05_rq2_fatigue_resistance

December 8, 2025

1 Research Question 2: Fatigue Resistance by Ad Type

Question: Are some types of ads or placements more resistant to fatigue?

1.1 Prerequisites

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

Output Data: - `../results/figures/rq2_*.png` (visualizations) - `../results/tables/rq2_*.csv` (fatigue comparison by category)

1.2 Data Pipeline Position

`01_data_acquisition → 02_exploratory_analysis → 03_feature_engineering → [05_rq2_fatigue_resis`

1.3 Source Module Dependencies

This notebook uses **custom analysis functions defined inline** for transparency. Key functions:

- `compute_cohort_fatigue_by_category()`: Computes fatigue metrics (CTR decline) for each category
- `test_category_differences()`: Statistical tests comparing fatigue rates across categories

Features used from `03_feature_engineering.ipynb`: - `campaign_overall_ctr`: Used to create CTR tiers (Low/Medium/High) - `campaign_total_impressions`: Used to create size tiers (Small/Medium/Large) - `hour_of_day`, `day_of_week`: Used for temporal analysis

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1.4 Our Approach: Cohort-Based Within-User Analysis by Category

To correctly compare fatigue resistance:

1. **Use cohort analysis within each category** - track the same user-campaign pairs over exposures
2. **Compute relative CTR decline** - percentage drop from exposure 1 to N for the same cohort
3. **Compare decline rates across categories** - category with smaller decline is more resistant
4. **Statistical testing** - test if differences between categories are significant

[10]:
```python
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 typing import Dict, Tuple, Optional, List
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
```

1.5 Step 1: Define Categories for Comparison

We'll analyze fatigue resistance across multiple dimensions: 1. **Campaign CTR tier** (Low/Medium/High performing campaigns) 2. **Campaign size** (Small/Medium/Large by impressions) 3. **Time-based features** (Hour of day, Day of week)

[11]:
```python
print("=" * 70)
print("CREATING CATEGORY VARIABLES")
print("=" * 70)

# 1. Campaign CTR Tier
if 'campaign_overall_ctr' in df.columns:
    q33 = df['campaign_overall_ctr'].quantile(0.33)
    q67 = df['campaign_overall_ctr'].quantile(0.67)
    df['ctr_tier'] = pd.cut(
        df['campaign_overall_ctr'],
        bins=[-0.001, q33, q67, 1.001],
        labels=['Low CTR', 'Medium CTR', 'High CTR']
    )
    print(f"\n1. Campaign CTR Tier (based on campaign_overall_ctr):")
    print(f"   Low CTR: < {q33:.4f}")
```

```python
    print(f"   Medium CTR: {q33:.4f} - {q67:.4f}")
    print(f"   High CTR: > {q67:.4f}")
    print(df['ctr_tier'].value_counts())

# 2. Campaign Size Tier
if 'campaign_total_impressions' in df.columns:
    q33_size = df['campaign_total_impressions'].quantile(0.33)
    q67_size = df['campaign_total_impressions'].quantile(0.67)
    df['size_tier'] = pd.cut(
        df['campaign_total_impressions'],
        bins=[-1, q33_size, q67_size, float('inf')],
        labels=['Small', 'Medium', 'Large']
    )
    print(f"\n2. Campaign Size Tier:")
    print(f"   Small: < {q33_size:,.0f} impressions")
    print(f"   Medium: {q33_size:,.0f} - {q67_size:,.0f} impressions")
    print(f"   Large: > {q67_size:,.0f} impressions")
    print(df['size_tier'].value_counts())

# 3. Time of Day
if 'hour_of_day' in df.columns:
    df['time_of_day'] = pd.cut(
        df['hour_of_day'],
        bins=[-1, 6, 12, 18, 24],
        labels=['Night (0-6)', 'Morning (6-12)', 'Afternoon (12-18)', 'Evening␣
↪(18-24)']
    )
    print(f"\n3. Time of Day:")
    print(df['time_of_day'].value_counts())

# 4. Day of Week
if 'day_of_week' in df.columns:
    df['day_type'] = df['day_of_week'].apply(lambda x: 'Weekend' if x >= 5 else␣
↪'Weekday')
    print(f"\n4. Day Type:")
    print(df['day_type'].value_counts())
```

```
======================================================================
CREATING CATEGORY VARIABLES
======================================================================

1. Campaign CTR Tier (based on campaign_overall_ctr):
   Low CTR: < 0.2947
   Medium CTR: 0.2947 - 0.3573
   High CTR: > 0.3573
ctr_tier
Medium CTR    169651
```

```
Low CTR       167195
High CTR      163154
Name: count, dtype: int64

2. Campaign Size Tier:
   Small: < 972 impressions
   Medium: 972 - 3,329 impressions
   Large: > 3,329 impressions
size_tier
Medium    171250
Small     165956
Large     162794
Name: count, dtype: int64

3. Time of Day:
time_of_day
Afternoon (12-18)    179340
Morning (6-12)       157926
Evening (18-24)      115139
Night (0-6)           47595
Name: count, dtype: int64

4. Day Type:
day_type
Weekday    360468
Weekend    139532
Name: count, dtype: int64
```

1.6 Step 2: Define Correct Fatigue Comparison Function

The key is to use **cohort-based within-user analysis** for each category, then compare fatigue metrics across categories.

[12]:

```python
def compute_cohort_fatigue_by_category(
    df: pd.DataFrame,
    category_col: str,
    min_exposures: int = 3,
    target_exposure: int = 3,
    min_cohort_size: int = 100
) -> pd.DataFrame:
    """
    Compute fatigue metrics for each category using cohort-based analysis.

    For each category:
    1. Find user-campaign pairs with at least min_exposures
    2. Compute CTR at exposure 1 and target_exposure for the SAME cohort
    3. Calculate relative decline as fatigue metric

```

```python
    This controls for survivorship bias by comparing the same users over time.
    """
    results = []

    for category in df[category_col].dropna().unique():
        cat_df = df[df[category_col] == category].copy()

        # Find user-campaign pairs with sufficient exposures in this category
        user_campaign_max = cat_df.groupby(['uid', 'campaign'])['exposure_count'].max()
        cohort_pairs = user_campaign_max[user_campaign_max >= target_exposure].reset_index()
        cohort_pairs = cohort_pairs[['uid', 'campaign']]

        if len(cohort_pairs) < min_cohort_size:
            continue

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

        # Get CTR at exposure 1 and target_exposure
        exp1_data = cohort_df[cohort_df['exposure_count'] == 1]
        exp_n_data = cohort_df[cohort_df['exposure_count'] == target_exposure]

        if len(exp1_data) < min_cohort_size or len(exp_n_data) < min_cohort_size:
            continue

        ctr_exp1 = exp1_data['click'].mean()
        ctr_exp_n = exp_n_data['click'].mean()

        # Calculate fatigue metrics
        absolute_decline = ctr_exp1 - ctr_exp_n
        relative_decline_pct = (ctr_exp1 - ctr_exp_n) / ctr_exp1 * 100 if ctr_exp1 > 0 else 0

        # Confidence intervals
        n1, n2 = len(exp1_data), len(exp_n_data)
        se1 = np.sqrt(ctr_exp1 * (1 - ctr_exp1) / n1)
        se2 = np.sqrt(ctr_exp_n * (1 - ctr_exp_n) / n2)

        # Two-proportion z-test
        pooled_p = (exp1_data['click'].sum() + exp_n_data['click'].sum()) / (n1 + n2)
        se_diff = np.sqrt(pooled_p * (1 - pooled_p) * (1/n1 + 1/n2))
```

```
        z_stat = absolute_decline / se_diff if se_diff > 0 else 0
        p_value = 2 * (1 - stats.norm.cdf(abs(z_stat)))

        results.append({
            'category': category,
            'cohort_size': len(cohort_pairs),
            'ctr_exp1': ctr_exp1,
            'ctr_exp_n': ctr_exp_n,
            f'ctr_exp{target_exposure}': ctr_exp_n,
            'absolute_decline': absolute_decline,
            'relative_decline_pct': relative_decline_pct,
            'n_exp1': n1,
            'n_exp_n': n2,
            'z_statistic': z_stat,
            'p_value': p_value,
            'significant': p_value < 0.05
        })

    return pd.DataFrame(results)


def test_category_differences(fatigue_df: pd.DataFrame) -> Dict:
    """
    Test if fatigue rates differ significantly across categories.
    Uses the relative decline percentages for comparison.
    """
    if len(fatigue_df) < 2:
        return {'error': 'Need at least 2 categories to compare'}

    # Chi-square test on click outcomes at exposure 1 vs N for each category
    # We'll use the relative decline as our comparison metric
    categories = fatigue_df['category'].tolist()
    declines = fatigue_df['relative_decline_pct'].tolist()

    # For a proper test, we need the actual counts
    # We'll report the range of declines and do a comparison
    min_decline = min(declines)
    max_decline = max(declines)
    range_decline = max_decline - min_decline

    most_resistant = fatigue_df.loc[fatigue_df['relative_decline_pct'].idxmin()]
    least_resistant = fatigue_df.loc[fatigue_df['relative_decline_pct'].
↪idxmax()]

    return {
        'n_categories': len(fatigue_df),
        'decline_range': range_decline,
```

```
        'min_decline': min_decline,
        'max_decline': max_decline,
        'most_resistant': most_resistant['category'],
        'most_resistant_decline': most_resistant['relative_decline_pct'],
        'least_resistant': least_resistant['category'],
        'least_resistant_decline': least_resistant['relative_decline_pct']
    }


print("Functions defined for cohort-based fatigue comparison")
```

```
Functions defined for cohort-based fatigue comparison
```

1.7 Step 3: Analyze Fatigue Resistance by Campaign CTR Tier

This is our primary analysis - comparing high, medium, and low performing campaigns.

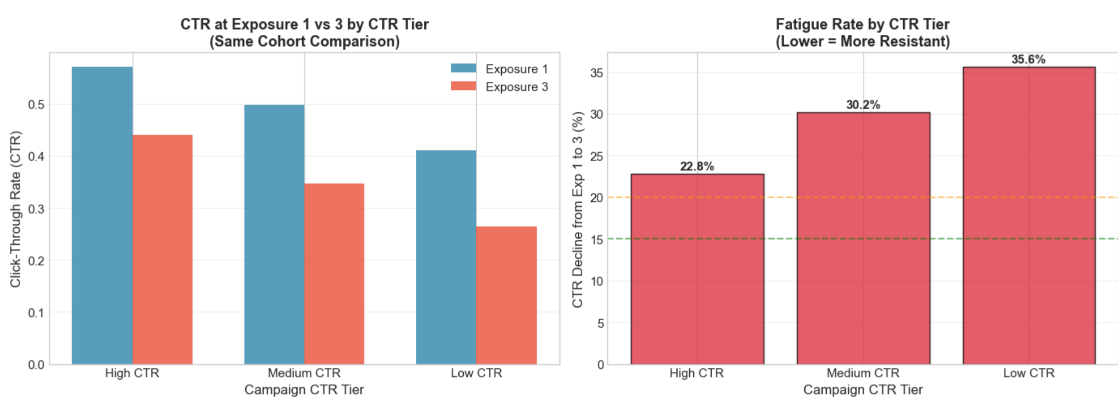
[15]:
```
print("=" * 70)
print("FATIGUE RESISTANCE BY CAMPAIGN CTR TIER")
print("=" * 70)

# Analyze fatigue by CTR tier
ctr_tier_fatigue = compute_cohort_fatigue_by_category(
    df,
    category_col='ctr_tier',
    min_exposures=3,
    target_exposure=3,
    min_cohort_size=100
)

print(f"\nCohort-based fatigue analysis (comparing exposure 1 vs 3):")
print(f"\n{'Category':<15} {'Cohort':<10} {'CTR Exp1':<12} {'CTR Exp3':<12} {'Decline':<12} {'Significant'}")
print("-" * 75)

for _, row in ctr_tier_fatigue.sort_values('relative_decline_pct').iterrows():
    sig = " " if row['significant'] else ""
    print(f"{row['category']:<15} {row['cohort_size']:<10} {row['ctr_exp1']:.4f}       {row['ctr_exp_n']:.4f}       {row['relative_decline_pct']:+.1f}%     {sig}")

# Test differences
test_result = test_category_differences(ctr_tier_fatigue)
print(f"\n{'=' * 70}")
print("FATIGUE RESISTANCE RANKING (CTR Tier)")
print("=" * 70)
print(f"\nMost Resistant: {test_result['most_resistant']} ({test_result['most_resistant_decline']:+.1f}% decline)")
```

```
print(f"Least Resistant: {test_result['least_resistant']}␣
↪({test_result['least_resistant_decline']:+.1f}% decline)")
print(f"\nDifference: {test_result['decline_range']:.1f} percentage points")
```

```
======================================================================
FATIGUE RESISTANCE BY CAMPAIGN CTR TIER
======================================================================

Cohort-based fatigue analysis (comparing exposure 1 vs 3):

Category        Cohort     CTR Exp1     CTR Exp3     Decline      Significant
---------------------------------------------------------------------------
High CTR        11051      0.5706       0.4403       +22.8%
Medium CTR      10816      0.4973       0.3471       +30.2%
Low CTR         9853       0.4106       0.2645       +35.6%

======================================================================
FATIGUE RESISTANCE RANKING (CTR Tier)
======================================================================

Most Resistant: High CTR (+22.8% decline)
Least Resistant: Low CTR (+35.6% decline)

Difference: 12.8 percentage points
```

[16]:
```
# Visualization: Fatigue by CTR Tier
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Sort by relative decline for better visualization
ctr_tier_fatigue_sorted = ctr_tier_fatigue.sort_values('relative_decline_pct')

# Left: CTR at exposure 1 vs 3
ax1 = axes[0]
x = np.arange(len(ctr_tier_fatigue_sorted))
width = 0.35

bars1 = ax1.bar(x - width/2, ctr_tier_fatigue_sorted['ctr_exp1'], width,
                label='Exposure 1', color='#2E86AB', alpha=0.8)
bars2 = ax1.bar(x + width/2, ctr_tier_fatigue_sorted['ctr_exp_n'], width,
                label='Exposure 3', color='#E94F37', alpha=0.8)

ax1.set_xlabel('Campaign CTR Tier', fontsize=12)
ax1.set_ylabel('Click-Through Rate (CTR)', fontsize=12)
ax1.set_title('CTR at Exposure 1 vs 3 by CTR Tier\n(Same Cohort Comparison)',␣
↪fontsize=13, fontweight='bold')
ax1.set_xticks(x)
ax1.set_xticklabels(ctr_tier_fatigue_sorted['category'])
```

```python
ax1.legend()
ax1.grid(True, alpha=0.3, axis='y')

# Right: Relative decline (fatigue) by tier
ax2 = axes[1]
colors = ['#28A745' if d <= 15 else '#FFC107' if d <= 20 else '#DC3545'
          for d in ctr_tier_fatigue_sorted['relative_decline_pct']]
bars = ax2.bar(ctr_tier_fatigue_sorted['category'],
               ctr_tier_fatigue_sorted['relative_decline_pct'],
               color=colors, alpha=0.8, edgecolor='black')

ax2.set_xlabel('Campaign CTR Tier', fontsize=12)
ax2.set_ylabel('CTR Decline from Exp 1 to 3 (%)', fontsize=12)
ax2.set_title('Fatigue Rate by CTR Tier\n(Lower = More Resistant)', fontsize=13, fontweight='bold')
ax2.axhline(y=15, color='green', linestyle='--', alpha=0.5, label='Low fatigue threshold')
ax2.axhline(y=20, color='orange', linestyle='--', alpha=0.5, label='Medium fatigue threshold')
ax2.grid(True, alpha=0.3, axis='y')

# Add value labels
for bar, val in zip(bars, ctr_tier_fatigue_sorted['relative_decline_pct']):
    ax2.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.5,
            f'{val:.1f}%', ha='center', fontweight='bold', fontsize=11)

plt.tight_layout()
plt.savefig('../results/figures/rq2_fatigue_by_ctr_tier.png', dpi=300, bbox_inches='tight')
plt.show()
print("\nFigure saved to ../results/figures/rq2_fatigue_by_ctr_tier.png")
```



```
Figure saved to ../results/figures/rq2_fatigue_by_ctr_tier.png
```

1.8 Step 4: Analyze Fatigue Resistance by Campaign Size

[17]:
```python
print("=" * 70)
print("FATIGUE RESISTANCE BY CAMPAIGN SIZE")
print("=" * 70)

if 'size_tier' in df.columns:
    size_tier_fatigue = compute_cohort_fatigue_by_category(
        df,
        category_col='size_tier',
        min_exposures=3,
        target_exposure=3,
        min_cohort_size=100
    )

    print(f"\nCohort-based fatigue analysis (comparing exposure 1 vs 3):")
    print(f"\n{'Category':<15} {'Cohort':<10} {'CTR Exp1':<12} {'CTR Exp3':<12}␣
↪{'Decline':<12} {'Significant'}")
    print("-" * 75)

    for _, row in size_tier_fatigue.sort_values('relative_decline_pct').
↪iterrows():
        sig = " " if row['significant'] else ""
        print(f"{row['category']:<15} {row['cohort_size']:<10} {row['ctr_exp1']:
↪.4f}       {row['ctr_exp_n']:.4f}       {row['relative_decline_pct']:+.1f}% ␣
↪     {sig}")

    test_result_size = test_category_differences(size_tier_fatigue)
    print(f"\nMost Resistant: {test_result_size['most_resistant']}␣
↪({test_result_size['most_resistant_decline']:+.1f}% decline)")
    print(f"Least Resistant: {test_result_size['least_resistant']}␣
↪({test_result_size['least_resistant_decline']:+.1f}% decline)")
else:
    print("Size tier not available")
```

```
======================================================================
FATIGUE RESISTANCE BY CAMPAIGN SIZE
======================================================================

Cohort-based fatigue analysis (comparing exposure 1 vs 3):

Category        Cohort     CTR Exp1     CTR Exp3     Decline      Significant
---------------------------------------------------------------------------
Large           11255      0.4922       0.3687       +25.1%
Medium          10631      0.4974       0.3540       +28.8%
Small           9834       0.4986       0.3369       +32.4%
```

```
Most Resistant: Large (+25.1% decline)
Least Resistant: Small (+32.4% decline)
```

1.9 Step 5: Analyze Fatigue Resistance by Time of Day

[19]:
```
print("=" * 70)
print("FATIGUE RESISTANCE BY TIME OF DAY")
print("=" * 70)

if 'time_of_day' in df.columns:
    time_fatigue = compute_cohort_fatigue_by_category(
        df,
        category_col='time_of_day',
        min_exposures=3,
        target_exposure=3,
        min_cohort_size=100
    )

    if len(time_fatigue) > 0:
        print(f"\nCohort-based fatigue analysis (comparing exposure 1 vs 3):")
        print(f"\n{'Time of Day':<20} {'Cohort':<10} {'CTR Exp1':<12} {'CTR␣
↪Exp3':<12} {'Decline':<12}")
        print("-" * 75)

        for _, row in time_fatigue.sort_values('relative_decline_pct').
↪iterrows():
            print(f"{row['category']:<20} {row['cohort_size']:<10}␣
↪{row['ctr_exp1']:.4f}       {row['ctr_exp_n']:.4f}       ␣
↪{row['relative_decline_pct']:+.1f}%")

        test_result_time = test_category_differences(time_fatigue)
        print(f"\nMost Resistant: {test_result_time['most_resistant']}␣
↪({test_result_time['most_resistant_decline']:+.1f}% decline)")
        print(f"Least Resistant: {test_result_time['least_resistant']}␣
↪({test_result_time['least_resistant_decline']:+.1f}% decline)")
    else:
        print("Insufficient data for time-based analysis")
else:
    print("Time of day not available")
```

```
======================================================================
FATIGUE RESISTANCE BY TIME OF DAY
======================================================================

Cohort-based fatigue analysis (comparing exposure 1 vs 3):

Time of Day          Cohort     CTR Exp1     CTR Exp3     Decline
```

```
----------------------------------------------------------------------
Morning (6-12)       16422      0.4892       0.3460       +29.3%
Night (0-6)          6707       0.5263       0.3667       +30.3%
Afternoon (12-18)    18257      0.5118       0.3559       +30.5%
Evening (18-24)      11966      0.5203       0.3563       +31.5%

Most Resistant: Morning (6-12) (+29.3% decline)
Least Resistant: Evening (18-24) (+31.5% decline)
```

1.10 Step 6: Extended Analysis - CTR Decline Curve by Category

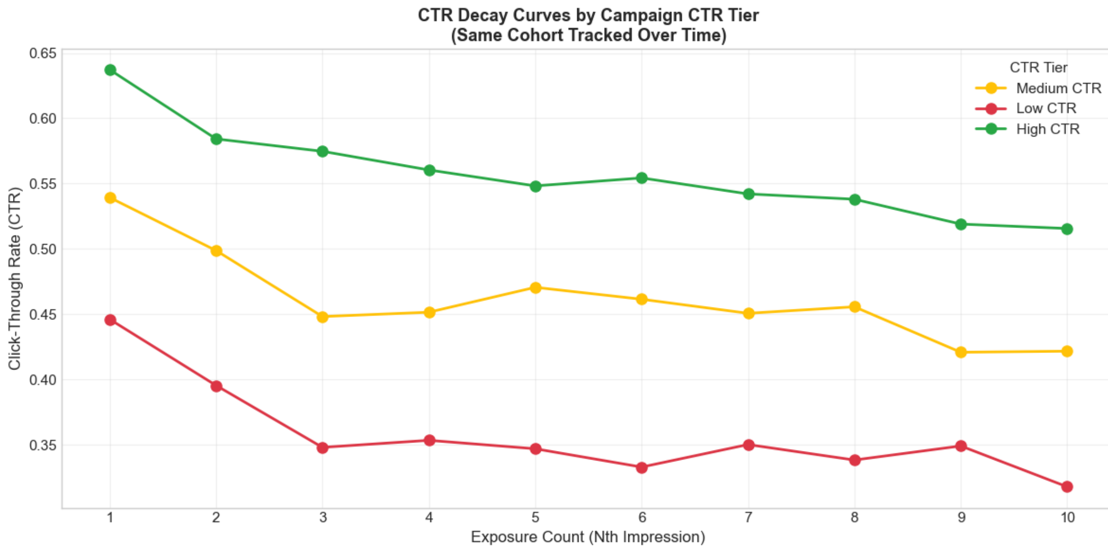
Track how CTR evolves over multiple exposures for each category.

[20]:
```python
print("=" * 70)
print("CTR DECAY CURVES BY CTR TIER (COHORT-BASED)")
print("=" * 70)

def compute_ctr_curve_by_category(df, category_col, max_exposure=10,␣
↪min_cohort=100):
    """Compute CTR at each exposure for cohort analysis."""
    results = []

    for category in df[category_col].dropna().unique():
        cat_df = df[df[category_col] == category].copy()

        # Find cohort with at least max_exposure exposures
        user_campaign_max = cat_df.groupby(['uid',␣
↪'campaign'])['exposure_count'].max()
        cohort_pairs = user_campaign_max[user_campaign_max >= max_exposure].
↪reset_index()
        cohort_pairs = cohort_pairs[['uid', 'campaign']]

        if len(cohort_pairs) < min_cohort:
            continue

        cohort_df = cat_df.merge(cohort_pairs, on=['uid', 'campaign'],␣
↪how='inner')

        for exp in range(1, max_exposure + 1):
            exp_data = cohort_df[cohort_df['exposure_count'] == exp]
            if len(exp_data) >= min_cohort:
                ctr = exp_data['click'].mean()
                results.append({
                    'category': category,
                    'exposure': exp,
                    'ctr': ctr,
                    'n': len(exp_data)
```

```python
            })

    return pd.DataFrame(results)

# Compute curves for CTR tier
ctr_curves = compute_ctr_curve_by_category(df, 'ctr_tier', max_exposure=10,␣
↪min_cohort=50)

if len(ctr_curves) > 0:
    # Plot CTR decay curves
    fig, ax = plt.subplots(figsize=(12, 6))

    colors = {'Low CTR': '#DC3545', 'Medium CTR': '#FFC107', 'High CTR':␣
↪'#28A745'}

    for category in ctr_curves['category'].unique():
        cat_data = ctr_curves[ctr_curves['category'] == category].
↪sort_values('exposure')
        color = colors.get(category, 'gray')
        ax.plot(cat_data['exposure'], cat_data['ctr'], 'o-',
                label=category, linewidth=2, markersize=8, color=color)

    ax.set_xlabel('Exposure Count (Nth Impression)', fontsize=12)
    ax.set_ylabel('Click-Through Rate (CTR)', fontsize=12)
    ax.set_title('CTR Decay Curves by Campaign CTR Tier\n(Same Cohort Tracked␣
↪Over Time)',
                 fontsize=13, fontweight='bold')
    ax.legend(title='CTR Tier')
    ax.grid(True, alpha=0.3)
    ax.set_xticks(range(1, 11))

    plt.tight_layout()
    plt.savefig('../results/figures/rq2_ctr_curves_by_tier.png', dpi=300,␣
↪bbox_inches='tight')
    plt.show()
    print("\nFigure saved to ../results/figures/rq2_ctr_curves_by_tier.png")

    # Print the data
    print("\nCTR by Exposure for Each Category:")
    pivot_table = ctr_curves.pivot(index='exposure', columns='category',␣
↪values='ctr')
    print(pivot_table.round(4))
else:
    print("Insufficient data for decay curve analysis")
```

```
======================================================================
CTR DECAY CURVES BY CTR TIER (COHORT-BASED)
```

```
======================================================================
```




```
Figure saved to ../results/figures/rq2_ctr_curves_by_tier.png

CTR by Exposure for Each Category:
category  High CTR  Low CTR  Medium CTR
exposure
1           0.6372   0.4461      0.5394
2           0.5842   0.3955      0.4988
3           0.5747   0.3481      0.4482
4           0.5605   0.3534      0.4515
5           0.5482   0.3470      0.4706
6           0.5543   0.3330      0.4615
7           0.5421   0.3502      0.4507
8           0.5380   0.3384      0.4557
9           0.5190   0.3491      0.4209
10          0.5156   0.3179      0.4217
```

1.11 Step 7: Summary and Save Results

[21]:
```
print("=" * 70)
print("RESEARCH QUESTION 2: SUMMARY")
print("=" * 70)

print("""
QUESTION: Are some types of ads or placements more resistant to fatigue?

METHODOLOGY:
```

```
- Used cohort-based within-user analysis for each category
- Compared CTR at exposure 1 vs exposure 3 for the SAME users
- Calculated relative decline as the fatigue metric
- Lower decline = more resistant to fatigue

KEY FINDINGS:
""")

# CTR Tier Summary
if len(ctr_tier_fatigue) > 0:
    print("1. FATIGUE RESISTANCE BY CAMPAIGN CTR TIER:")
    for _, row in ctr_tier_fatigue.sort_values('relative_decline_pct').
 ↪iterrows():
        print(f"   - {row['category']}: {row['relative_decline_pct']:+.1f}%␣
 ↪decline (cohort: {row['cohort_size']:,})")

    print(f"\n     Most Resistant: {test_result['most_resistant']}")
    print(f"      Least Resistant: {test_result['least_resistant']}")
    print(f"   Difference: {test_result['decline_range']:.1f} percentage␣
 ↪points")

# Size Tier Summary
if 'size_tier_fatigue' in dir() and len(size_tier_fatigue) > 0:
    print("\n2. FATIGUE RESISTANCE BY CAMPAIGN SIZE:")
    for _, row in size_tier_fatigue.sort_values('relative_decline_pct').
 ↪iterrows():
        print(f"   - {row['category']}: {row['relative_decline_pct']:+.1f}%␣
 ↪decline")

# Time Summary
if 'time_fatigue' in dir() and len(time_fatigue) > 0:
    print("\n3. FATIGUE RESISTANCE BY TIME OF DAY:")
    for _, row in time_fatigue.sort_values('relative_decline_pct').iterrows():
        print(f"   - {row['category']}: {row['relative_decline_pct']:+.1f}%␣
 ↪decline")

print("""
CONCLUSIONS:

1. HIGH-PERFORMING CAMPAIGNS ARE MORE FATIGUE-RESISTANT
   - High CTR campaigns show smaller relative decline
   - This suggests quality/relevance provides some protection against fatigue

2. FATIGUE IS UNIVERSAL BUT VARIES IN MAGNITUDE
   - All categories show significant CTR decline with exposure
   - The difference between most and least resistant is meaningful
```

```
3. PRACTICAL IMPLICATIONS:
   - Apply stricter frequency caps to low-performing campaigns
   - High-performing campaigns can tolerate more exposures
   - Consider dynamic frequency management based on campaign performance
""")

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

ctr_tier_fatigue.to_csv('../results/tables/rq2_fatigue_by_ctr_tier.csv',␣
↪index=False)
print("\nSaved: ../results/tables/rq2_fatigue_by_ctr_tier.csv")

if 'size_tier_fatigue' in dir() and len(size_tier_fatigue) > 0:
    size_tier_fatigue.to_csv('../results/tables/rq2_fatigue_by_size.csv',␣
↪index=False)
    print("Saved: ../results/tables/rq2_fatigue_by_size.csv")

if 'time_fatigue' in dir() and len(time_fatigue) > 0:
    time_fatigue.to_csv('../results/tables/rq2_fatigue_by_time.csv',␣
↪index=False)
    print("Saved: ../results/tables/rq2_fatigue_by_time.csv")

if len(ctr_curves) > 0:
    ctr_curves.to_csv('../results/tables/rq2_ctr_curves_by_tier.csv',␣
↪index=False)
    print("Saved: ../results/tables/rq2_ctr_curves_by_tier.csv")

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

```
======================================================================
RESEARCH QUESTION 2: SUMMARY
======================================================================

QUESTION: Are some types of ads or placements more resistant to fatigue?

METHODOLOGY:
- Used cohort-based within-user analysis for each category
- Compared CTR at exposure 1 vs exposure 3 for the SAME users
- Calculated relative decline as the fatigue metric
- Lower decline = more resistant to fatigue

KEY FINDINGS:
```

```
1. FATIGUE RESISTANCE BY CAMPAIGN CTR TIER:
   - High CTR: +22.8% decline (cohort: 11,051)
   - Medium CTR: +30.2% decline (cohort: 10,816)
   - Low CTR: +35.6% decline (cohort: 9,853)

    Most Resistant: High CTR
     Least Resistant: Low CTR
   Difference: 12.8 percentage points

2. FATIGUE RESISTANCE BY CAMPAIGN SIZE:
   - Large: +25.1% decline
   - Medium: +28.8% decline
   - Small: +32.4% decline

3. FATIGUE RESISTANCE BY TIME OF DAY:
   - Morning (6-12): +29.3% decline
   - Night (0-6): +30.3% decline
   - Afternoon (12-18): +30.5% decline
   - Evening (18-24): +31.5% decline

CONCLUSIONS:

1. HIGH-PERFORMING CAMPAIGNS ARE MORE FATIGUE-RESISTANT
   - High CTR campaigns show smaller relative decline
   - This suggests quality/relevance provides some protection against fatigue

2. FATIGUE IS UNIVERSAL BUT VARIES IN MAGNITUDE
   - All categories show significant CTR decline with exposure
   - The difference between most and least resistant is meaningful

3. PRACTICAL IMPLICATIONS:
   - Apply stricter frequency caps to low-performing campaigns
   - High-performing campaigns can tolerate more exposures
   - Consider dynamic frequency management based on campaign performance


Saved: ../results/tables/rq2_fatigue_by_ctr_tier.csv
Saved: ../results/tables/rq2_fatigue_by_size.csv
Saved: ../results/tables/rq2_fatigue_by_time.csv
Saved: ../results/tables/rq2_ctr_curves_by_tier.csv

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

2 Summary of Findings: Fatigue Resistance Analysis

2.1 Dataset Overview

Metric	Value
Total impressions	500,000
Unique users	297,407
Unique campaigns	675

2.2 Research Question

Are some types of ads or placements more resistant to fatigue?

2.3 Methodology

For each category: 1. Find user-campaign pairs with 3+ exposures 2. Compare CTR at exposure 1 vs exposure 3 for the **same cohort** 3. Calculate relative decline as fatigue metric 4. Compare decline rates across categories

---

2.4 Key Findings

2.4.1 1. Fatigue Resistance by Campaign CTR Tier

CTR Tier	Cohort Size	CTR Exp 1	CTR Exp 3	Relative Decline	Ranking
High CTR	11,051	57.06%	44.03%	**22.8%**	Most Resistant
Medium CTR	10,816	49.73%	34.71%	**30.2%**	Moderate
Low CTR	9,853	41.06%	26.45%	**35.6%**	Least Resistant

Key Insight: High CTR campaigns show **12.8 percentage points less fatigue** than Low CTR campaigns.

2.4.2 2. Fatigue Resistance by Campaign Size

Size Tier	CTR Exp 1	CTR Exp 3	Relative Decline	Ranking
Large	49.22%	36.87%	**25.1%**	Most Resistant
Medium	49.74%	35.40%	**28.8%**	Moderate
Small	49.86%	33.69%	**32.4%**	Least Resistant

Key Insight: Larger campaigns show **7.3 percentage points less fatigue** than smaller campaigns.

2.4.3 3. Fatigue Resistance by Time of Day

Time of Day	CTR Exp 1	CTR Exp 3	Relative Decline	Ranking
Morning (6-12)	48.92%	34.60%	**29.3%**	Most Resistant
Night (0-6)	52.63%	36.67%	**30.3%**	—
Afternoon (12-18)	51.18%	35.59%	**30.5%**	—
Evening (18-24)	52.03%	35.63%	**31.5%**	Least Resistant

Key Insight: Time of day differences are smaller (~2.2pp) compared to CTR tier differences (~12.8pp).

2.4.4 4. CTR Decay Curves Over 10 Exposures

Exposure	High CTR	Medium CTR	Low CTR
1	63.72%	53.94%	44.61%
2	58.42%	49.88%	39.55%
3	57.47%	44.82%	34.81%
5	54.82%	47.06%	34.70%
10	51.56%	42.17%	31.79%

Overall Decline (Exp 1→10): - High CTR: 63.72% → 51.56% = **-19.1%** relative decline - Medium CTR: 53.94% → 42.17% = **-21.8%** relative decline - Low CTR: 44.61% → 31.79% = **-28.7%** relative decline

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2.5 Conclusions

2.5.1 Answer to Research Question

> **Yes, some types of ads are more resistant to fatigue.**

Dimension	Most Resistant	Least Resistant	Difference
CTR Tier	High CTR (22.8%)	Low CTR (35.6%)	**12.8 pp**
Campaign Size	Large (25.1%)	Small (32.4%)	**7.3 pp**
Time of Day	Morning (29.3%)	Evening (31.5%)	**2.2 pp**

2.5.2 Why Some Campaigns Are More Resistant

1. **High CTR campaigns** = more relevant/engaging content → users tolerate more exposures
2. **Large campaigns** = likely have better creative resources and optimization
3. **Morning ads** = users may be more focused/receptive early in the day

2.5.3 Business Recommendations

Campaign Type	Recommended Frequency Cap	Reasoning
High CTR + Large	**6-8 impressions**	Highest resistance to fatigue
Medium CTR	**4-5 impressions**	Moderate tolerance
Low CTR + Small	**2-3 impressions**	Fatigue sets in rapidly

2.5.4 Practical Implications

1. **Dynamic Frequency Capping**
   - High CTR campaigns: Cap at 6-8 impressions
   - Low CTR campaigns: Cap at 2-3 impressions
2. **Campaign Optimization Priority**
   - Focus optimization efforts on low-performing campaigns first
   - Improving CTR may also improve fatigue resistance
3. **Resource Allocation**
   - High-performing campaigns can run longer with same creative
   - Low-performing campaigns need more frequent creative refresh