Addressing Membership Challenges: Insights and Strategies for Amour Beauty Box

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Objective

Amour Beauty Box, a subscription-based makeup company, has recently faced declining new member sign-ups despite strong retention among existing customers. To identify the key drivers behind this trend, we implemented a two-pronged research strategy: a Voice of the Customer survey and an A/B testing experiment. Our survey (312 responses) revealed that unclear pricing, the absence of customer reviews, and a lack of product previews were major barriers to signing up, while incentives like first-time discounts and clearer product information significantly boosted interest. Concurrently, our A/B testing was designed to measure the impact of offering additional incentives on signup and revenue rates, using a controlled randomized design with 10,000 visitors over 20 days. Based on the results, we recommend enhancing the visibility of the "Join Now" button, introducing product previews and social proof earlier in the customer journey, and piloting first-time discount offers to increase new member acquisition.

Background

Amour Beauty Box is a beauty subscription company with a clear mission: to be the go-to destination for trend-savvy, socially conscious makeup lovers. What sets Amour apart from other subscription services is its distinctive focus on indie and emerging beauty brands, combined with a deep responsiveness to TikTok and Instagram trends**.** This means subscribers aren't just getting mainstream products - they're discovering what's *next* in beauty before it hits the shelves.

In line with its commitment to sustainability, Amour Beauty Box is also eco-friendly, using recyclable packaging and partnering with brands that prioritize clean ingredients and ethical sourcing. The brand resonates most strongly with Gen Z and young millennial consumers, who value both innovation and social responsibility in their beauty choices.

Subscribers receive curated boxes based on their personal preferences and skin type, ensuring that each delivery feels personalized and exciting. Each box includes exclusive promotions, free shipping, and access to premium products from popular and up-and-coming brands alike.
Amour offers a versatile subscription model with three plans tailored to different budgets and preferences:

- **Monthly Plan**: $19.99 for the first box, $29.99 for subsequent boxes
- **Quarterly Plan**: Three boxes for $79
- **Annual Plan**: Twelve boxes for $287

Sample size and duration of the experiment

Last year, Amour Beauty Box reportedly had around 30,000 subscribers and received approximately 15,000 website visits per month, which averages to about 500 visits per day.
The estimated proportion is calculated as the number of subscribers divided by the total visits.

$$p = \frac{30{,}000 \text{ subscribers}}{15{,}000 \text{ visits per month } \times 12 \text{ months per year}} \approx 0.167$$

We want to construct a 95% confidence interval for p = 16.7% with a margin of error M = 1.3%. The minimum sample size is:

$$n = \left(\frac{z}{M}\right)^2 \cdot p(1-p) = \left(\frac{1.960}{0.013}\right)^2 \cdot 0.167 \cdot (1-0.167) \approx 3{,}162.2$$

We aimed to collect at least 3,162 samples for each group. Additionally, to account for duplicate users accessing the website, we set a goal of collecting 10,000 samples.

The duration of the experiment is calculated by dividing the number of samples that need to be collected by the number of daily visits.

$$\text{Duration} = \frac{10{,}000 \text{ samples}}{500 \text{ visits per day}} = 20 \text{ days}$$

We will test changes to the website and signup flow to evaluate their impact on conversion rates. The control and variant groups will each consist of 3,162 samples (6,324 total, accounting for duplicates, aiming for 10,000 samples overall). The test will run for approximately 20 days.

Testing Metric
There are two ways to conduct an A/B test, depending on the metric used:

- **Conversion** refers to any action taken online that aligns with a business's goals, such as filling out a form, making a purchase, or completing a survey.
- **Revenue** is a continuous metric that directly impacts the business's bottom line.

Firstly, we consider conversion rate, which represents the number of conversions within a given timeframe and is typically expressed as a percentage. For example, if 100 visitors access a website and 10 make a purchase, the conversion rate is 10%. This metric helps businesses assess how effectively their website converts visitors into customers.

Secondly, we also conduct an A/B test on revenue, as a high conversion rate does not necessarily imply high revenue. For example, Amour Beauty Box may have more people signing up for the monthly box, resulting in a high conversion rate but lower revenue. Conversely, if fewer people sign up but opt for annual payments, it would yield a lower conversion rate but higher revenue.

Design A/B testing
To evaluate the effectiveness of the proposed improvements to the signup flow at Amour Beauty Box, we carefully defined two sets of hypotheses: one addressing the conversion rate and the other examining revenue per user based on the position of the 'Join Now' button on the homepage. In the control design, the button had been placed in the top left corner, while in the variant design, it had been repositioned prominently in the center to enhance visibility and encourage user engagement.

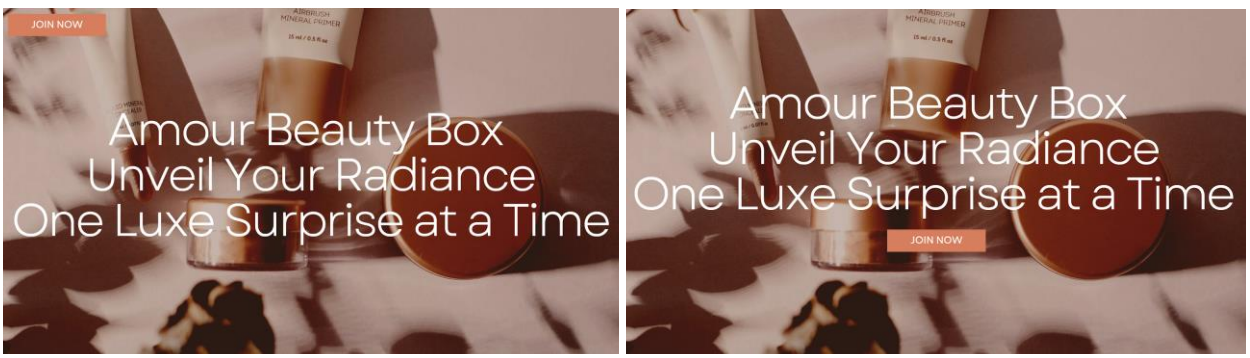

Figure. (Left)The control group, where the 'Join Now' button is positioned at the top left. (Right) The variant group, where the 'Join Now' button is positioned at the center.

For **conversion rate:**

- N**ull hypothesis (H_{01})** asserted that the proportion of users signing up was the same between the control group and the variant group. That is, the change implemented in the variant group does not lead to a statistically significant increase in conversion rate.
- **Alternative hypothesis (H_{11})** proposed that signup rates differed between the two groups, indicating that the implemented change has led to a statistically significant increase in conversion rate.

Similarly, for **revenue**:

- **Null hypothesis (H_{02})** posited that there was no difference in revenue per user between the control and variant groups
- **Alternative hypothesis (H_{12})** suggested that revenue differs across groups.

Data Analysis
After 20 days, we successfully collected 10,000 samples for the experiment. To prevent inaccurate results, we needed to remove duplicate users, as having the same individuals in both the control and variant groups would skew the data by counting them twice.

Given our large sample size, we chose not to use the T-test and initially considered applying a Z-test. However, preliminary normality testing showed that the underlying data distributions were not normal, making Z-tests unsuitable for analysis. Instead, we selected Mann-Whitney U-tests to compare the distributions of signup behavior and revenue between the two groups.

Our results indicated that the p-values for U-statistics in both conversion rate and revenue exceeded the significance level of 0.05. As a result, we failed to reject both null hypotheses. Please see GitHub for the details of our analyses.

Conclusion
We failed to reject the null hypothesis for the conversion rate, indicating that the implemented change did not lead to a statistically significant increase in sign-ups. In other words, the adjustment had little to no impact on user behavior, suggesting that additional factors may be influencing conversion rates. This outcome highlights the need for further analysis to explore elements such as user preferences, market conditions, and potential website optimizations that could enhance engagement and drive sign-ups.

Similarly, we failed to reject the second null hypothesis, meaning the change did not result in a statistically significant increase in revenue. The modification did not contribute to higher earnings, implying that user spending and purchasing behavior remained largely unaffected. This finding underscores the importance of further investigation into potential revenue-driving factors, including pricing strategies, customer retention efforts, and external market dynamics that may support financial growth.