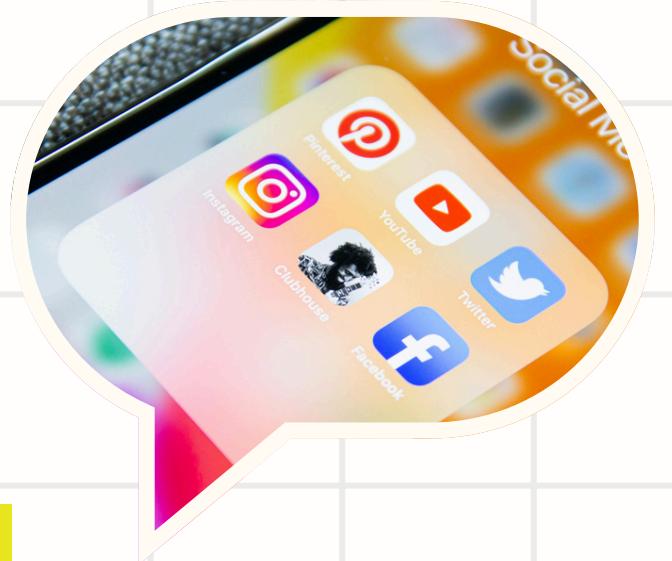




Analysis & Prediction of Online Ad Click Behavior



Problem & Objectives

! Problem

Companies must understand the **key factors that influence the effectiveness of online advertising** in order to **improve click-through rates** and **optimize digital marketing strategies** based on user demographics and behavioral patterns.

Goal

Develop and implement a **machine learning model** to **predict click probability** in online advertising with a **minimum precision of 90%**, aiming to increase campaign **CTR from 50% to 65%** (a 30% improvement) and **reduce CPC by 20%** within a **three-month period** from January to March 2025.

Objectives

- Analyze the **impact of demographic variables** and **online behavior** on **ad responsiveness**.
- Develop a **high-performance classification model** to **predict 'Clicked on Ad'** outcomes.

Success Metrics

+30%

Click Through Rate (CTR)

More users are clicking on ads after optimization

-20%

Cost per Click (CPC)

Lower cost per click through improved targeting

Dataset Overview

Dataset Summary

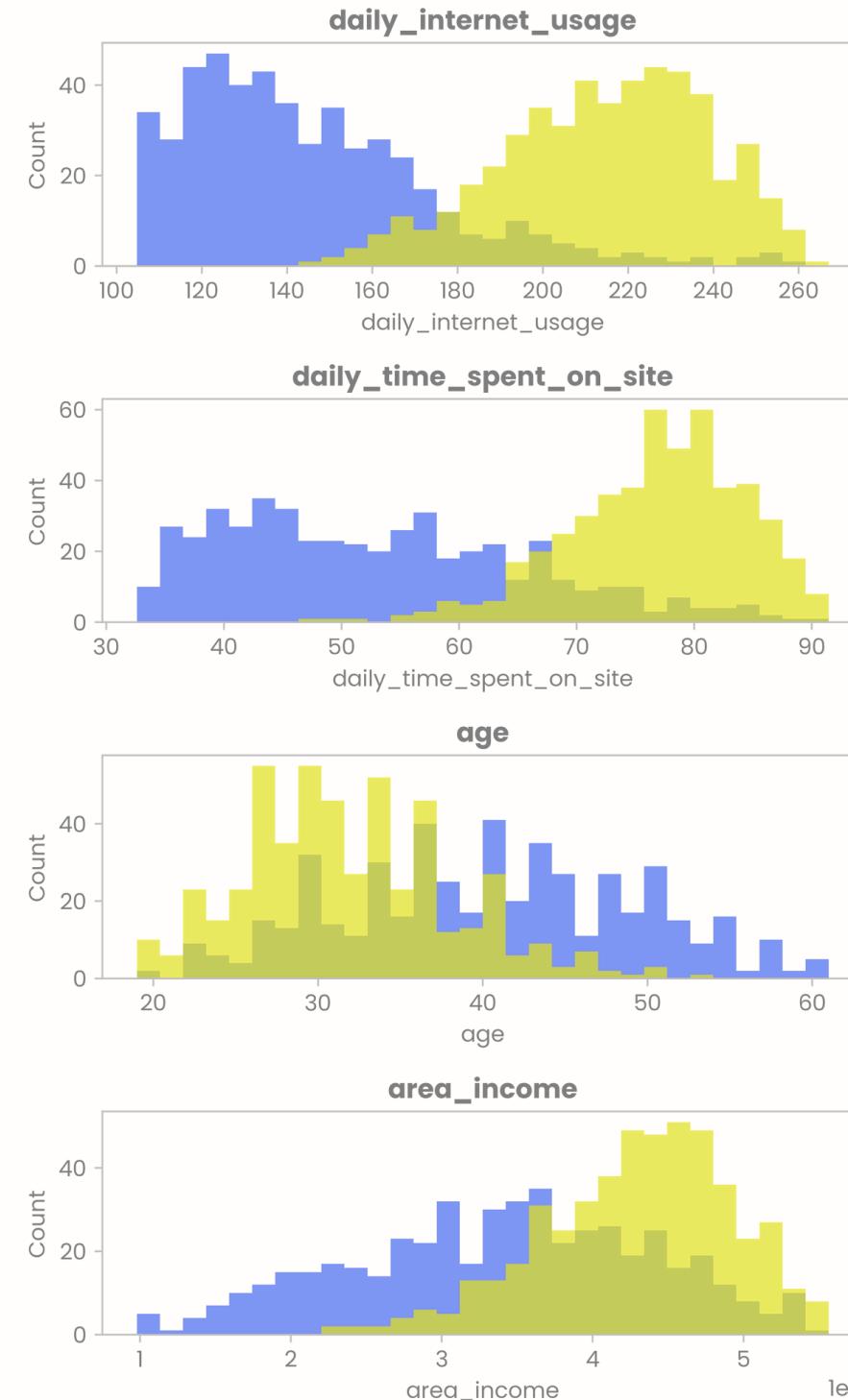
- Total Records: 1,000 rows
- Total Features: 16 columns
- Data Period: January 1 – July 24, 2016

Features

- Daily Time Spent on Site (minutes)
- Age (years)
- Daily Internet Usage (minutes)
- Gender (Male)
- Location (City, Province)
- Product Category
- Clicked on Ad (Yes / No)
- Timestamp (interaction time)
- Area Income (average income in user's area)

 [Source Data](#)

Profiling Ad Click Behavior



Non-Clickers



Daily internet usage
216 minutes



Daily time spent on site
77.5 minutes

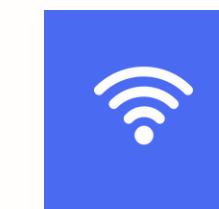


Age
31 years old

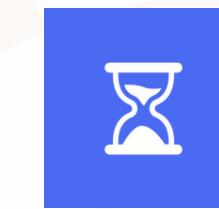


Area income
435 million

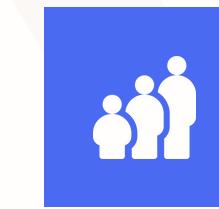
Ad Clickers



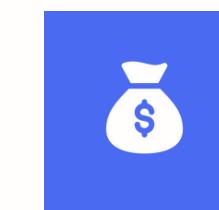
Daily internet usage
139 minutes



Daily time spent on site
51.6 minutes



Age
40 years old

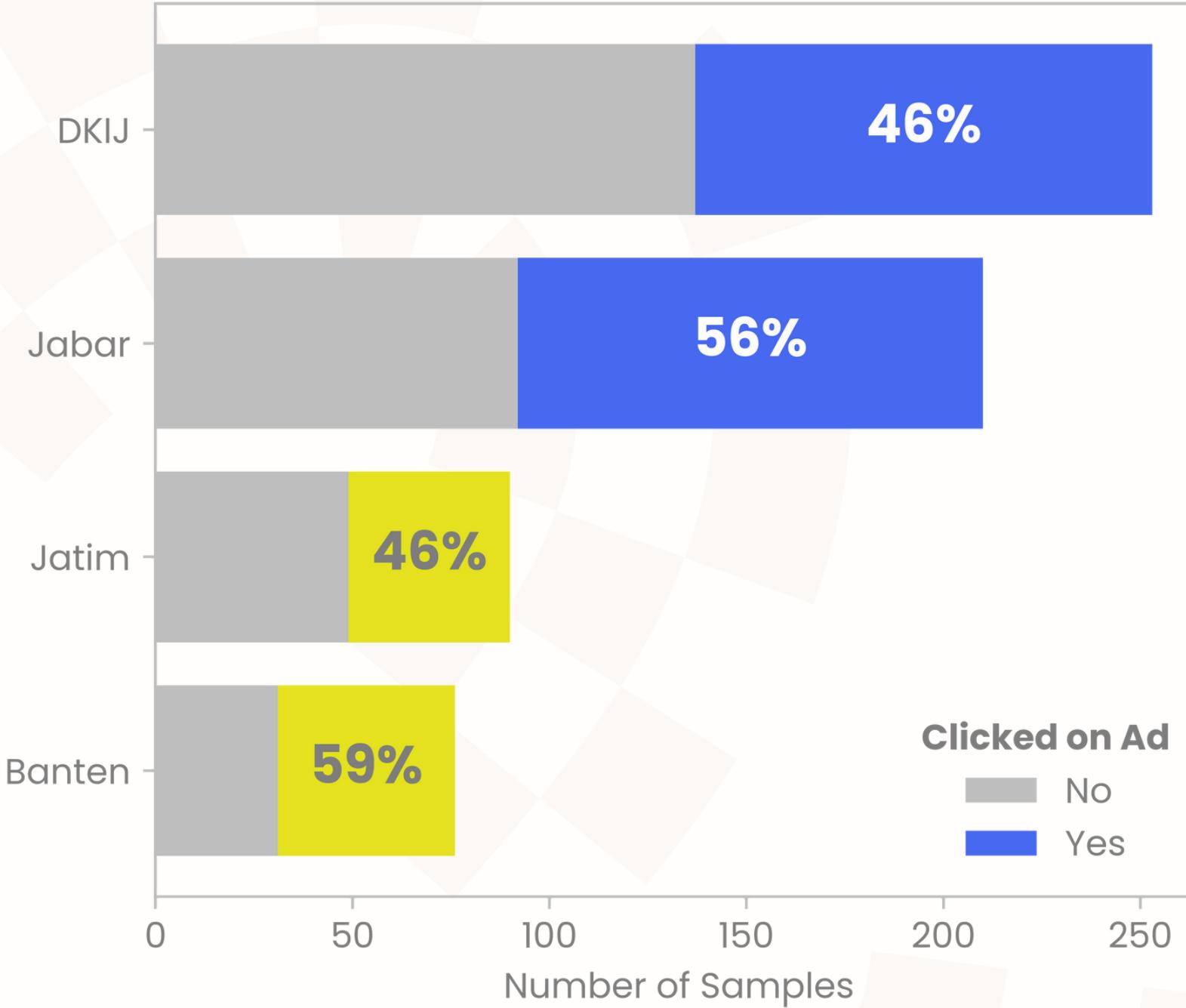


Area income
347 million



Budget Allocation Optimization

CTR by Province



The chart highlights the top **4 provinces** with the **largest audiences**. **West Java** and **Jakarta** stand out with high volume and strong CTR, making them the main focus. **East Java** shows growth potential, while **Banten** is experimental with the highest CTR despite low volume.

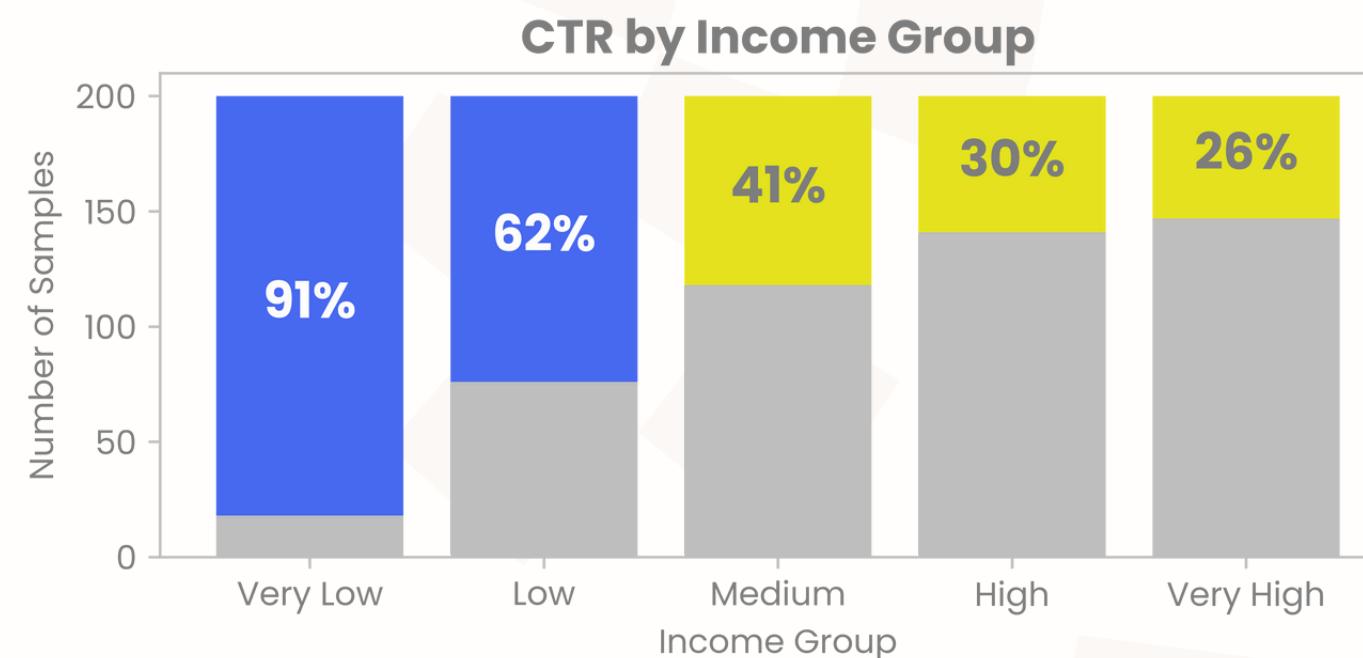
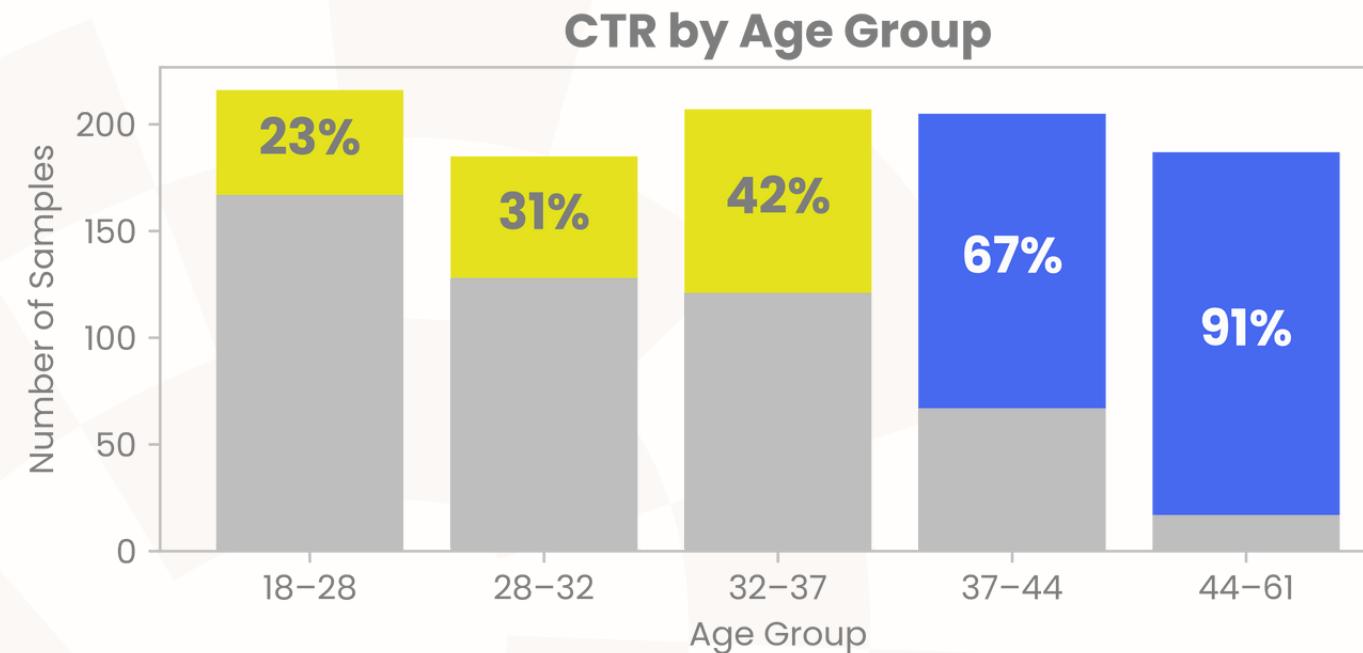
 **Actionable Item**

 **Primary Focus**

- **Jawa Barat & DKI Jakarta**

High-volume, high-performing channels. Core investment goes here to maintain consistent results and drive reliable ROI.

Audience Targeting Adjustments



CTR is significantly **higher** among **older audiences** and **lower-income groups**, while younger audiences and higher-income segments underperform and present room for improvement. These patterns show that both age and income are **strongly linked to CTR**, making them key factors to focus on for adjustments.

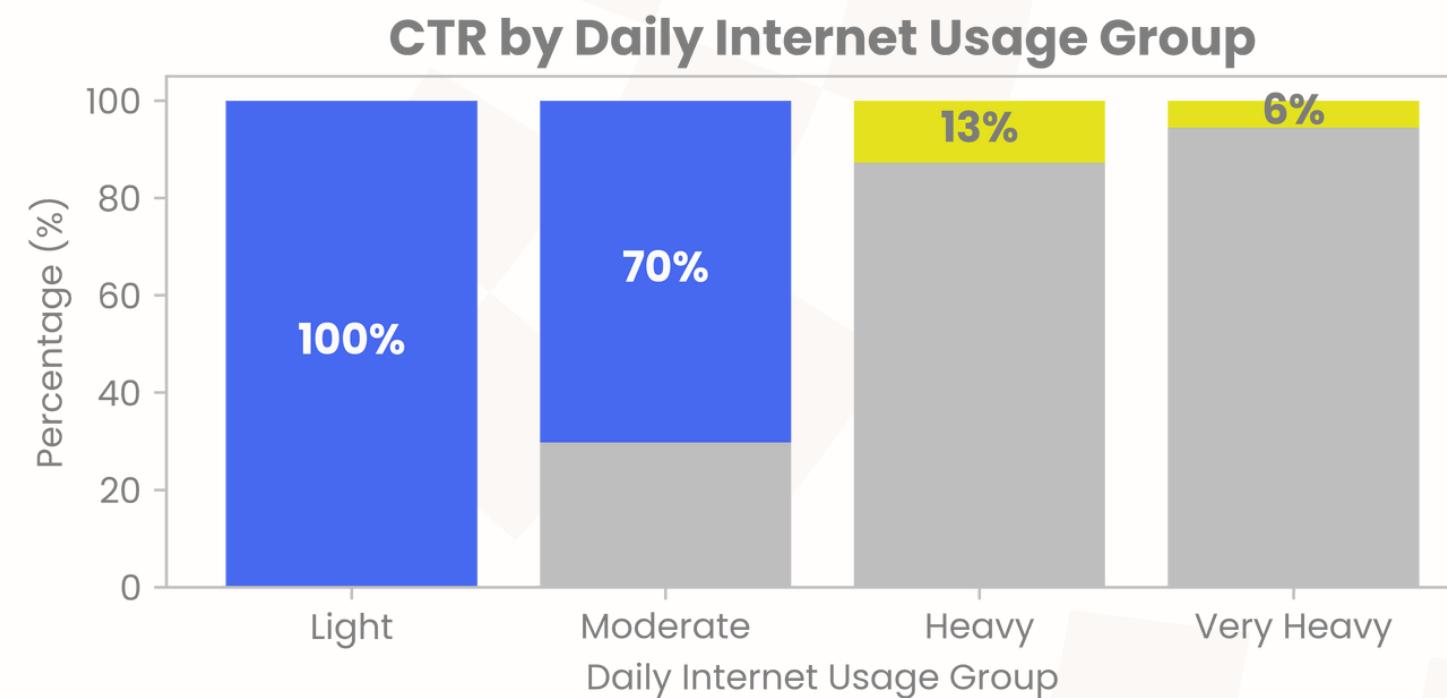
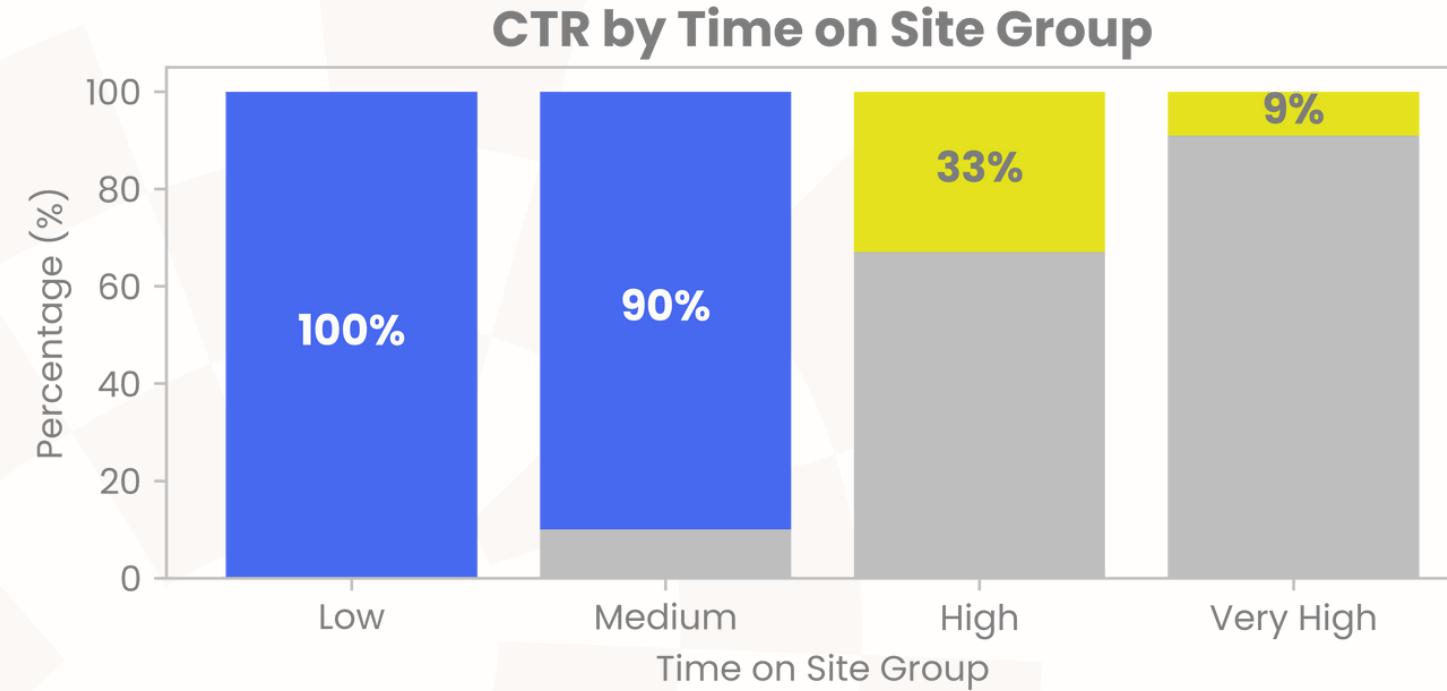
 **Actionable Item**

 **Maintain & Optimize**

- **Age 46-55**
- **Age 36-45**
- **Low income segment**
- **Low-medium income**

Strategy: Maintain momentum with emotional messaging, practical benefits, and relatable testimonials.

Behavioral Insights & Action Plan



The charts show that **fast site visitors** and **light internet users** deliver the **highest CTR** (up to 100%), indicating strong intent and quick decision-making. In contrast, **CTR drops sharply** among **heavy users** and **long-time visitors**, suggesting they require nurturing strategies instead of direct conversion pushes.

 **Actionable Item**

 **Target High-Intent Segments**

Prioritize light internet users and fast site visitors. These users show clear purchase intent and deliver 100% conversion.

Data Preprocessing



Dataset Splitting

- **70%** training
- **30%** testing
- **Stratified by target** variable to preserve class distribution

Missing Values Handling

- **Numerical** columns filled with **median** values from training set
- **Categorical** columns filled with **mode** values from training set

Outliers Handling

- Applied **IQR clipping** to **numerical** features
- Outliers outside were **clipped**

Features Encoding

- **Frequency Encoding:** city, province, category
- **Ordinal Encoding:** age_group
- **One-Hot Encoding:** day_of_week

Data Preprocessing

O Feature Scaling

- Applied **StandardScaler** to all numerical features

O Feature Extraction

- time_usage_ratio
- age_group
- hour
- day_of_week

O Feature Selection

- Dropped features with high VIF
- Applied Logistic Regression with **L1 regularization** to select the most predictive features

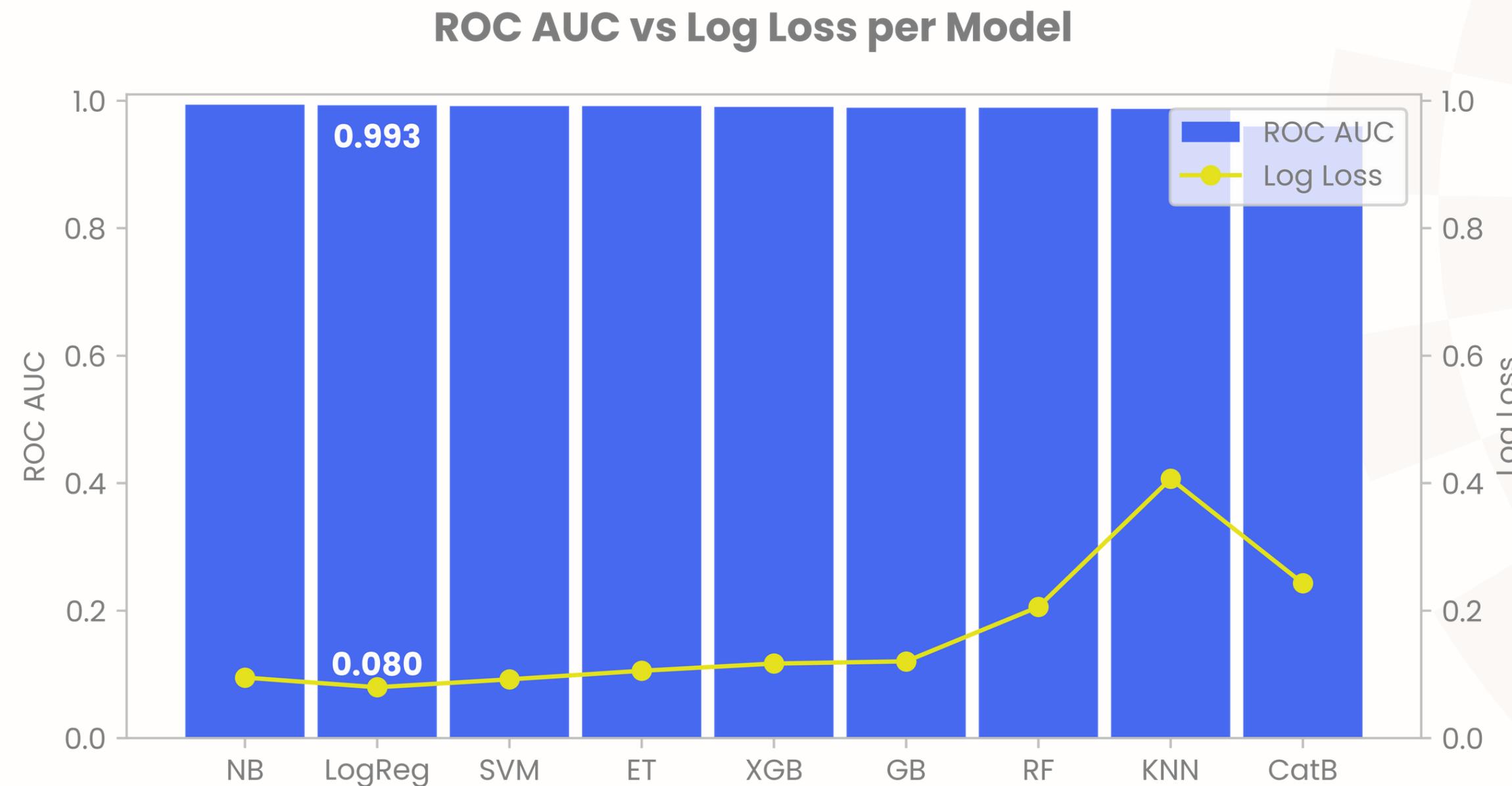
Selected Features

- daily_time_spent_on_site
- age
- area_income
- time_usage_ratio





Baseline Models

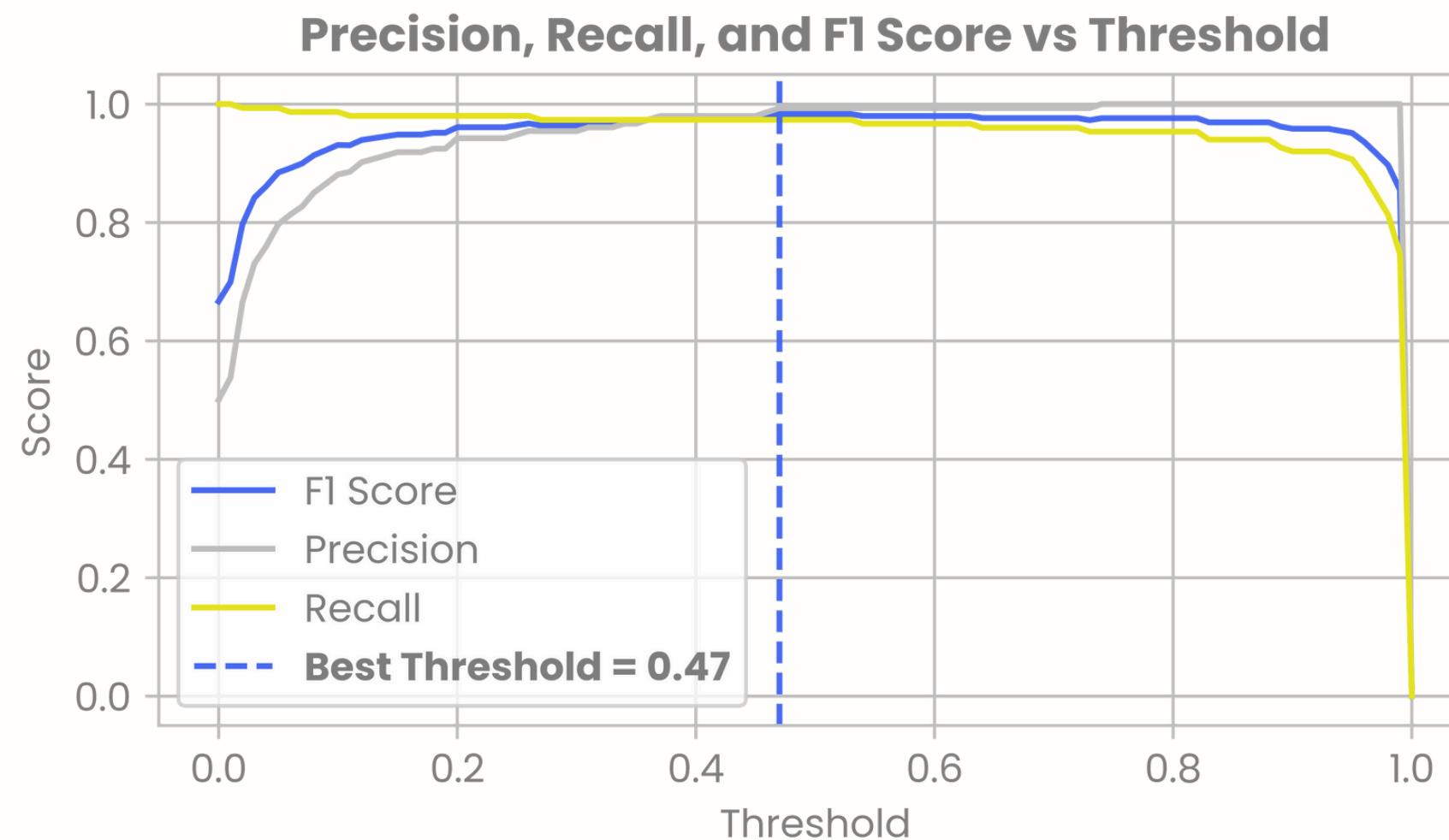


Best Model Selection

Logistic Regression emerged as the top model from nine algorithms, combining **high precision** with **strong interpretability**. Using just 4 features, it delivers precise predictions with efficient performance.

- Precision: **99.32%**
- AUC: **99.29%**
- F1 Score: **98.32%**
- Log loss: **0.079**

Model Optimization



⚙️ Hyperparameter Tuning

- **GridSearchCV + Stratified K-Fold** (5 splits)
- Best Parameters:
 - C: 1
 - penalty: 'l2'
 - solver: 'liblinear'
 - max_iter: 500
- Best AUC (Train): **0.9907**

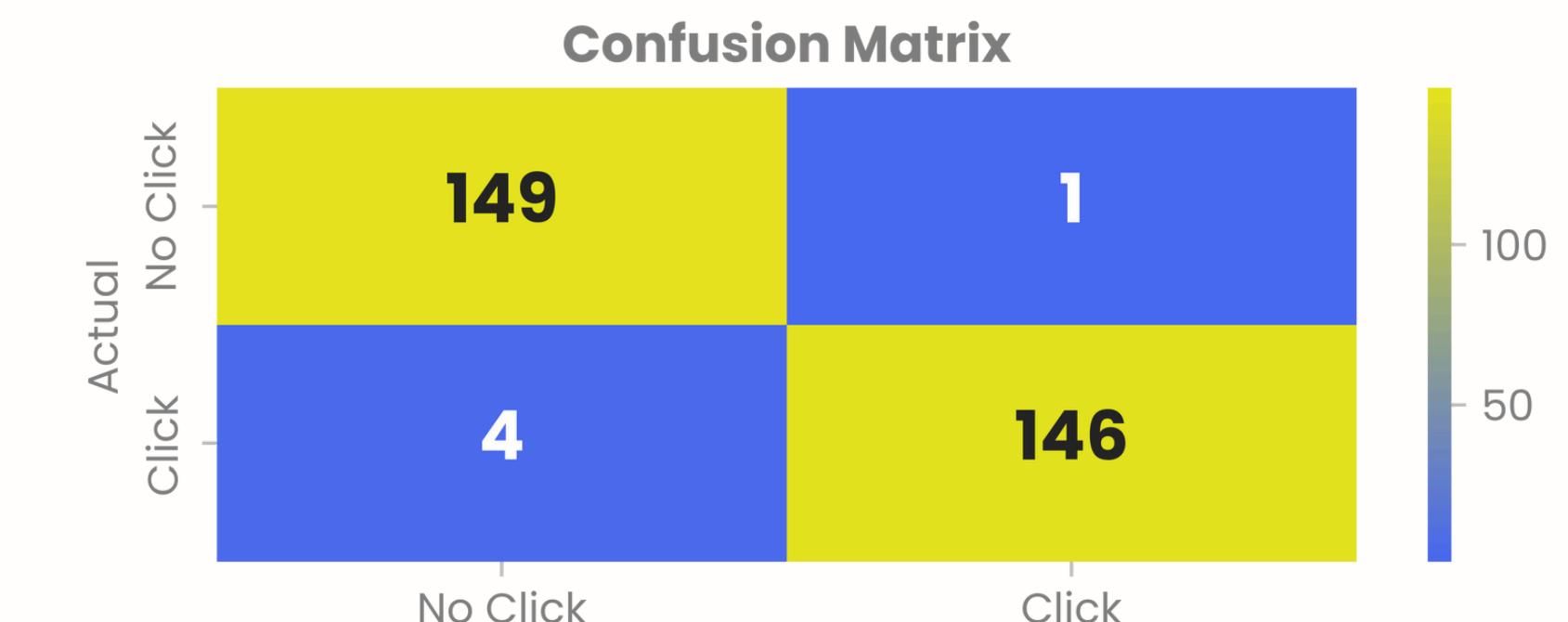
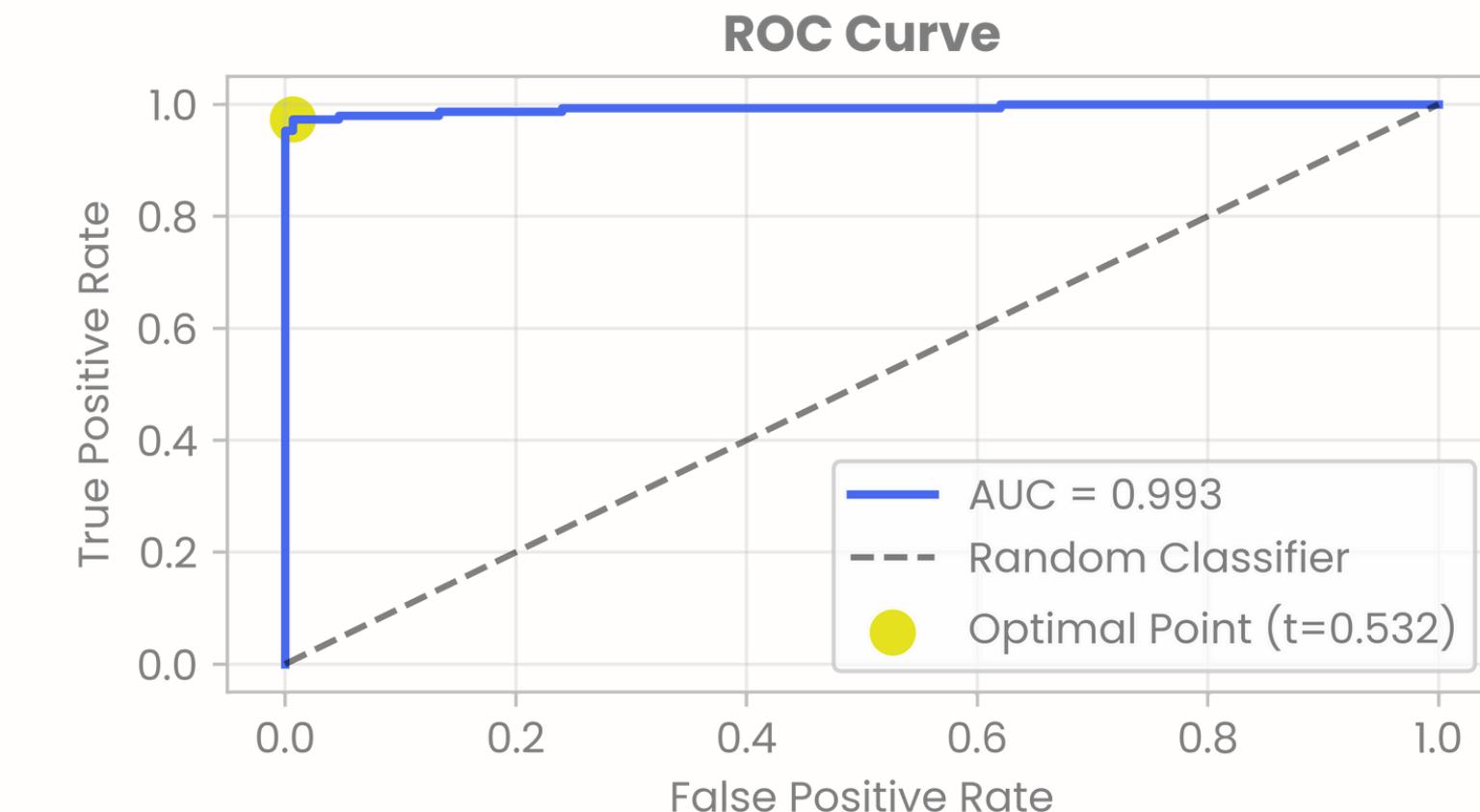
❖ Threshold Tuning

- Optimal Threshold: **0.47**
- Performance Metrics:
 - F1 Score: **0.9832**
 - Precision: **0.9931**
 - Recall: **0.9733**
 - AUC (Test): **0.9929**

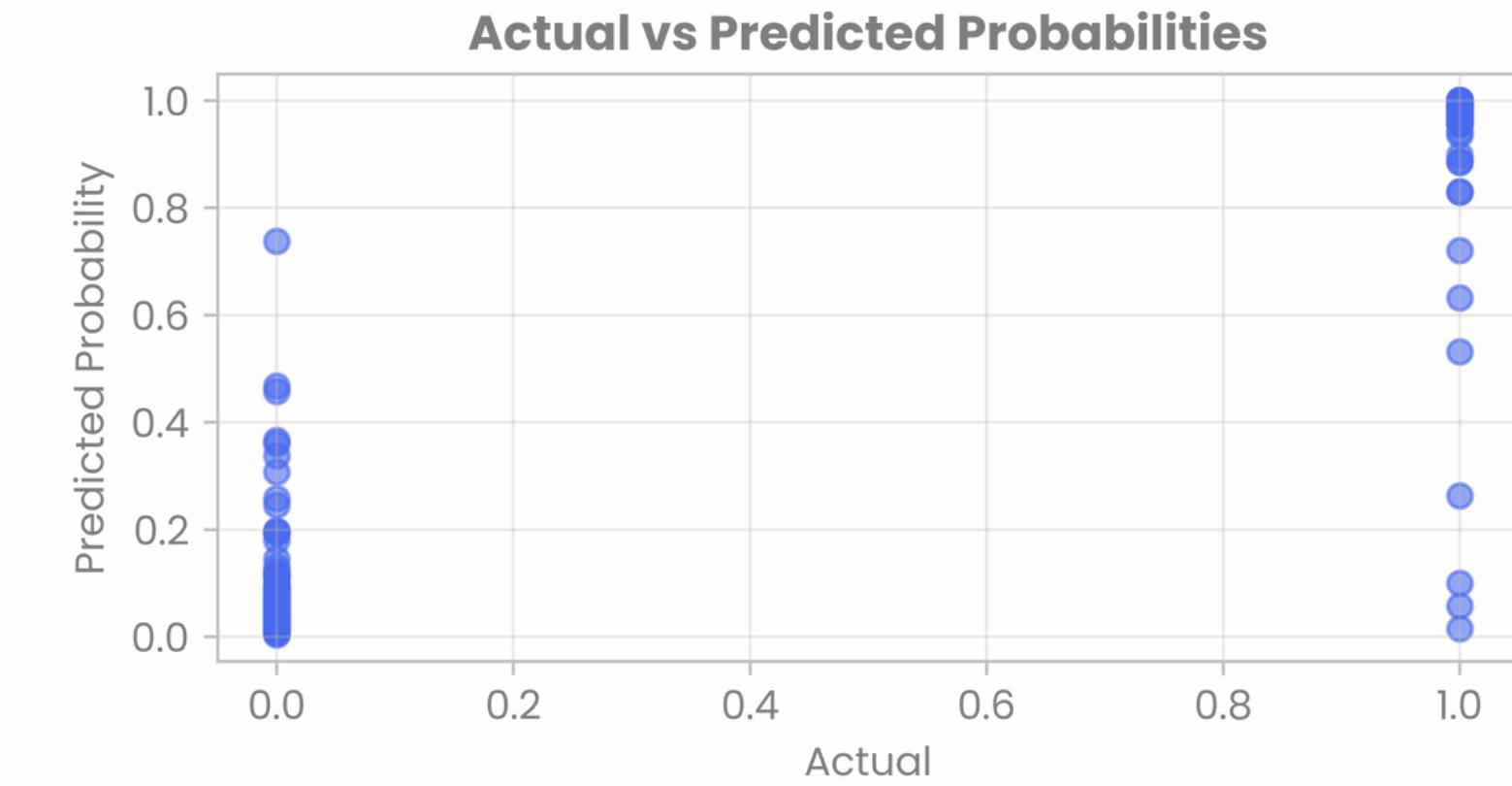
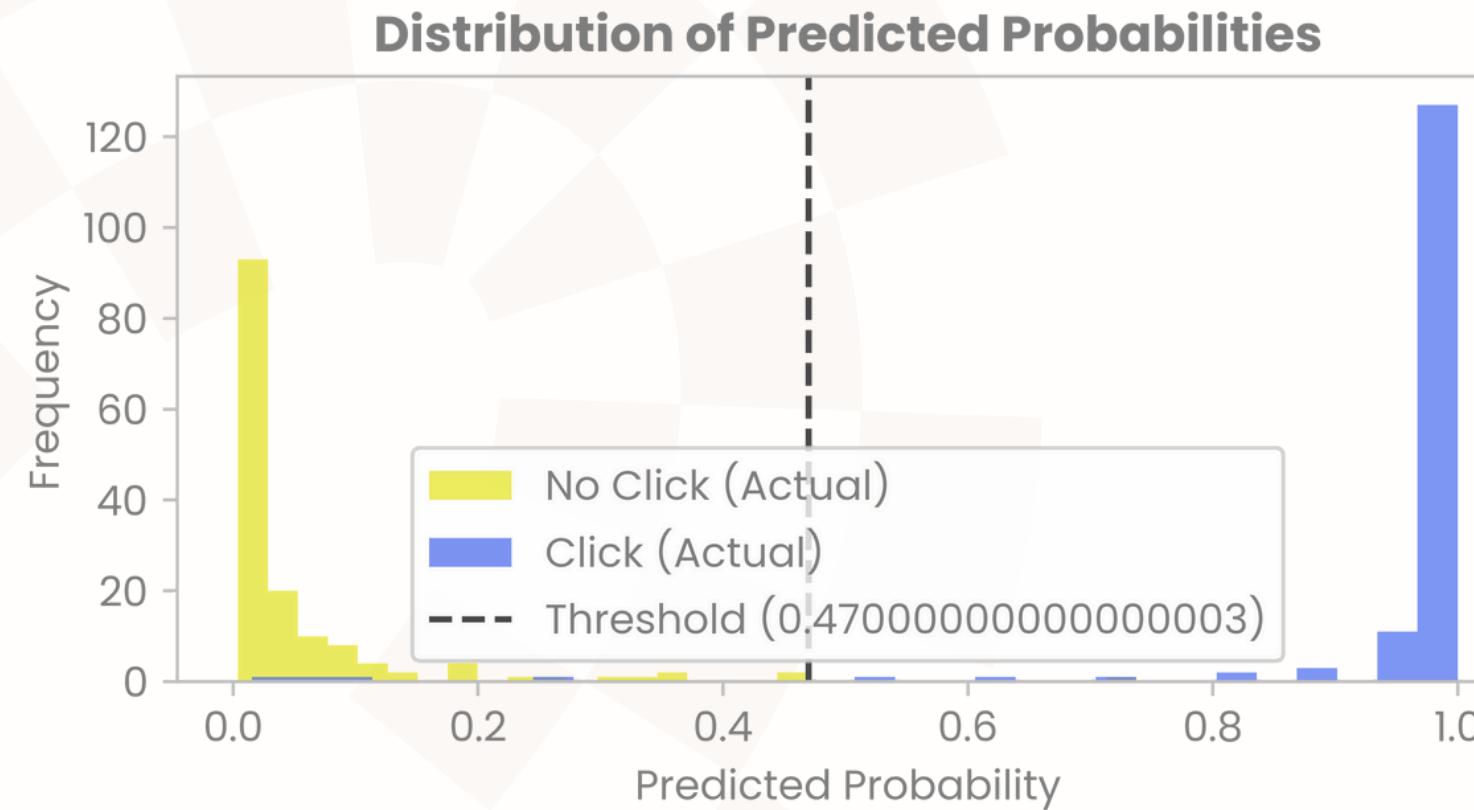
Model Evaluation

- Precision: 0.9932
- Recall: 0.9733
- F1-Score: 0.9832
- AUC-ROC: 0.9929

The classification model shows outstanding performance with **near-perfect metrics**. The ROC curve confirms **strong discriminative power**, and only **5 out of 300 test samples were misclassified**. With high accuracy and minimal error, the model is ready for production.



Prediction Distribution



The model **shows strong performance in predicting user clicks, clearly separating the two classes with high accuracy.** "No Click" cases are mostly near 0, while "Click" cases are near 1, demonstrating strong discriminative power. The scatter plot confirms this with two distinct clusters and minimal outliers, indicating a reliable classifier.

Model Stability

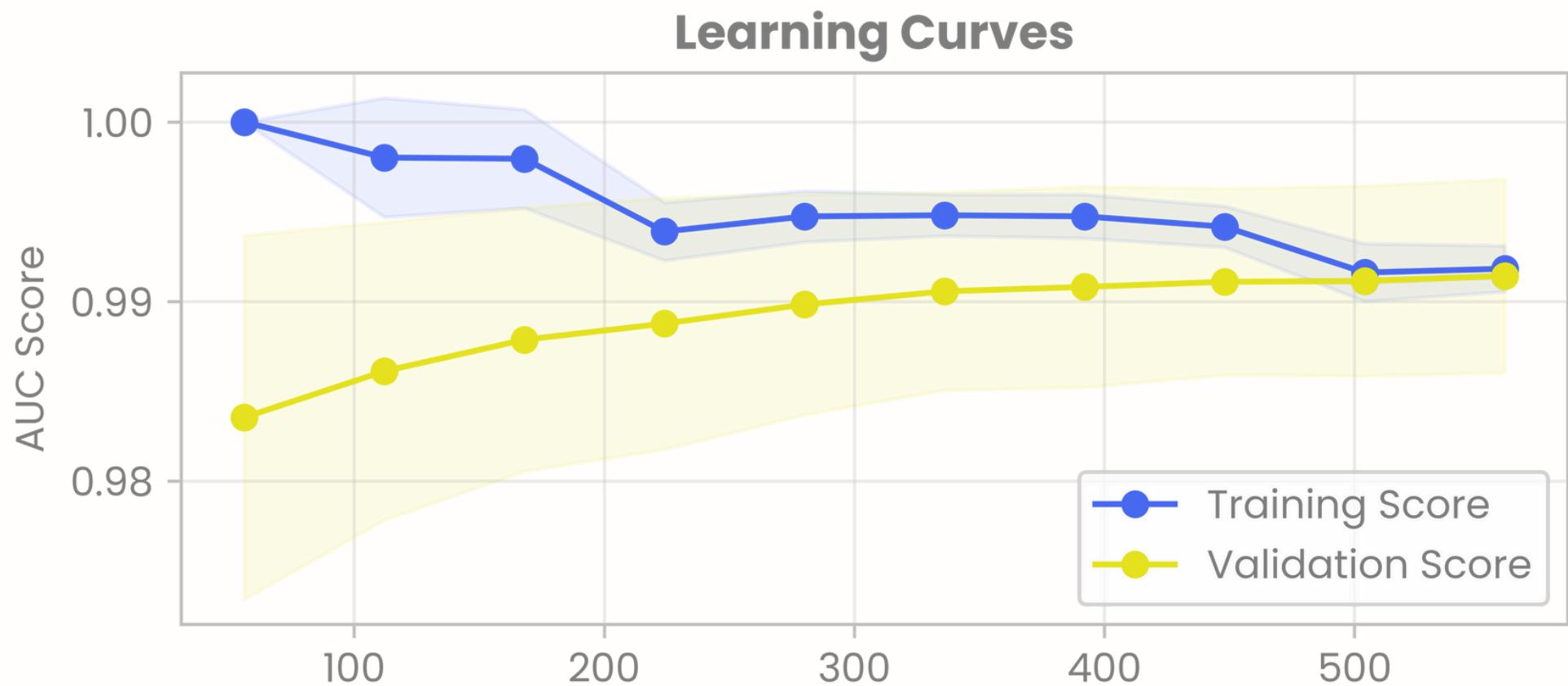
 Cross-Validation (5-Fold Stratified)

* ROC-AUC: 0.9909 ± 0.0058 | Gap: 0.0006

* F1-Score: 0.9511 ± 0.0165 | Gap: 0.0074

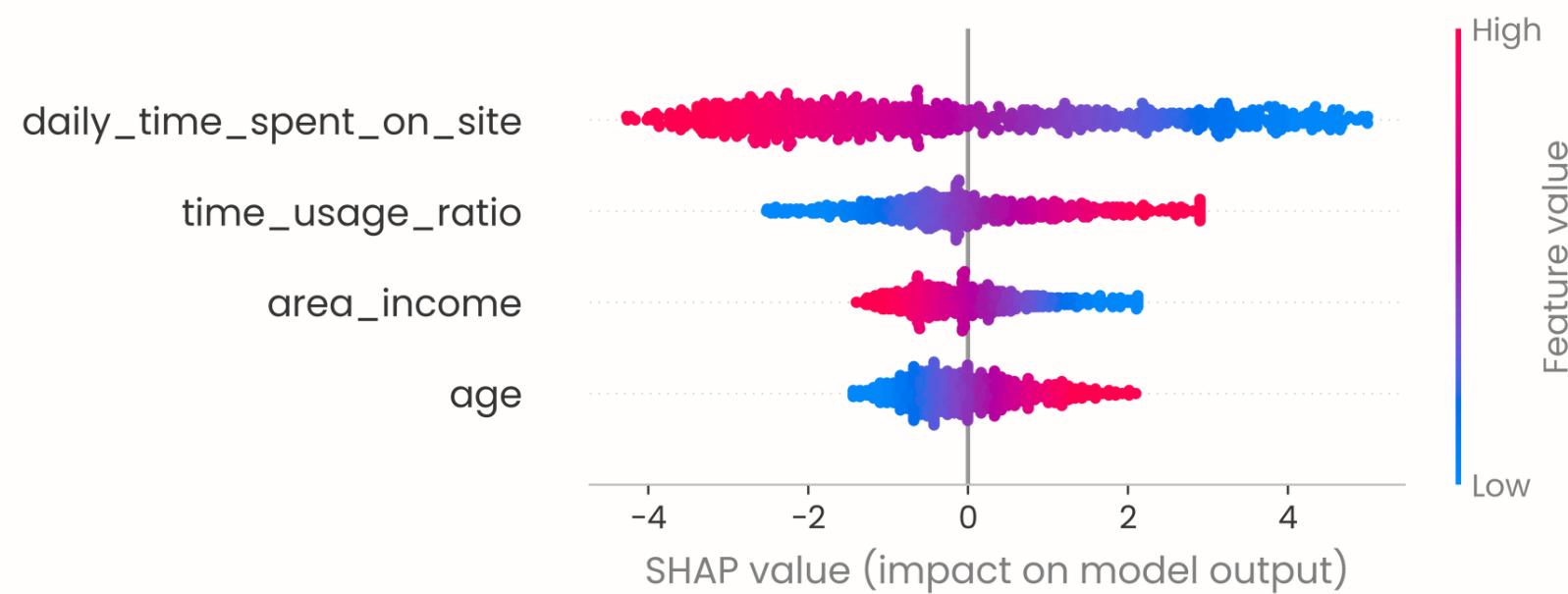
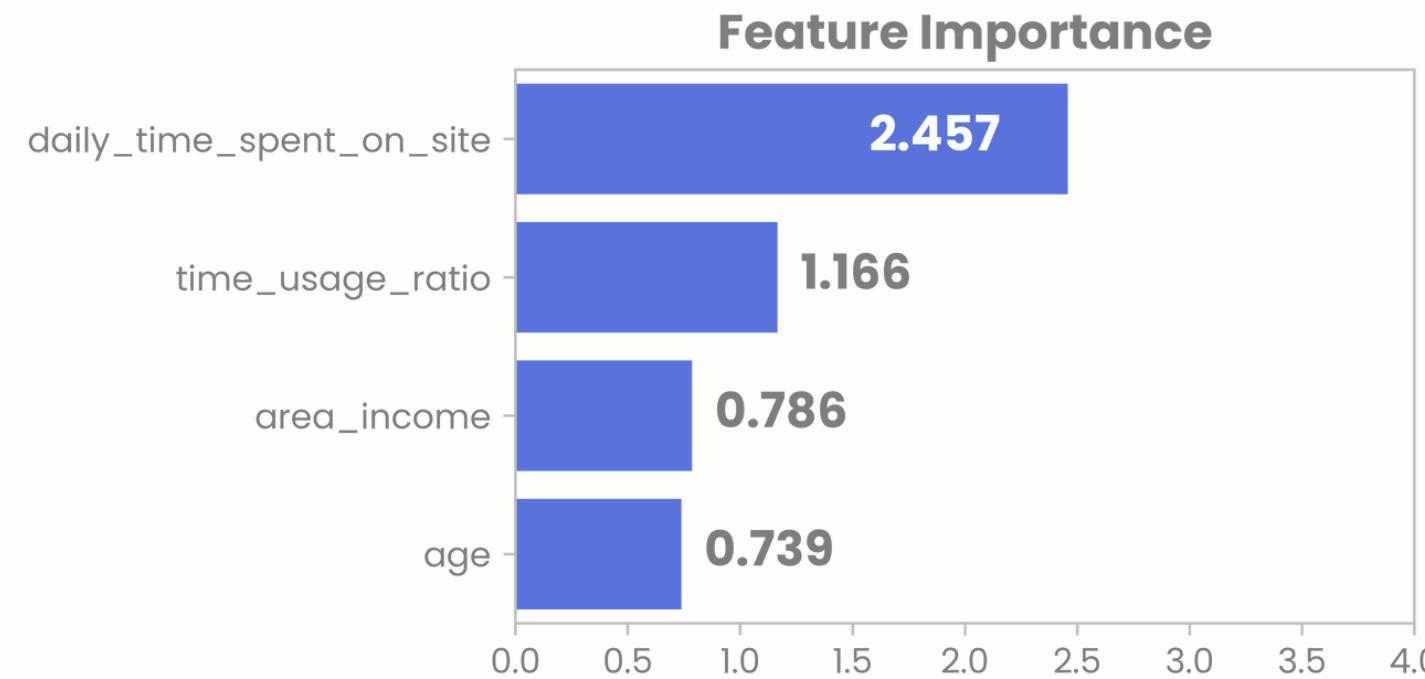
* Precision: 0.9794 ± 0.0115 | Gap: 0.0055

* Recall: 0.9257 ± 0.0398 | Gap: 0.0079



The learning curves show **strong model stability**, with **training and validation scores converging consistently** across dataset sizes. No signs of overfitting are observed, training remains at ~0.99 while validation steadily improves to 0.989 with minimal gap. Cross-validation confirms **excellent generalization**, with **low variance and small training-validation gaps** (0.06%–0.79%).

Feature Importance



⭐ Top Influential Features

- Daily Time Spent on Site
- Time Usage Ratio
- Area Income
- Age

These features align with our previous analysis, confirming that targeting based on online behavior, income, and age is the most effective strategy.

💡 Business Strategic

Targeting high-engagement users from higher-income areas is likely to deliver higher ad click-through rates and better campaign efficiency

Strategic Campaign Summary



Geographic Targeting

- **Primary Focus:** West Java & Jakarta (High volume & strong performance)
- **Experimental Area:** Banten (Highest CTR despite low volume)



Behavioral Intent Signals

- **High-Intent Users:** Short site visits & light internet usage (CTR near 100%)
- **Heavy Users:** Apply nurturing strategy (e.g., retargeting with tailored messaging)



Demographic Prioritization

- **Age Group:** 36–55+ years (Highest CTR)
- **Income Level:** Low to lower-middle (Highest click conversion)



Creative Messaging Strategy

- Use **emotional appeal**
- Highlight **practical benefits**
- Include **relevant testimonials**



Recommendation

Conduct a 1–2 week **A/B test** comparing **current targeting methods (Control Group)** vs. **model-driven targeting (Experiment Group)** to validate these projections in real-world conditions.

Business Impact Simulation

■ Simulation Parameters

- Ad budget per user: **IDR 10,000**
- Simulation dataset: **1,000 users (500 per class)**
- Revenue per conversion: **IDR 12,000**
- Baseline conversion rate: **50%**

■ Traditional Approach

Metric	Value
Target Users	1,000 users (all)
Ad Spend	IDR 10,000,000
Click-Through Rate	50% (500 users)
Revenue from Clicks	IDR 7,500,000
Net Profit/Loss	-IDR 2,500,000

IDR 4,635,000

From 2.5M loss to 2.135M profit

 **Improvement**

■ ML-Powered Targeting

Metric	Value
Target Users	487 users (predicted positive)
Ad Spend	IDR 4,870,000
Click-Through Rate	95.89% (467 users)
Revenue from Clicks	IDR 7,005,000
Net Profit/Loss	+IDR 2,135,000

Business Impact

99.32%

Click Through Rate (CTR)

Based on model precision of 99.32%, indicating nearly all predicted users are likely to click

-49.6%

Cost per Click (CPC)

Estimated from reduced impressions needed per click, leading to lower cost per acquisition

Executive Summary

This project enhances digital ad campaign performance by **predicting user click behavior** using **machine learning**. The goal is to **boost Click-Through Rate (CTR)** from 50% to 65% and **cut Cost Per Click (CPC)** by 20%.

Analyzing **1,000 user interactions**, **Logistic Regression** was chosen for its accuracy and interpretability, then fine-tuned for optimal results. Key insights show the **most responsive audience** is **aged 37–61**, with **low to middle income**, **short website visits**, and **light internet usage**. **West Java** and **Jakarta** stand out as high-potential regions.

The model achieved **98.33% accuracy**, **99.32% precision**, and **99.34% AUC**, with only **5 misclassifications** out of 300 test records. It's projected to raise **CTR to 99.32% (+98.6%)** and **reduce CPC by 49.6%**, far surpassing initial targets.

To validate these projections, a **1–2 week A/B testing** phase is recommended before full-scale implementation.