THE TRILLION-DOLLAR LEAK : WHY MOST ONLINE SHOPPERS NEVER SAY "YES."

<u>DO YOU KNOW HOW DO THEY OPTIMIZE THE SITE VISIT INTO PURCHASE ..?</u>

Imagine a physical store where 100 people walk in, 66 immediately walk back out after looking at one shelf, and only 33 ever pick up a basket. Of those 33, only a handful make it to the cash register.

In the world of E-commerce, this isn't a disaster—it’s the daily reality. Brands spend millions on "Recommendation Engines" designed to nudge users toward that final click. But as user attention spans shrink, the traditional 4-step funnel is dying. Today’s shoppers don't want a "journey"; they want the shortest path to "Purchase Confirmed."

When we change the interface to help them, are we actually making it easier—or are we just adding more friction?

A/B Test Report: Recommendation System Interface (EU Region)

What this project focuses on:
This analysis deep-dives into the interface_eu_test, an A/B experiment launched to optimize the shopping experience for new users in the European market.

The Mission:
The goal was clear: Introduce a new recommendation interface and achieve a 10% lift in conversion at every stage of the funnel.

By Thennarasu

OPTIMIZATION OR FRICTION? A DEEP DIVE INTO THE EU RECOMMENDATION SYSTEM'S FUNNEL PERFORMANCE

A/B Test Report: Recommendation System Interface (EU Region)

1. EXECUTIVE SUMMARY

- **Goal:** Evaluate the effectiveness of a new interface for the recommendation system specifically targeting new EU users.
- **Target KPI:** A minimum **10% increase** in conversion across all funnel stages (product_page, product_cart, and purchase).
- **Result:** The test **did not meet** the expected 10% lift across the entire funnel. While the purchase stage showed a slight absolute improvement of 1.11%, the results were not statistically significant enough to reject the null hypothesis for the overall journey.
- **Recommendation:** Do not roll out the new interface globally. Instead, investigate the high drop-off between the product_page and product_cart and consider optimizing for "one-click" buying behaviours.

2. EXPERIMENTAL DESIGN & METHODOLOGY

- **Test Name:** interface_eu_test.
- **Audience:** New users from the EU region who signed up between Dec 7 and Dec 21, 2020.
- **Groups:**
  Control (Group A): 4,521 users (current interface).
  Test (Group B): 4,438 users (new recommendation interface).
- **Analysis Window:** 14 days of data (Dec 7 – Dec 21, 2020)

By Thennarasu

3. DATA QUALITY & PREPROCESSING

- **Data Integrity:** The final dataset was refined from multiple sources, including a calendar of marketing events, user sign-up logs, and participant assignments.

- **Participant Volume:** After cleaning and ensuring users were correctly attributed to the EU region, the study analyzed **8,959 unique users** performing **51,848 different events**.

- **Splitting Integrity:** Statistical checks confirmed that the population proportions of Groups A and B were split properly, ensuring that any differences in results were likely due to the interface rather than a sampling bias.

- **Sanity Checks Performed:**

1. Verified no user appeared in both test groups
2. Confirmed balanced group split
3. Validated event timestamps and funnel ordering
4. Confirmed categorical consistency for event types

4. STATISTICAL RESULTS & ANALYSIS

Funnel Stages Evaluated

Login → Product Page → Product Cart → Purchase

Hypothesis:

- H0: there is not a statistically significant difference in conversion between the samples A and B
- H1: there is a statistically significant difference in conversion between the samples A and B

The report utilized a series of hypothesis tests (proportions tests) to compare conversion rates at each stage:

	event_name	p_value	significant	decision
0	login	0.321767	False	Fail to Reject H_0
1	product_cart	0.147028	False	Fail to Reject H_0
2	product_page	0.166090	False	Fail to Reject H_0
3	purchase	0.020365	True	Reject H_0

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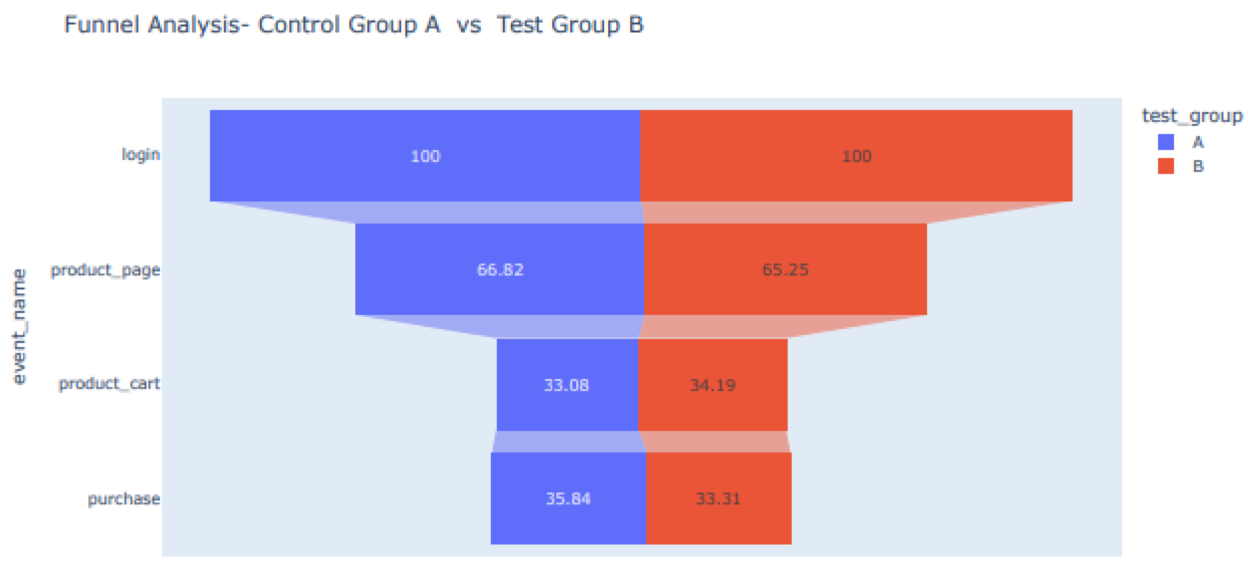
Key Insight: While the purchase stage showed significance, it did not reach the target 10% lift. Interestingly, the data suggests some users are bypassing the product_cart entirely, moving directly from the product_page to purchase.

5. DATA QUALITY & FUNNEL INTEGRITY AUDIT

	event_name	n_users	conversion_pct	test_group
0	login	11247	100.00	A
2	product_page	7515	66.82	A
1	product_cart	3720	33.08	A
3	purchase	4031	35.84	A
0	login	10885	100.00	B
2	product_page	7102	65.25	B
1	product_cart	3722	34.19	B
3	purchase	3626	33.31	B



1. The Logical Funnel Discrepancy

A standard e-commerce funnel requires a linear progression: **Login → Product Page → Product Cart → Purchase.** Mathematically, each subsequent stage must be a subset of the previous stage's unique users.

- **Group B (Test Group):** Exhibits a Healthy Funnel
  - **Conversion Flow:** 100% (Login) → 65.64% (Product Page) → 34.16% (Product Cart) → 33.33% (Purchase).
  - **Observation:** This follows a logical "decay" model. Every step has fewer unique users than the one before it, representing a realistic and clean user journey.

- **Group A (Control Group): Exhibits a Broken Funnel**

- **Conversion Flow:** 100% (Login) → 66.82% (Product Page) → 33.08% (Product Cart) → 35.84% (Purchase).
- **Observation**: **The "Purchase" rate is higher than the "Product Cart" rate**. It is logically impossible for more unique users to complete a purchase than those who reached the cart stage in a sequential flow. This confirms a structural anomaly in the Control group's data.

2. Statistical Significance vs. Logical Validity

While the Z-test for proportions yielded a "statistically significant" result at the Purchase stage **(p = 0.020)**, this result must be interpreted with extreme caution:

- The significance is a by product of the **Control Group's data anomaly**, not necessarily the Test group's performance.
- When the baseline (Group A) is logically inconsistent, any "lift" measured against it is mathematically unreliable.

3. Root Cause Analysis (Technical Hypotheses)

Why is Group A's data defying logic? The discrepancy in the Control Group suggests a failure in the underlying tracking architecture. We have two primary theories for this anomaly:

- **Tracking Failure:** The product_cart event in the legacy interface (Group A) may not be firing consistently across all sessions. This results in an undercount of unique users at the cart stage while still successfully capturing the final purchase event.
- **Legacy Shortcuts:** The old interface may contain a "Buy Now" button or "Direct Checkout" feature that was not accounted for in the initial funnel mapping. This allows users to bypass the cart stage entirely, creating a non-linear journey that the current tracking logic cannot reconcile.

4. Final Strategic Recommendation

Verdict: Inconclusive — Deployment Halted. I recommend against a full rollout of the new interface at this time. To reach a data-driven conclusion, we must:

- **Synchronize Tracking:** Audit and fix the event triggers in the legacy system to ensure both groups are tracked identically.
- **Re-Test:** Re-run the experiment once both funnels are "healthy." This ensures the final decision is based on actual user behavior rather than tracking discrepancies.

6. STRATEGIC RECOMMENDATIONS & NEXT STEPS

Based on the statistical analysis and the funnel integrity audit, I recommend the following:

- **Immediate Action:**
  Technical Audit of Control Group (A) The "Purchase > Cart" inversion in Group A is our most significant finding. We must investigate the legacy interface to see if a "Direct Buy" feature exists that is not currently being tracked as a product_cart event.

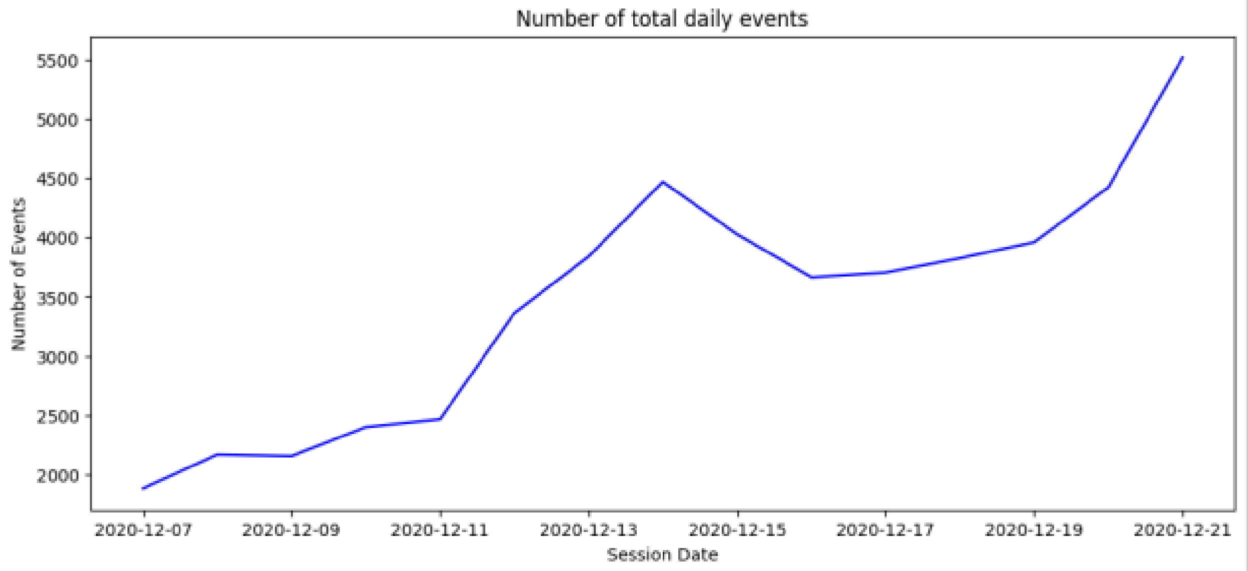
- **Investigate "Buy Now" as a Global Standard:**
  The data from Group A suggests that a significant portion of our users are already finding ways to bypass the cart to complete purchases faster. Instead of forcing users through a traditional recommendation/cart funnel (like in Group B), we should consider making **"Fast-Track Checkout"** a standardized, properly tracked feature for all users.

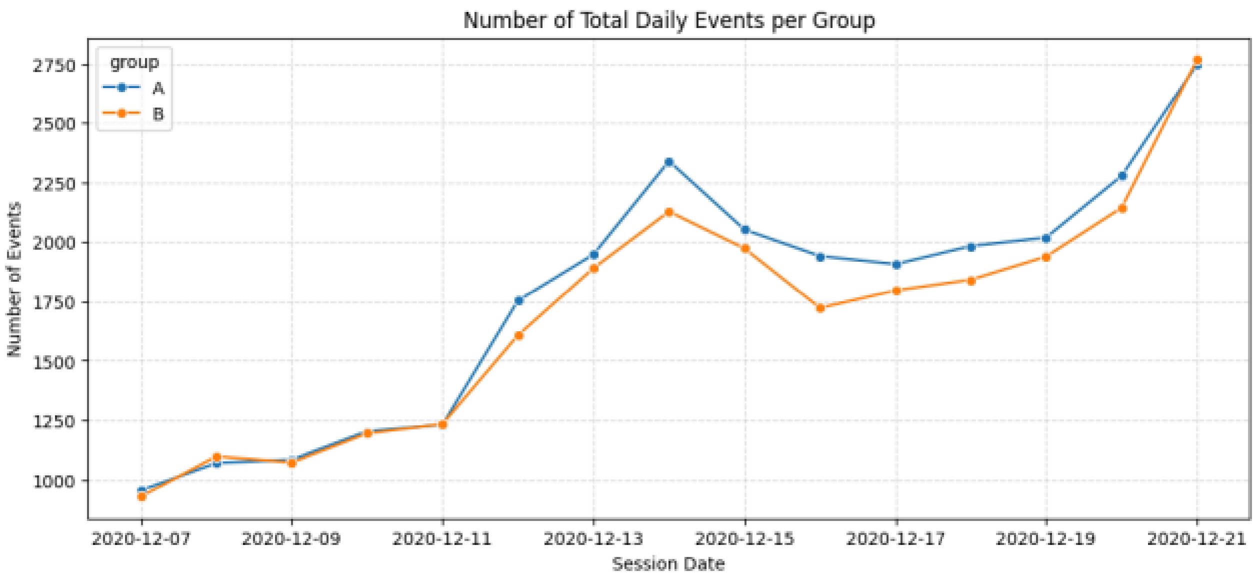
- **Standardize Event Tracking**
  Before re-running this test, ensure that both "Add to Cart" and "Direct Buy" actions are captured as distinct events. This will prevent future funnel discrepancies and allow for a true "apples-to-apples" comparison between new designs and the legacy site.

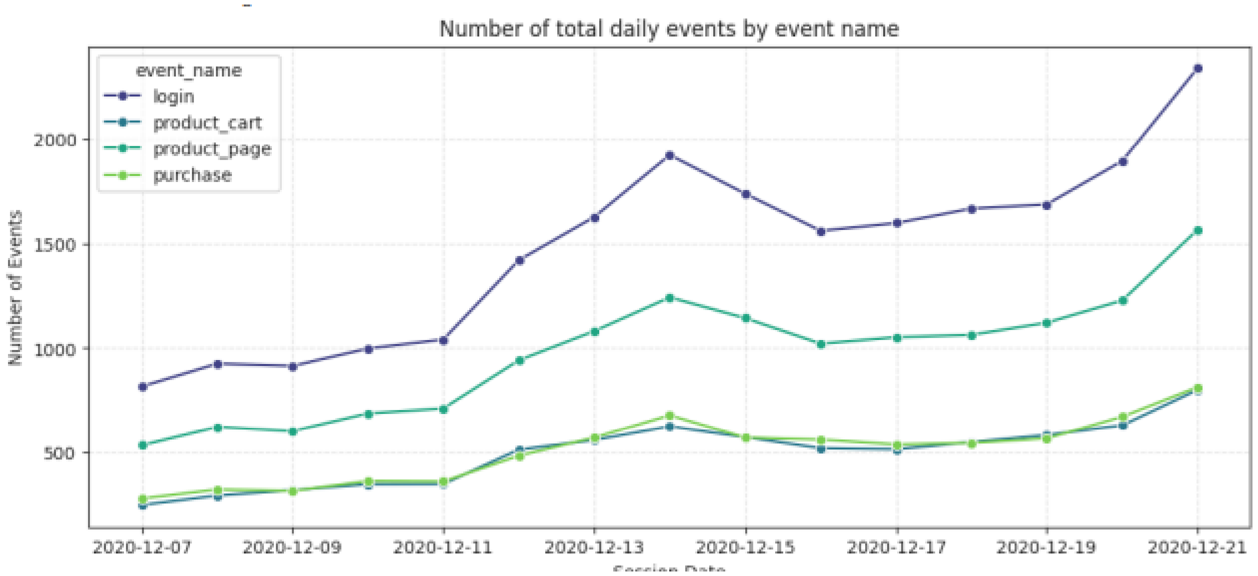
- **Decision:**
  Pause Global Rollout We should not deploy the interface_eu_test globally yet. While Group B's funnel is "cleaner," it didn't achieve the 10% lift. More importantly, we cannot make a final decision until we understand why the Control group (A) is outperforming the funnel logic.

7. VISUAL EVIDENCE

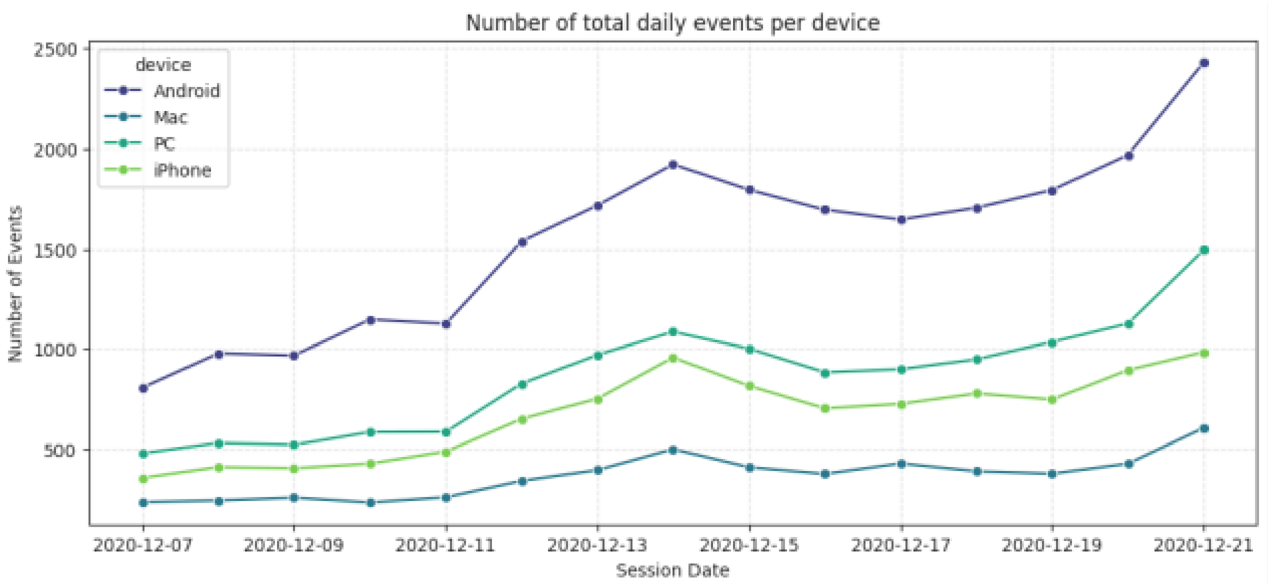
How is the number of events distributed by days?







By Thennarasu



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Project description

Project goals

Testing changes:

The introduction of a new interface for an improved recommendation system for EU users.

Test name:

interface_eu_test

Audience:

The audience is new users from the EU who were encouraged to sign up in the online store. Expected number of test participants: 6000

Test duration:

From December 7 to December 21, 2020.

Expected result:

Increase total conversion by at least 10% at each stage of the funnel product_page → product_cart → purchase in test group B.

Data description

- ab_project_marketing_events_us.csv — the calendar of marketing events for 2020
- final_ab_new_users_us.csv — all users who signed up in the online store from December 7 to 21, 2020
- final_ab_events_us.csv — all events of the new users within the period from December 7, 2020 to January 1, 2021
- final_ab_participants_us.csv — table containing test participants

Project Settings

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Data sources

```
Events = pd.read_csv("https://raw.githubusercontent.com/alona808/ab_testing_online_store/refs/heads/main/datasets/final_ab_
```

```
Marketing_Events = pd.read_csv("https://raw.githubusercontent.com/alona808/ab_testing_online_store/refs/heads/main/dataset
```

```
New_Users = pd.read_csv("https://raw.githubusercontent.com/alona808/ab_testing_online_store/refs/heads/main/datasets/final_
```

```
Participants = pd.read_csv("https://raw.githubusercontent.com/alona808/ab_testing_online_store/refs/heads/main/datasets/fir
```

```
datasets = [('Events',Events), ('Marketing_Events',Marketing_Events), ('New_Users',New_Users), ('Participants',Participant
```

Data Overview and Preprocessing

```
for name,dataset in datasets:
    print(f"Dataset_Name : {name}")
    print('    ')
    print(dataset.info())
    print('-----------------------________---------------------------')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 423761 entries, 0 to 423760
Data columns (total 4 columns):
 #   Column      Non-Null Count   Dtype
```

```
 0   user_id     423761 non-null  object 
 1   event_dt    423761 non-null  object 
 2   event_name  423761 non-null  object 
 3   details     60314 non-null   float64
dtypes: float64(1), object(3)
memory usage: 12.9+ MB
None
-----------------------________---------------------------
Dataset_Name : Marketing_Events

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   name       14 non-null     object
 1   regions    14 non-null     object
 2   start_dt   14 non-null     object
 3   finish_dt  14 non-null     object
dtypes: object(4)
memory usage: 580.0+ bytes
None
-----------------------________---------------------------
Dataset_Name : New_Users

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61733 entries, 0 to 61732
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   user_id     61733 non-null  object
 1   first_date  61733 non-null  object
 2   region      61733 non-null  object
 3   device      61733 non-null  object
dtypes: object(4)
memory usage: 1.9+ MB
None
-----------------------________---------------------------
Dataset_Name : Participants

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18268 entries, 0 to 18267
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   user_id  18268 non-null  object
 1   group    18268 non-null  object
 2   ab_test  18268 non-null  object
dtypes: object(3)
memory usage: 428.3+ KB
None
-----------------------        ---------------------------
```

```python
for name,dataset in datasets:
    print(f"Dataset_Name : {name}")
    print('     ')
    print(dataset.head())
    print('-----------------------________---------------------------')
```

```
Dataset_Name : Events

            user_id             event_dt event_name  details
0  E1BDDCE0DAFA2679  2020-12-07 20:22:03   purchase    99.99
1  7B6452F081F49504  2020-12-07 09:22:53   purchase     9.99
2  9CD9F34546DF254C  2020-12-07 12:59:29   purchase     4.99
3  96F27A054B191457  2020-12-07 04:02:40   purchase     4.99
4  1FD7660FDF94CA1F  2020-12-07 10:15:09   purchase     4.99
-----------------------________---------------------------
Dataset_Name : Marketing_Events

                           name                   regions    start_dt  \
0      Christmas&New Year Promo             EU, N.America  2020-12-25   
1  St. Valentine's Day Giveaway  EU, CIS, APAC, N.America  2020-02-14   
2        St. Patric's Day Promo             EU, N.America  2020-03-17   
3                  Easter Promo  EU, CIS, APAC, N.America  2020-04-12   
4             4th of July Promo                 N.America  2020-07-04   

    finish_dt  
0  2021-01-03  
1  2020-02-16  
2  2020-03-19  
3  2020-04-19  
4  2020-07-11  
-----------------------________---------------------------
Dataset_Name : New_Users

            user_id  first_date     region   device
0  D72A72121175D8BE  2020-12-07         EU       PC
1  F1C668619DFE6E65  2020-12-07  N.America  Android
2  2E1BF1D4C37EA01F  2020-12-07         EU       PC
```

```
3  50734A22C0C63768  2020-12-07         EU   iPhone
4  E1BDDCE0DAFA2679  2020-12-07  N.America   iPhone
------------------------________---------------------------
Dataset_Name : Participants

            user_id group                  ab_test
0  D1ABA3E2887B6A73     A  recommender_system_test
1  A7A3664BD6242119     A  recommender_system_test
2  DABC14FDDFADD29E     A  recommender_system_test
3  04988C5DF189632E     A  recommender_system_test
4  482F14783456D21B     B  recommender_system_test
------------------------________---------------------------
```

```
for name,dataset in datasets:
    print(f"Dataset_Name : {name}")
    print('    ')
    print(dataset.describe())
    print('------------------------________---------------------------')
```

```
Dataset_Name : Events

            details
count  60314.000000
mean      23.881219
std       72.228884
min        4.990000
25%        4.990000
50%        4.990000
75%        9.990000
max      499.990000
------------------------________---------------------------
Dataset_Name : Marketing_Events

                            name regions    start_dt   finish_dt
count                         14      14          14          14
unique                        14       6          14          14
top     Christmas&New Year Promo    APAC  2020-12-25  2021-01-03
freq                           1       4           1           1
------------------------________---------------------------
Dataset_Name : New_Users

                 user_id  first_date region   device
count              61733       61733  61733    61733
unique             61733          17      4        4
top     8F04273BB2860229  2020-12-21     EU  Android
freq                   1        6290  46270    27520
------------------------________---------------------------
Dataset_Name : Participants

                 user_id  group            ab_test
count              18268  18268              18268
unique             16666      2                  2
top     95401934D6D6D4FC      A  interface_eu_test
freq                   2   9655              11567
------------------------________---------------------------
```

The Marketing Events Dataset

```
Marketing_Events[['start_dt','finish_dt']]=Marketing_Events[['start_dt','finish_dt']].apply(pd.to_datetime)

Marketing_Events=Marketing_Events.sort_values(by='start_dt')

Marketing_Events['n_days']=(Marketing_Events['finish_dt']-Marketing_Events['start_dt']).dt.days

Marketing_Events
```

	name	regions	start_dt	finish_dt	n_days
6	Chinese New Year Promo	APAC	2020-01-25	2020-02-07	13
1	St. Valentine's Day Giveaway	EU, CIS, APAC, N.America	2020-02-14	2020-02-16	2
8	International Women's Day Promo	EU, CIS, APAC	2020-03-08	2020-03-10	2
2	St. Patric's Day Promo	EU, N.America	2020-03-17	2020-03-19	2
3	Easter Promo	EU, CIS, APAC, N.America	2020-04-12	2020-04-19	7
7	Labor day (May 1st) Ads Campaign	EU, CIS, APAC	2020-05-01	2020-05-03	2
9	Victory Day CIS (May 9th) Event	CIS	2020-05-09	2020-05-11	2
11	Dragon Boat Festival Giveaway	APAC	2020-06-25	2020-07-01	6
4	4th of July Promo	N.America	2020-07-04	2020-07-11	7
13	Chinese Moon Festival	APAC	2020-10-01	2020-10-07	6
12	Single's Day Gift Promo	APAC	2020-11-11	2020-11-12	1
5	Black Friday Ads Campaign	EU, CIS, APAC, N.America	2020-11-26	2020-12-01	5
0	Christmas&New Year Promo	EU, N.America	2020-12-25	2021-01-03	9
10	CIS New Year Gift Lottery	CIS	2020-12-30	2021-01-07	8

Next steps: Generate code with Marketing_Events New interactive sheet

```
Marketing_Events.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 14 entries, 6 to 10
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   name       14 non-null     object
 1   regions    14 non-null     object
 2   start_dt   14 non-null     datetime64[ns]
 3   finish_dt  14 non-null     datetime64[ns]
 4   n_days     14 non-null     int64
dtypes: datetime64[ns](2), int64(1), object(2)
memory usage: 672.0+ bytes
```

Preliminary overview:

- The df_calendar_events dataset contains 14 events over the year 2020.
- The longest event duration is 13 days and belongs to 'Chinese New Year Promo'.
- The shortest event is 1 day. This is 'Single's Day Gift Promo'.
- There are no marketing events in August and September.
- The 'CIS New Year Gift Lottery' event coincides with the 'Christmas&New Year Promo' event. They overlap from December 30 to January 3 inclusive.
- There is no null values.
- The 14 days of A / B testing from December 7 to 21 did not coincide with any marketing event.

Test_Participants_Dataset

```
Participants[['group', 'ab_test']].nunique()
```

	0
group	2
ab_test	2

dtype: int64

```
Participants[['group', 'ab_test']].apply(pd.unique)
```

	group	ab_test
0	A	recommender_system_test
1	B	interface_eu_test

```
Participants.duplicated ().sum()
```

```
np.int64(0)
```

Preliminary overview:

- The Participants dataset contains 18,268 records
- All users are divided into 2 test groups and 2 types of A / B tests.
- There are no duplicates and Nan values.
- However, there are noticeably fewer unique test participants (16,666) than entries. This means that we have users in the dataset who passed both tests, recommender_system_test and in interface_eu_test.

I think we need to delete users who participate in two tests because we don't know which version of the interface the participants in the second test saw.

```
users_2_tests = (
    Participants
    .groupby('user_id')['ab_test']
    .nunique()
    .loc[lambda x: x > 1]
    .reset_index(name='test_count'))

users_2_tests.shape
```

```
(1602, 2)
```

```
users_2_tests.head()
```

	user_id	test_count
0	001064FEAAB631A1	2
1	00341D8401F0F665	2
2	003B6786B4FF5B03	2
3	0082295A41A867B5	2
4	00E68F103C66C1F7	2

Next steps: Generate code with users_2_tests New interactive sheet

```
Participants[Participants['user_id']=='0082295A41A867B5']
```

	user_id	group	ab_test
4768	0082295A41A867B5	A	recommender_system_test
14161	0082295A41A867B5	B	interface_eu_test

As we can see, the dataset contains 1602 records of users who participate in both tests. Let's remove them.

```
Participants=Participants[~Participants['user_id'].isin(users_2_tests['user_id'])]

uid = users_2_tests['user_id'].iloc[0]
Participants[Participants['user_id'] == uid]
```

user_id	group	ab_test

```
Participants.shape[0]
```

```
15064
```

The test_groups dataset has 2 types of A/B test:

recommender_system_test, interface_eu_test. For the purposes of our current project, we have to use data related to interface_eu_test test.

So let's split the dataset to get the necessary data and study it.

```
Participants_EU = Participants[Participants['ab_test']=="interface_eu_test"]
Participants_EU.shape[0]
```

```
9965
```

```
Participants_by_group = Participants_EU.groupby('group')['user_id'].nunique()
Participants_by_group
```

group	user_id
A	5012
B	4953

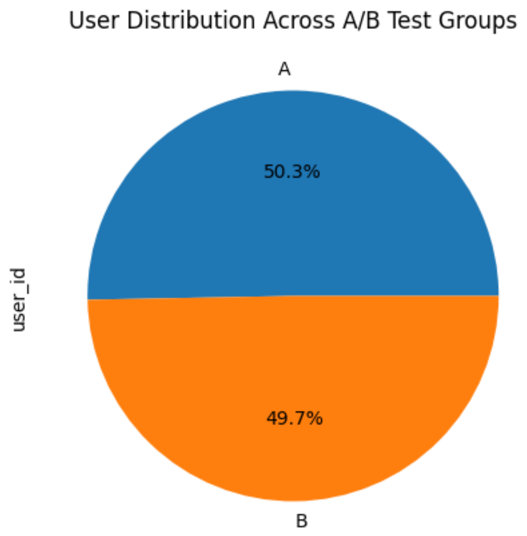
dtype: int64

Now let's check if the dataset has users who are in both test groups A and B.

```
EU_2 = Participants_EU.groupby('user_id')['group'].nunique().loc[lambda x: x > 1].reset_index(name='group_count')
EU_2.shape[0]
```

```
0
```

```
Participants_by_group.plot(kind='pie',autopct='%1.1f%%',figsize=(5,5),title='User Distribution Across A/B Test Groups')
plt.show()
```



Conclusion:

- After preprocessing, we have a dataset named df_eu_test, which contains the users and groups of data we need, interface_eu_test A / B test.
- The dataset df_eu_test has 9965 unique participants which are almost equally split: * 5012 users - in group A, * 4953 users - in group B
- In our dataset we do not have users that got into both test types or into both test groups.

New_Users_Dataset

```
New_Users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 61733 entries, 0 to 61732
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   user_id     61733 non-null  object
 1   first_date  61733 non-null  object
 2   region      61733 non-null  object
 3   device      61733 non-null  object
dtypes: object(4)
memory usage: 1.9+ MB
```

Count unique values in the columns:

```
New_Users.nunique()
```

	0
user_id	61733
first_date	17
region	4
device	4

dtype: int64

```
New_Users[['region', 'device']].agg(pd.unique)
```

	region	device
0	EU	PC
1	N.America	Android
2	APAC	iPhone
3	CIS	Mac

```
New_Users.duplicated ().sum()
```

```
np.int64(0)
```

Preliminary overview:

- The new_users dataset contains 61733 unique entries.
- New users signed up in the online store from December 7 to 23, 2020.
- New users have come from 4 regions: EU, N.America, APAC, CIS.
- They utilize 4 types of devices: PC, Android, iPhone, Mac.
- There are no duplicates and Nan values.

To test the new interface of the online store, we have 2 mandatory testing conditions:

- Testing lasted 14 days, from December 7 to December 21. So these days are included in the scope of the project;
- We have to research new EU users.

Firstly, let's look at the days of December 22nd and 23rd as outside the scope of our task and remove them.

```
New_Users= New_Users[New_Users['first_date']<"2020-12-22"]
```

```
New_Users['first_date'].max()
```

```
'2020-12-21'
```

Secondly, we have to extract data on new EU users from the dataset. Moreover, they must be our test participants.

```
New_Users_EU = New_Users[(New_Users['user_id'].isin (Participants_EU['user_id'])) & (New_Users['region']== "EU")]
New_Users_EU.shape[0]
```

```
8963
```

The dataset of new EU users who signed up in the online store from December 7 to 21, 2020 contains fewer unique users than the dataset containing test participants:

- dataset df_new_eu_users: 8963 users
- dataset df_eu_test: 9965 users

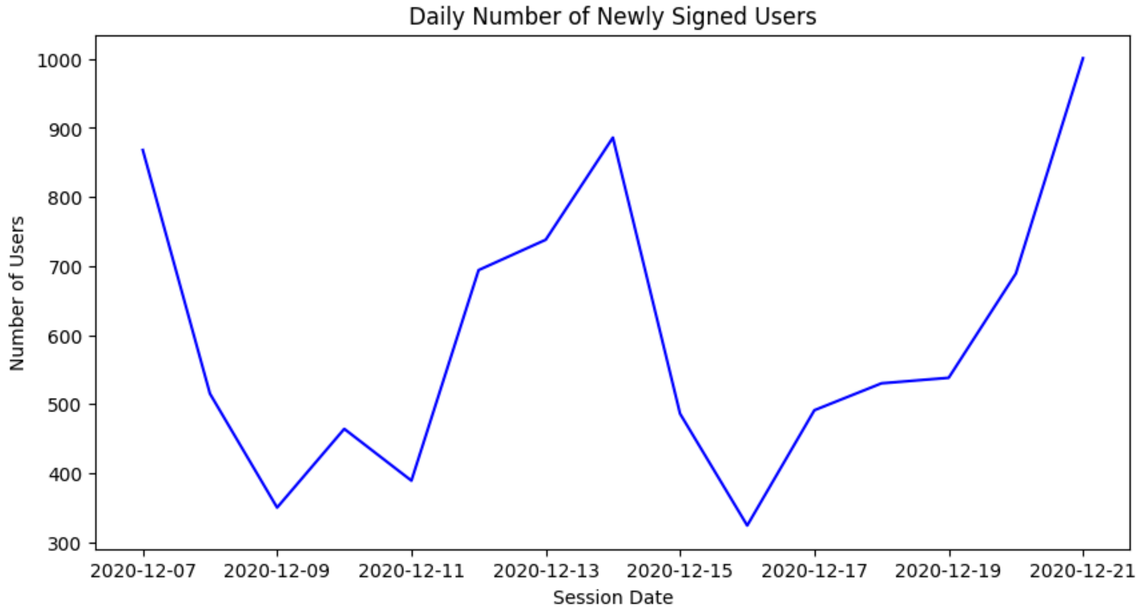
I can assume that some users took part in A / B testing without prior registration in the online store, for example, using the 'Buy Now' button, etc. We can check this version later.

So let's continue with our new EU users.

```
Daily_New_Users = (New_Users_EU.groupby('first_date')['user_id'].nunique())
print(Daily_New_Users)

Daily_New_Users.plot(kind='line',figsize=(10,5),title='Daily Number of Newly Signed Users',color='blue',xlabel='Session Dat
plt.show()
```

```
first_date
2020-12-07     868
2020-12-08     515
2020-12-09     350
2020-12-10     464
2020-12-11     389
2020-12-12     694
2020-12-13     738
2020-12-14     886
2020-12-15     486
2020-12-16     324
2020-12-17     491
2020-12-18     530
2020-12-19     538
2020-12-20     689
2020-12-21    1001
Name: user_id, dtype: int64
```

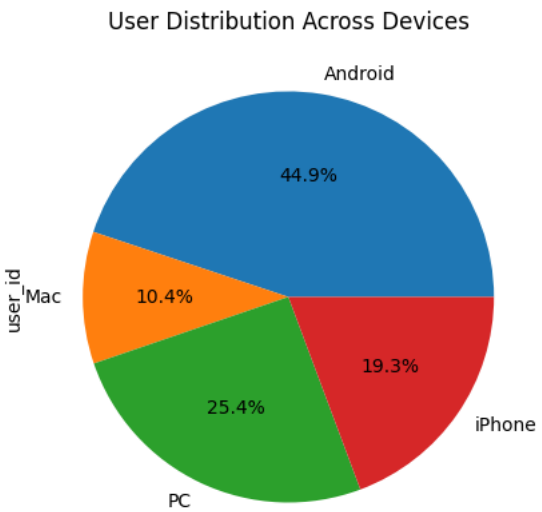


- However, in fact, EU users make up 82% of our dataset.

```
New_Users_by_Device = (New_Users_EU.groupby('device')['user_id'].nunique())
print(New_Users_by_Device)

New_Users_by_Device.plot(kind='pie',autopct='%1.1f%%',figsize=(5,5),title='User Distribution Across Devices')
plt.show()
```

```
device
Android    4022
Mac         930
PC         2281
iPhone     1730
Name: user_id, dtype: int64
```



Conclusion:

- After preprocessing we have the df_new_eu_users dataset 8963 unique entries.
- All new users in the dataset are from the EU who signed up in the online store from December 7 to 21, 2020.
- New EU user registrations for 14 days of testing varied greatly:
    - The maximum number of new users came on December 21st - 1001 new users,
    - The minimum - on December 16th - 324 new users,
    - The number of new user registrations depends on the day of week.
- They utilize 4 types of devices: PC, Android, iPhone, Mac:
    - Almost half of the new users are Android users, 44.9%.
    - The smallest number of users came using the Mac, 10.4%.
- There are no null values and duplicates in the dataset.
- **According to the assignment, the estimated number of test participants must be at least 6000. We have 8963 users, which meets the conditions of testing.**

Events dataset

```
print(Events.shape)
Events.head()
```

```
(423761, 4)
```

	user_id	event_dt	event_name	details
0	E1BDDCE0DAFA2679	2020-12-07 20:22:03	purchase	99.99
1	7B6452F081F49504	2020-12-07 09:22:53	purchase	9.99
2	9CD9F34546DF254C	2020-12-07 12:59:29	purchase	4.99
3	96F27A054B191457	2020-12-07 04:02:40	purchase	4.99
4	1FD7660FDF94CA1F	2020-12-07 10:15:09	purchase	4.99

Count unique values in the columns:

```
Events.nunique()
```

	0
user_id	58703
event_dt	257138
event_name	4
details	4

dtype: int64

```
Events[['event_name','details']].agg(pd.unique)
```

	0
event_name	[purchase, product_cart, product_page, login]
details	[99.99, 9.99, 4.99, 499.99, nan]

dtype: object

Let's explore Nan values in the details column:

```
details_null = Events['details'].isna().sum()
details_null_pct = (Events['details'].isna().mean() * 100).round(2)

details_null, details_null_pct
```

```
(np.int64(363447), np.float64(85.77))
```

As we can see, our event dataset has 85.77% NaN values in the details column.

I think this happened because not all of our users did reach the purchase event. We can check this version)

```
Events[(Events['event_name']=='purchase') & (Events['details'].isna())].shape[0]
```

```
0
```

There is no 'purchase' event with NaN value in the 'details' column. But previous steps of funnel have Nan's.

I consider that we can fill Nan's with 0.

```
Events.details.fillna(0,inplace=True)
Events.isna().sum()
```

	0
user_id	0
event_dt	0
event_name	0
details	0

dtype: int64

```
Events.duplicated ().sum()
```

```
np.int64(0)
```

```
Events
Events.event_dt.describe()
```

	event_dt
count	423761
unique	257138
top	2020-12-23 02:37:24
freq	10

dtype: object

```
Events['event_dt']=pd.to_datetime(Events['event_dt'])
Events=Events.sort_values(by='event_dt')
Events['event_dt'].describe()
```

	event_dt
count	423761
mean	2020-12-18 10:10:17.282395136
min	2020-12-07 00:00:33
25%	2020-12-14 03:05:18
50%	2020-12-18 17:40:52
75%	2020-12-22 13:51:17
max	2020-12-30 23:36:33

dtype: object

Preliminary overview:

- The events dataset contains 423761 records from December 7 to December 30, 2020.
- The funnel consists 4 events: login, product_page, product_cart, and purchase. However, in accordance with our task, we are interested in a funnel of these 3 steps: product_page → product_card → purchase.
- There are no duplicates.
- Nan values of the variable details were filled with 0.

To prepare the dataset for further exploration, we need to perform the same data transformation as for the new user dataset, namely:

- First, get the data for our testing from December 7 to December 21;
- Second, we need to retrieve the events that were executed by our test participants.*

Let's create the df_test_events for our goals and explore it:

```
Events_EU = Events[(Events['user_id'].isin(Participants_EU['user_id'])) & (Events['event_dt'] < "2020-12-22")]
Events_EU.shape[0]
```

```
51848
```

Count unique values in the columns:

```
Events_EU.nunique()
```

	0
user_id	8959
event_dt	33338
event_name	4
details	5

dtype: int64

```
print (Events_EU.sample(5))

print('   ')

print (Events_EU.event_name.value_counts())

print('   ')

Events_EU.duplicated ().sum()
```

```
                 user_id            event_dt    event_name  details
196620  CE8B1BCBCA042768 2020-12-20 19:52:29  product_page      0.0
339043  233653C0930FD807 2020-12-19 17:02:47         login      0.0
265953  80BE72C98A257C69 2020-12-11 10:20:44         login      0.0
285678  7B125EC357070D0E 2020-12-14 16:52:24         login      0.0
293795  8155910F11B56B21 2020-12-14 10:27:23         login      0.0

event_name
login           22132
product_page    14617
purchase         7657
product_cart     7442
Name: count, dtype: int64

np.int64(0)
```

First look at the number of events per user:

```
Events_EU_per_user = Events_EU.groupby('user_id')['event_dt'].count()
Events_EU_per_user.describe()
```

	event_dt
count	8959.000000
mean	5.787253
std	3.727047
min	1.000000
25%	3.000000
50%	6.000000
75%	8.000000
max	24.000000

dtype: float64

```
Events_EU_per_user.mode()
```

	event_dt
0	6

dtype: int64

Conclusion

- The df_test_events dataset contains 51848 events.
- The dataset includes data that was collected from December 7 to December 21, 2020.
- All events presented in the dataset were performed by test takers.
- Each participant completed at least 1 event. Maximum events performed by user is 24.
- An average number of events per user is 6.
- Most often the number of events per user is 6, which coincides with the average number of events.

Merging Datasets

After preprocessing our datasets, we can combine them for deeper exploratory analysis. But first, a small reminder of which ones we will use and what they look like :)

```
Participants_EU.head()
```

	user_id	group	ab_test
6701	D4E530F6595A05A3	A	interface_eu_test
6703	6BCB0F33D3BAB8C2	A	interface_eu_test
6707	2D2E7AA539CF348F	B	interface_eu_test
6708	4BA448BCE1343C6F	A	interface_eu_test
6709	76B6CDF2A8B1DBFC	B	interface_eu_test

Next steps: Generate code with Participants_EU New interactive sheet

```
New_Users_EU.head()
```

	user_id	first_date	region	device
2	2E1BF1D4C37EA01F	2020-12-07	EU	PC
3	50734A22C0C63768	2020-12-07	EU	iPhone
14	5BE017E9C8CC42F8	2020-12-07	EU	Android
18	96F27A054B191457	2020-12-07	EU	iPhone
21	E6AF85675078215D	2020-12-07	EU	Android

```
Events_EU.head()
```

	user_id	event_dt	event_name	details
245271	B13A53A1EB2038EE	2020-12-07 00:02:48	login	0.0
245598	4C4BA430AAA820F8	2020-12-07 00:03:18	login	0.0
123266	4C4BA430AAA820F8	2020-12-07 00:03:19	product_page	0.0
242531	4B7C59A60FE1DA69	2020-12-07 00:03:51	login	0.0
60719	4B7C59A60FE1DA69	2020-12-07 00:03:54	product_cart	0.0

Next steps: Generate code with Events_EU New interactive sheet

```
print('Participants_EU :', Participants_EU.shape[0],'  New_users_EU :', New_Users_EU.shape[0],'  Events_EU :',Events_EU.sha
```

```
Participants_EU : 9965    New_users_EU : 8963    Events_EU : 51848
```

Combining the datasets:

```
df_ab_testing = Events_EU.merge(Participants_EU[['user_id','group']],on='user_id',how='left').merge(New_Users_EU[['user_id
df_ab_testing.head()
```

	user_id	event_dt	event_name	details	group	first_date	device
0	B13A53A1EB2038EE	2020-12-07 00:02:48	login	0.0	A	2020-12-07	PC
1	4C4BA430AAA820F8	2020-12-07 00:03:18	login	0.0	A	2020-12-07	PC
2	4C4BA430AAA820F8	2020-12-07 00:03:19	product_page	0.0	A	2020-12-07	PC
3	4B7C59A60FE1DA69	2020-12-07 00:03:51	login	0.0	B	2020-12-07	Android
4	4B7C59A60FE1DA69	2020-12-07 00:03:54	product_cart	0.0	B	2020-12-07	Android

Next steps: Generate code with `df_ab_testing` New interactive sheet

```
df_ab_testing.isnull().sum()
```

	0
user_id	0
event_dt	0
event_name	0
details	0
group	0
first_date	0
device	0

dtype: int64

```
df_ab_testing.duplicated().sum()
```

```
np.int64(0)
```

Exploratory Data Analysis (EDA)

Study conversion at different funnel stages.

The main goal of our test is to make sure that the total conversion [1] on each stage in Test Group B is better than the total conversion at the same stage in Control Group A.

[1] 'Total conversion is the ratio of users at a particular stage to the number of users at the first stage.'

Let's plot the funnel and compare the groups.

1. Calculate the number of users for each stage in group A:
2. Calculating total conversion for each funnel stage in group A:

```
funnel_order=['login','product_page','product_cart','purchase']

df_funnel_A = (
    df_ab_testing[df_ab_testing['group'] == 'A']
    .groupby('event_name')['user_id']
    .count()
    .reset_index(name='n_users')
)

# enforce logical order
df_funnel_A['event_name'] = pd.Categorical(
    df_funnel_A['event_name'],
    categories=funnel_order,
    ordered=True)

df_funnel_A = df_funnel_A.sort_values('event_name')

first_stage_A = df_funnel_A['n_users'].iloc[0]
print(f'First Stage Users : {first_stage_A}')

print('        ')

df_funnel_A['conversion_pct'] = (df_funnel_A['n_users'] / first_stage_A * 100).round(2)
df_funnel_A['test_group'] = 'A'
print(df_funnel_A)
```

```
First Stage Users : 11247

      event_name  n_users  conversion_pct test_group
0          login    11247          100.00          A
2   product_page     7515           66.82          A
1   product_cart     3720           33.08          A
3       purchase     4031           35.84          A
```

The same steps for the group B:

```
df_funnel_B = (
    df_ab_testing[df_ab_testing['group'] == 'B']
    .groupby('event_name')['user_id']
    .count()
    .reset_index(name='n_users'))

df_funnel_B['event_name'] = pd.Categorical(
    df_funnel_B['event_name'],
    categories=funnel_order,
    ordered=True)

df_funnel_B = df_funnel_B.sort_values('event_name')

first_stage_B = df_funnel_B['n_users'].iloc[0]
print(f'First Stage Users : {first_stage_B}')

print('        ')

df_funnel_B['conversion_pct'] = (df_funnel_B['n_users'] / first_stage_B * 100).round(2)
df_funnel_B['test_group'] = 'B'
print(df_funnel_B)
```

```
First Stage Users : 10885

      event_name  n_users  conversion_pct test_group
0          login    10885          100.00          B
2   product_page     7102           65.25          B
1   product_cart     3722           34.19          B
3       purchase     3626           33.31          B
```

Concatenating test groups and plotting funnel chart:

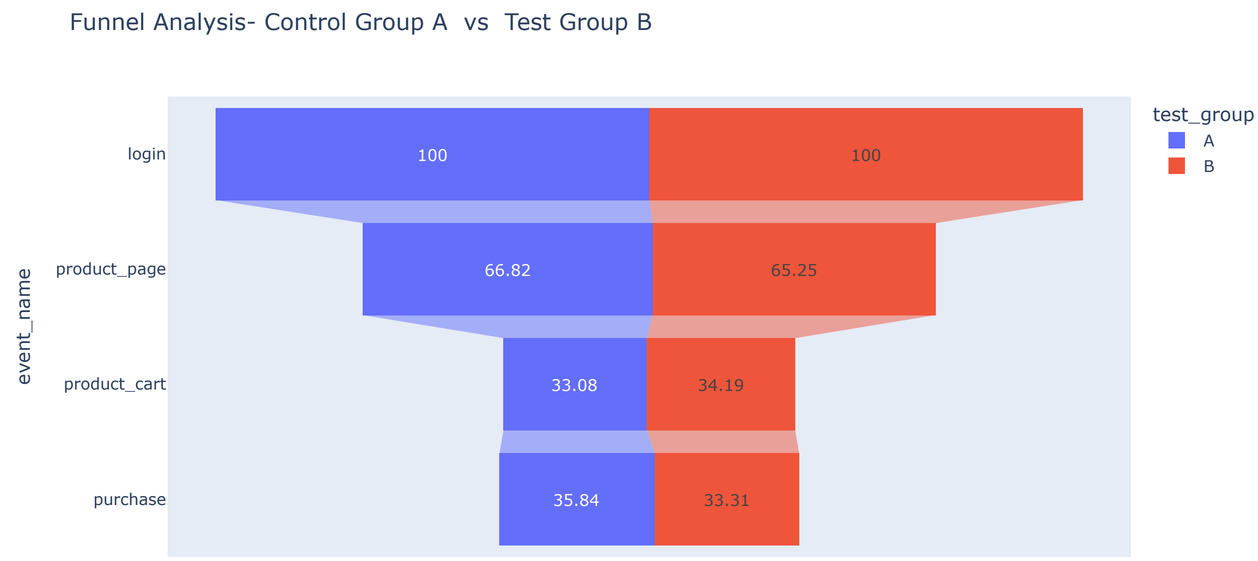
```
df_funnel = pd.concat([df_funnel_A, df_funnel_B], axis=0)
print(df_funnel)

print('      ')

import plotly.express as px

Funnel = px.funnel(df_funnel, x='conversion_pct',y='event_name',color='test_group',title='Funnel Analysis- Control Group A
Funnel.show()
```

```
     event_name  n_users  conversion_pct test_group
0         login    11247          100.00          A
2  product_page     7515           66.82          A
1  product_cart     3720           33.08          A
3      purchase     4031           35.84          A
0         login    10885          100.00          B
2  product_page     7102           65.25          B
1  product_cart     3722           34.19          B
3      purchase     3626           33.31          B
```



- According to the test, it was expected that 'At each stage of the funnel product_page → product_cart → purchase, there will be at least a 10% increase."
- However, the funnel chart shows that the conversion in the control group A is even slightly higher than in the test group B in the first two stages.
- Only the Product_Cart stage showed 1.11% better in test group B than in group A.
- Moreover, at purchase stage in group A, the total conversion is higher than at the previous stage. I assume this was due to the 'Buy Now' button, which allowed users to buy by skipping some steps.

Is the number of events per user distributed equally in the samples?

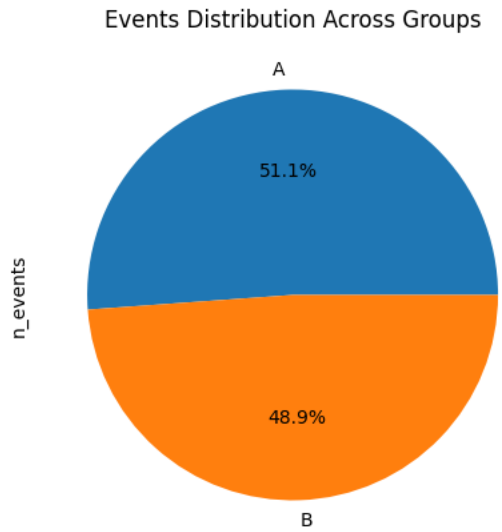
```
summary = df_ab_testing.groupby('group').agg(
    n_users=('user_id', 'nunique'),
    n_events=('event_dt', 'count')
).reset_index()

summary['events_per_user'] = (summary['n_events'] / summary['n_users']).round(2)

print(summary)


summary['n_events'].plot(kind='pie',labels=summary['group'],autopct='%1.1f%%',figsize=(5,5),title='Events Distribution Acr
plt.show()
```

```
  group  n_users  n_events  events_per_user
0     A     4521     26513             5.86
1     B     4438     25335             5.71
```



As we can see, the share of users and events is close to 50/50.

Thus, we can claim that the number of events per user distributed equally in the samples

Are there users who enter both samples?

```
users_in_multiple_groups = (
    df_ab_testing
    .groupby('user_id')['group']
    .nunique()
)

users_in_multiple_groups[users_in_multiple_groups > 1].shape[0]
```

```
0
```

There is no users who enter both samples.

How is the number of events distributed by days?

```
df_ab_testing['event_date']=df_ab_testing['event_dt'].dt.date
df_ab_testing.head()
```

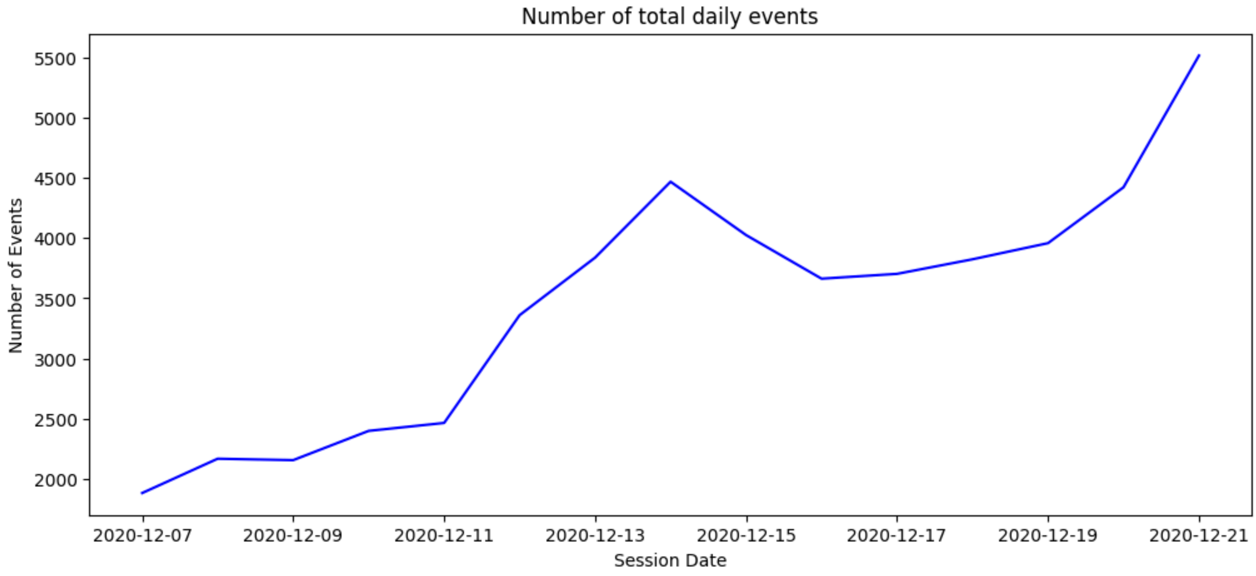
	user_id	event_dt	event_name	details	group	first_date	device	event_date
0	B13A53A1EB2038EE	2020-12-07 00:02:48	login	0.0	A	2020-12-07	PC	2020-12-07
1	4C4BA430AAA820F8	2020-12-07 00:03:18	login	0.0	A	2020-12-07	PC	2020-12-07
2	4C4BA430AAA820F8	2020-12-07 00:03:19	product_page	0.0	A	2020-12-07	PC	2020-12-07
3	4B7C59A60FE1DA69	2020-12-07 00:03:51	login	0.0	B	2020-12-07	Android	2020-12-07
4	4B7C59A60FE1DA69	2020-12-07 00:03:54	product_cart	0.0	B	2020-12-07	Android	2020-12-07

Next steps: Generate code with df_ab_testing New interactive sheet

Number of total daily events:

```
Events_per_day = df_ab_testing.groupby('event_date')['user_id'].count()

Events_per_day.plot(kind='line',figsize=(12,5),title='Number of total daily events',color='blue',xlabel='Session Date',ylal
plt.show()
```



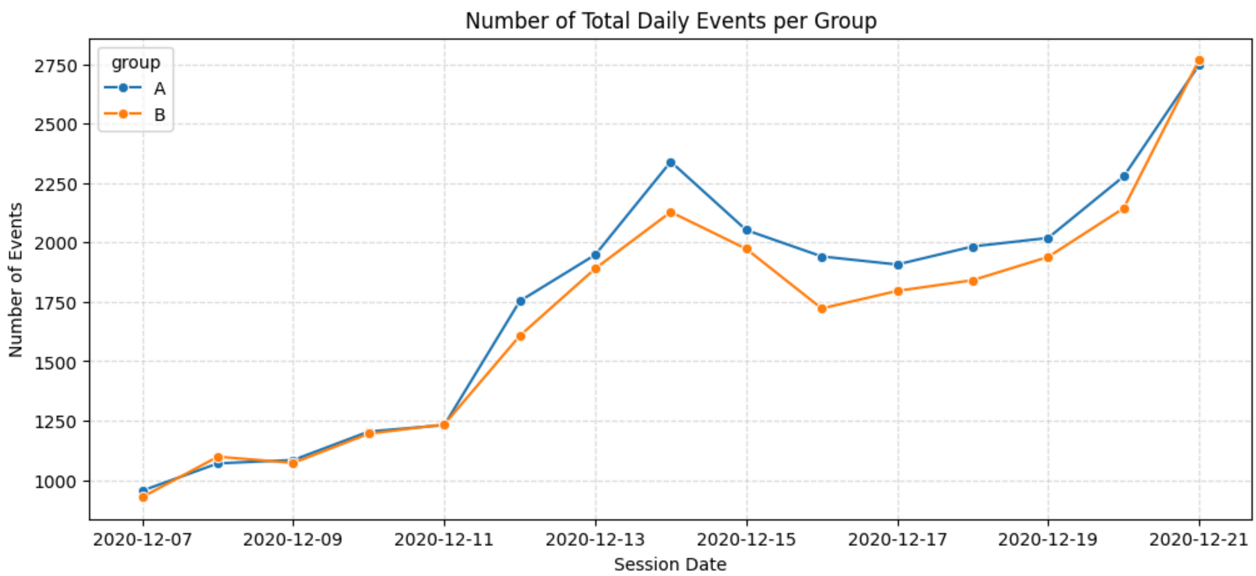
Number of total daily events per test groups:

```
Events_per_group = df_ab_testing.groupby(['event_date','group'])['event_dt'].count().reset_index(name = 'n_events')
print(Events_per_group.head())

plt.figure(figsize=(12,5))
sns.lineplot(data=Events_per_group,x='event_date',y='n_events',hue='group',marker='o')
plt.title('Number of Total Daily Events per Group')
plt.xlabel('Session Date')
plt.ylabel('Number of Events')

sns.set_style("ticks")
plt.grid(True, linestyle='--', alpha=0.4)
plt.show()
```

```
   event_date group  n_events
0  2020-12-07     A       955
1  2020-12-07     B       928
2  2020-12-08     A      1070
3  2020-12-08     B      1098
4  2020-12-09     A      1084
```



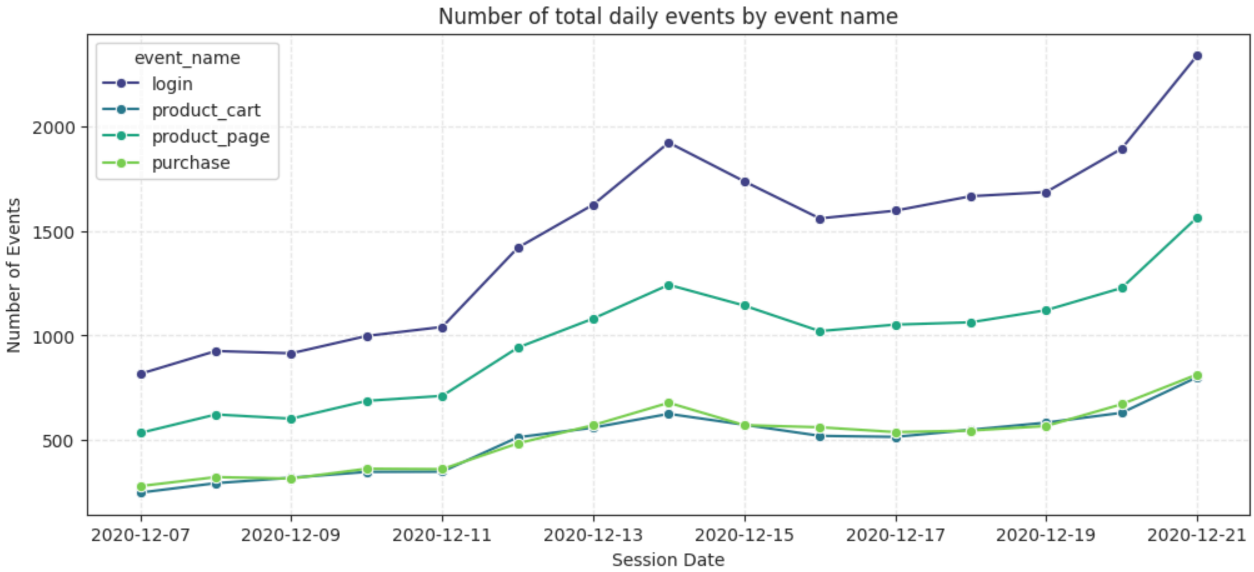
Number of total daily events by event name:

```
Events_by_eventname = df_ab_testing.groupby(['event_date','event_name'])['event_dt'].count().reset_index(name = 'n_events'
print(Events_by_eventname.head())
```

```
plt.figure(figsize=(12,5))
sns.lineplot(data=Events_by_eventname,x='event_date',y='n_events',hue='event_name',marker='o',palette='viridis')
plt.title('Number of total daily events by event name')
plt.xlabel('Session Date')
plt.ylabel('Number of Events')

sns.set_style("ticks")
plt.grid(True, linestyle='--', alpha=0.4)
plt.show()
```

```
   event_date    event_name  n_events
0  2020-12-07         login       817
1  2020-12-07  product_cart       250
2  2020-12-07  product_page       535
3  2020-12-07      purchase       281
4  2020-12-08         login       926
```



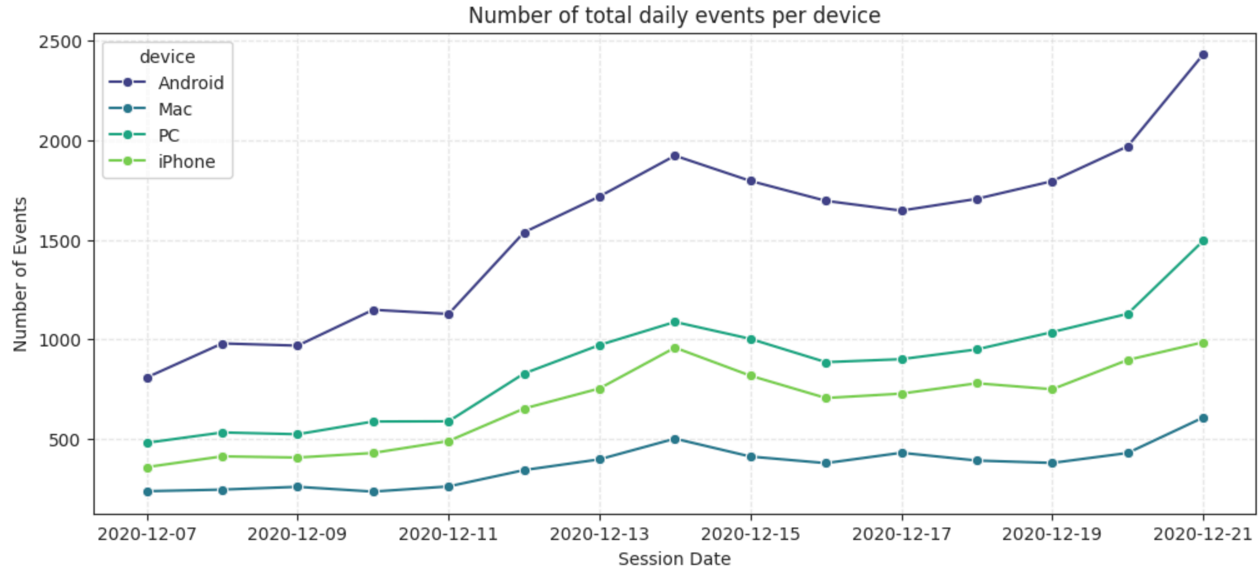
Number of total daily events by device:

```
Events_by_device = df_ab_testing.groupby(['event_date','device'])['event_dt'].count().reset_index(name = 'n_events')
print(Events_by_device.head())

plt.figure(figsize=(12,5))
sns.lineplot(data=Events_by_device,x='event_date',y='n_events',hue='device',marker='o',palette='viridis')
plt.title('Number of total daily events per device')
plt.xlabel('Session Date')
plt.ylabel('Number of Events')

sns.set_style("ticks")
plt.grid(True, linestyle='--', alpha=0.4)
plt.show()
```

```
  event_date   device  n_events
0  2020-12-07  Android       808
1  2020-12-07      Mac       237
2  2020-12-07       PC       480
3  2020-12-07   iPhone       358
4  2020-12-08  Android       979
```



- The total number of events during the test increased significantly, 3 times.
- This feature is typical for both Groups A and B, for each event name and for number of events per device.
- Most of the events were performed by Android users, with the smallest user group being Mac fans.
- It is clear from the graphs that we can say that there were spikes of events on a certain weekday. In our case, it was on Thursdays.
- To funnel stages, product_cart and purchase have almost the same number of events during the test weeks. I can assume that the abandoned cart percentage is very low, or the 'Buy Now' button works better than the whole funnel.

Think of the possible details in the data that you have to take into account before starting the A/B test?

- The datasets had users who were assigned to multiple groups and who performed both tests at the same time. We have processed our data to avoid exposure to these factors.
- We also checked if the users are equally split.
- But there is an external factor that influences the test result. I consider that we have to take into account that the A / B test was carried out on the eve of Christmas. And even if the specific testing time did not last at the same time as the marketing activities, we cannot trust the results 100% due to the well-known increase in consumer activity before the Christmas holidays.

Conclusion:

- The test group B did not achieve expected result of increasing total conversion at least 10% on each stage of the funnel product_page → product_cart → purchase.
- The test group B showed better result on the purchase stage.
- There is no users who enter both samples.
- The number of events per user distributed equally in the samples.

Evaluate the A/B test results

What can you tell about the A/A test results?

```
df_users_pivot = df_ab_testing.pivot_table(index='event_name',columns='group',values='user_id',aggfunc='nunique').reset_inc
df_users_pivot
```

group	event_name	A	B
0	login	4520	4438
1	product_cart	1479	1516
2	product_page	3030	2913
3	purchase	1612	1479

Next steps: Generate code with df_users_pivot New interactive sheet

```
df_users_pivot['diff_n_users'] = df_users_pivot['A'] - df_users_pivot['B']
df_users_pivot
```

group	event_name	A	B	diff_n_users
0	login	4520	4438	82
1	product_cart	1479	1516	-37
2	product_page	3030	2913	117
3	purchase	1612	1479	133

Next steps: Generate code with df_users_pivot New interactive sheet

```
df_users_crosstab = pd.crosstab(index= df_ab_testing['event_name'], columns=df_ab_testing['group'],values=df_ab_testing['us
                                aggfunc='nunique',normalize=True,margins=True,margins_name='Total').reset_index()

df_users_crosstab
```

group	event_name	A	B	Total
0	login	0.215371	0.211464	0.426836
1	product_cart	0.070472	0.072235	0.142707
2	product_page	0.144375	0.138800	0.283175
3	purchase	0.076809	0.070472	0.147282
4	Total	0.504632	0.495368	1.000000

Next steps: Generate code with df_users_crosstab New interactive sheet

```
df_users_crosstab['diff_share_stage']=((df_users_crosstab['A']-df_users_crosstab['B'])*100).round(2)
df_users_crosstab
```

group	event_name	A	B	Total	diff_share_stage
0	login	0.215371	0.211464	0.426836	0.39
1	product_cart	0.070472	0.072235	0.142707	-0.18
2	product_page	0.144375	0.138800	0.283175	0.56
3	purchase	0.076809	0.070472	0.147282	0.63
4	Total	0.504632	0.495368	1.000000	0.93

Next steps: Generate code with df_users_crosstab New interactive sheet

We can argue that all the criteria we have for a successful A/A test:

- As can be seen from the aggregated tables, there is no significant difference between the samples. On Each stage the difference is less then 1%.
- For all groups, data on the same event is recorded.
- Users remain within their groups until the end of the test.
- Users who may see different versions of the page during the test were removed from the groups.

Use the z-criterion to check the statistical difference between the proportions

H0: there is not a statistically significant difference in conversion between the samples A and B

H1: there is a statistically significant difference in conversion between the samples A and B

```
event = df_users_pivot['event_name'].unique()   ## Preparing event data

alpha = 0.05

results=[]
from statsmodels.stats.proportion import proportions_ztest
```

```
for eve in event:          ## Loop for all event Z-test
  a_sucess = df_users_pivot.loc[df_users_pivot['event_name']==eve,'A'].iloc[0]
  b_sucess = df_users_pivot.loc[df_users_pivot['event_name']==eve,'B'].iloc[0]

  a_total=df_ab_testing[df_ab_testing['group']=='A']['user_id'].nunique()
  b_total=df_ab_testing[df_ab_testing['group']=='B']['user_id'].nunique()

  z_stat,p_value=proportions_ztest(count=[a_sucess,b_sucess],nobs=[a_total,b_total])

  results.append({'event_name':eve,'p_value':round(p_value,6),'significant':p_value <alpha,'decision': 'Reject H₀' if p_va
```

```
ab_test_results = pd.DataFrame(results)
ab_test_results
```

	event_name	p_value	significant	decision
0	login	0.321767	False	Fail to Reject H_0
1	product_cart	0.147028	False	Fail to Reject H_0
2	product_page	0.166090	False	Fail to Reject H_0
3	purchase	0.020365	True	Reject H_0

Next steps: Generate code with ab_test_results New interactive sheet

Conclusion:

- As a result of checking the hypothesis, we cannot reject H0 for all the events.
- Thus, we can accept the equality of the proportions of the population of A and B groups. It means that the groups were split properly.

General conclusion

Datasets:

- The logs were collected in several tables for the period from December 7 to December 30, 2020.
- The two types of tests were run simultaneously and overlapped using the same test participants.

New interface for EU users test:

- The test was carried out within 14 days, from December 7 to December 21, 2020.
- After preprocessing, we got a dataset that contains 51848 different events performed by 8959 unique users.
- Users are split equally into two groups: - A control group - 4521 users - B test group - 4438 users
- Control group A gets the old site version and one test group B gets the new ones:

The funnel:

- Consists of 4 events: login -> product_page -> product_cart -> purchase
- The number of events per user distributed equally in the samples.

Performing tests:

- The A/A test shows that the control groups were split properly.
- A / B tests show that we cannot reject null hypotheses. In other words, there are no statistically significant differences in conversions between two groups across all 4 events.

External factors:

- The A / B test was carried out on the eve of Christmas during the period of increased buying activity before the Christmas holidays. Thus, we cannot trust the results 100%.

Test result:

- The test group B did not achieve the expected result of increasing total conversion at least 10% on each stage of the funnel product_page ⟶ product_cart ⟶ purchase.
- Moreover, total conversion in group B is almost the same or less than total conversion in group A on stages product_page -> product_cart.
- Only at the last stage,purchase, test group B showed a 1.11% better result than in group A and than at the product_cart stage in their group. It means that some EU users made purchasing in one-click using the 'Buy Now' button.

Recommendation:

- It can be assumed that EU users prefer to shop in the shortest and fastest way, skipping stages in the usual sales funnel order. This hypothesis should be tested.

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CHECKOUT THE PORTFOLIO

FOR

COMPLETE WORKBOOK

THENNARASU M