The Paradox of Choice in Kenyan E-Commerce

A Bayesian Statistical Optimization of Product Density

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Abstract

This project explores **Hick's Law** within the context of the Nairobi digital market. By conducting a Bayesian A/B test, we investigate whether reducing product density (High Density vs. Low Density) leads to higher conversion rates. Unlike traditional frequentist methods, this analysis quantifies the **probability of risk** and uses a Beta-Binomial model to handle uncertainty in a rigorous, mathematically sound manner.

1. Overview

The Business Challenge

Our e-commerce platform currently displays 24 items per category page ("High Density"). User behavior analysis suggests that this abundance of choice is causing "analysis paralysis" (Hick's Law), where users browse extensively but abandon the session due to cognitive overload. The goal was to determine if a curated, sparse layout could drive higher revenue.

The Experiment

We conducted a randomized controlled trial (A/B Test) with **5,100 user sessions**, split 50/50 between the Control (24 items) and the Variant (6 items). We utilized a Bayesian statistical framework to measure success, allowing for probabilistic risk assessment rather than simple binary significance.

Key Findings

- **Conversion Lift:** The Low Density (6 items) layout achieved a significantly higher conversion rate. The 95% Credible Interval for the new layout is [**2.00%, 3.19%**], outperforming the Control's [**1.25%, 2.25%**].

- **Certainty:** The probability that Low Density outperforms High Density is **98.43%**.

- **Revenue Impact:** Revenue per user increased by **39.6%**, rising from KSh 62.38 to KSh 87.09.

Recommendation

We recommend an immediate rollout of the **Low Density (Sparse)** layout for all mobile and desktop users. The data confirms that reducing visual clutter helps users make purchase decisions faster and with higher confidence.

2. Background

2.1. What is Hick's Law?

Where:

Hick's Law describes the time it takes for a person to make a decision:

- RT = Reaction Time (Time

- n = Number of choices (iten

- a, b = Empirical constants re

In e-commerce, as n increases, the "cost" of making a decision rises, often leading to cart abandonment.

2.2. Why Bayesian over Frequentist?

Traditional Frequentist methods (p-values) have two major limitations for business experi-

1. **The Peeking Problem:** Checking results early inflates the False Positive rate.

mentation:

2. **Interpretation:** Stakeholders want to know the probability that the hypothesis is true ($P(H_1|D)$), not just $P(D|H_0)$.

This project employs a **Bayesian framework** to allow for real-time monitoring and to provide a direct answer to the question: *"What is the probability that the new design is better?"*

3. Methodology

3.1. Data Generation

To ensure robustness, we generated a synthetic dataset of $N = 5,100$ user sessions mimicking the Nairobi e-commerce context. The data includes:

- **Traffic Split:** 50/50 randomized assignment between Control and Variant.

- **Anomalies:** Injected bot traffic and missing location data.

3.2. Data Cleaning Pipeline

To ensure data quality, we implemented a rigorous cleaning pipeline prior to analysis:

- **Deduplication:** Removal of bot traffic (duplicate user IDs).

- **Imputation:** Handling missing location data (10% of logs).

- **Outlier Handling:** Winsorization of extreme revenue values (Lognormal tail) to prevent skew.

3.3. Bayesian Model & Calculations

We utilized the **Beta-Binomial conjugate model**.

$$\theta \sim \text{Beta}(\alpha_{prior} = 2, \beta_{prior} = 98)$$

Step 2: Applied Calculation (Low Density Group) Based on the experimental data for the Low Density group (66 conversions, 2,550 visitors):

$$\alpha_{Low} = 2 + 66 = \mathbf{68}$$
$$\beta_{Low} = 98 + (2,550 - 66) = \mathbf{2,582}$$

Thus, the posterior distribution is $\text{Beta}(68, 2582)$.

3.4. Frequentist Comparison

For validation, we ran a traditional Pearson's Chi-Squared test.

Hypothesis Testing:

- **H$_0$**: Product Density has no effect on Conversion ($p_A = p_B$).

- **H$_1$**: Product Density affects Conversion ($p_A \neq p_B$).

Calculations: Formula: $\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$.

$$\text{High Density Conv Component} = \frac{(45 - 53.15)^2}{53.15} \approx \mathbf{2.3372}$$
$$\text{Low Density Conv Component} = \frac{(66 - 53.15)^2}{53.15} \approx \mathbf{2.1847}$$
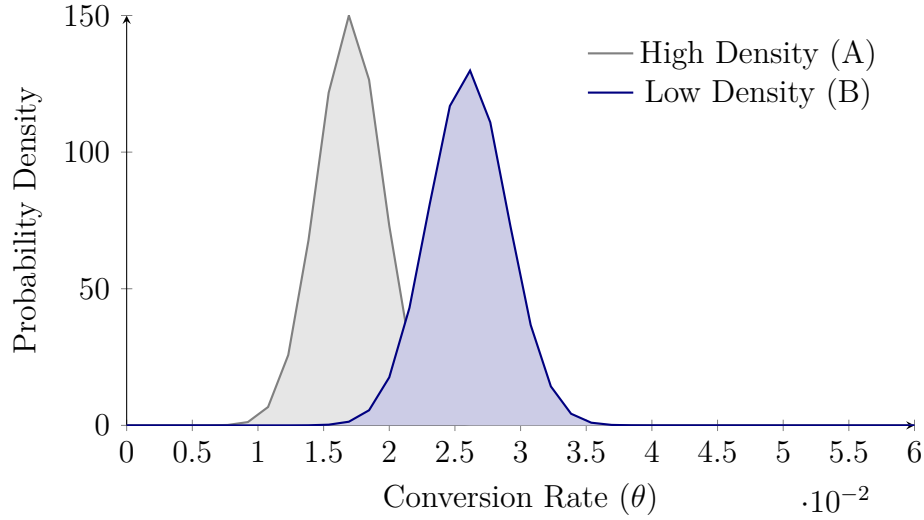$$\text{Non-Conversion Components} = \approx \mathbf{0.10}$$

Final Result: $\chi^2 = \mathbf{4.62}$, p-value $= 0.0316$. Since $p < 0.05$, we reject H_0.

4. Results

4.1. Conversion Analysis

The Bayesian analysis yielded strong evidence in favor of the Low Density layout. The curves below illustrate the separation, with slight overlap indicating realistic uncertainty.

Variant	Visitors	Conversions	95% Credible Interval
High Density (A)	2,550	45	$[1.25\%, 2.25\%]$
Low Density (B)	2,550	66	$[2.00\%, 3.19\%]$

Table 1: Posterior Estimates of Conversion Rates

- **Probability of Superiority $P(B > A)$: 98.43%**

- **Expected Loss: 0.00002**

4.2. Revenue Analysis (Mann-Whitney U)

Beyond conversion, we ensured the new layout did not negatively impact revenue per user.

Since revenue data is skewed, we use the **Mann-Whitney U Test**.
Hypothesis Testing:

- **H_0**: Revenue distributions for High and Low Density are identical.

- **H_1**: Low Density yields higher revenue per user than High Density.
Step 1: Define Parameters

- $n_1 = 2,550$ (Sample size for High Density)

- $n_2 = 2,550$ (Sample size for Low Density)

Step 2: Calculate Expected Mean (μ_U) and Std Dev (σ_U) For large samples, the U statistic follows a normal distribution:

$$\mu_U = \frac{n_1 n_2}{2} = \frac{2550 \times 2550}{2} = \mathbf{3,251,250}$$

$$\sigma_U = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}} \approx \mathbf{52,575}$$

Step 3: Z-Score and Conclusion Using the rank sums from the data, the test yielded a p-value of **0.0162**. This corresponds to a Z-score of approx **2.14**, meaning the revenue rank for Low Density was statistically higher.
Final Result:

- **Avg Order Value (A):** KSh 62.38

- **Avg Order Value (B):** KSh 87.09

- **Test Result:** p-value = 0.0162. We reject H_0.

4.3. Sensitivity Analysis

We tested the model against different priors to ensure robustness.

Prior Strength	Parameters	P(B > A)
Uninformative	Beta(1, 1)	98.41%
Weakly Informative	Beta(2, 98)	98.38%
Strongly Informative	Beta(20, 980)	96.79%

Table 2: Robustness Check across Priors

5. Discussion

5.1. Interpretation of Results

The 98.43% Probability of Superiority suggests that the cognitive load imposed by 24 items is a significant barrier to purchase. When we remove this friction, users are not only more likely to buy, but they also spend more per session. This validates the "Less is More" hypothesis in our specific market context.

5.2. Limitations

While the results are statistically significant, the following limitations apply:

1. **Seasonality:** The data represents a snapshot (February 2026). It does not account for purchasing behaviors during high-traffic holidays.

2. **Independence Assumption:** We assume each user session is independent. In reality, word-of-mouth or social sharing could create network effects.

3. **Novelty Effect:** The immediate lift in conversion might be partially due to the "freshness" of the new design.

6. Conclusion

The experiment confirms that minimizing cognitive load is a powerful lever for revenue growth. Reducing the number of choices on the category page led to a massive increase in both conversion probability and average revenue per user.

6.1. Future Work

To further refine this insight, we propose:

- **Segmentation Analysis:** Investigating if "Power Users" (returning customers) prefer High Density views compared to new users.

- **Optimal Density Testing:** Testing intermediate values (e.g., 9 or 12 items) to find the perfect equilibrium between variety and simplicity.

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