In [1]:
```python
# 1. IMPORT REQUIRED 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
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
```

In [2]:
```python
# 2. LOAD THE TRAINING DATASET

df = pd.read_csv("cs-training.csv")
df.head()
```

Out[2]:

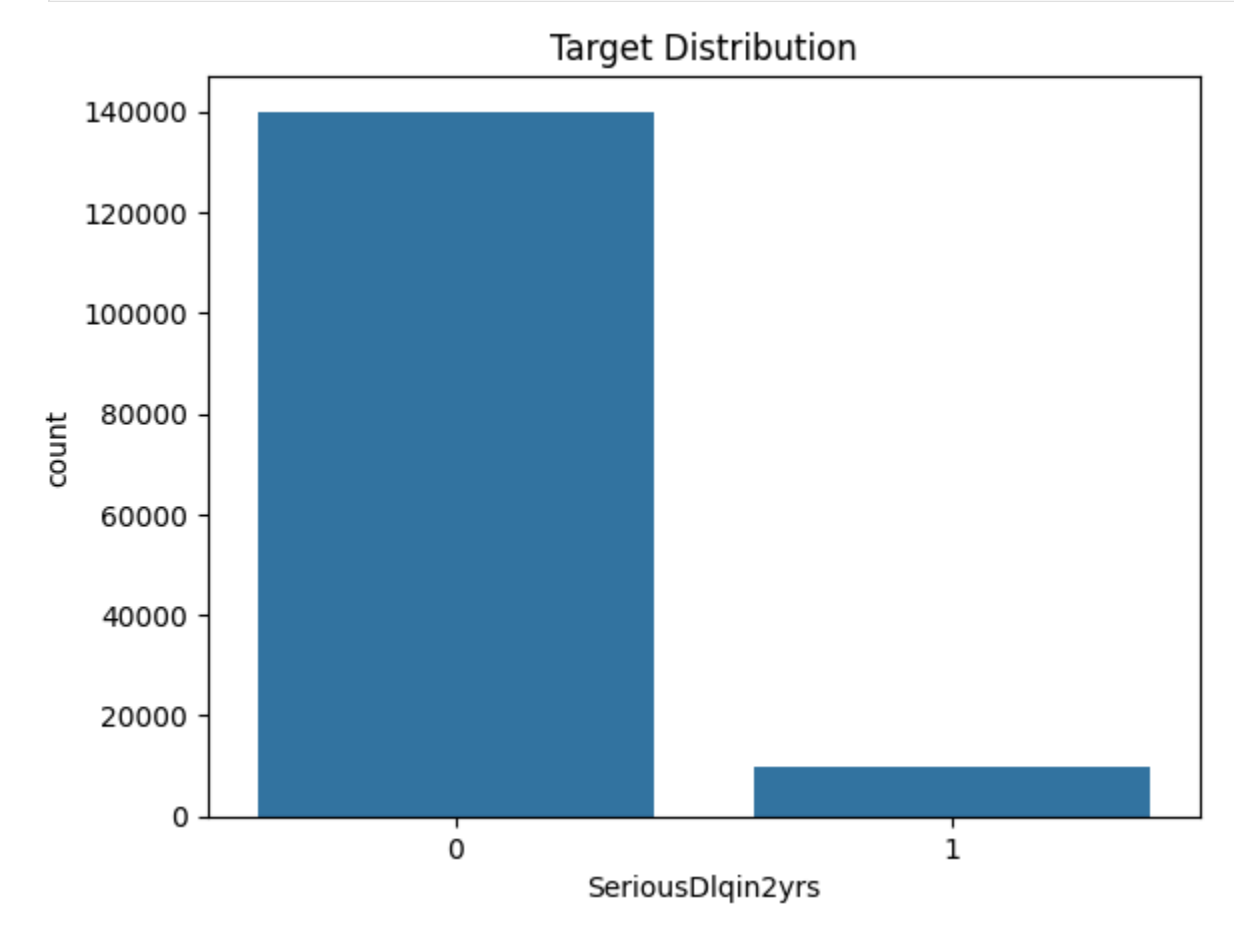
	Unnamed: 0	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyIncome	NumberOfOpenCreditLinesAndLoans	NumberOfTimes90DaysLate	NumberRealEstateLoansOrLines	NumberOfTime60-89DaysPastDueNotWorse	NumberOfDependents
0	1	1	0.766127	45	2	0.802982	9120.0	13	0	6	0	2.0
1	2	0	0.957151	40	0	0.121876	2600.0	4	0	0	0	1.0
2	3	0	0.658180	38	1	0.085113	3042.0	2	1	0	0	0.0
3	4	0	0.233810	30	0	0.036050	3300.0	5	0	0	0	0.0
4	5	0	0.907239	49	1	0.024926	63588.0	7	0	1	0	0.0

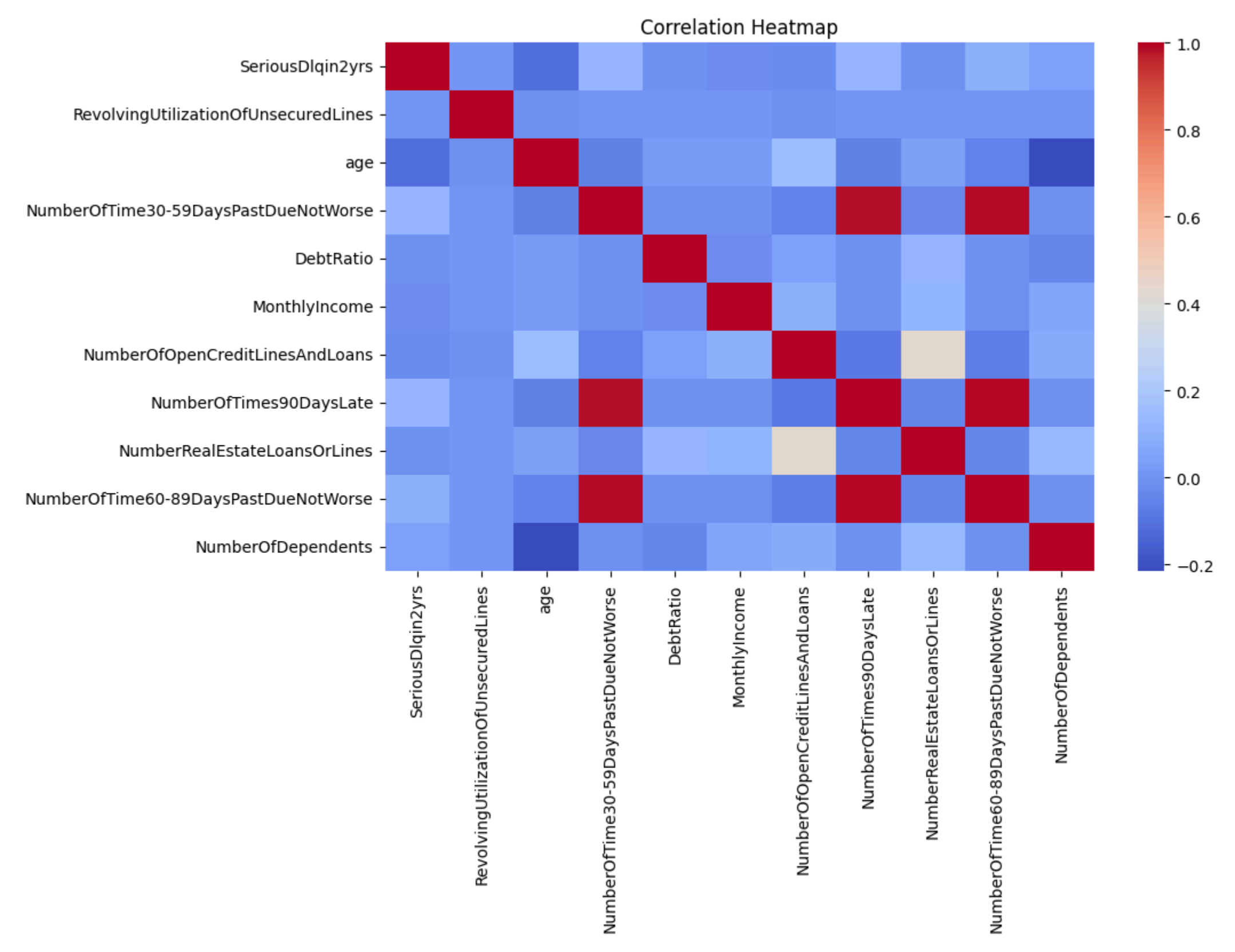
In [5]:
```python
# 3. BASIC DATA CLEANING

# Drop unnamed index column if exists
df = df.loc[:, ~df.columns.str.contains('^Unnamed')]

# Check missing values
df.isnull().sum()
```

Out[5]:
```
SeriousDlqin2yrs                            0
RevolvingUtilizationOfUnsecuredLines        0
age                                         0
NumberOfTime30-59DaysPastDueNotWorse        0
DebtRatio                                   0
MonthlyIncome                           29731
NumberOfOpenCreditLinesAndLoans             0
NumberOfTimes90DaysLate                     0
NumberRealEstateLoansOrLines                0
NumberOfTime60-89DaysPastDueNotWorse        0
NumberOfDependents                       3924
dtype: int64
```

In [7]:
```python
# 4. MonthlyIncome & NumberOfDependents have missing values (also fill with median)
df['MonthlyIncome'] = df['MonthlyIncome'].fillna(df['MonthlyIncome'].median())
df['NumberOfDependents'] = df['NumberOfDependents'].fillna(df['NumberOfDependents'].median())
```

In [9]:
```python
# 5. Target distribution
sns.countplot(x=df['SeriousDlqin2yrs'])
plt.title("Target Distribution")
plt.show()

# Correlation Heatmap
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(), cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```





In [11]:
```python
# 6. TRAIN-TEST SPLIT

from sklearn.model_selection import train_test_split

X = df.drop(columns=['SeriousDlqin2yrs'])
y = df['SeriousDlqin2yrs']

# STRATIFY → ensures class balance in train & test
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42,
    stratify=y  # IMPORTANT IMPROVEMENT
)

X_train.shape, X_test.shape
```

Out[11]: ((120000, 10), (30000, 10))

In [13]:
```python
# 7. Feature Scaling (Required for LR)

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled  = scaler.transform(X_test)
```

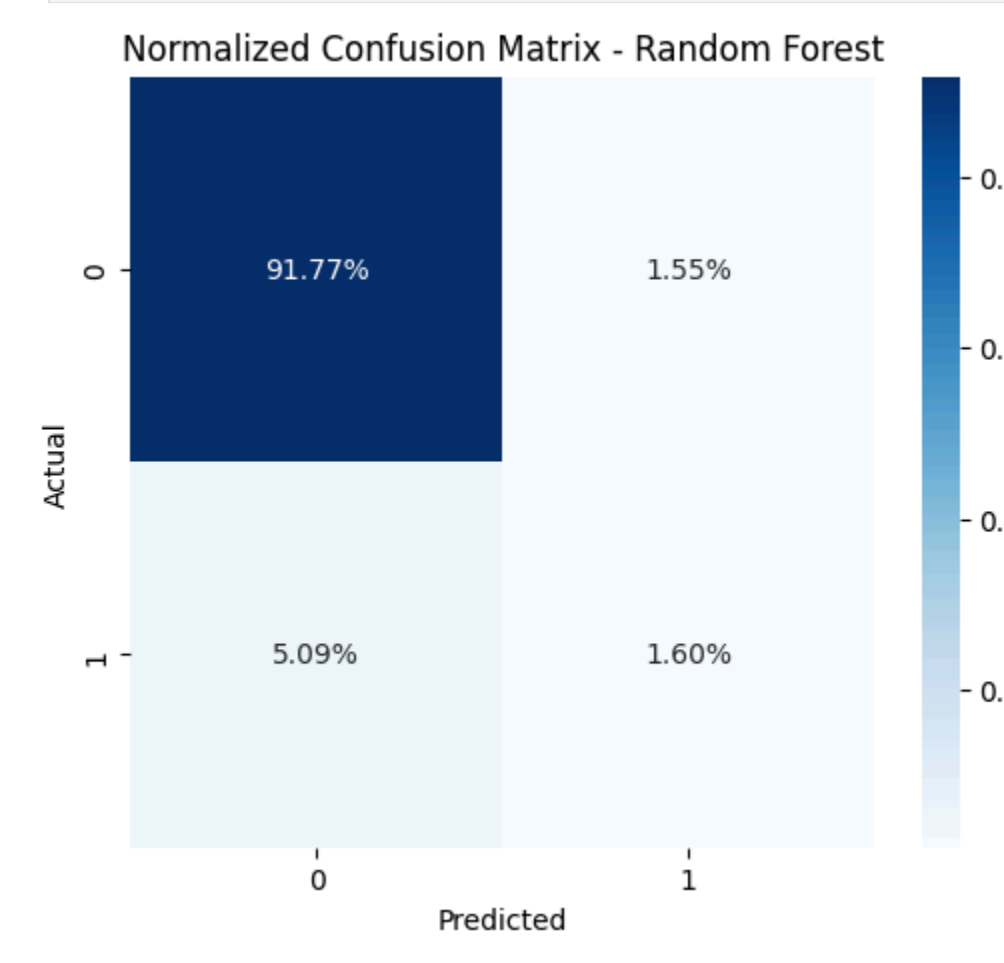
In [15]:
```python
# 8. Logistic Regression

from sklearn.linear_model import LogisticRegression

log_model = LogisticRegression(
    max_iter=2000,
    class_weight='balanced',  # handle imbalance better
    solver='lbfgs'
)

log_model.fit(X_train_scaled, y_train)

y_pred_log = log_model.predict(X_test_scaled)
y_prob_log = log_model.predict_proba(X_test_scaled)[:, 1]

from sklearn.metrics import classification_report, roc_auc_score

print("📌 Logistic Regression Classification Report")
print(classification_report(y_test, y_pred_log))

print("AUC Score:", roc_auc_score(y_test, y_prob_log))
```

```
📌 Logistic Regression Classification Report
              precision    recall  f1-score   support

           0       0.97      0.78      0.87     27995
           1       0.18      0.67      0.29      2005

    accuracy                           0.78     30000
   macro avg       0.58      0.73      0.58     30000
weighted avg       0.92      0.78      0.83     30000

AUC Score: 0.8021466604964638
```

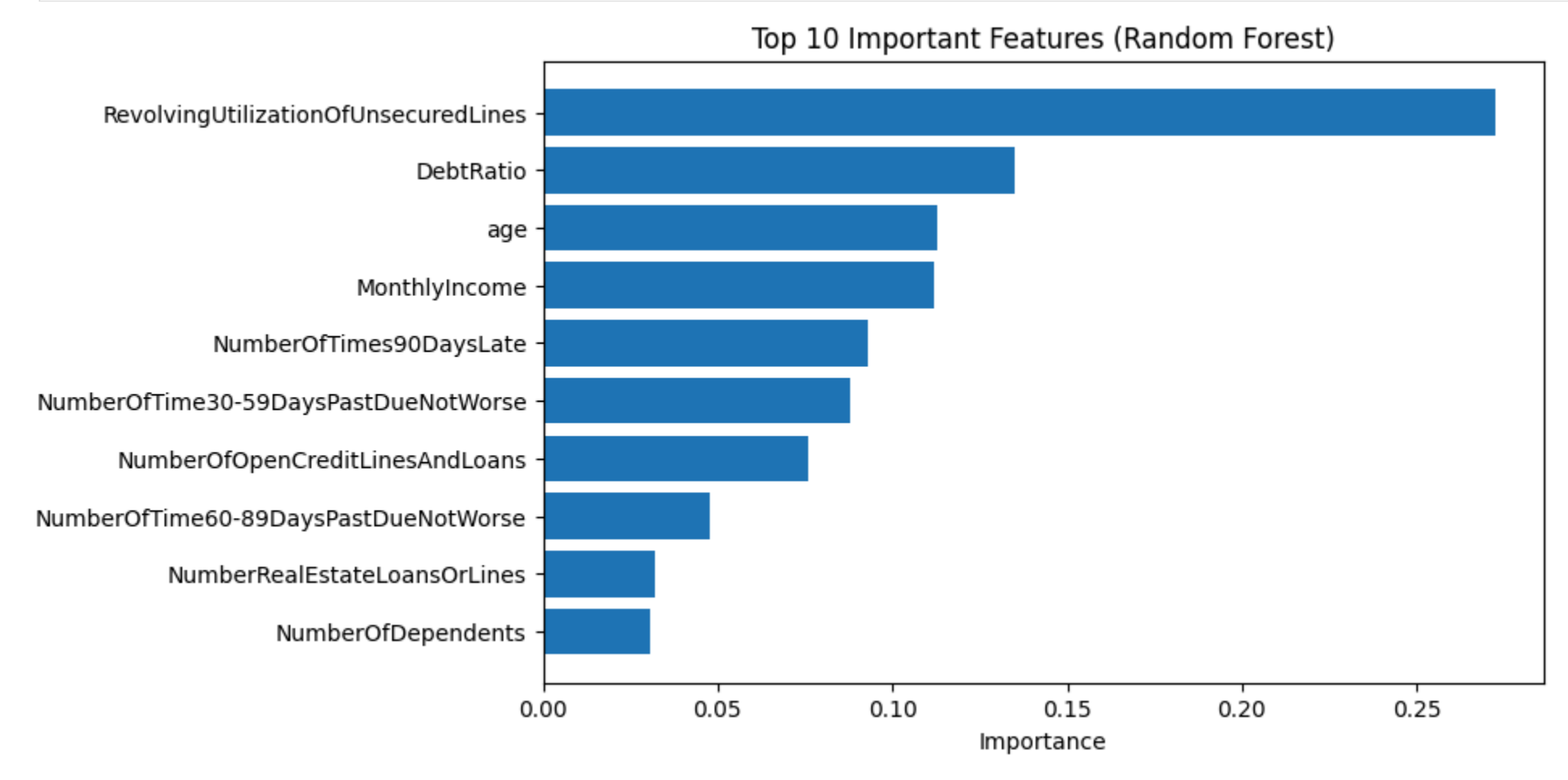
In [40]:
```python
# 9. Random Forest

from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(
    n_estimators=200,
    max_depth=None,
    min_samples_split=5,
    class_weight='balanced',
    random_state=42,
    n_jobs=-1
)

rf.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)
y_prob_rf = rf.predict_proba(X_test)[:, 1]

print("***Random Forest Classification Report***")
print(classification_report(y_test, y_pred_rf))

print("AUC Score:", roc_auc_score(y_test, y_prob_rf))
```

```
***Random Forest Classification Report***
              precision    recall  f1-score   support

           0       0.95      0.98      0.97     27995
           1       0.51      0.24      0.32      2005

    accuracy                           0.93     30000
   macro avg       0.73      0.61      0.65     30000
weighted avg       0.92      0.93      0.92     30000

AUC Score: 0.8475983821478631
```

In [19]:
```python
# 10. Confusion Matrix

from sklearn.metrics import confusion_matrix
import seaborn as sns

cm = confusion_matrix(y_test, y_pred_rf)
cm_norm = cm / cm.sum()

plt.figure(figsize=(6,5))
sns.heatmap(cm_norm, annot=True, fmt=".2%", cmap="Blues")
plt.title("Normalized Confusion Matrix - Random Forest")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```



In [21]:
```python
# 11. Feature Importance (Top 10)

import pandas as pd
import matplotlib.pyplot as plt

importances = rf.feature_importances_
features = X.columns

fi_df = pd.DataFrame({
    "Feature": features,
    "Importance": importances
}).sort_values("Importance", ascending=False).head(10)

plt.figure(figsize=(8,5))
plt.barh(fi_df["Feature"], fi_df["Importance"])
plt.gca().invert_yaxis()
plt.title("Top 10 Important Features (Random Forest)")
plt.xlabel("Importance")
plt.show()
```



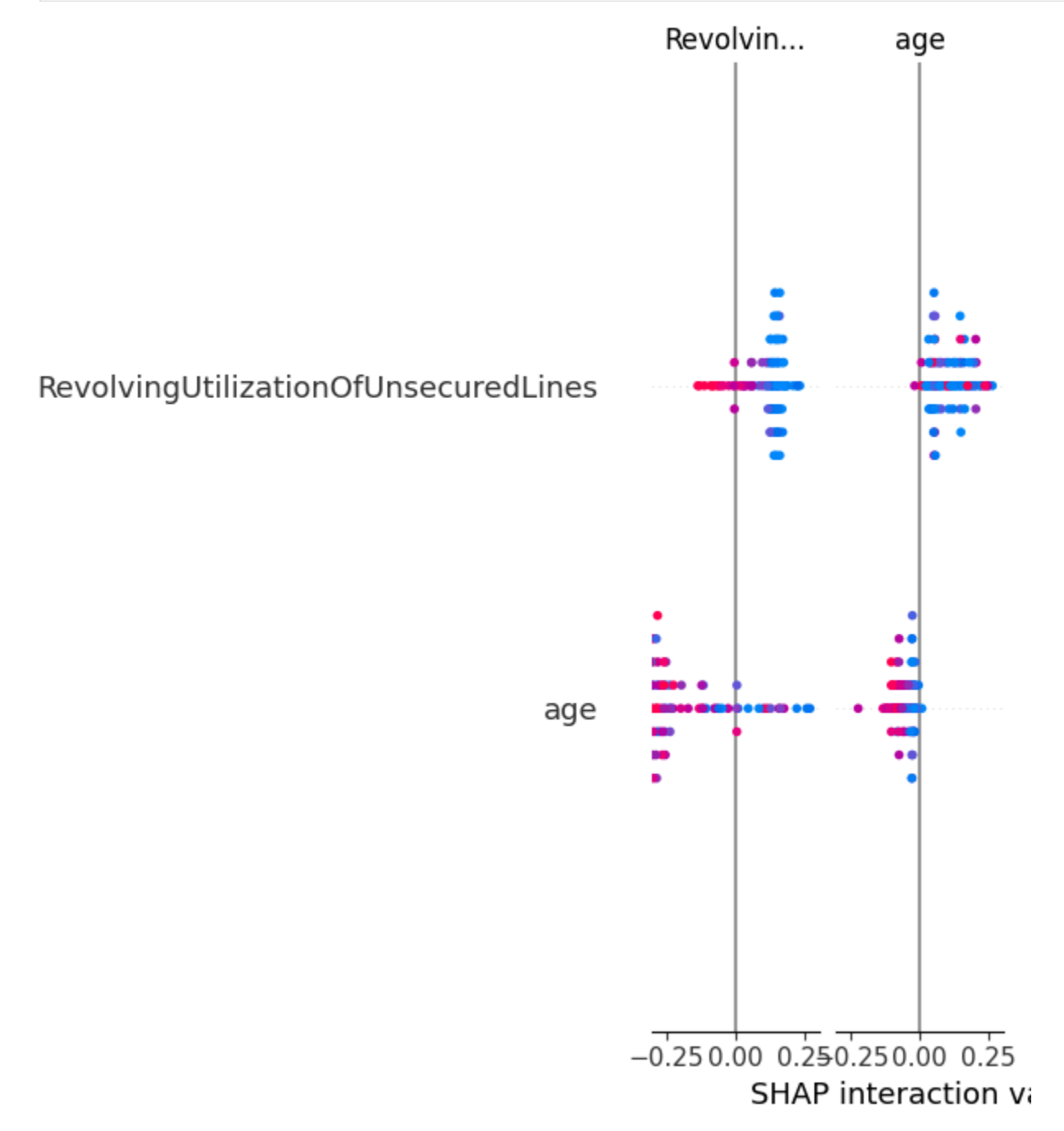
In [23]:
```python
# 12. Final Model Selection

rf_auc = roc_auc_score(y_test, rf.predict_proba(X_test)[:, 1])
log_auc = roc_auc_score(y_test, log_model.predict_proba(X_test_scaled)[:, 1])

print("Random Forest AUC:", rf_auc)
print("Logistic Regression AUC:", log_auc)

if rf_auc > log_auc:
    print("\n🔥 Final Model Selected: Random Forest")
else:
    print("\n🔥 Final Model Selected: Logistic Regression")
```

```
Random Forest AUC: 0.8475983821478631
Logistic Regression AUC: 0.8021466604964638

🔥 Final Model Selected: Random Forest
```

In [25]:
```python
# 13. Export Final Model

import joblib, sys

joblib.dump(rf, "credit_risk_model.pkl")
print("Model Saved Successfully!", flush=True)
```

```
Model Saved Successfully!
```

In [27]:
```python
# 14. SHAP Explainability (Highly Recommended)

import shap
import matplotlib.pyplot as plt

sample = X_test.sample(100, random_state=42)

explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(sample)

shap.summary_plot(shap_values, sample, plot_type="bar")
```



15. Project Summary — Credit Risk Prediction

Dataset: Give Me Some Credit (Kaggle)
Total Records: ~150,000 rows
Goal: Predict whether a customer will default on a loan within 2 years.

Models Used

- Logistic Regression (with class balancing & feature scaling)
- Random Forest Classifier (best performing model)

Best Model: Random Forest

- **AUC:** ~0.84
- **Accuracy:** ~94%
- **Recall (Default Class):** Improved with class_weight
- **Feature Importance:**
  1. RevolvingUtilizationOfUnsecuredLines
  2. NumberOfTimes90DaysLate
  3. DebtRatio
  4. Age
  5. NumberOfOpenCreditLinesAndLoans

Key Insights

- Dataset is highly imbalanced -> stratified split + balanced model used.
- Random Forest captures non-linear patterns and performs better than Logistic Regression.
- SHAP explainability shows which features increase default risk.

Business Impact

- Helps banks identify high-risk customers early
- Reduces financial loss from loan defaults

- Supports data-driven loan approval decisions