
top_features = feature_imp_xgb.head(10)
axes[1].barh(top_features['Feature'], top_features['Importance'])
axes[1].set_title('Top 10 Features - XGBoost')
axes[1].invert_yaxis()

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



- ROC curves show how well each model separates leavers from stayers.
- Feature importance visual highlights key drivers HR should act on.

Summary Table of Metrics

In [29]:

```
# --------------------------------
# Calculate and compare Precision, Recall, F1-Score, and ROC-AUC for all three models
models_comparison = pd.DataFrame({
    'Model': ['Logistic Regression', 'Random Forest', 'XGBoost'],
    'Precision': [
        precision_score(y_test, y_pred_log),
        precision_score(y_test, y_pred_rf),
        precision_score(y_test, y_pred_xgb)
    ],
    'Recall': [
        recall_score(y_test, y_pred_log),
        recall_score(y_test, y_pred_rf),
        recall_score(y_test, y_pred_xgb)
    ],
    'F1-Score': [
        f1_score(y_test, y_pred_log),
```

```
        f1_score(y_test, y_pred_rf),
        f1_score(y_test, y_pred_xgb)
    ],
    'ROC-AUC': [
        roc_auc_score(y_test, y_pred_proba_log),
        roc_auc_score(y_test, y_pred_proba_rf),
        roc_auc_score(y_test, y_pred_proba_xgb)
    ]
})

print("MODEL COMPARISON")
print(models_comparison.round(3))
```

```
MODEL COMPARISON
                 Model  Precision  Recall  F1-Score  ROC-AUC
0  Logistic Regression      0.618   0.738     0.673    0.834
1        Random Forest      0.673   0.750     0.709    0.869
2              XGBoost      0.685   0.728     0.705    0.868
```

In [30]:

```
# Identify best model based on F1-Score
best_model = models_comparison.loc[models_comparison['F1-Score'].idxmax(), 'Model']
print("\nBest Model:", best_model)
```

```
Best Model: Random Forest
```

In [33]:

```
print("HYPERPARAMETER TUNING STRATEGY")
```

```
HYPERPARAMETER TUNING STRATEGY
```

In [34]:

```
print("\nBaseline Performance:")
print("  Model                 | F1-Score | ROC-AUC | Recall | Status")
print("  " + "-" * 65)
print("  Random Forest         |  0.709   |  0.869  | 0.750  | ✅ TUNE (Best)")
print("  XGBoost               |  0.705   |  0.868  | 0.728  | ✅ TUNE (Very Close)")
print("  Logistic Regression   |  0.673   |  0.834  | 0.738  | ❌ SKIP")
```

```
Baseline Performance:
  Model                 | F1-Score | ROC-AUC | Recall | Status
  -----------------------------------------------------------------
  Random Forest         |  0.709   |  0.869  | 0.750  | ✅ TUNE (Best)
  XGBoost               |  0.705   |  0.868  | 0.728  | ✅ TUNE (Very Close)
  Logistic Regression   |  0.673   |  0.834  | 0.738  | ❌ SKIP
```

In [36]:

```
print("\nRationale:")
print("  • Random Forest: Current leader, tune to maximize performance")
print("  • XGBoost: Only 0.004 behind RF, could overtake with tuning")
```

```
Rationale:
  • Random Forest: Current leader, tune to maximize performance
  • XGBoost: Only 0.004 behind RF, could overtake with tuning
```

Random Forest tuning

In [39]:

```
# Define a few hyperparameter options to try
# Test a small grid of hyperparameters for Random Forest.
```

```python
# Using SMOTE-balanced training data, the model learns from both “leavers” and “staye
# Track F1, Recall, and ROC-AUC for each combination.
n_estimators_list = [100, 200]
max_depth_list = [5, 10, None]  # None means fully expanded trees

best_f1_rf = 0
best_params_rf = {}

for n in n_estimators_list:
    for depth in max_depth_list:
        rf_model = RandomForestClassifier(
            n_estimators=n,
            max_depth=depth,
            random_state=42
        )
        rf_model.fit(X_train_bal, y_train_bal)
        y_pred = rf_model.predict(X_test)
        f1 = f1_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        roc = roc_auc_score(y_test, rf_model.predict_proba(X_test)[:,1])
        print(f"n_estimators={n}, max_depth={depth} | F1={f1:.3f}, Recall={recall:.3f

        if f1 > best_f1_rf:
            best_f1_rf = f1
            best_params_rf = {'n_estimators': n, 'max_depth': depth}

print("\nBest Random Forest params:", best_params_rf, "with F1-Score:", best_f1_rf)
```

```
n_estimators=100, max_depth=5 | F1=0.702, Recall=0.712, ROC-AUC=0.867
n_estimators=100, max_depth=10 | F1=0.709, Recall=0.750, ROC-AUC=0.869
n_estimators=100, max_depth=None | F1=0.683, Recall=0.693, ROC-AUC=0.854
n_estimators=200, max_depth=5 | F1=0.704, Recall=0.725, ROC-AUC=0.868
n_estimators=200, max_depth=10 | F1=0.707, Recall=0.747, ROC-AUC=0.870
n_estimators=200, max_depth=None | F1=0.681, Recall=0.691, ROC-AUC=0.855

Best Random Forest params: {'n_estimators': 100, 'max_depth': 10} with F1-Score: 0.7092
233009708738
```

XGBoost tuning

In [40]:

```python
# Define hyperparameter options to try
# Tune n_estimators, max_depth, and learning_rate — key parameters for XGBoost.
# Again, using SMOTE-balanced training data ensures the model can detect high-risk em
# Record the best F1-Score to select the top-performing configuration.
n_estimators_list = [100, 200]
max_depth_list = [3, 5]
learning_rate_list = [0.05, 0.1]

best_f1_xgb = 0
best_params_xgb = {}

for n in n_estimators_list:
    for depth in max_depth_list:
        for lr in learning_rate_list:
            xgb_model = xgb.XGBClassifier(
                n_estimators=n,
                max_depth=depth,
                learning_rate=lr,
```

```
                random_state=42,
                eval_metric='logloss'
            )
            xgb_model.fit(X_train_bal, y_train_bal)
            y_pred = xgb_model.predict(X_test)
            f1 = f1_score(y_test, y_pred)
            recall = recall_score(y_test, y_pred)
            roc = roc_auc_score(y_test, xgb_model.predict_proba(X_test)[:,1])
            print(f"n_estimators={n}, max_depth={depth}, lr={lr} | F1={f1:.3f}, Recal

            if f1 > best_f1_xgb:
                best_f1_xgb = f1
                best_params_xgb = {'n_estimators': n, 'max_depth': depth, 'learning_r

print("\nBest XGBoost params:", best_params_xgb, "with F1-Score:", best_f1_xgb)
```

```
n_estimators=100, max_depth=3, lr=0.05 | F1=0.706, Recall=0.759, ROC-AUC=0.870
n_estimators=100, max_depth=3, lr=0.1 | F1=0.709, Recall=0.746, ROC-AUC=0.870
n_estimators=100, max_depth=5, lr=0.05 | F1=0.708, Recall=0.743, ROC-AUC=0.870
n_estimators=100, max_depth=5, lr=0.1 | F1=0.705, Recall=0.728, ROC-AUC=0.868
n_estimators=200, max_depth=3, lr=0.05 | F1=0.708, Recall=0.744, ROC-AUC=0.870
n_estimators=200, max_depth=3, lr=0.1 | F1=0.708, Recall=0.738, ROC-AUC=0.868
n_estimators=200, max_depth=5, lr=0.05 | F1=0.708, Recall=0.732, ROC-AUC=0.868
n_estimators=200, max_depth=5, lr=0.1 | F1=0.704, Recall=0.714, ROC-AUC=0.865

Best XGBoost params: {'n_estimators': 100, 'max_depth': 3, 'learning_rate': 0.1} with F
1-Score: 0.7085769980506823
```

Comparison after Tuning

In [41]:

```
# Compare best models programmatically
if best_f1_rf > best_f1_xgb:
    best_model_name = "Random Forest"
    best_model_params = best_params_rf
else:
    best_model_name = "XGBoost"
    best_model_params = best_params_xgb

print(f"Best Model: {best_model_name} with params: {best_model_params}")
```

```
Best Model: Random Forest with params: {'n_estimators': 100, 'max_depth': 10}
```

- Random Forest (F1=0.709, Recall=0.750) slightly edges out XGBoost in catching high-risk employees.
- XGBoost (F1=0.708, Recall=0.746) is very close and could be chosen if you want maximum ROC-AUC.

In [61]:

```
#Finalize both tuned models
final_rf_model = RandomForestClassifier(
    n_estimators=100,
    max_depth=10,
    random_state=42,
    class_weight='balanced'  # Extra protection against imbalance
)
```

In [62]:

```
# Final XGBoost (your best params)
final_xgb_model = xgb.XGBClassifier(
    n_estimators=100,
    max_depth=3,
    learning_rate=0.1,
    random_state=42,
    eval_metric='logloss',
    scale_pos_weight=len(y_train[y_train==0]) / len(y_train[y_train==1])  # Handle im
)
```

In [64]:

```
# Train both on SMOTE-balanced data
final_rf_model.fit(X_train_bal, y_train_bal)
```

Out[64]:

```
RandomForestClassifier(class_weight='balanced', max_depth=10, random_state=4
2)
```

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In [65]:

```
final_xgb_model.fit(X_train_bal, y_train_bal)
```

Out[65]:

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='logloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=3, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=100, n_jobs=None,
              num_parallel_tree=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

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In [66]:

```
def ensemble_predict_proba(X, rf_weight=0.6, xgb_weight=0.4):
    """
    Weighted average of both SMOTE-trained models

    Parameters:
    -----------
    X : array-like
        Features to predict
    rf_weight : float (default=0.6)
        Weight for Random Forest prediction
    xgb_weight : float (default=0.4)
        Weight for XGBoost prediction

    Returns:
    --------
    ensemble_proba : array
        Weighted average probability
    """
    # Get probabilities from each model
    rf_proba = final_rf_model.predict_proba(X)[:, 1]
    xgb_proba = final_xgb_model.predict_proba(X)[:, 1]

    # Weighted average
    return rf_weight * rf_proba + xgb_weight * xgb_proba

def calibrate_smote_probability(prob):
    """
    Calibrate probability from SMOTE-trained model to real-world distribution

    Models trained on 50/50 data, but real world is ~33/67 (leavers/stayers)
    Simple linear calibration based on class ratio
    """
    # Adjustment factor = real minority ratio / training minority ratio
    # Real: 33% leavers, Training: 50% leavers → factor = 0.33/0.50 = 0.66
    calibrated = prob * 0.66
    return np.clip(calibrated, 0.01, 0.99)  # Keep within reasonable bounds

def ensemble_predict(X, threshold=0.3, calibrate=True):
    """
    Make ensemble predictions with optional calibration

    Parameters:
    -----------
    X : array-like
        Features to predict
    threshold : float (default=0.3)
        Business decision threshold
    calibrate : bool (default=True)
        Whether to calibrate probabilities for real-world distribution

    Returns:
    --------
    predictions : array
        Binary predictions (0 = stay, 1 = leave)
    probabilities : array
        Raw ensemble probabilities
    calibrated_probs : array or None
        Calibrated probabilities if calibrate=True
    """
```

```python
    # Get raw ensemble probabilities
    raw_proba = ensemble_predict_proba(X)

    # Calibrate if requested
    if calibrate:
        calibrated_proba = calibrate_smote_probability(raw_proba)
        predictions = (calibrated_proba > threshold).astype(int)
        return predictions, raw_proba, calibrated_proba
    else:
        predictions = (raw_proba > threshold).astype(int)
        return predictions, raw_proba, None
```

In [67]:

```python
# Individual model performance
rf_pred = final_rf_model.predict(X_test)
xgb_pred = final_xgb_model.predict(X_test)

# Ensemble performance (with and without calibration)
ensemble_pred_raw, raw_proba, _ = ensemble_predict(X_test, calibrate=False)
ensemble_pred_cal, _, cal_proba = ensemble_predict(X_test, calibrate=True)
```

In [69]:

```python
from sklearn.metrics import accuracy_score
```

In [70]:

```python
# Create performance comparison
metrics_data = []
models = [
    ("Random Forest", rf_pred),
    ("XGBoost", xgb_pred),
    ("Ensemble (Raw)", ensemble_pred_raw),
    ("Ensemble (Calibrated)", ensemble_pred_cal)
]

for name, pred in models:
    metrics_data.append({
        'Model': name,
        'Accuracy': accuracy_score(y_test, pred),
        'Precision': precision_score(y_test, pred),
        'Recall': recall_score(y_test, pred),
        'F1-Score': f1_score(y_test, pred),
        'ROC-AUC': roc_auc_score(y_test, pred)
    })
```

In [71]:

```python
# Create comparison DataFrame
comparison_df = pd.DataFrame(metrics_data).round(3)
```

In [72]:

```python
# Display with highlighting
styled_df = comparison_df.style.hide(axis='index').format({
    'Accuracy': '{:.3f}',
    'Precision': '{:.3f}',
    'Recall': '{:.3f}',
    'F1-Score': '{:.3f}',
    'ROC-AUC': '{:.3f}'
}).background_gradient(subset=['Recall', 'F1-Score'], cmap='RdYlGn')
```

```python
print(styled_df.to_string())
```

```
Model Accuracy Precision Recall F1-Score ROC-AUC
Random Forest 0.797 0.673 0.750 0.709 0.785
XGBoost 0.735 0.564 0.862 0.682 0.767
Ensemble (Raw) 0.668 0.498 0.924 0.647 0.733
Ensemble (Calibrated) 0.756 0.594 0.829 0.692 0.775
```

In [74]:

```python
import joblib
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import make_pipeline
```

In [79]:

```python
import os
import joblib
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.metrics import recall_score
```

In [80]:

```python
# Save the COMPLETE pipeline including SMOTE
def save_complete_pipeline():
    """
    Save the entire preprocessing and modeling pipeline
    Important: SMOTE is only applied during training, not prediction!
    """

    # Ensure folder exists
    os.makedirs('deployment/models', exist_ok=True)

    # 1. Save the models
    joblib.dump(final_rf_model, 'deployment/models/random_forest_smote.pkl')
    joblib.dump(final_xgb_model, 'deployment/models/xgboost_smote.pkl')

    # 2. Save preprocessing steps (excluding SMOTE for prediction)
    numerical_features = ['Age', 'SatisfactionScore', 'LastEvaluationScore',
                          'NumProjects', 'AvgMonthlyHours', 'YearsAtCompany',
                          'HoursPerProject', 'PerformanceRatio']

    categorical_features = ['TenureCategory_encoded', 'Department_hr',
                            'Department_it', 'Department_operations',
                            'Department_sales', 'Department_unknown',
                            'High_Risk_Employee']

    preprocessor = ColumnTransformer(
        transformers=[
            ('num', StandardScaler(), numerical_features),
            ('cat', 'passthrough', categorical_features)  # Already encoded
        ])

    preprocessor.fit(X_train)  # Fit on original training data (pre-SMOTE)
    joblib.dump(preprocessor, 'deployment/models/preprocessor.pkl')

    # 3. Save SMOTE configuration separately
```

```python
    smote_config = {
        'sampling_strategy': 'auto',
        'random_state': 42,
        'k_neighbors': 5
    }
    joblib.dump(smote_config, 'deployment/models/smote_config.pkl')

    # 4. Save feature names and metadata
    metadata = {
        'feature_names': X_train.columns.tolist(),
        'numerical_features': numerical_features,
        'categorical_features': categorical_features,
        'target_name': 'Attrition',
        'smote_applied': True,
        'training_samples_original': len(X_train),
        'training_samples_after_smote': len(X_train_bal),
        'class_distribution_original': dict(y_train.value_counts()),
        'class_distribution_after_smote': dict(y_train_bal.value_counts()),
        'model_performance': {
            'rf_f1': best_f1_rf,
            'xgb_f1': best_f1_xgb,
            'rf_recall': recall_score(y_test, final_rf_model.predict(X_test)),
            'xgb_recall': recall_score(y_test, final_xgb_model.predict(X_test))
        }
    }
    joblib.dump(metadata, 'deployment/models/metadata.pkl')

    print("✅ Complete pipeline saved successfully!")
    print(f"   Original training size: {len(X_train)}")
    print(f"   SMOTE-balanced size: {len(X_train_bal)}")
    print(f"   Class balance achieved: {dict(y_train_bal.value_counts())}")

# Call the function
save_complete_pipeline()
```

```
✅ Complete pipeline saved successfully!
   Original training size: 23619
   SMOTE-balanced size: 31650
   Class balance achieved: {1: np.int64(15825), 0: np.int64(15825)}
```

In [ ]:

```python

```