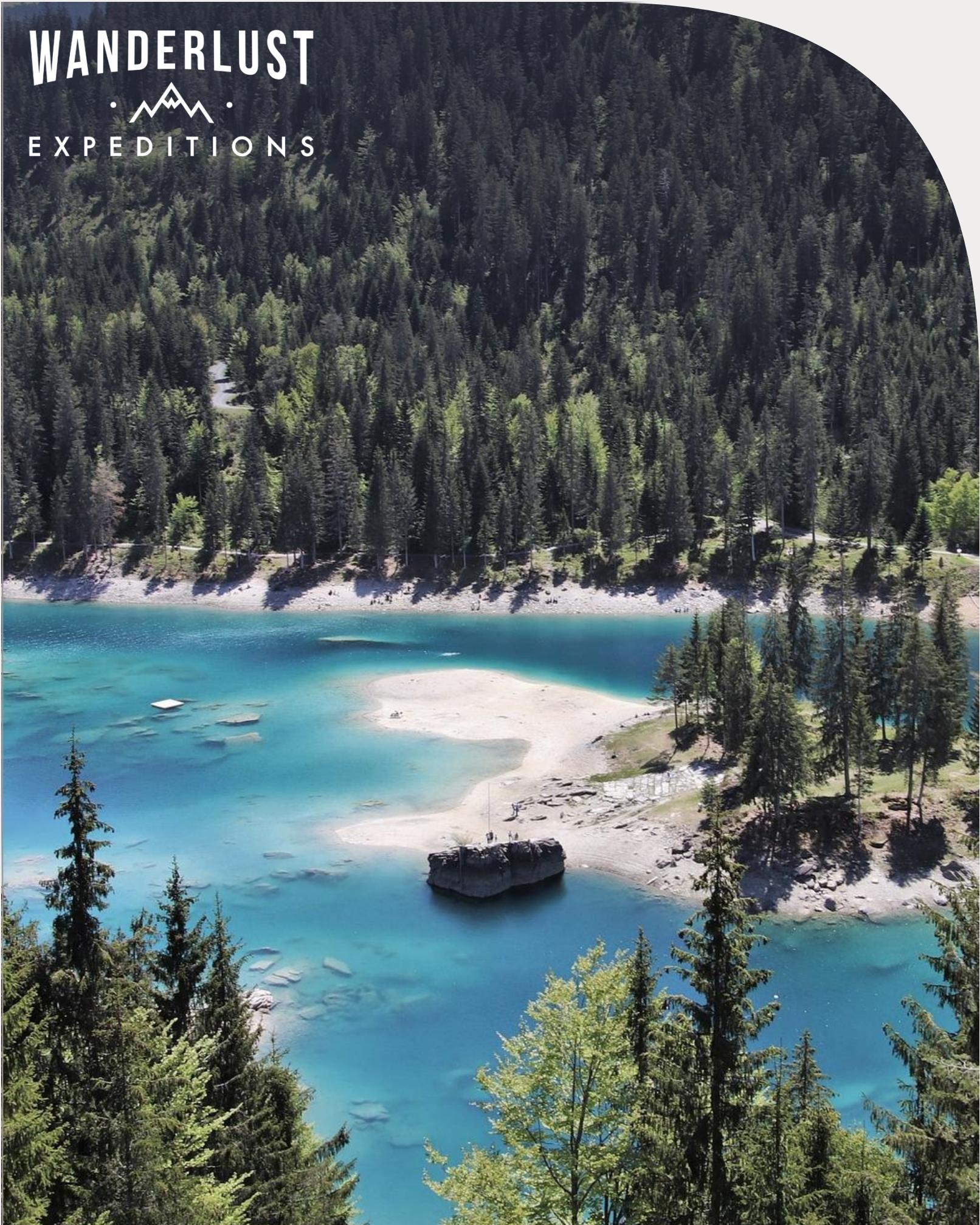




Decoding the Explorer

Cracking the Ad Click Code for Wanderlust Expeditions.
Unveiling the Generational Gap in Adventure Travel
Engagement





A Story ...

At Wanderlust Expeditions, we curate unforgettable travel experiences for adventurous souls. We've launched our "Off-the-Beaten-Path" campaign, targeting millennial and Gen Z travelers, but we've encountered an unexpected challenge. While we anticipated strong engagement from younger explorers, our data reveals -

- that older travelers are clicking on our ads more frequently. This generational divide in ad response is crucial to understand. We know that in today's digital age, the average human attention span is shrinking, as evidenced by a Microsoft study.

(Source: [Microsoft, 'Attention Spans,' 2015](#))

A Question

How do we **capture** the attention of our desired demographic amidst the noise and inspire them to explore?

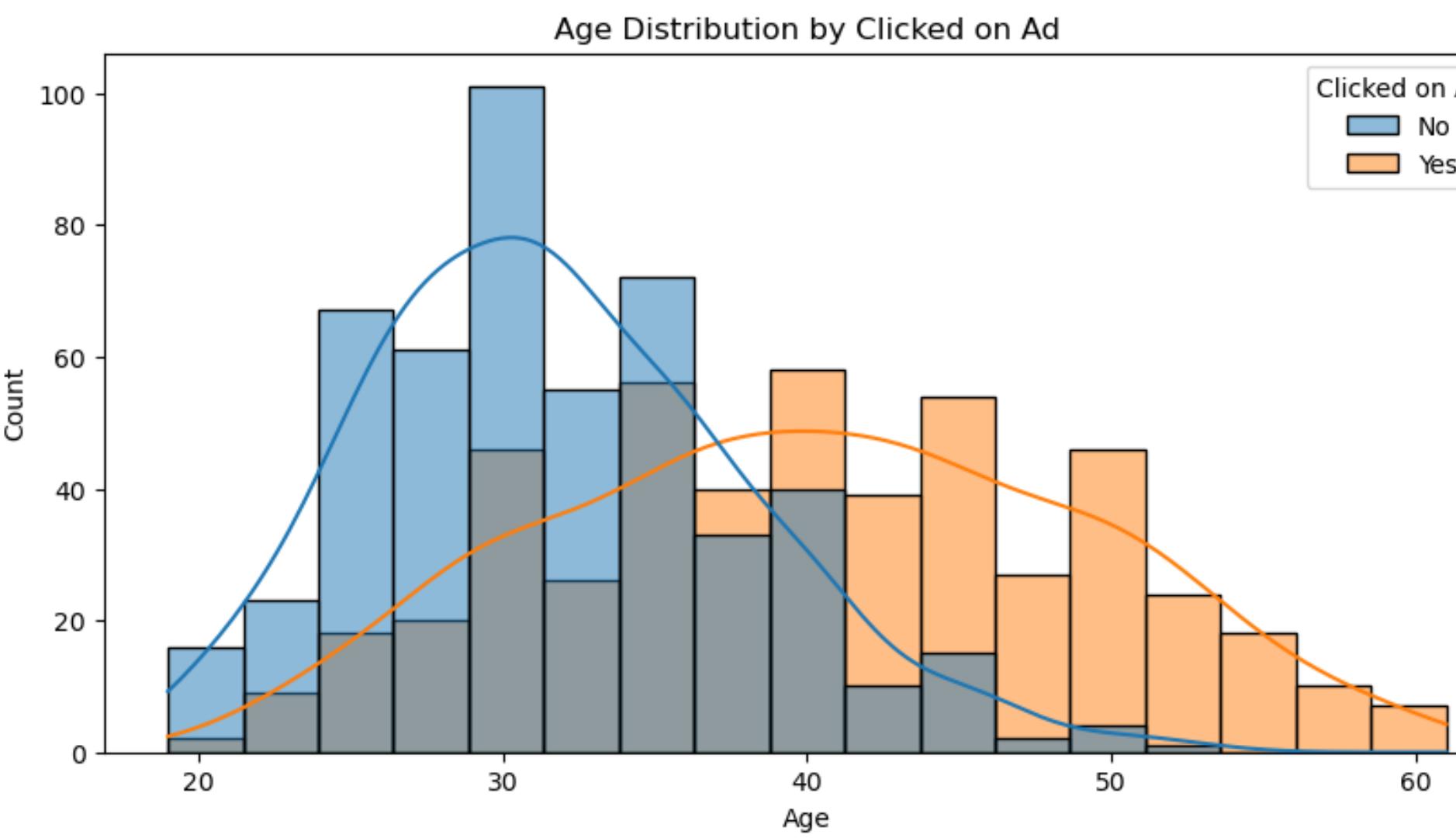
Mapping the Traveler's Journey

We've collected data on traveler age, online behavior, site engagement, and ad clicks.

Our goal: to map the traveler's journey and understand what drives their engagement.



The Experienced Adventurers?



A Surprising Trend !

We discovered a surprising trend: older travelers are more likely to click on our adventure ads.

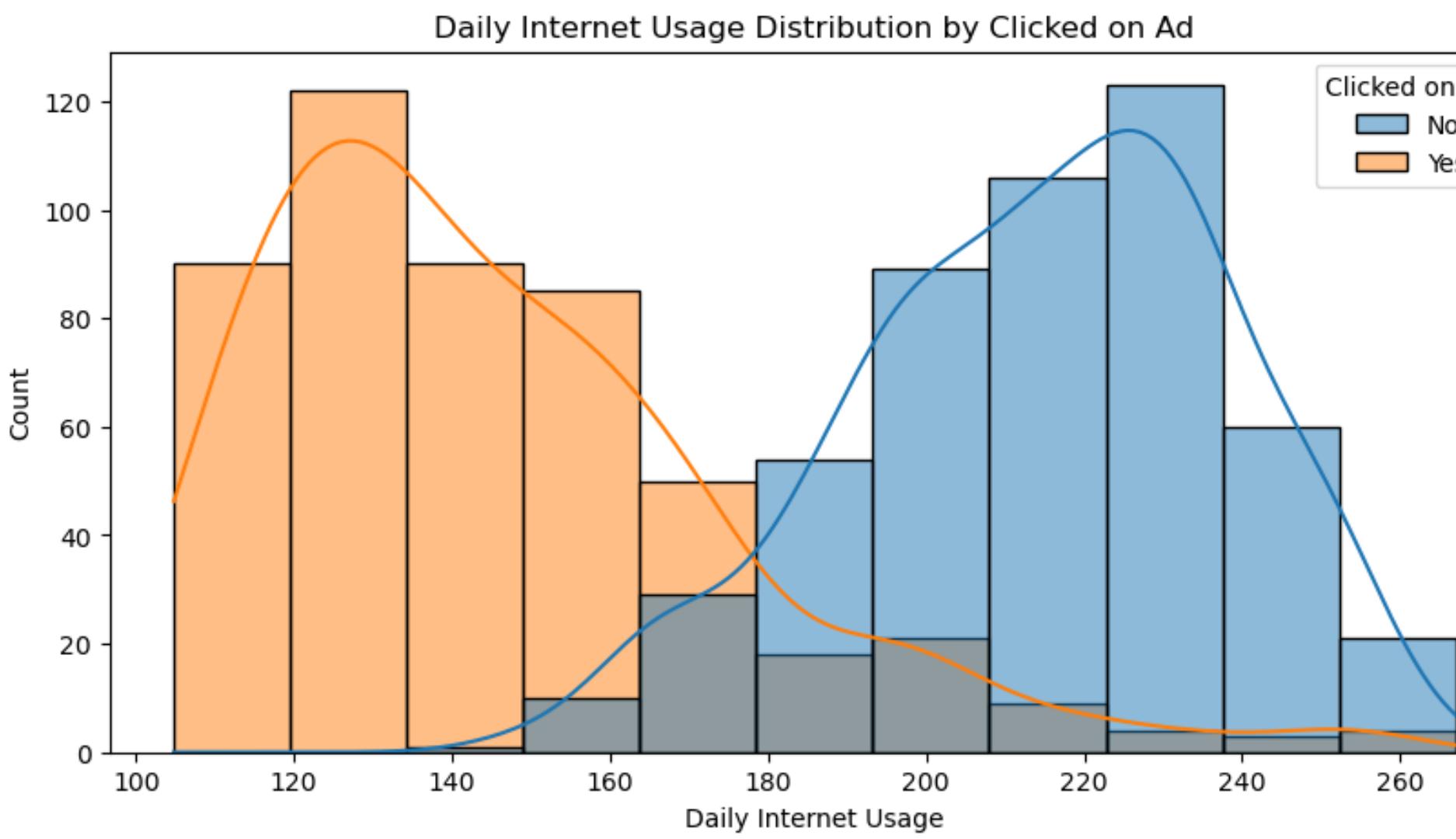


Market Insight

Why? Perhaps they have more disposable income and time for travel? Or do they appreciate the curated, authentic experiences we offer?

Insight: Experienced travelers are a key demographic.

Online Behavior: The Digital Trailblazers?



Another Trend Observed !

We see those with lower daily internet usage, are clicking more.

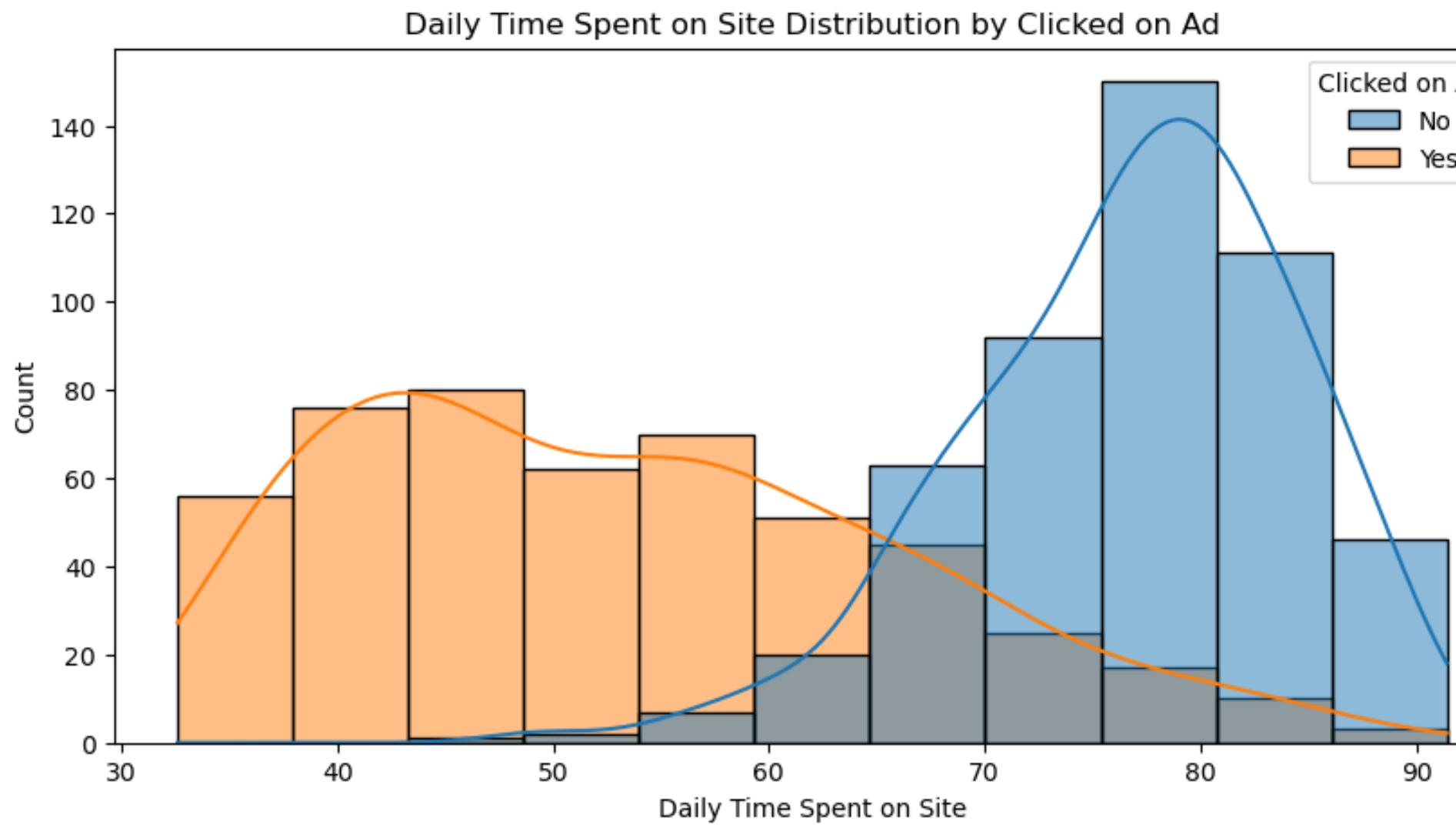


Market Insight

Why? Are they more focused when online? Are they using specific platforms that we should be targeting?

Insight: We need to refine our platform targeting.

Site Engagement: The Quick Discovery?



Another Trend Observed !

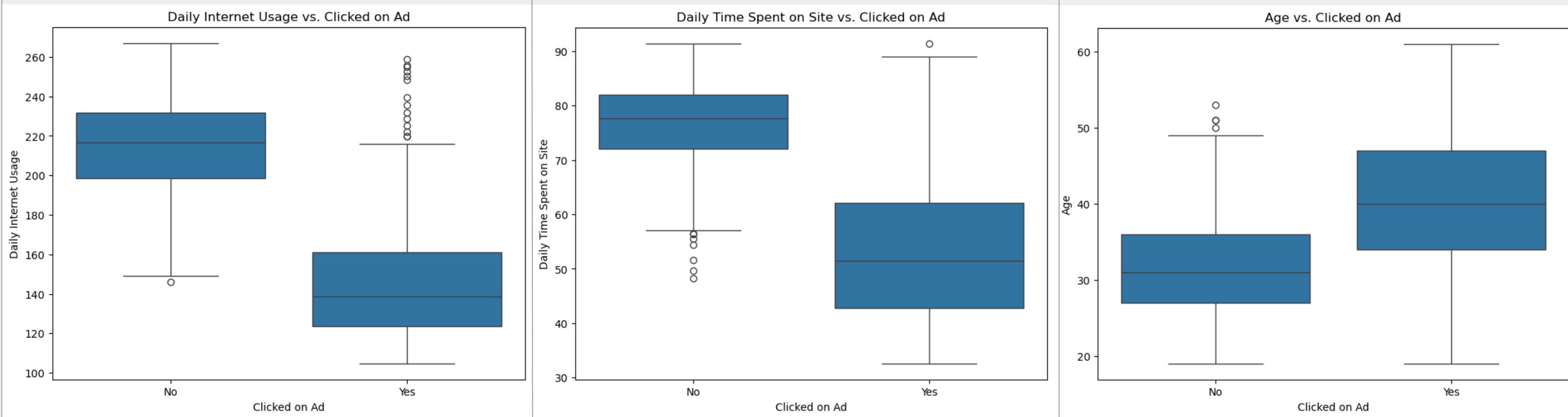
We see that those who click, spend less time on the site.



Market Insight

Why? Are our ads capturing attention immediately? Are they clicking out of curiosity, and then leaving?

Insight: We need to analyze our landing page experience.



Boxplots: Visualizing the Persona



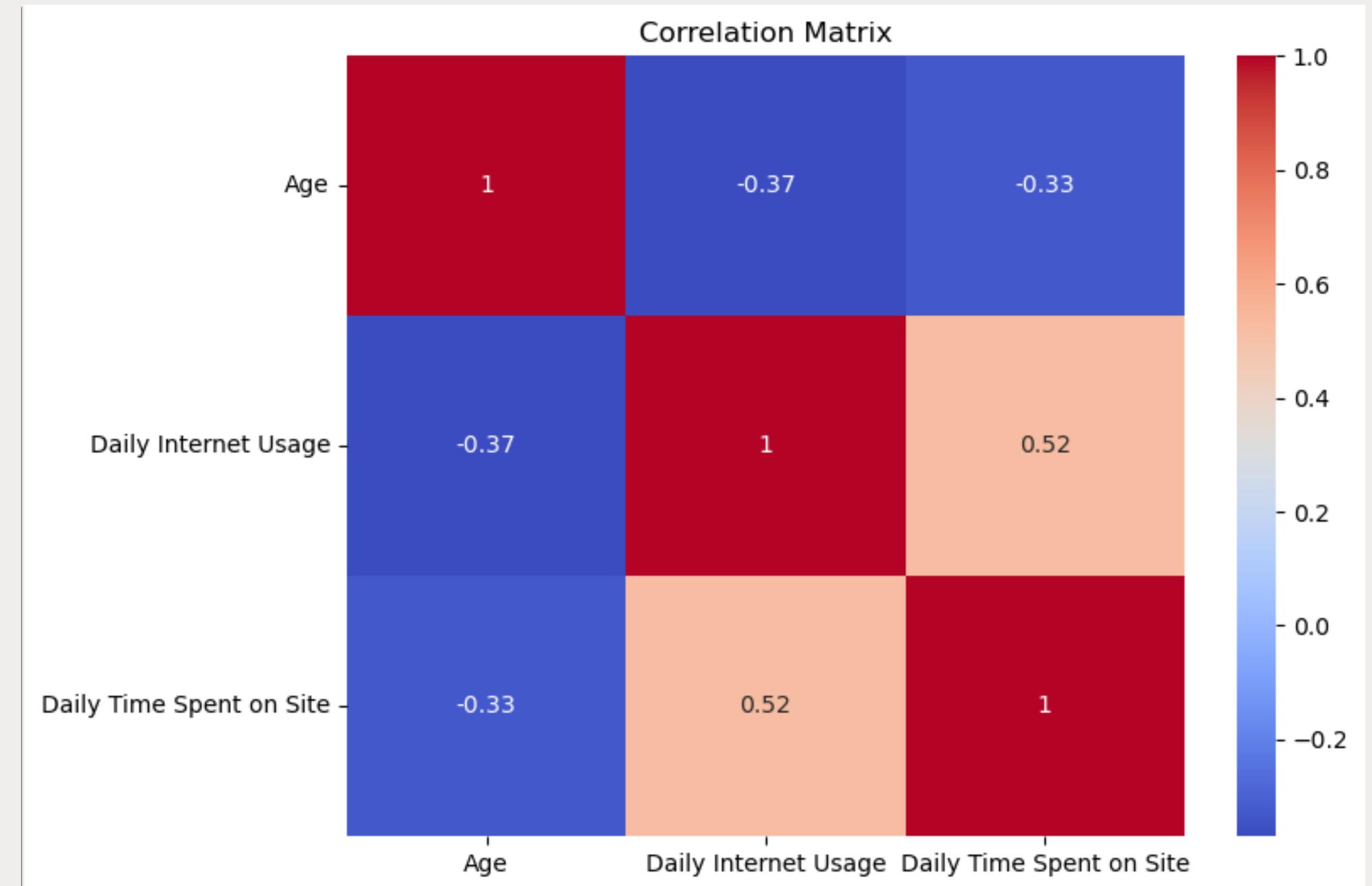
Market Insight

The boxplots solidify our findings, creating a distinct Wanderlust persona.

Older, less frequent online users, who spend less time on site, are our target clickers.

[Source code](#)

Correlation: Navigating the Relationships

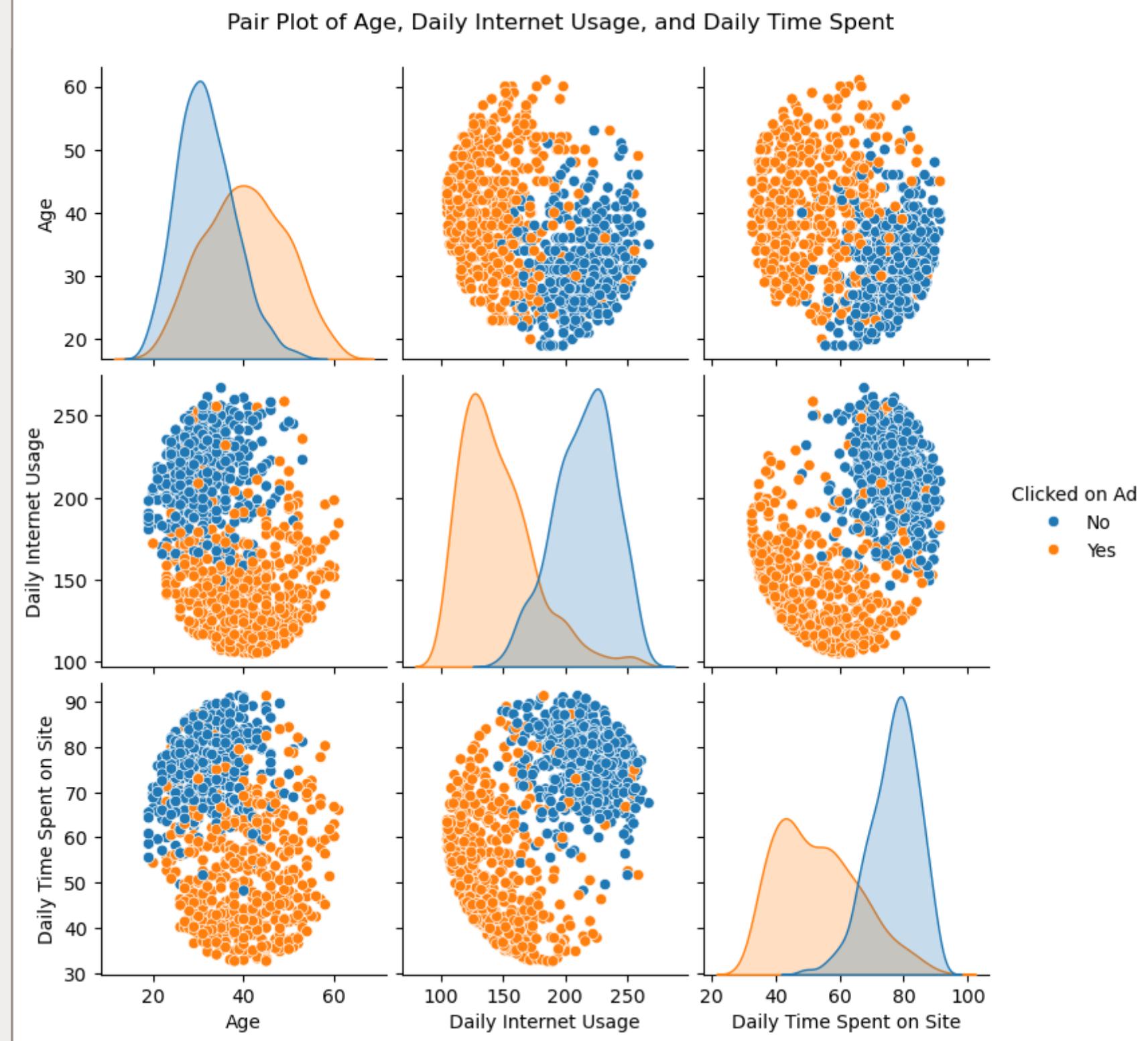


Market Insight

Moderate negative correlation between age and internet usage.

Strong positive correlation between internet usage and time on site.

Pair Plot: The Global View



Market Insight

The pair plot visually confirms our findings, showing clear patterns.

Data Preparation

Setting Up The Stage

Missing Values

Filled numerical columns with the median and categorical columns with the mode.

Feature Encoding

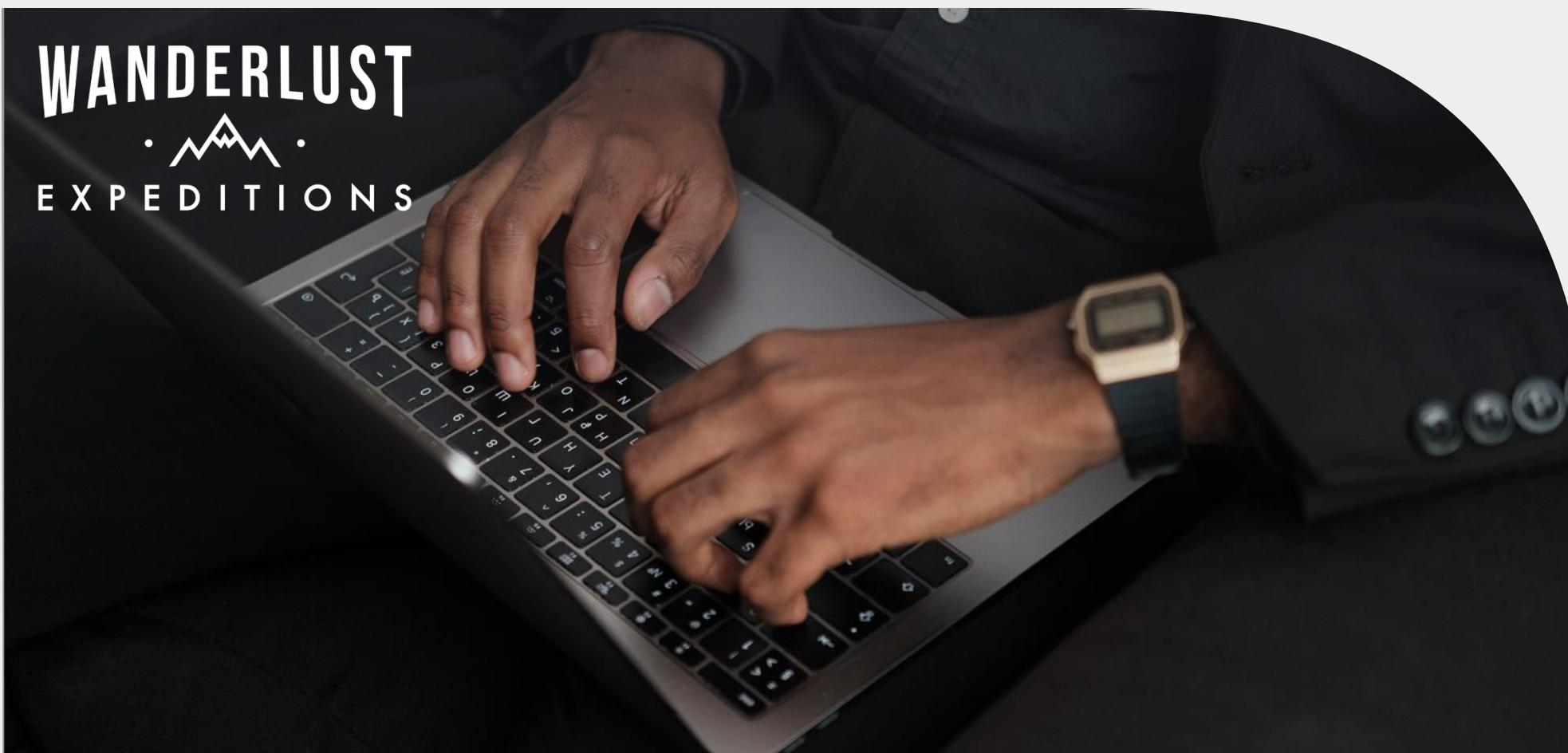
Binary columns ("Male," "Clicked on Ad") were encoded using Label Encoding. Categorical columns ("city," "province," "category") were encoded using One-Hot Encoding.

Time Feature Extraction

From the "Timestamp" column, we extracted "Year," "Month," "Week," and "Day" to analyze temporal patterns.

Feature and Target Split

We separated the features (X) from the target variable (y), "Clicked on Ad."



Experimentation

We experimented with several machine learning models to predict ad clicks, Random Forest, Logistic Regression, Support Vector Machine (SVM) in two ways, “Non-Normalized” and “Normalized”.

With a Conclusion, **Logistic Regression** significantly improved with scaling, outperforming the other models whilst **Random Forest** remained strong in both scenarios.

01

Without Normalization

Random Forest: Achieved an accuracy of 94%

Logistic Regression: Achieved an accuracy of 90%

SVM: Achieved an accuracy of 69%

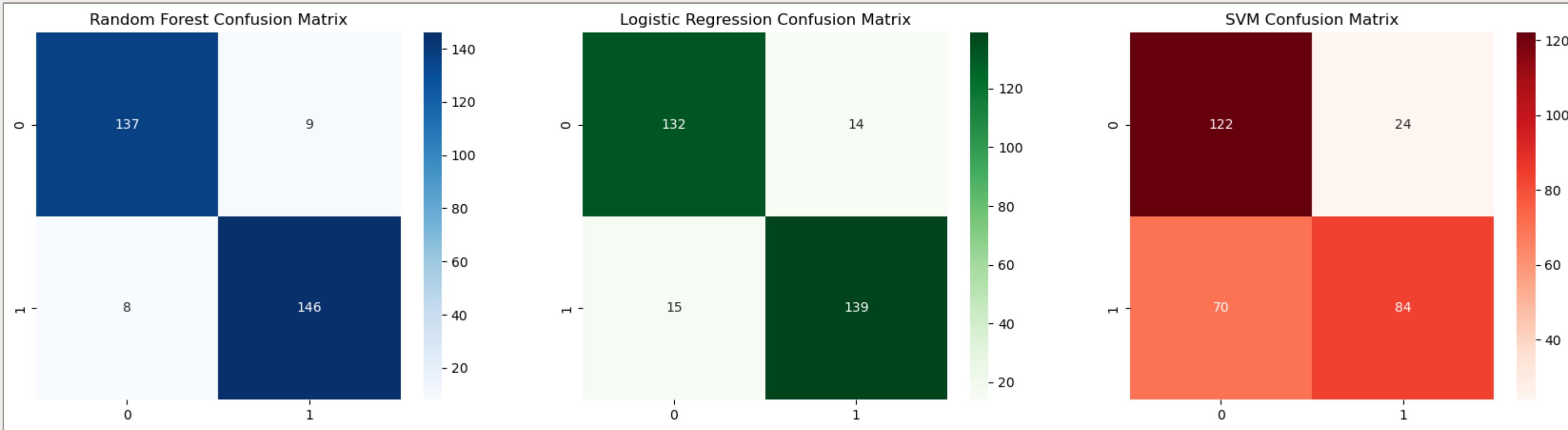
02

With Normalization

Random Forest: Achieved an accuracy of 94%

Logistic Regression: Achieved an accuracy of 96%

SVM: Achieved an accuracy of 95%



Confusion Matrix

Scaled Logistic Regression

High precision and recall for both classes (travelers who clicked and didn't click), indicating strong predictive power. However not so much for the "Non-scaled".

Random Forest

Consistently high precision and recall, demonstrating robustness.

Feature Importance (RF)

Non-Normalized

Feature	Importance
Daily Internet Usage	0.340821
Daily Time Spent on Site	0.254569
Age	0.1141
Area Income	0.109575
Unnamed: 0	0.028111
city_Pontianak	0.000574
city_Tasikmalaya	0.000545
city_Surakarta	0.000344
province_Kalimantan Barat	0.000237
Year	0
... (and 53 more features)	

Normalized

Feature	Importance
Daily Internet Usage	0.340821
Daily Time Spent on Site	0.254569
Age	0.1141
Area Income	0.109575
Unnamed: 0	0.028111
city_Pontianak	0.000574
city_Tasikmalaya	0.000545
city_Surakarta	0.000344
province_Kalimantan Barat	0.000237
Year	0
... (and 53 more features)	

For Random Forest, "Importance" indicates the relative contribution of each feature in the model's decision-making.



Feature Importance (LR)

Non-Normalized

Feature	Coefficient
Age	0.011231
Year	0.010662
Male	0.000058
category_Otomotif	0.000053
category_House	0.000042
Unnamed: 0	-0.000208
Week	-0.000433
Day	-0.000501
Daily Time Spent on Site	-0.02777
Daily Internet Usage	-0.081796
... (and 53 more features)	

Normalized

Feature	Coefficient
Age	1.333317
Month	0.32931
city_Jakarta Selatan	0.279987
province_Sumatra Selatan	0.196859
city_Palembang	0.196859
category_Travel	-0.492797
category_Furniture	-0.716152
Area Income	-1.584624
Daily Time Spent on Site	-2.588491
Daily Internet Usage	-2.982785
... (and 53 more features)	

For Logistic Regression, "Coefficient" indicates the feature's impact on the log-odds of the outcome (i.e., clicking on the ad). A positive coefficient means the feature increases the likelihood of a click, while a negative coefficient decreases it. The scaled coefficients are directly comparable in magnitude.



Choosing the Model



Why Random Forest ?



Behavior Understanding

Random Forest excels at capturing complex non-linear relationships in data, which is crucial for understanding diverse traveler behavior.



Built-in Utils

It provides feature importance scores, helping us identify the most influential factors in ad clicks.



Credibility

"Random Forest is often favored for its robustness and ability to handle high dimensionality," as noted by Scikit-learn's documentation.

Recommendation

& Actionables

Target users with lower "Daily Internet Usage" more aggressively, as they are more likely to click.

Refine ad placements to appear on platforms or sites that these users frequent.

Tailor ad content to resonate with specific age groups (it clearly shows it worked for the older age group). The language, visuals, and offers should align with their interests and preferences.

Consider age-based targeting on advertising platforms to reach the most receptive audiences.

Design ads that quickly capture attention and convey the message, catering to users with shorter site visits.

Experiment with ad formats (e.g., short videos, interactive ads) that are effective for users with shorter attention spans.

Segment campaigns based on Area Income to offer products or services that align with their purchasing power.

Customize messaging to emphasize value and affordability or exclusivity, depending on the income bracket.

Business Simulation



This simulation demonstrates the significant impact of machine learning on marketing ROI.”

Metric	Value	Feature	Coefficient
Total Users Targeted	10,000	Total Users Targeted	10,000
Marketing Cost	\$5,000	Marketing Cost	\$5,000
Base Conversion Rate	2%	Targeted Conversion Rate	5%
Conversions	200	Conversions	500
Revenue	\$10,000	Revenue	\$25,000
Profit	\$5,000	Profit	\$20,000
Traditional Approach		AI-Powered Optimization	

By using AI to target users based on key features like Daily Internet Usage, Daily Time Spent on Site, Age, and Area Income, we can increase the conversion rate from 2% to 5%. This results in a substantial profit increase from \$5,000 to \$20,000.

Let's Build Together



Phone :
[+62813-3353-2005](tel:+6281333532005)



Email :
brambsns@gmail.com



LinkedIn
linkedin.com/in/bramraka666

