Sip the Difference: Unveiling Consumer Preferences with Vyu's A/B Ad Experiment

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Abstract

Does a paid Google ad search campaign focused on holistic wellness and balanced lifestyle generate more interest in a natural supplement drink product than a campaign centered on productivity and success? In recent times, there has been a noticeable shift in consumer preferences towards a lifestyle that emphasizes not just productivity and efficiency, but overall well-being, and as a result, advertising campaigns have increasingly focused on messages of self-care, mindfulness, and sustainable living. This study uses Google's native A/B test tool to compare the performance of two ads containing two different messages (one focused on holistic wellness, and one focused on productivity). The performance of each ad was measured by the amount of site traffic each generated, which was defined as the average click-through rate. The results showed that there was no significant difference in the interest generated by the wellness message versus the productivity message. As these findings are qualified based on the limited data available through Google Analytics, additional experimentation is needed to inform relevant companies about the most effective marketing strategies for these products.

***K*eywords** A/B Test · Ad Campaigns · Wellness · Productivity

1 Introduction

The dynamic nature of the marketing field creates a need for an in-depth understanding of current trends in consumer attitudes, emotions, and preferences in order to design successful advertising campaigns to promote products. The impact of a marketing message is largely dependent on how well it aligns with the values and goals of the target audience. Recently, a clear trend has emerged in consumer behavior, favoring a more balanced lifestyle that values not just productivity, but also holistic wellness (Callaghan, 2022). This change has been primarily driven by growing consumer awareness and demand for a more integrated approach to health and well-being; even to the point of natural diets gaining popularity above over-the-counter prescriptions (Park & Zavislak, 2019). Products and services are now frequently advertised not only as means to enhance productivity or efficiency, but also as tools to nurture mental, physical, and emotional wellness. This trend extends from the fitness industry to tech, food, and even fashion sectors, reflecting a societal shift towards seeking balance in every aspect of life. As a result, brands are increasingly incorporating messages of self-care, mindfulness, and sustainable living into their campaigns (Pickford, 2018). All these developments indicate a distinct move away from the previously dominant focus on relentless productivity and forward towards wellness.

1.1 Research Question

Our study investigated the following research question:

Does a paid Google ad search campaign focused on holistic wellness and balanced lifestyle generate more interest in a natural supplement drink product than a campaign centered on productivity and success?

We partnered with Vyu, a company that specializes in drinks made from a blend of nootropics, adaptogens, vitamins, and functional mushrooms and intended to boost consumers' energy levels and increase their productivity. To investigate which messaging would generate more interest, we wrote two sets of advertising copies. The set of statements in Treatment A emphasized enhancing clarity, focus, and productivity, primarily targeting individuals seeking a boost in their daily performance. The set of statements in Treatment B, on the other hand, focuses towards wellness, offering a natural, low-caffeine alternative to mainstream caffeine products, appealing to those leaning towards a healthier lifestyle.

Using Google's native A/B testing tool, we compared the performance of the two messages against each other. The performance of each message was measured by the amount of site traffic each ad generated.

1.2 Hypothesis

Based on the growing popularity of wellness products, we predicted that the wellness-focused advertisements would outperform productivity-focused advertisements in terms of user click-through rate, generating an increased amount of site traffic.

2 Experimental Design

Our study aims to draw a comparative analysis between two distinctive advertising treatments on the Google Ads platform, namely (A) and (B). We chose A/B testing for this experiment because it offers a direct and controlled comparison between the two advertising treatments, ensuring that any observed differences in click-through rates can be attributed specifically to the messaging strategy, thereby providing clear insights into audience preferences.

2.1 Ad Treatment Description

Our objective is to discern whether a productivity-based or wellness-centric message attracts a greater number of clicks for the natural supplement drink, Vyu.

1. Treatment A (Productivity): This advertisement series is designed to tap into the desire of users to enhance their productivity and focus. The potential outcome here is an increased CTR from individuals who identify with the need to boost their clarity, mental acuity, and daily performance. If Treatment A is more effective, it would suggest that users on the Google Ads platform respond more favorably to messages emphasizing enhanced focus and productivity when considering a product like Vyu.

2. Treatment B (Wellness): These ads focus on the wellness and health benefits of the Vyu drink, emphasizing its natural composition and position as a healthier alternative to traditional caffeine products. The anticipated outcome for this treatment is to achieve a higher CTR from users who are health-conscious and are seeking a more natural and balanced lifestyle. If Treatment B emerges as more effective, it would point towards a trend where users are more inclined to natural, health-centric messaging for our product.

Table 1: Treatment Descriptions

Treatment	Headline	Description
A (Productivity)	Focus deeper, do more	Vyu | End hazy, unfocused days. Boost clarity & productivity.
A (Productivity)	Push the limits of your mind	Vyu | Boost focus, supercharge productivity, and elevate your mental performance.
A (Productivity)	Supplement your drive	Vyu | Supercharge your brain and kick your productivity into overdrive.
B (Wellness)	Embrace your natural brilliance	Vyu | an all-natural blend to let your mind flow freely and brilliantly like never before.
B (Wellness)	Live a more balanced life	Vyu | a blend of nature's powerhouses, crafted for your health and well-being.
B (Wellness)	Embrace your natural rhythm	Vyu | harmonize your body and mind with the earth's natural rhythms.

Three of each version of treatment A and B are shown to users based on various search terms such as "mushroom drink" and "nootropic" on the Google Search Engine over a period of one week within the U.S. region. The detailed ad copies for each treatment are shown in Table 1 above.

2.2 Outcome Measurement

Our experiment is a between-subjects study because each participant is exposed to only one level of the independent variable. In the context of this study, some participants see the "Productivity" ad while others see the "Wellness" ad, and the groups' outcomes are compared to each other. The potential outcome of interest is the click-through rate (CTR), a metric indicating the level of user clicks to the Vyu product website and audience engagement with each ad. Users' potential outcomes are counterfactual: we are only able to observe a user's response either to Treatment A or B, but not both. Therefore, our study will compare the potential treated outcomes for Treatment A of users assigned to the Treatment A group to the potential treated outcomes for Treatment B of users assigned to the Treatment B group. All measured outcomes, including covariates used in our randomization and balance tests, are described in detail in Figure 1.

Measured variable	Definition	Data type & values
Click-through-rate (CTR)	Average rate of clicks to website per ad impression	Binary: 0 (no click on ad), 1 (clicked ad)
Bounce Rate	Percentage of visitors that leave the Vyu website after viewing only one page on the site	Numeric
User Device Type	Type of device used for Google search	Nominal: tablet, computer, mobile
Traffic Type	Source and medium of users' traffic to the Vyu website	Nominal: Paid ad search, organic Google search
Time on site	Average time spent on Vyu website per site visit	Time in seconds
Number of pages viewed	Total number of pages on Vyu site viewed by users	Numeric: integer

Figure 1: Measured Variables Definitions

Given the design of the experiment and the A/B testing method employed, the potential outcomes to be compared include CTR for Treatment A (Productivity) vs. CTR for Treatment B (Wellness) across various scenarios. To achieve this, we will rely on Google's A/B testing tool, deploying the three different ad versions per treatment. To randomly assign subjects to each group, this test relied on the randomized assignment of the Google Ads Experiment Suite. As Google's methods to randomly assign ads are not provided in detail to advertisers on the platform, we performed covariate checks to evaluate whether the groups are balanced.

2.3 Consort Document

The consort document created for our study (Figure 2) shows the overview of the sample used in our experimental design. From the overall population of Google users in the United States, we focused our targeting on a subset of Google users in the United States who exhibited a higher likelihood of interest in becoming Vyu consumers. This targeting was based on their search behavior, specifically looking for those who had performed searches using keywords that were associated with the ad copy of our treatment. Of the 6,902 total user impressions we received for both ads, the productivity ad received 3,291 impressions (47.7%), and the wellness ad received 3,611 impressions (53.3%). The difference in the respective numbers of impressions per ad may have related to Google's cost-per-click scale, which varied over the timeframe of the experiment. In the initial stages of our study, our average cost-per-click was $1.16, but this value then more than doubled to $2.78 by the end of our weeklong data collection period. Because this cost rose much higher than our pre-experimental power calculations initially forecasted, it's possible that increased cost may have led to insufficient findings to detect a true existing average treatment effect.

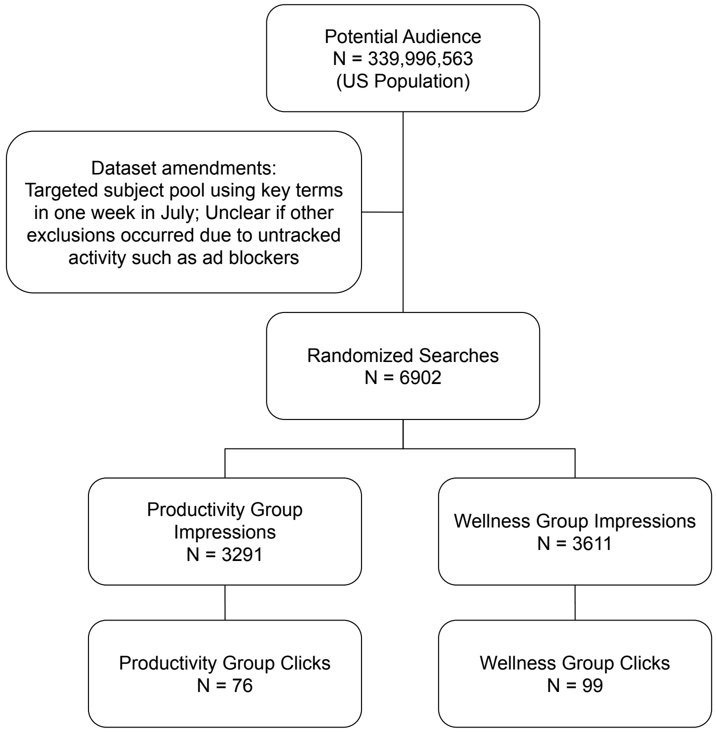

Figure 2: Consort Document

2.4 Power Analysis

Our hypothesis postulates that there exists a meaningful difference in CTR between the two treatments. By modeling three distinct simulations, in our power calculation (Figure 3) we anticipate detecting CTR variations of 1%, 10%, and 30% between the ads. The Average Treatment Effect (ATE) of these variations is projected to be 0.005, 0.01, and 0.02, respectively. To obtain an 80% power level, our analysis indicated that we would need to obtain approximately 1,250 ad impressions for a 2% difference in click-through-rates between treatment groups, and approximately 4,000 impressions for a 1% difference in click-through-rates. With an effect size of 0.5%, however, we would likely need far more than the 5,000 impressions that might be feasible with our budget (given our original assumption of an average cost-per-click of approximately $1.00).

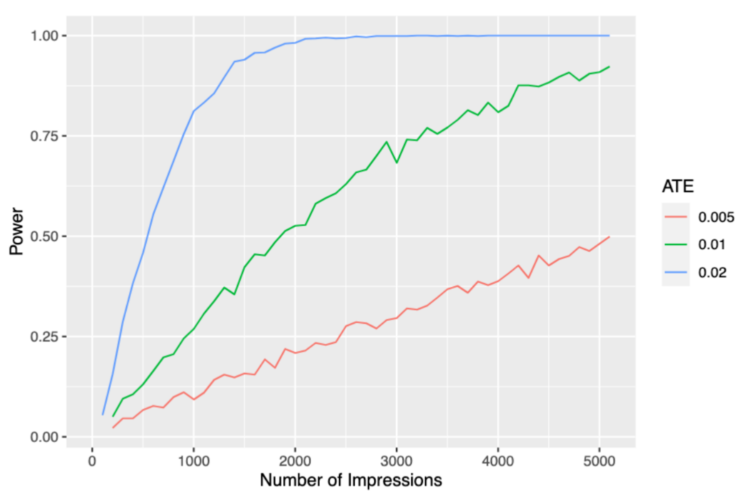

Figure 3: Power Analysis

3 Models & Analysis

In the initial stages of our experimental design, we planned to collect data at the individual user level, therefore enabling us to conduct a more fine-grained causal analysis of the estimated ATE and related covariates. However, the Google Analytics platform we used for data collection constrained the available data to aggregated means and totals, with few covariates (e.g., user demographic characteristics) that could be compared at the treatment level. As this scenario clearly precluded a regression analysis of our data, we addressed our research question via a series of three tests that could accommodate aggregated counts and proportions to analyze click-through-rates.

3.1 Primary Model: Did users respond differently to the ads in terms of their click-through-rates to the Vyu site?

To address our central research question regarding the relative performance of ad treatment A (productivity messaging) versus ad treatment B (wellness messaging) in driving traffic to the Vyu site, our design leverages a chi-squared test of proportions as our primary model. This test evaluates the null hypothesis that the proportions of click-through-rates (probabilities of user clicks in response to the treatments) are the same for each treatment group.

3.2 Covariate Balance Check: Were the treatments delivered to demographically comparable groups of users?

In order to evaluate whether Google's randomization was effective in delivering the ads to demographically comparable groups of users, we evaluated the relationship between assigned treatment and user characteristics. Without being able to collect more granular demographic information at the treatment level, we used the device type on which users accessed Google and received ad impressions. As users' characteristics tend to vary systematically based on the device type they use to perform internet searches (Vogels, 2019), substantial differences between the treatment groups in terms of impressions per device would indicate issues in our randomization approach.

3.3 Comparisons of Organic and Paid Google Search Traffic: Are the two groups meaningfully different?

Though not the direct focus of the A/B test, describing differences between paid and organic search visitors to the Vyu website can provide useful insights for the company's leadership team. Even though users have clicked the search ads, there is still an open question as to if these users are comparable in quality to those who found the product organically (Google searches). Metrics such as time on site, bounce rate, and device type are compared and used as proxies for propensity to purchase. Note that Vyu's product is not currently available for sale, so we were not able to measure conversion to sales directly.

4 Results

4.1 Estimated ATE and primary model

```r
# calculate ATE (values retrieved manually from Google Analytics)
n_clicks_a <- 76 # total clicks from treatment A users
n_clicks_b <- 99 # total clicks from treatment B users
n_impressions_a <- 3291 # total impressions, treatment A
n_impressions_b <- 3611 # total impressions, treatment B
ctr_a <- n_clicks_a/n_impressions_a # CTR group A
ctr_b <- n_clicks_b/n_impressions_b # CTR group B
print(ctr_b - ctr_a)
```

```
## [1] 0.004322943
```

The estimated ATE was calculated as the difference between the expectation of user CTR in group B and the expectation of user CTR in group A, resulting in an estimate of 0.004. The users in treatment B, on average, had an approximately 0.4% higher CTR, meaning that out of a hypothetical sample of 100 users in each treatment, we would expect approximately 4 more ad B viewers to click than ad A viewers. Figure 4 displays the total number of impressions, total number of clicks, and calculated CTR for each treatment group.

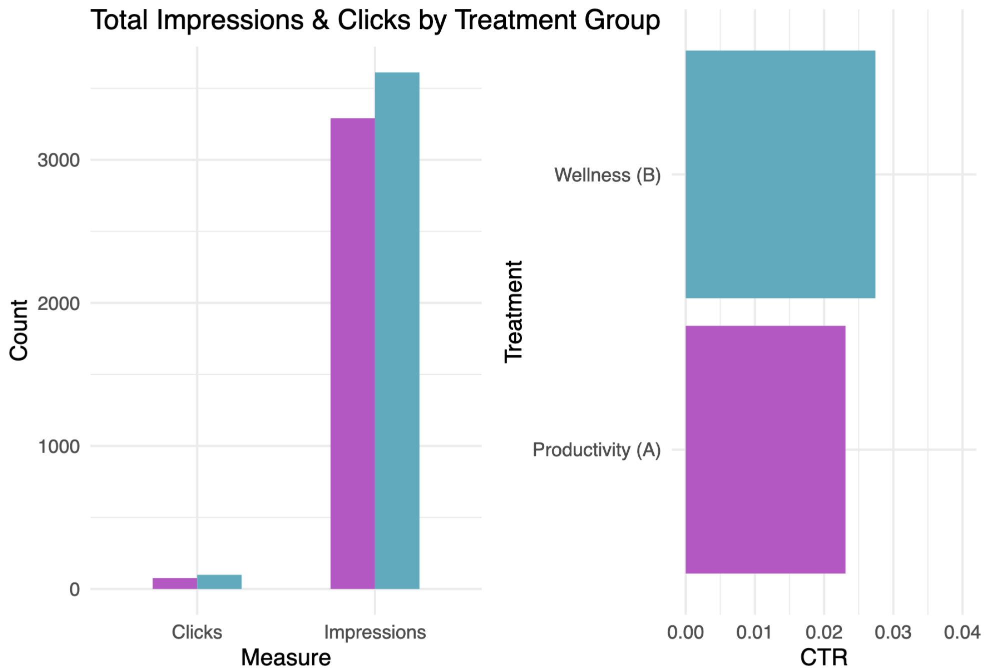

Figure 4: Impressions and clicks for each ad treatment

A two-sided chi-square test of equal proportions was conducted in R to determine whether the click-through-rate of users assigned to the two ad treatments significantly differed.

```
# conduct prop test of click through rates
clicks <- c(n_clicks_a,n_clicks_b)
trials <- c(n_impressions_a,n_impressions_b)
prop_test_res <- prop.test(clicks,trials)
prop_test_res
```

```
##
##  2-sample test for equality of proportions with continuity correction
##
## data:  clicks out of trials
## X-squared = 1.133, df = 1, p-value = 0.2871
## alternative hypothesis: two.sided
## 95 percent confidence interval:
##  -0.01200927  0.00336338
## sample estimates:
##     prop 1     prop 2
## 0.02309328 0.02741623
```

The results of this model indicated that the proportions of users who clicked on the ads did not significantly differ based on the treatment condition (X2(1, N=6902) = 1.13, p = 0.287). In other words, this test does not provide evidence that contradicts our null hypothesis, and we do not have reason to believe that one treatment was more appealing to users than the other.

4.2 Covariate Balance Check: User Device Type

Our initial descriptive results also suggested that the proportions of impressions based on users' device type varied by a few percentage points between the treatment groups. As Figure 5 indicates, the wellness ad group featured slightly higher rates of computer and mobile users, whereas the productivity group had slightly higher rates of tablet users.

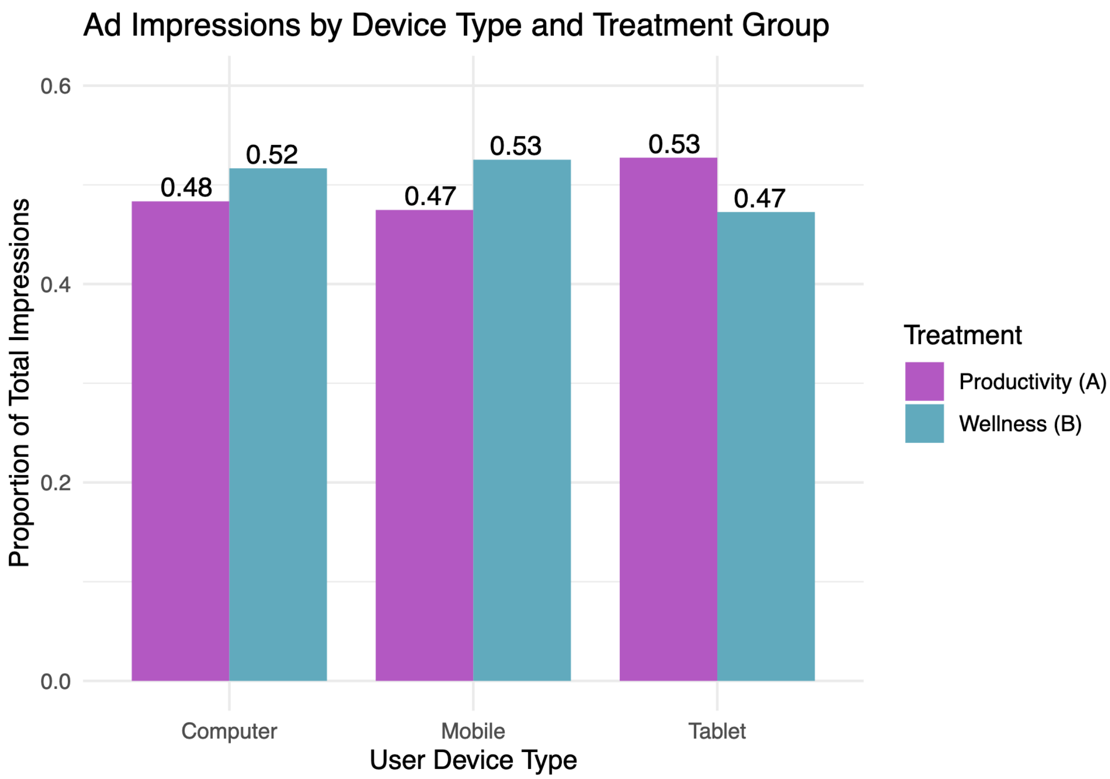

Figure 5: Distribution of ad impressions by device type for each ad group

```r
# create table to compare impressions by device type per treatment group
device_data <- matrix(c(392, 419, 2822, 3123, 77, 69), nrow = 3, byrow = TRUE)
rownames(device_data) <- c("Computers", "Mobile", "Tablet")
colnames(device_data) <- c("Impressions_A", "Impressions_B")

# run chi-squared test
cs_device_test <- chisq.test(device_data)
cs_device_test
```

```
##
##  Pearson's Chi-squared test
##
## data:  device_data
## X-squared = 1.7446, df = 2, p-value = 0.418
```

A chi-squared test comparing the total impressions for each device type by ad treatment group indicated that the proportions of devices used did not differ by treatment, X2(2, N=6902) = 1.74, p = 0.42. Although this result cannot rule out the possibility that other demographic characteristics may differ between users receiving each ad, it does suggest that the two groups did not vary in terms of device types and, potentially, their associated attributes.

4.3 Comparisons of Organic and Paid Google Search Traffic

4.3.1 iPhone Usage

Visual inspection of the proportions of iPhones used by the paid advertising subjects in our sample versus all organic site traffic source users (Figure 6) suggested that these groups might differ in terms of iPhone ownership. Given that iPhone users tend to be wealthier than non-iPhone users (Bertrand & Kamenica, 2018), this could be a crucial indicator of who is more likely to purchase the product in response to online advertising.

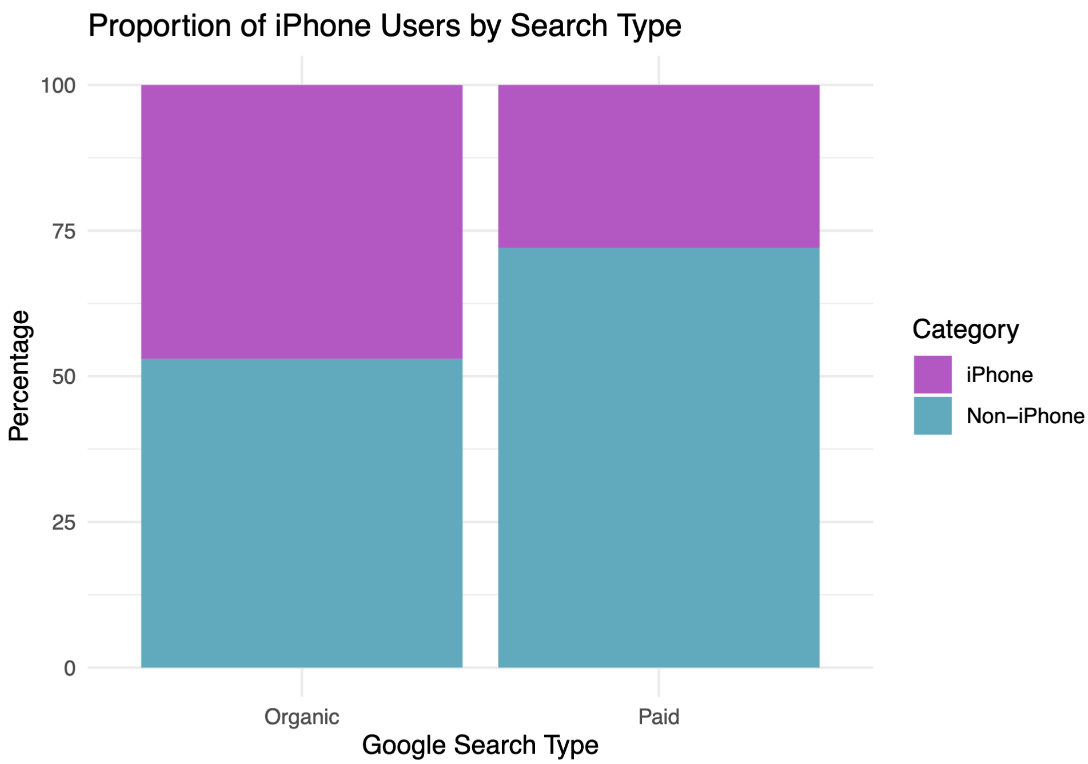

Figure 6: iPhone users for organic search traffic and paid advertising traffic

```r
# Prop test of iPhone and non-iPhone users

paid_users <- 153
paid_iphone <- 43

organic_users <- 607
organic_iphone <- 287

# Calculating proportions
prop_paid_iphone <- paid_iphone / paid_users
prop_organic_iphone <- organic_iphone / organic_users

# Performing the hypothesis test
result <- prop.test(x = c(paid_iphone, organic_iphone), n = c(paid_users, organic_users))

# Printing the test result
print(result)
```

```
##
##  2-sample test for equality of proportions with continuity correction
```

```
##
## data:  c(paid_iphone, organic_iphone) out of c(paid_users, organic_users)
## X-squared = 17.52, df = 1, p-value = 2.842e-05
## alternative hypothesis: two.sided
## 95 percent confidence interval:
##  -0.2774148 -0.1061280
## sample estimates:
##    prop 1    prop 2
## 0.2810458 0.4728171
```

An analysis of the comparison between paid and organic groups yields some significant differences between the paid and organic Google search groups. Specifically, the proportion of iPhone users higher in the organic search group (p ~= 0.00002).

4.3.2 Bounce rate & Google Chrome usage

In contrast to iPhone usage, as the following tests demonstrate, the differences in proportions of Google Chrome users (p ~= 0.08) and bounce rate (p ~=0.48) was not significant across traffic groups.

```r
# Prop test of Chrome and non-chrome users
paid_users <- 153
paid_chrome <- 88

organic_users <- 607
organic_chrome <- 300

# Calculating proportions
prop_paid_chrome <- paid_chrome / paid_users
prop_organic_chrome <- organic_chrome / organic_users

# Performing the hypothesis test
result <- prop.test(x = c(paid_chrome, organic_chrome), n = c(paid_users, organic_users))

# Printing the test result
print(result)
```

```
##
##  2-sample test for equality of proportions with continuity correction
##
## data:  c(paid_chrome, organic_chrome) out of c(paid_users, organic_users)
## X-squared = 2.8871, df = 1, p-value = 0.08929
## alternative hypothesis: two.sided
## 95 percent confidence interval:
##  -0.01100862  0.17286754
## sample estimates:
##    prop 1    prop 2
## 0.5751634 0.4942339
```

```r
# Prop test of bounce rates
# User total counts pulled from Google Analytics
paid_users <- 153
organic_users <- 607

prop_paid_bounce <- 0.6662
prop_organic_bounce <- 0.6306

# Calculating the number of bounces
paid_bounces <- prop_paid_bounce * paid_users
organic_bounces <- prop_organic_bounce * organic_users
```

```
# Performing the hypothesis test
result <- prop.test(x = c(paid_bounces, organic_bounces), n = c(paid_users, organic_users))

# Printing the test result
print(result)
```

```
##
##  2-sample test for equality of proportions with continuity correction
##
## data:  c(paid_bounces, organic_bounces) out of c(paid_users, organic_users)
## X-squared = 0.52513, df = 1, p-value = 0.4687
## alternative hypothesis: two.sided
## 95 percent confidence interval:
##  -0.05250103  0.12370103
## sample estimates:
## prop 1 prop 2
## 0.6662 0.6306
```

4.3.3 Average time on Vyu site & Average number of pages viewed

In the next set of tests, Welch's t-test was used by applying daily, user-weighted average data, group by Google paid and organic traffic. As shown in Figure 7 graph Time on Site for Paid vs. Organic, the time on site was significantly (p « 0.05) lower for the paid group versus the organic group (9 seconds vs. 63 seconds). Interestingly, the number of pages viewed (Figure 7 graph Average Paid vs. Organic Pages) was larger for the paid group (1.61 vs. 1.54 pages), which was significant (p « 0.05), though the size of the difference is small. While imperfect proxies, the above tests demonstrate important differences between the paid and organic groups, which may affect the viability of paid search as a long-term strategy for driving purchases.

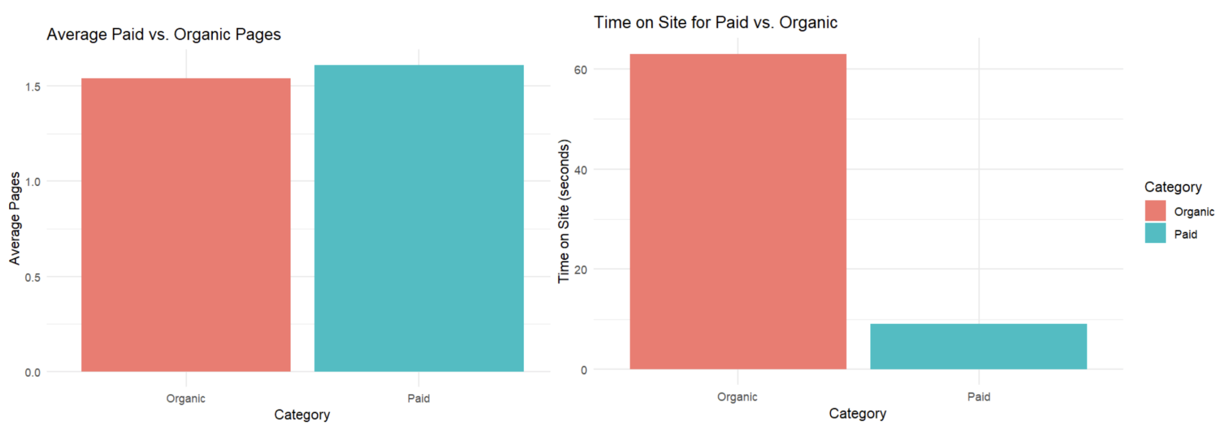

Figure 7: Average time on site and average page views for paid and organic search users

```
# Perform t-tests for time on site and pages/session
t_result_pages <- t.test(
  x = google_cpc_pages_vector,
  y = other_sources_pages_vector,
  alternative = "two.sided",
  mu = 0,  # Null hypothesis mean difference
  paired = FALSE,  # Independent samples
  var.equal = FALSE,  # Assuming unequal variances
  conf.level = 0.95  # Confidence level
)

# Print t-test results
print(t_result_pages)
```

```
##
##  Welch Two Sample t-test
##
## data:  google_cpc_pages_vector and other_sources_pages_vector
## t = 0.4028, df = 7.2006, p-value = 0.6988
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.9068917  1.2818311
## sample estimates:
## mean of x mean of y
##   1.86250   1.67503
```

```
t_result <- t.test(
  x = google_cpc_vector,
  y = other_sources_vector,
  alternative = "two.sided",  #
  mu = 0,  # Null hypothesis mean difference
  paired = FALSE,  # Independent samples
  var.equal = FALSE,  # Assuming unequal variances
  conf.level = 0.95  # Confidence level
)

# Print t-test results
print(t_result)
```

```
##
##  Welch Two Sample t-test
##
## data:  google_cpc_vector and other_sources_vector
## t = -4.0126, df = 19.915, p-value = 0.0006879
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -60.62928 -19.14648
## sample estimates:
## mean of x mean of y
##  12.50000  52.38788
```

5 Limitations

Our experiment featured a few strengths, including the use of as many covariate balance checks as possible to assess our results. By using a simple comparison of two experimental treatments, we obtained a greater degree of statistical power than we would have with a more complex experimental design (although still likely less than needed due to budget and time constraints). In addition, the checks we ran did not suggest errors in our random assignment of subjects to treatment groups. By using Google Analytics, we were able to leverage a fair degree of control over the timing and nature of the treatment delivery, rendering our results more plausible.

However, the fundamental limitation of our experiment is our unanticipated need to rely exclusively on aggregated data. Without access to many user- and treatment-specific measurements from Google Analytics, both the tests and insights we were able to produce were highly limited in terms of causal claims. Crucially, we were not able to report the errors of our estimates from the aggregated user data. As a result of the platform's restrictive data collection options, our team was also unable to evaluate a number of relevant covariates among the treatment groups. Without more fine-grained data, our analysis is therefore subject to concerns about omitted variable bias and/or unobserved heterogeneity in the sample. In particular, there is a strong possibility that our estimated treatment effect is biased by unmeasured confounds, and we were not able to explore heterogeneous treatment effects that might be highly relevant in the case of marketing a specialized, new-to-market product.

In our analysis, omitted variable bias (OVB) could potentially influence our results. OVB occurs when a variable correlated with both the dependent and independent variables is excluded from the analysis, leading to biased estimates. One example of this in our study might be gender. One treatment may appeal more to one gender over another. For example, if Treatment A is more appealing to males and Treatment B is more appealing to females, there would be a positive correlation between gender and treatment. If one gender is generally more likely to click on ads, then there would also be a similar correlation between gender and the click-through rate. Given this scenario, if the gender that is more likely to click on ads is also more attracted to one of the treatments, then the omission of gender might cause the estimated effect of that treatment to be biased away from zero. The estimated difference between the treatments would be overestimated because it would partly reflect the effects of the different genders. However, we consider OVB to be less of a concern, given the degree of control achieved over randomization and treatment delivery.

Furthermore, we were also prevented from evaluating the impact of non-compliance in the sample: for example, if some users were unable to receive the ad treatments due to electronic issues, we were not able to identify them or their characteristics without being able to pre-define the sample and collect individual-level data. The relative novelty of the Vyu product (only launched just after our experiment) compounded this issue, because no previous data was available to supplement our analysis. In the future, the implementation of a placebo design would be useful in extending and validating our preliminary findings. More generally, due to the obstacles we encountered in using Google Analytics as an experimental platform, we would strongly caution future 241 project teams against relying exclusively on Google Analytics to collect data for their designs.

6 Discussion

The outcomes of this research did not discover significant differences between “Wellness” targeted ads and “Productivity” targeted ads. The study’s results were inconclusive, providing no evidence of a significant preference among users for either of the advertising treatments. Although minor variations were noted in user device types between the two groups, these differences did not substantially influence the overall findings. The initial intention to collect individual user-level data for a more nuanced analysis was constrained by the limitations of the Google Analytics platform, which provided only aggregated means and totals. Consequently, the analysis was conducted through tests suitable for aggregated counts and proportions.

From a practical standpoint, these findings are significant in that the results suggest companies such as Vyu may have to identify more robust experimental avenues in order to establish a competitive marketing edge. Failure to reject the null hypothesis may not be due to the absence of a difference between the advertising messaging, but rather variations in quality of ad copy or other unmeasured variables. The low statistical power, combined with the aggregated data constraints, leaves the question of user preference between the wellness and productivity-oriented products open, signaling the need for future research with more detailed data collection and analysis, assuming the assumptions such as random assignment and excludability have been satisfied. For further studies or analyses, we recommend continuing this research with additional funds as the data was trending towards significant results but we had to stop the research due to budget constraints.

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