

# A/B Testing Dashboard Project — Approach & Process

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## 1. About the Dataset

The dataset (sourced from Kaggle) simulates an A/B test scenario with user-level data. Columns include user\_id (anonymized), group (A/B), page\_views, time\_spent, conversion status, device, and location. It mimics real-world experimentation data used in e-commerce/product analytics.

## 2. Objective

To evaluate whether Variant B of the experience leads to a statistically significant uplift in conversions compared to Variant A, and to provide business-ready insights and recommendations.

## 3. Assumptions

- The dataset is randomly assigned between groups A and B.
- Conversion definition is consistent across groups.
- No major external factors influence one group disproportionately.
- Minimum Detectable Effect (MDE) threshold set at 5pp (percentage points).
- Business value of a conversion is assumed for illustrative calculation in €M.

## 4. Process

1. Data cleaning & sanity checks: Verified balance between A and B, checked duplicates.
2. Statistical setup: Calculated conversion rates, applied two-proportion z-test in Excel.
3. MDE validation: Ensured uplift exceeds pre-defined business threshold.
4. Segmentation: Analyzed results by device type and location.
5. Power BI modeling: Created measures (conversion rates, lift, p-values) in DAX.
6. Dashboard design: Developed two pages — Overview (executive KPIs) and Deep Dive (detailed segment analysis).
7. Projected monthly uplift: Estimated the additional conversions and potential revenue impact (in €M) if Variant B is rolled out, based on observed uplift and assumed business value per conversion.

## 5. Results

- Conversion Rate (A): 5.40%
- Conversion Rate (B): 14.07%
- Uplift: +8.67 percentage points
- Statistical significance:  $p < 0.05$
- MDE threshold: Met and exceeded

## 6. Insights

- **Conversion Drivers** (not engagement): Average page views (~7.5) and time spent (~242s) are essentially identical between groups, so the uplift is due to conversion efficiency, not higher engagement.
- **Conversion by Page Views**: Conversion rate rises with page views and peaks in the 7-10 pages range → a clear segment for targeted offers. Users who browse 0-1 pages also convert at materially higher rates.
- **Confidence Intervals**: CI for A and B do not overlap → high confidence that  $B > A$ .
- **Device Robustness**: Lift is consistent across Desktop and Mobile, indicating variant performance is platform-agnostic.
- **Geographic Consistency**: Uplift appears across major UK regions (England, Wales, Scotland, Northern Ireland) — no regional bias detected.
- **Statistical Strength**:  $Z = 10.35$ ,  $p < 0.001$  (conversion); t-test for time spent  $p = 0.64$  → conversion uplift is highly significant and not influenced by differences in user engagement time.

## 7. Recommendations

- **Roll out Variant B gradually**: Deploy B broadly but roll out by cohort (e.g. country/device slices) so performance can be closely monitored before making it available to all users.
- **Monitor guardrails**: Track error rates, bounce, checkout completion, and retention for 2–4 weeks post-rollout.
- **Leverage page-view behaviour**: Target users in the 2–6 page bucket with personalized incentives or CTAs to maximize conversion efficiency.
- **Follow-up tests**: Run targeted experiments for low-converting buckets (0–1 and 11+ page views) to understand and improve their funnel behavior.
- **Post-release audit**: Recompute key metrics (conversion, ARPU, retention) after 4 weeks and present a short ROI report comparing projected vs. actual uplift.

## 8. Key Takeaways

This project demonstrates an industry-standard A/B testing workflow: from raw dataset to executive-ready dashboards. It highlights technical rigor (Excel + statistical testing), business alignment (MDE & impact in €M), and data storytelling (Power BI dashboards).