Applying Iterative Design Principles to a Live Product

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Step 1

Select KPIs

&

Evaluate Previous Multivariate Experiment Results

Select KPIs for Flyber Analyses

- **In MVP phase** I have chosen the MAU/DAU, NPS, MRR

- For the data available, which KPI(s) best match Flyber's business model? (using supplement materials: link)

‚KPIs are quantifiable measurements or data points used to gauge your company's performance relative to some goal. For instance, a KPI could be related to your goal of increasing sales, improving the return on investment of your marketing efforts, or improving customer service.'

We have data logs available which help Flyber in the **growth stage:**

KPI 1: Acquisition: the number of new visitors in a day

KPI 2: Activation: the number of visitors who sign up for a drive

KPI 3: Retention: % churn in searh phase

Abc Flyber_event_logs.csv event_uuid	Abc Flyber_event_logs.csv user_uuid	Flyber_event_logs.csv event_time	Abc Flyber_event_l... age	Abc Flyber_event_logs.csv session_uuid	Abc Flyber_event_logs.csv experiment_group	Abc Flyber_event_logs.csv user_neighborhood	Abc Flyber_event_logs.csv event_type
46e60fb9-aa35-4a19-...	d3deed54-1c5b-47c1-...	2019. 10. 11. 9:00:34	40-49	2a45992a-ff51-4fc8-b...	experiment_2	Manhattan	open
9e858786-9186-4951...	42e0e448-07c4-4837-...	2019. 10. 10. 22:55:11	50+	bd1fe39b-2f18-4561-...	experiment_1	Manhattan	open
980cb36b-bf49-4fb1-...	42e0e448-07c4-4837-...	2019. 10. 10. 22:55:18	50+	bd1fe39b-2f18-4561-...	experiment_1	Manhattan	#_of_users
204a3dfc-1460-4f21-...	42e0e448-07c4-4837-...	2019. 10. 10. 14:56:06	40-49	8caeec15-9058-452a-...	control	Manhattan	open
422efc1a-5eaf-4ba2-...	9acde266-30b5-46a5-...	2019. 10. 09. 23:00:54	40-49	4508f6eb-1429-4a80-...	experiment_3	Manhattan	open

Select KPIs for Flyber Analyses

- How would you calculate these KPI(s) using the available event data logs?

i., *Acquisition: the number of new visitors in a day = nr of new user_id / event time (day)*

ii., Activation: the number of visitors who sign up for a drive = nr of user_id with event type (#_of_users)

- List other KPIs that might be important to Flyber but are not calculable based on available data

Activation: The time users spend browsing the Flyber app on the first visit

Retention: The number of users who renew their trip with Flyber

Revenue: Customer Acquisition Cost (CAC), Customer lifetime value (LTV)

Describe the First Multivariate Experiment

Describe the elements tested during the multivariate experiment. You can use the image below when referencing the tests

Describe the First Multivariate Experiment

Describe the elements tested during the multivariate experiment. You can use the image below when referencing the tests

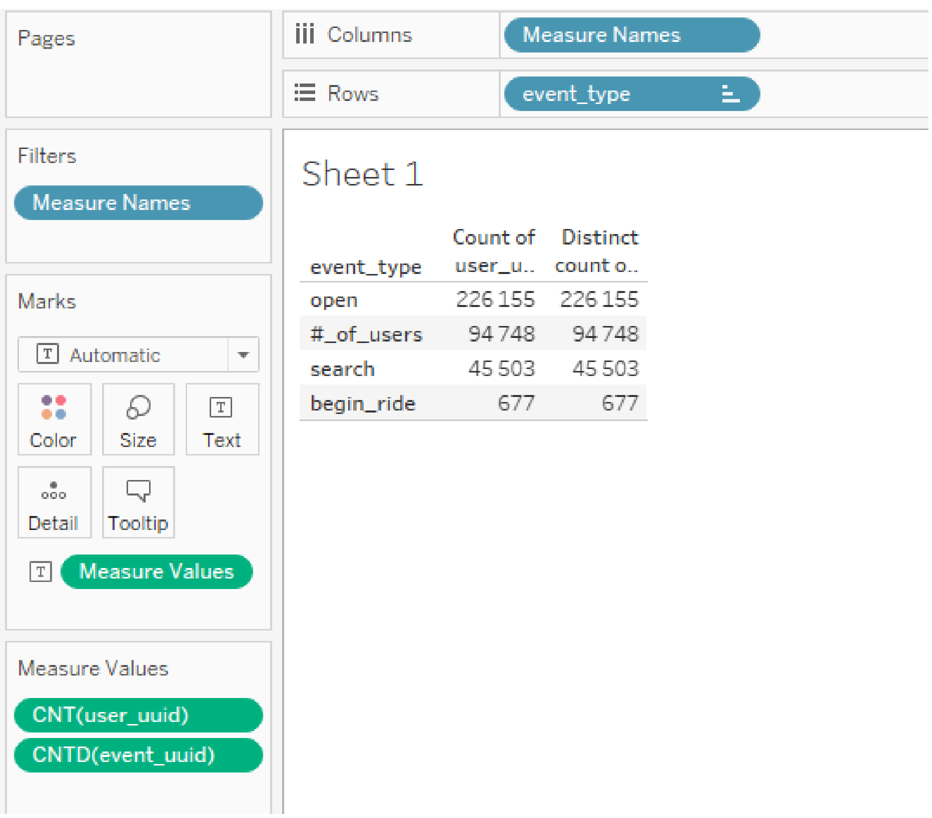
There are 2 variables in this multivariate experiment. The first one is the text field **"Tip Included"**, the second one is the the **text on the CTA button** (Fly Now or Book Flight).

- Control: CTA (Book Flight) + Tip included
- Experiment 1: vs Control CTA is changed to Fly Now
- Experiment 2: vs Control without Tip included
- Experiment 3: vs Control witthout Tip included and CTA is changed to Fly Now

Review Multivariate Test Results: Visualization

Provide a visual representation of the impact of the experiment on the conversion rate of users booking a flight (out of all users opening the app)

Step 1: comparing user_uuid vs records ➔ same



Review Multivariate Test Results: Visualization

Provide a visual representation of the impact of the experiment on the conversion rate of users booking a flight (out of all users opening the app)

Step 2: conversion rate

experiment conversion rate

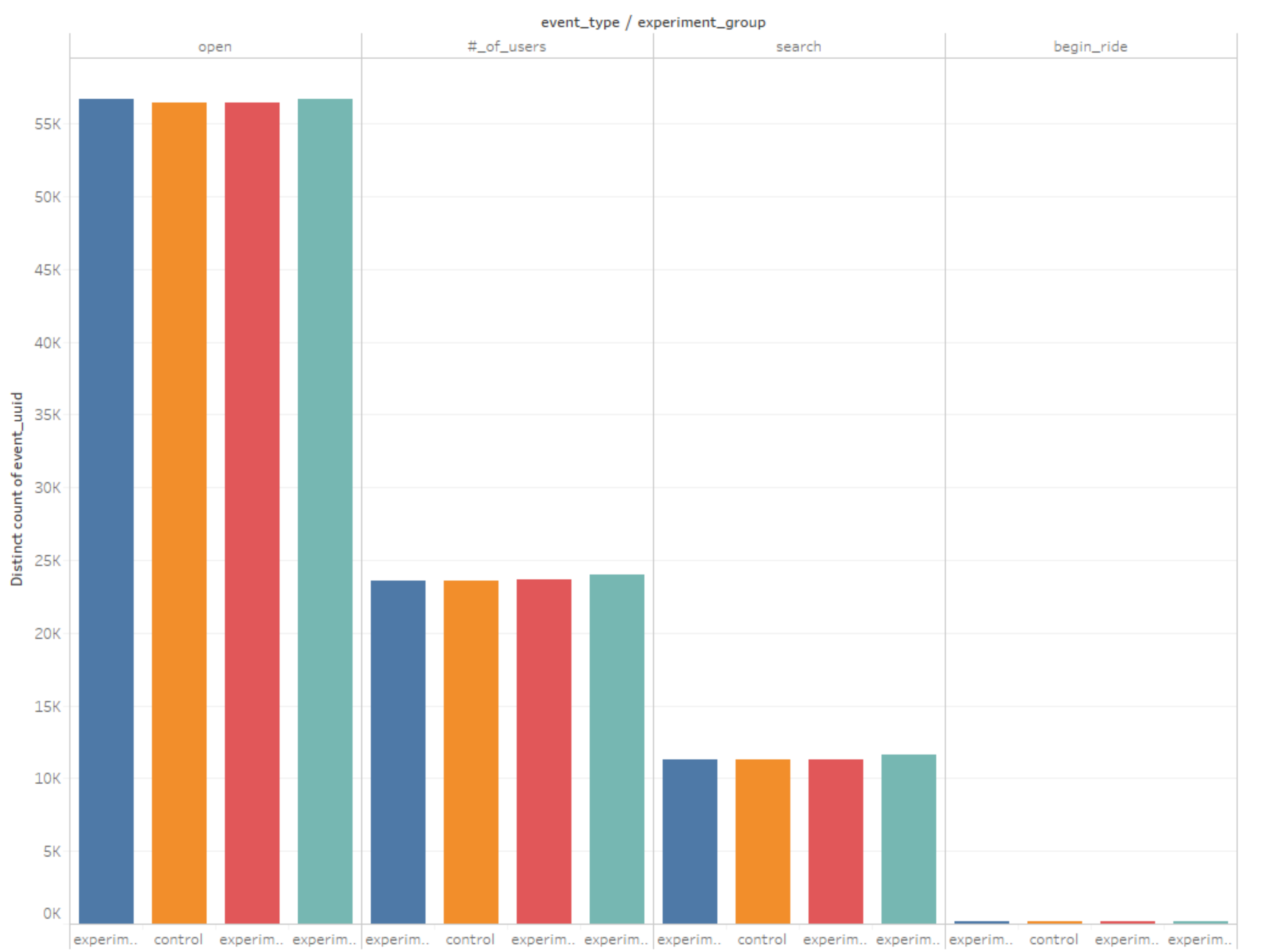
	experiment_group			
event_type	control	experi..	experi..	experi..
open	56 390	56 390	56 688	56 687
#_of_users	23 612	23 626	23 953	23 557
search	11 323	11 300	11 581	11 299
begin_ride	154	172	180	171

Review Multivariate Test Results: Visualization

Provide a visual representation of the impact of the experiment on the conversion rate of users booking a flight (out of all users opening the app)

Step 3: Visual representation

User Drop off per Conversion



Review Multivariate Test Results: Visualization

Step 4: Analyzing by convesion stage: Begin_Ride

Review Multivariate Test Results: Significance Test

Determine if there was a significant difference between the experiments and control states.

Explain how you would perform a t-test to determine if the experimental results had a greater impact on the booking conversion rate than the control state

In order to perform the t-test, we will first make hypothesis

- **Null hypothesis**: Users do not convert better with the test state as compared to control state
- **Alternative hypothesis**: Users will convert differently with the test state
- **Confidence interval**:- 95% confidence
- **p- value** < 0.025, difference is statistically significant, the null is rejected.

Review Multivariate Test Results: Significance Test

Determine if there was a significant difference between the experiments and control states.

List the test results (p value) for each experiment compared to the control

Data:

T-test Analysis

experiment_gr..	event_type	
control	open	56 390
	#_of_users	23 612
	search	11 323
	begin_ride	154
experiment_1	open	56 390
	#_of_users	23 626
	search	11 300
	begin_ride	172
experiment_2	open	56 688
	#_of_users	23 953
	search	11 581
	begin_ride	180
experiment_3	open	56 687
	#_of_users	23 557
	search	11 299
	begin_ride	171

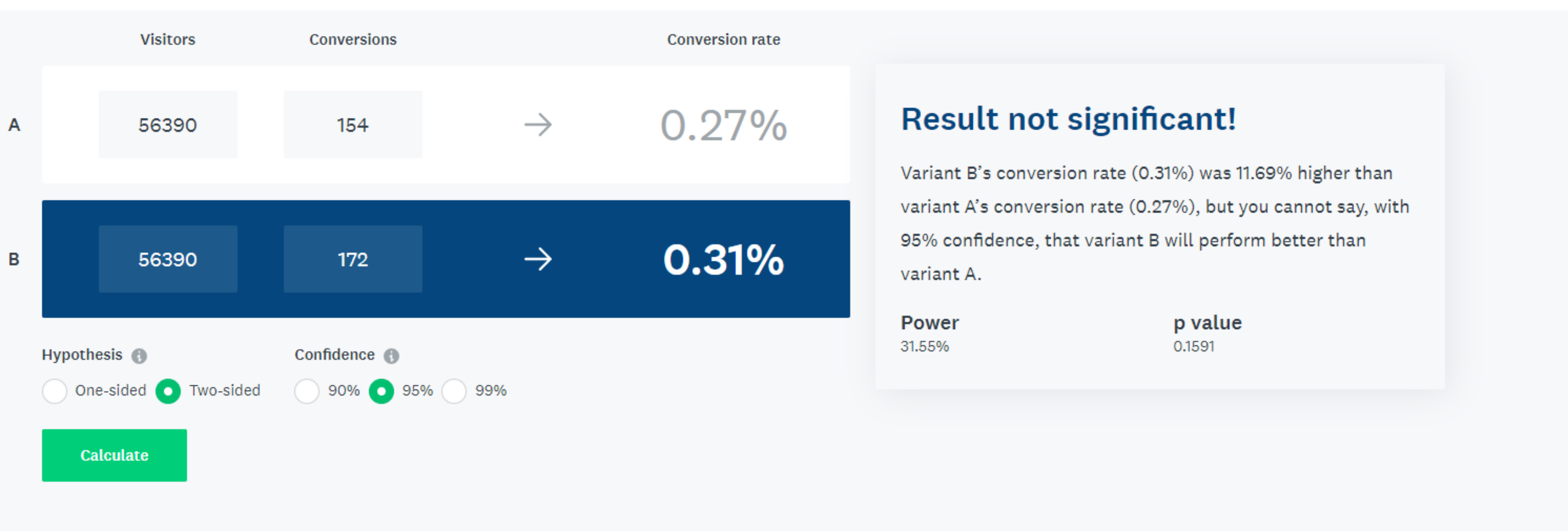
Review Multivariate Test Results: Significance Test

Determine if there was a significant difference between the experiments and control states.

List the test results (p value) for each experiment compared to the control

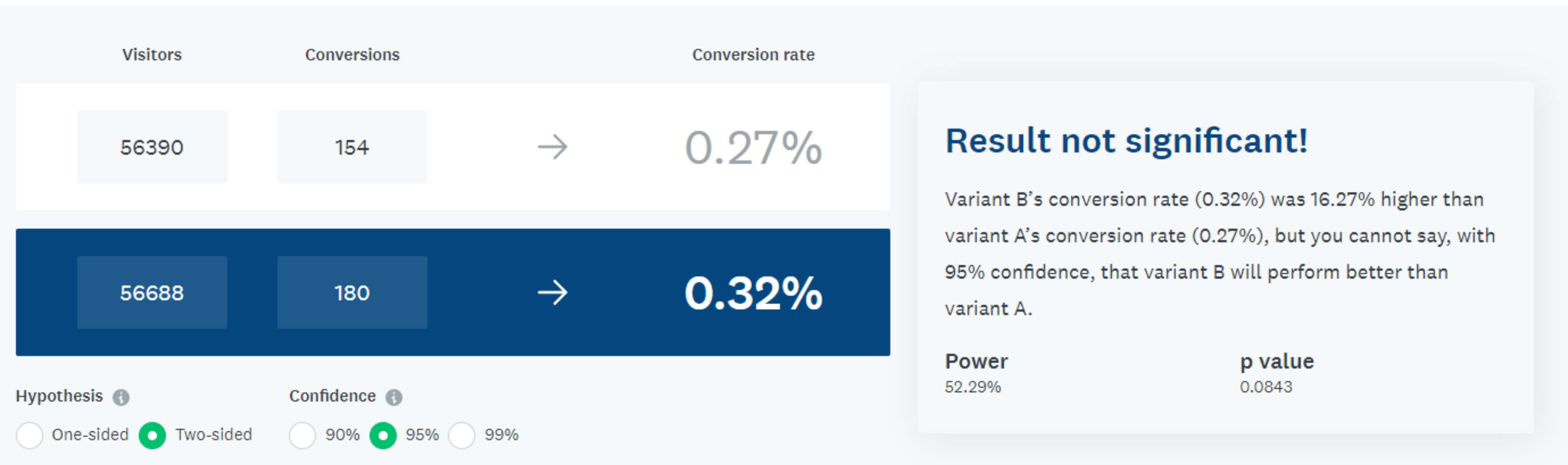
Results: (using https://www.surveymonkey.com/mp/ab-testing-significance-calculator/)

Control vs Experiment 1: p value: 0.1591

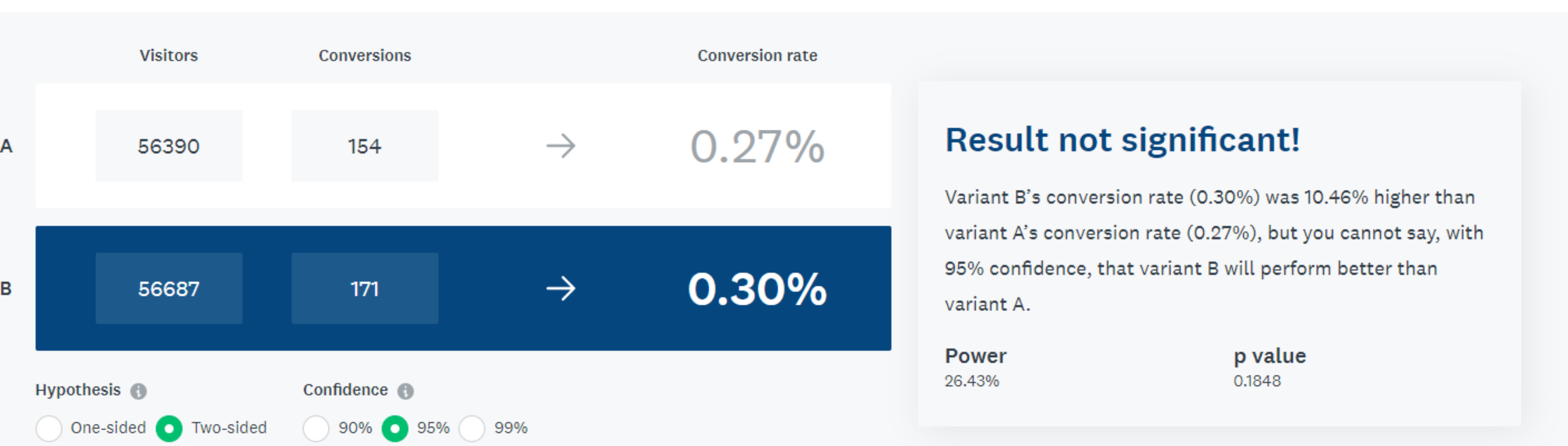


Review Multivariate Test Results: Significance Test

Control vs Experiment 2: p value: 0.0843



Control vs Experiment 3: p value: 0.1848



Review Multivariate Test Results: Significance Test

Determine if there was a significant difference between the experiments and control states.

- Using the statistical significance calculator of your choice, determine which experiments, if any, had a significant result at the 95% level. Include your calculations as part of your explanation:

        * ***see onthe above slides the calculator screenshots***

- Based on your statistical significance calculations, recommend if any of the experiments should be expanded

        * ***Result not significant for all three cases based on p value at 95% confidence level***

Step 2

Funnel & Cohort

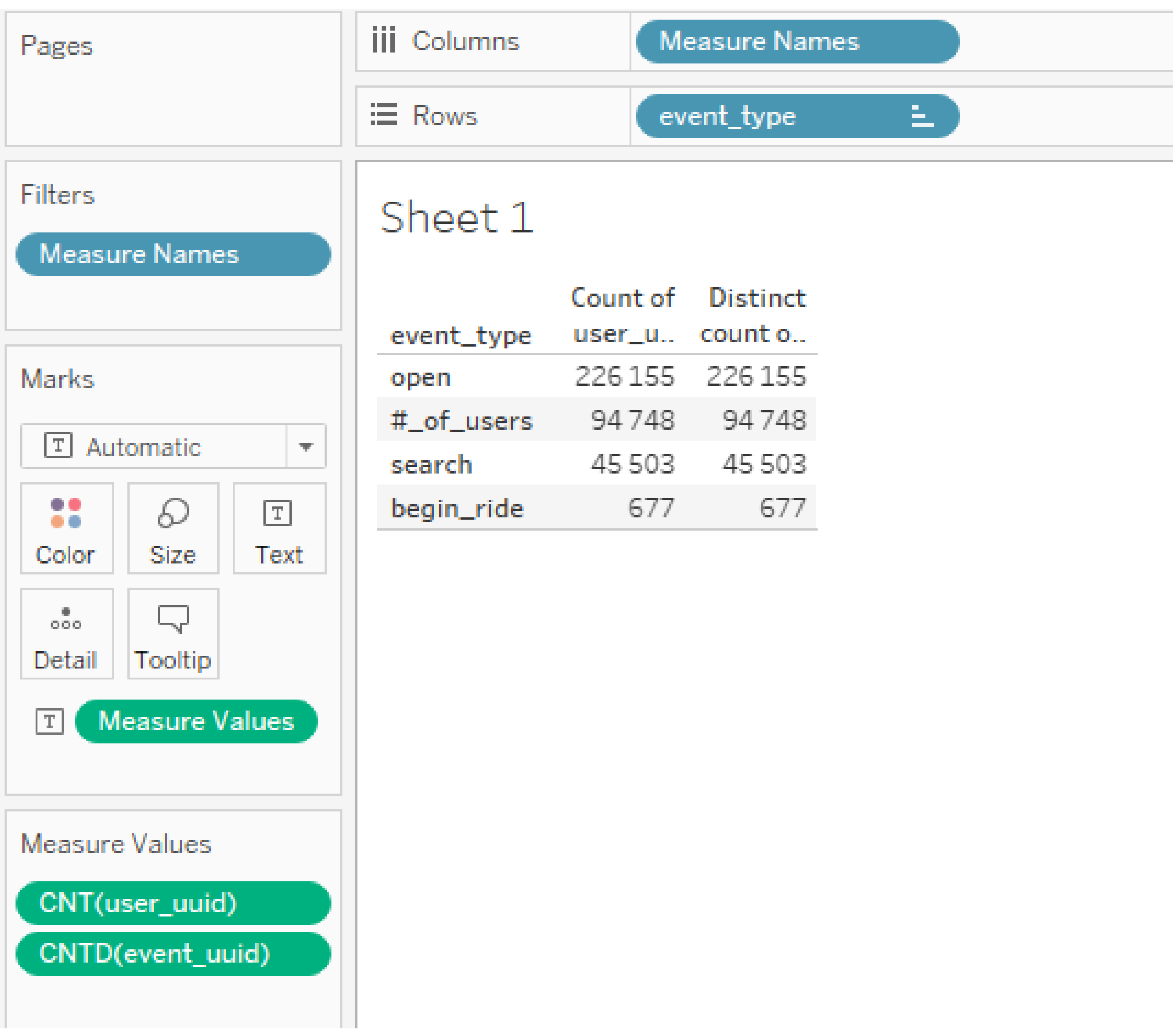
Analyses

User Funnel

Identifying the different stages the user funnel

Based on the event types in the data provided, list the 3 or more steps a user can take from opening the app to final booking of a ride

Event_type: open, #_of_users, search, begin_ride



event_type	Count of user_u..	Distinct count o..
open	226 155	226 155
#_of_users	94 748	94 748
search	45 503	45 503
begin_ride	677	677

User Funnel

Identifying the different stages the user funnel

Provide a graph showing the funnel from step to step, including drop off rates.

Using data set

experiments conversion rate

	experiment_group			
event_type	control	experi..	experi..	experi..
open	56 390	56 390	56 688	56 687
#_of_users	23 612	23 626	23 953	23 557
search	11 323	11 300	11 581	11 299
begin_ride	154	172	180	171

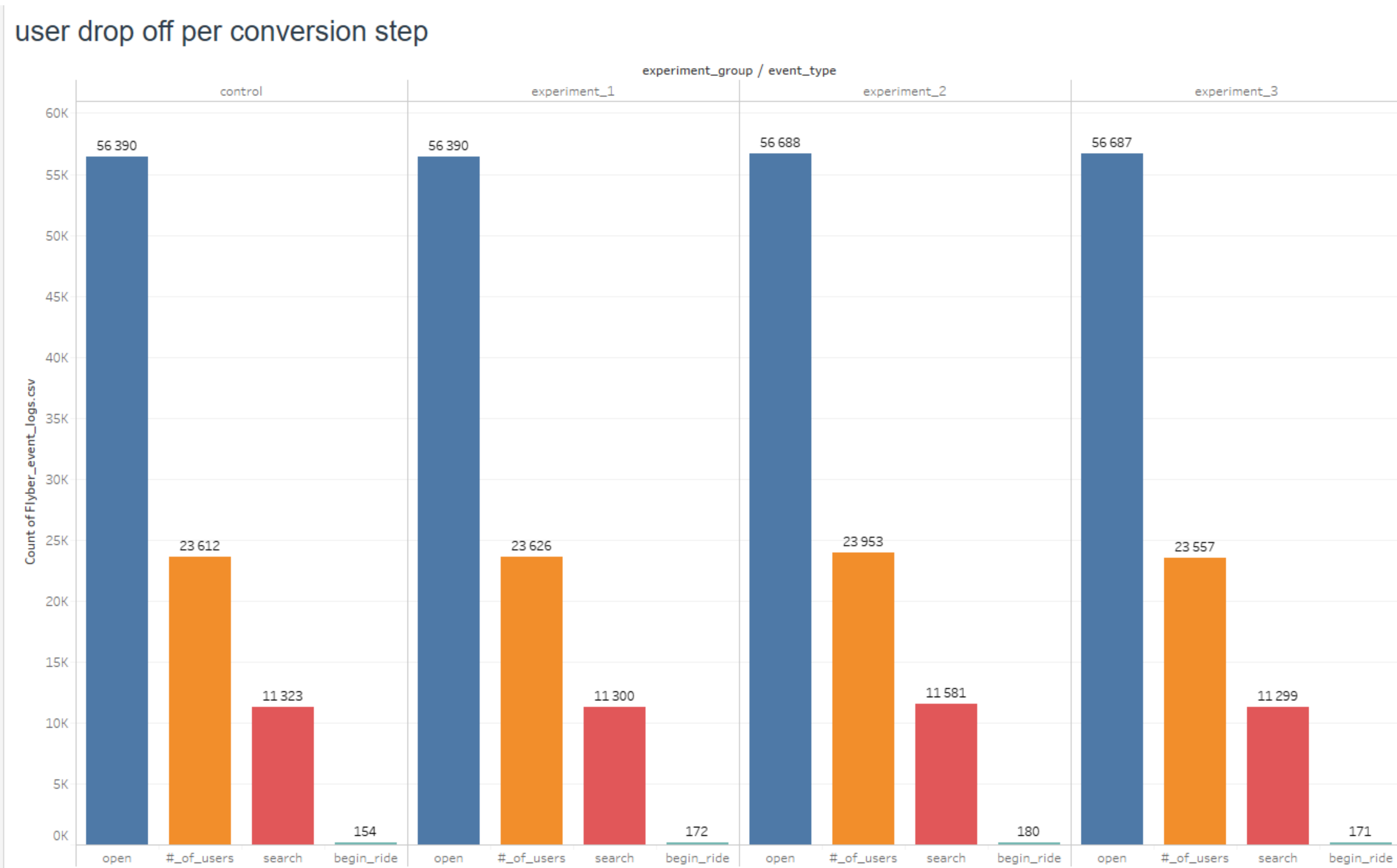
experiments conversion rate

	experiment_group			
event_type	control	experi..	experi..	experi..
open	0,00%	0,00%	0,00%	0,00%
#_of_users	-58,13%	-58,10%	-57,75%	-58,44%
search	-79,92%	-79,96%	-79,57%	-80,07%
begin_ride	-99,73%	-99,69%	-99,68%	-99,70%

User Funnel

Identifying the different stages the user funnel

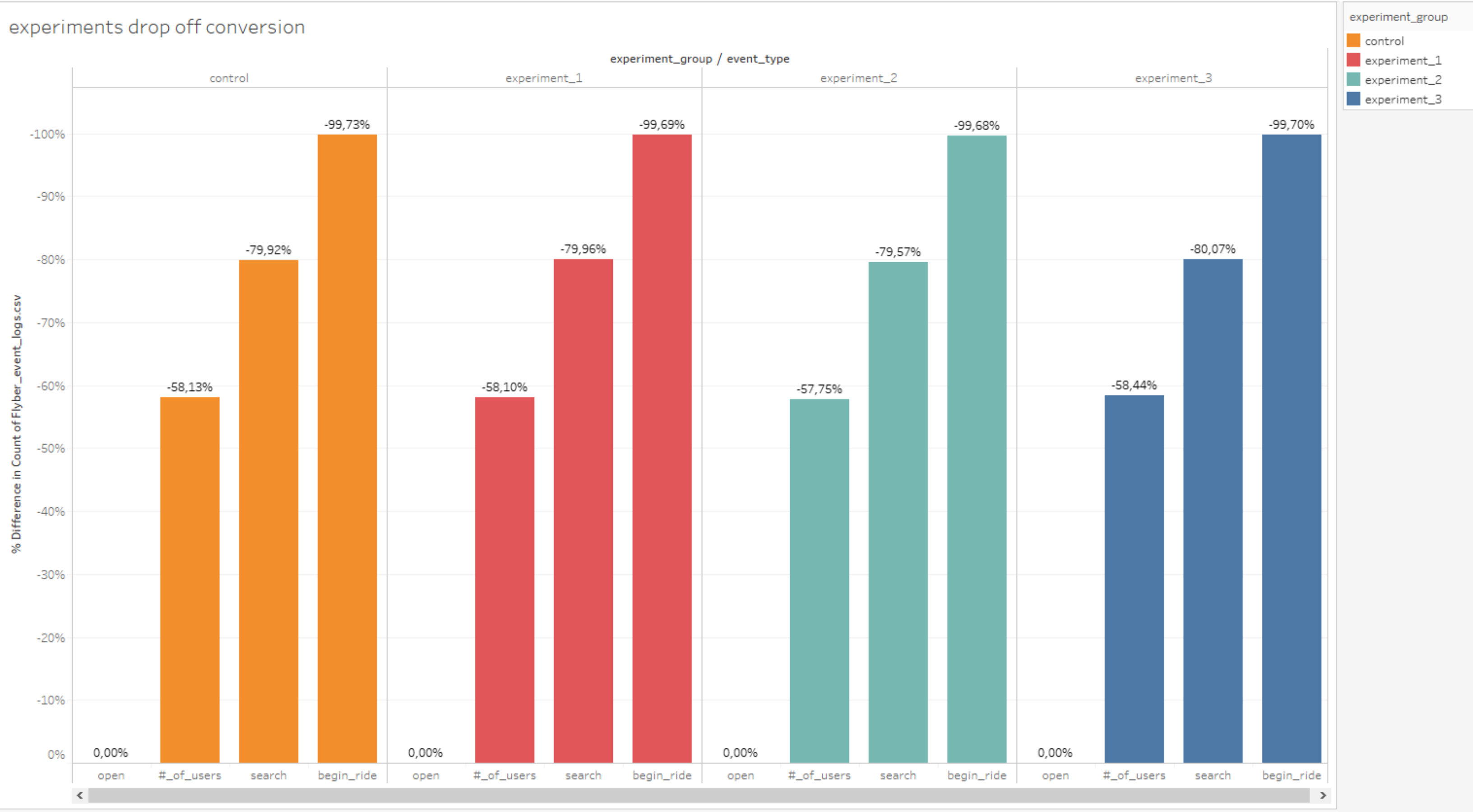
Provide a graph showing the funnel from step to step, including drop off rates.



User Funnel

Identifying the different stages the user funnel

Provide a graph showing the funnel from step to step, including drop off rates.



User Segments

- Identify 2 demographic attributes present in the data that allow for segment analysis

'Demographic segments group users that share the *same personal characteristics*'

Product managers use demographic segmentation to understand if personal characteristics result in different product experiences. When significant differences among different groups occur, product managers can form a hypothesis for the cause of these results and then investigate further. Such investigations often lead to discoveries about the unmet needs of the underperforming segment. These unmet needs to become opportunities to boost KPIs with targeted product changes.

Demographic attributes: age, user_neighborhood

age	
18-29	57 364
30-39	38 356
40-49	95 168
50+	176 195

user_neighbor..	
Bronx	10 802
Brooklyn	73 880
Manhattan	257 259
Queens	18 088
Staten Island	7 054

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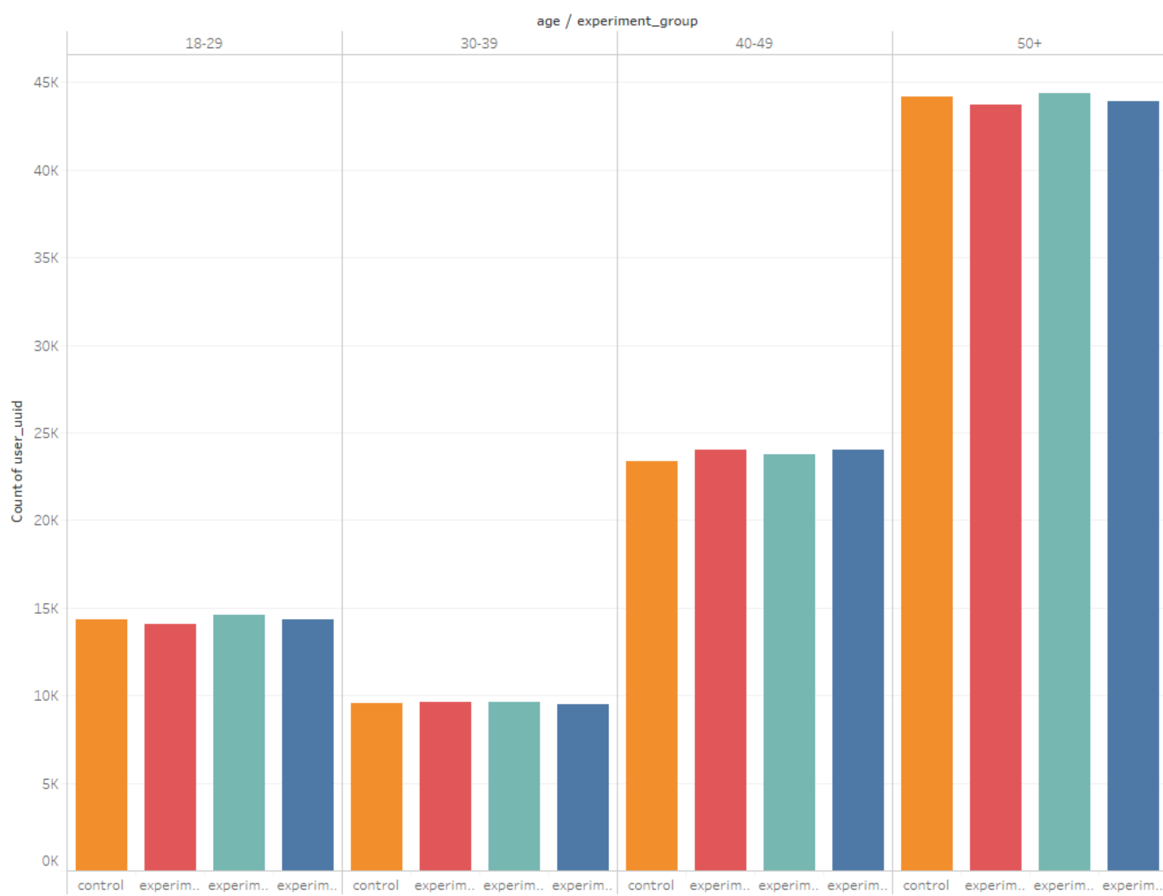
User Segments

For each demographic attribute, provide the number of users in each segment group

nr of user for age groups

	experiment_group			
age	control	experiment_1	experiment_2	experiment_3
18-29	14 350	14 083	14 613	14 318
30-39	9 570	9 635	9 641	9 510
40-49	23 363	24 036	23 768	24 001
50+	44 196	43 734	44 380	43 885

nr of user for age groups



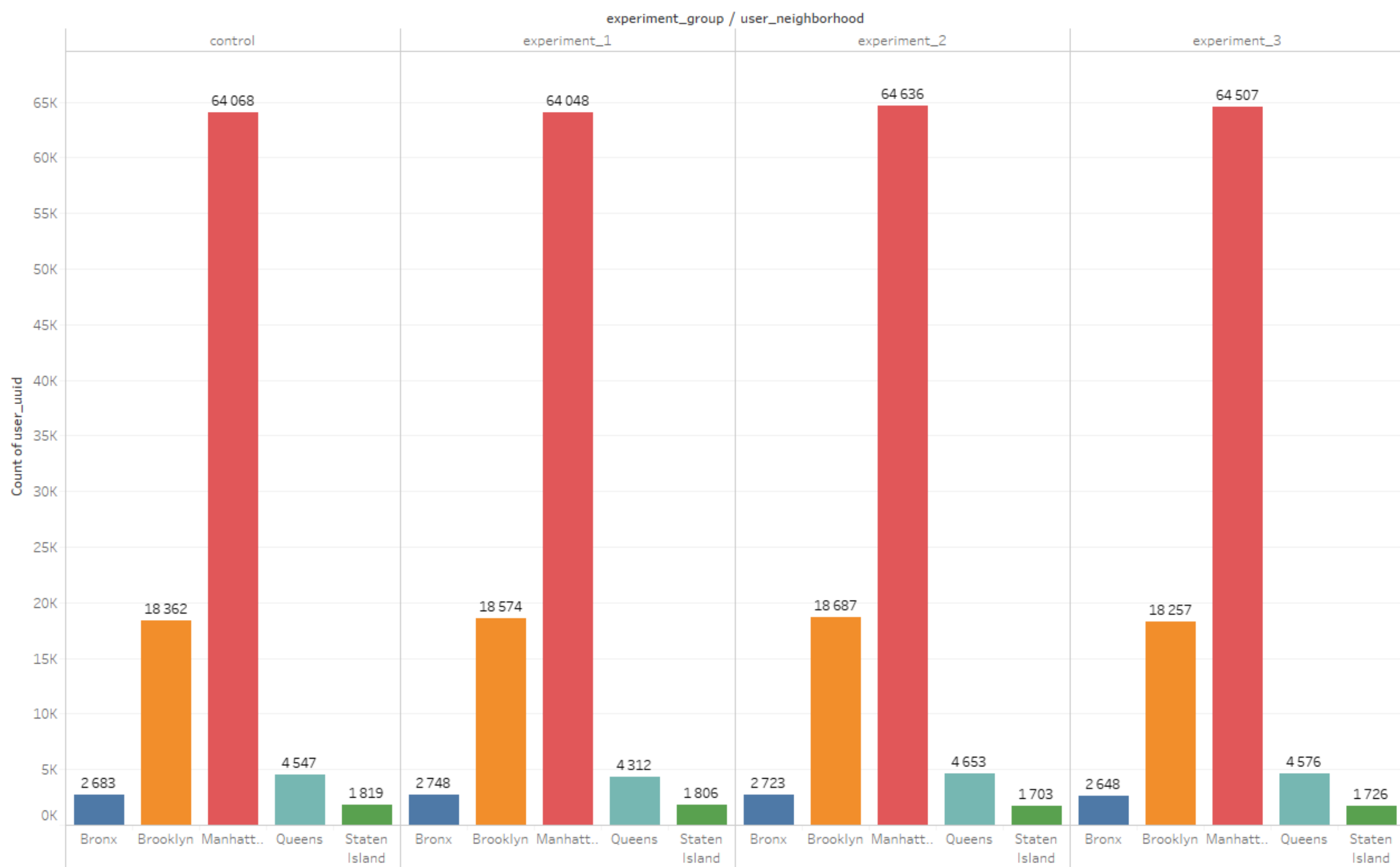
User Segments

For each demographic attribute, provide the number of users in each segment group

nr of users for locations

	experiment_group			
user_neighbor..	control	experiment_1	experiment_2	experiment_3
Bronx	2 683	2 748	2 723	2 648
Brooklyn	18 362	18 574	18 687	18 257
Manhattan	64 068	64 048	64 636	64 507
Queens	4 547	4 312	4 653	4 576
Staten Island	1 819	1 806	1 703	1 726

nr of users for locations



User Segments

For each demographic attribute, identify the segment group with the largest number of users

segment group with the largest number of users

experiment_group / user_neighborhood

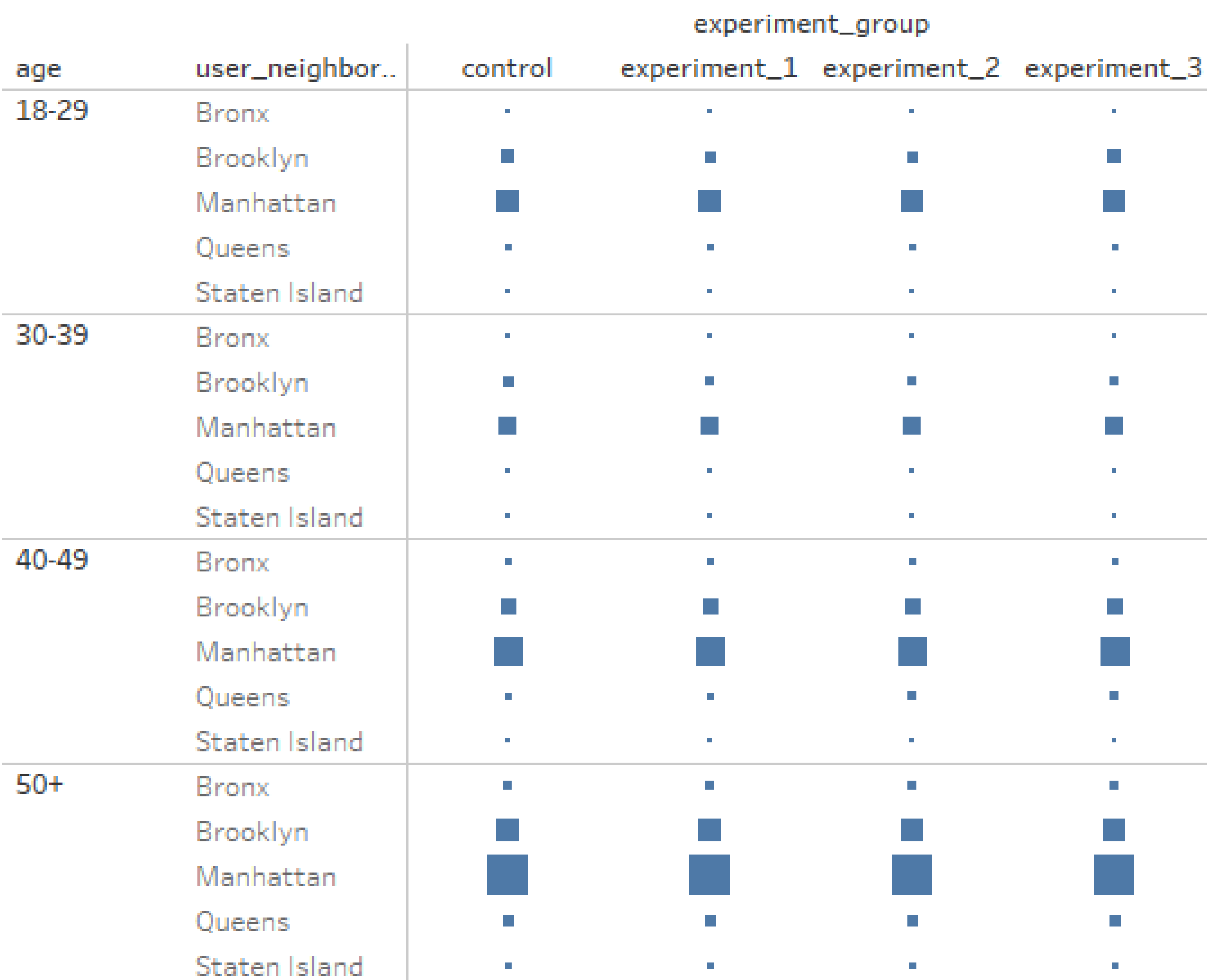
age	control Bronx	control Brooklyn	control Manhatt..	control Queens	control Staten Island	experiment_1 Bronx	experiment_1 Brooklyn	experiment_1 Manhatt..	experiment_1 Queens	experiment_1 Staten Island
18-29	376	2 930	10 023	730	291	434	2 900	9 825	669	255
30-39	288	2 009	6 564	545	164	330	1 916	6 756	444	189
40-49	692	4 544	16 500	1 141	486	657	4 940	16 833	1 140	466
50+	1 327	8 879	30 981	2 131	878	1 327	8 818	30 634	2 059	896

age	experiment_2 Bronx	experiment_2 Brooklyn	experiment_2 Manhatt..	experiment_2 Queens	experiment_2 Staten Island	experiment_3 Bronx	experiment_3 Brooklyn	experiment_3 Manhatt..	experiment_3 Queens	experiment_3 Staten Island
18-29	454	2 897	10 259	734	269	422	2 914	10 058	702	222
30-39	275	1 905	6 809	496	156	293	1 847	6 721	445	204
40-49	708	4 875	16 501	1 228	456	683	4 824	16 765	1 211	518
50+	1 286	9 010	31 067	2 195	822	1 250	8 672	30 963	2 218	782

User Segments

For each demographic attribute, identify the segment group with the largest number of users

segment group with the largest number of users



Segment Analysis of Funnel

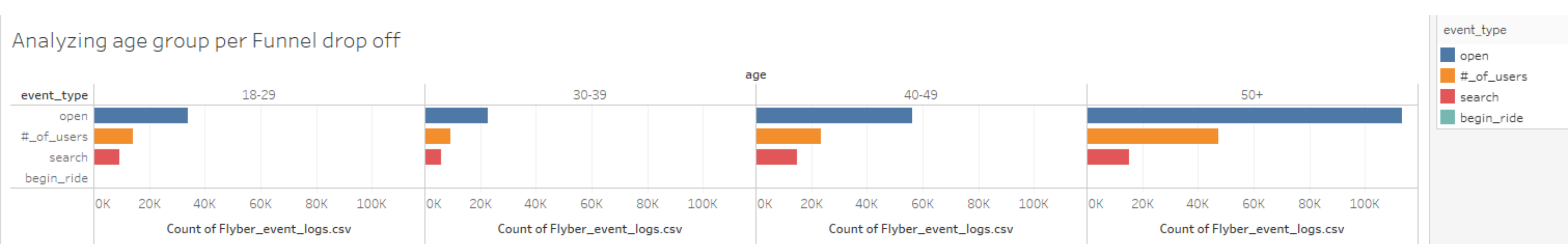
Identify Opportunities for Improvement

- Perform a funnel analysis by segment for all identified demographic attributes and describe the results

Age analysis I.

Analyzing age group per Funnel drop off

	age			
event_type	18-29	30-39	40-49	50+
open	33 878	22 760	56 256	113 261
#_of_users	14 222	9 477	23 566	47 483
search	9 138	6 019	15 090	15 256
begin_ride	126	100	256	195



Segment Analysis of Funnel

Identify Opportunities for Improvement

Perform a funnel analysis by segment for all identified demographic attributes and describe the results

Age analysis II.

Analyzing age group per Funnel drop off

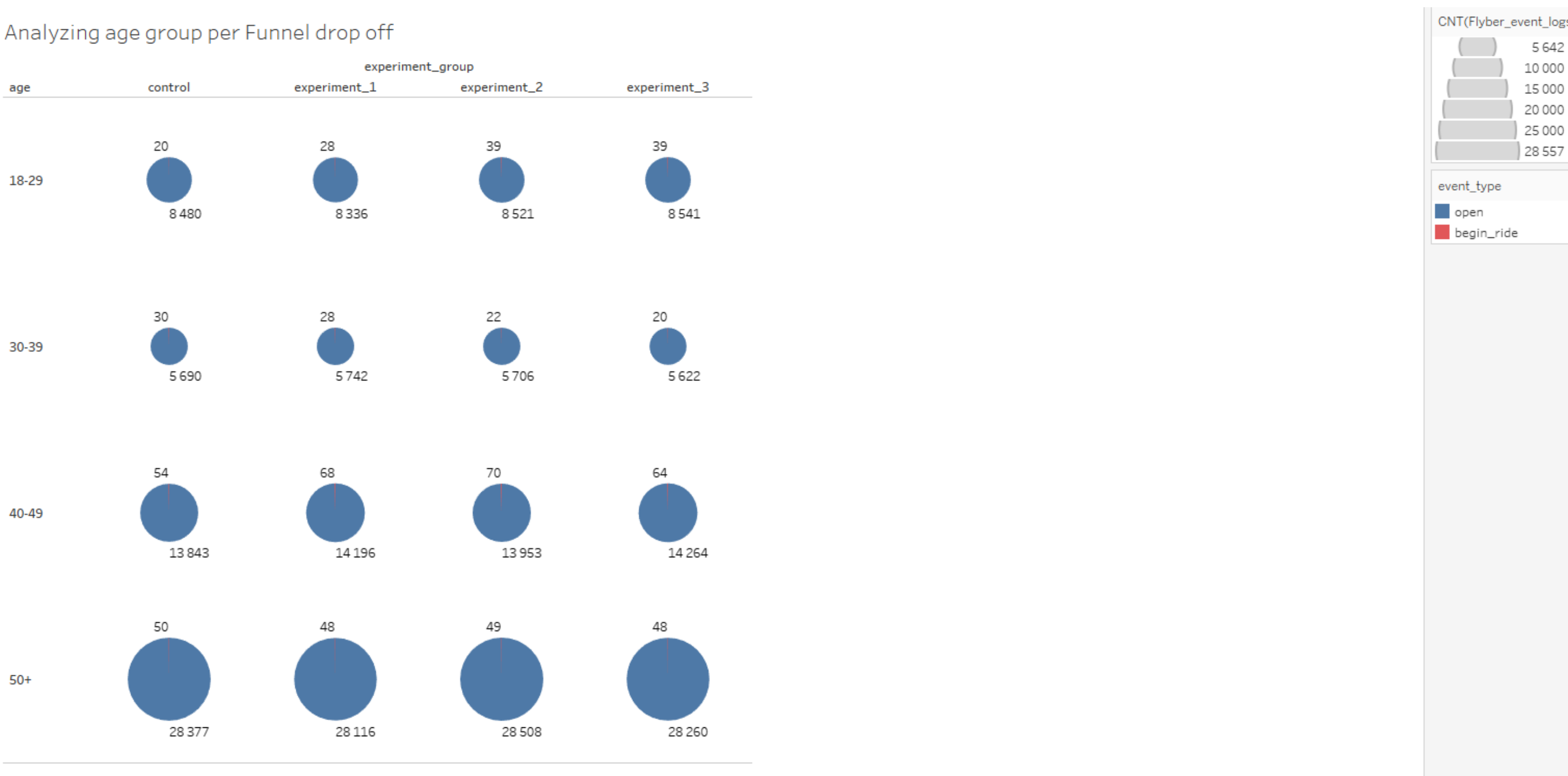
		event_type			
age	experiment_gr..	open	#_of_users	search	begin_ride
18-29	control	8 480	3 559	2 291	20
	experiment_1	8 336	3 490	2 229	28
	experiment_2	8 521	3 672	2 381	39
	experiment_3	8 541	3 501	2 237	39
30-39	control	5 690	2 352	1 498	30
	experiment_1	5 742	2 384	1 481	28
	experiment_2	5 706	2 378	1 535	22
	experiment_3	5 622	2 363	1 505	20
40-49	control	13 843	5 787	3 679	54
	experiment_1	14 196	5 982	3 790	68
	experiment_2	13 953	5 928	3 817	70
	experiment_3	14 264	5 869	3 804	64
50+	control	28 377	11 914	3 855	50
	experiment_1	28 116	11 770	3 800	48
	experiment_2	28 508	11 975	3 848	49
	experiment_3	28 260	11 824	3 753	48

Segment Analysis of Funnel

Identify Opportunities for Improvement

Perform a funnel analysis by segment for all identified demographic attributes and describe the results

Age analysis III.



Segment Analysis of Funnel

Identify Opportunities for Improvement

Perform a funnel analysis by segment for all identified demographic attributes and describe the results

Age analysis summary

In the 50+ age group, there is a large mass of interest (open) and finally a very low use of the service (begin_ride) can be observed. ***What is the reason of this age group has a high drop off rate in the conversion funnel?***

While the 30-39 and 18-29 ages have a much healthier funnel, but they have a lower initial opening rate. The analysis shows that an experiment should be conducted for these two age segments. ***Why is the opening rate so low and how can be improved.***

Segment Analysis of Funnel

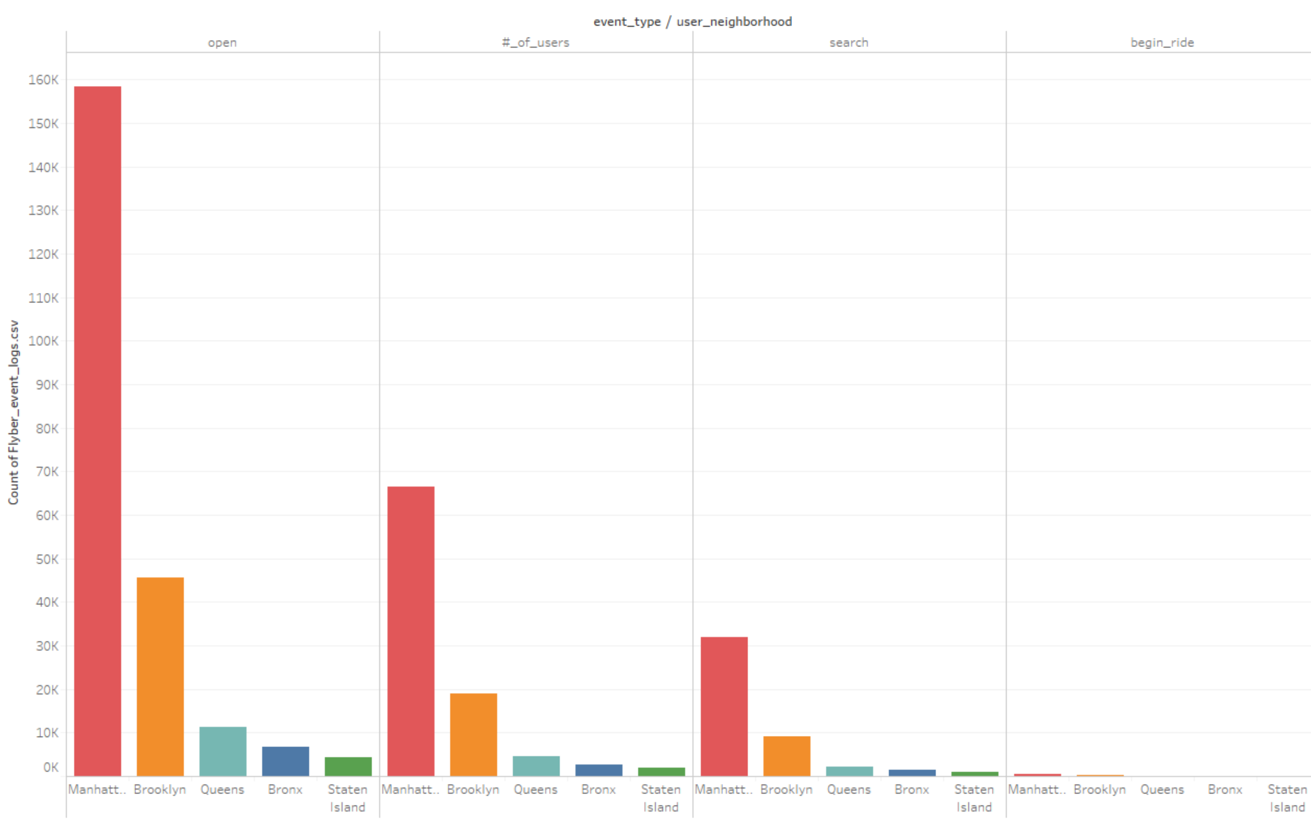
Identify Opportunities for Improvement

Neighborhood Analysis I.

analyzing neighborhood vs funnel drop off

	user_neighborhood				
event_type	Manhat..	Brooklyn	Queens	Bronx	Staten Island
open	158 366	45 583	11 172	6 693	4 341
#_of_users	66 471	19 059	4 628	2 758	1 832
search	31 948	9 103	2 257	1 328	867
begin_ride	474	135	31	23	14

analyzing neighborhood vs funnel drop off



Segment Analysis of Funnel

Identify Opportunities for Improvement

Neighborhood Analysis I.

analyzing neighborhood vs funnel drop off

		experiment_group			
event_type	user_neighbor..	control	experiment_1	experiment_2	experiment_3
open	Manhattan	39 407	39 413	39 688	39 858
	Brooklyn	11 363	11 458	11 456	11 306
	Queens	2 810	2 716	2 821	2 825
	Bronx	1 700	1 673	1 671	1 649
	Staten Island	1 110	1 130	1 052	1 049
#_of_users	Manhattan	16 574	16 542	16 758	16 597
	Brooklyn	4 733	4 820	4 848	4 658
	Queens	1 161	1 082	1 217	1 168
	Bronx	669	727	689	673
	Staten Island	475	455	441	461
search	Manhattan	7 981	7 976	8 057	7 934
	Brooklyn	2 234	2 260	2 351	2 258
	Queens	570	507	607	573
	Bronx	308	340	358	322
	Staten Island	230	217	208	212
begin_ride	Manhattan	106	117	133	118
	Brooklyn	32	36	32	35
	Queens	6	7	8	10
	Bronx	6	8	5	4
	Staten Island	4	4	2	4

Segment Analysis of Funnel

Identify Opportunities for Improvement

Neighborhood Analysis I.

analyzing neighborhood vs funnel drop off

		experiment_group			
event_type	user_neighbor..	control	experiment_1	experiment_2	experiment_3
open	Manhattan	0,00%	0,00%	0,00%	0,00%
	Brooklyn	-71,17%	-70,93%	-71,13%	-71,63%
	Queens	-92,87%	-93,11%	-92,89%	-92,91%
	Bronx	-95,69%	-95,76%	-95,79%	-95,86%
	Staten Island	-97,18%	-97,13%	-97,35%	-97,37%
#_of_users	Manhattan	-57,94%	-58,03%	-57,78%	-58,36%
	Brooklyn	-87,99%	-87,77%	-87,78%	-88,31%
	Queens	-97,05%	-97,25%	-96,93%	-97,07%
	Bronx	-98,30%	-98,16%	-98,26%	-98,31%
	Staten Island	-98,79%	-98,85%	-98,89%	-98,84%
search	Manhattan	-79,75%	-79,76%	-79,70%	-80,09%
	Brooklyn	-94,33%	-94,27%	-94,08%	-94,33%
	Queens	-98,55%	-98,71%	-98,47%	-98,56%
	Bronx	-99,22%	-99,14%	-99,10%	-99,19%
	Staten Island	-99,42%	-99,45%	-99,48%	-99,47%
begin_ride	Manhattan	-99,73%	-99,70%	-99,66%	-99,70%
	Brooklyn	-99,92%	-99,91%	-99,92%	-99,91%
	Queens	-99,98%	-99,98%	-99,98%	-99,97%
	Bronx	-99,98%	-99,98%	-99,99%	-99,99%
	Staten Island	-99,99%	-99,99%	-99,99%	-99,99%

Segment Analysis of Funnel

Identify Opportunities for Improvement

Neighborhood Analysis II.

Segment Analysis of Funnel

Identify Opportunities for Improvement

Neighborhood Analysis summary

Manhattan has the largest nr of usage of the service, Brooklyn come after it.
Drop off calculation: State of Island has the lowest #_nr_user drop off rate (57.80%), in the search pahe Manhattan has the lowest nr (79.83%) and Bronx has the best begin_ride rate 99.66%.
Analysing by experiements: by the largest nr of usage Manhattan experiment_2 has the best conversion rate and Bronx experiment_1

	Manhattan			
event_type	control	experiment_1	experiment_2	experiment_3
open	0,00%	0,00%	0,00%	0,00%
#_of_users	-57,94%	-58,03%	-57,78%	-58,36%
search	-79,75%	-79,76%	-79,70%	-80,09%
begin_ride	-99,73%	-99,70%	-99,66%	-99,70%

Bronx			
control	experiment_1	experiment_2	experiment_3
0,00%	0,00%	0,00%	0,00%
-60,65%	-56,55%	-58,77%	-59,19%
-81,88%	-79,68%	-78,58%	-80,47%
-99,65%	-99,52%	-99,70%	-99,76%

Segment Analysis of Funnel

Identify Opportunities for Improvement

Neighborhood & Age funnel drop analysis

Age & Neighborhood funnel drop analysis

		event_type			
age	user_neighbor..	open	#_of_users	search	begin_ride
18-29	Manhattan	23 708	9 944	6 418	95
	Brooklyn	6 894	2 903	1 824	20
	Queens	1 647	709	474	5
	Bronx	1 003	413	267	3
	Staten Island	626	253	155	3
30-39	Manhattan	15 892	6 645	4 244	69
	Brooklyn	4 587	1 900	1 171	19
	Queens	1 146	466	312	6
	Bronx	715	285	182	4
	Staten Island	420	181	110	2
40-49	Manhattan	39 341	16 502	10 576	180
	Brooklyn	11 361	4 740	3 031	51
	Queens	2 797	1 162	751	10
	Bronx	1 631	669	430	10
	Staten Island	1 126	493	302	5
50+	Manhattan	79 425	33 380	10 710	130
	Brooklyn	22 741	9 516	3 077	45
	Queens	5 582	2 291	720	10
	Bronx	3 344	1 391	449	6
	Staten Island	2 169	905	300	4

Segment Analysis of Funnel

Identify Opportunities for Improvement

Neighborhood & Age funnel drop analysis

Age & Neighborhood funnel drop analysis by percent total

		event_type			
age	user_neighbor..	open	#_of_users	search	begin_ride
18-29	Manhattan	59,03%	24,76%	15,98%	0,24%
	Brooklyn	59,22%	24,94%	15,67%	0,17%
	Queens	58,10%	25,01%	16,72%	0,18%
	Bronx	59,49%	24,50%	15,84%	0,18%
	Staten Island	60,37%	24,40%	14,95%	0,29%
30-39	Manhattan	59,19%	24,75%	15,81%	0,26%
	Brooklyn	59,75%	24,75%	15,25%	0,25%
	Queens	59,38%	24,15%	16,17%	0,31%
	Bronx	60,29%	24,03%	15,35%	0,34%
	Staten Island	58,91%	25,39%	15,43%	0,28%
40-49	Manhattan	59,07%	24,78%	15,88%	0,27%
	Brooklyn	59,22%	24,71%	15,80%	0,27%
	Queens	59,26%	24,62%	15,91%	0,21%
	Bronx	59,53%	24,42%	15,69%	0,36%
	Staten Island	58,46%	25,60%	15,68%	0,26%
50+	Manhattan	64,24%	27,00%	8,66%	0,11%
	Brooklyn	64,28%	26,90%	8,70%	0,13%
	Queens	64,88%	26,63%	8,37%	0,12%
	Bronx	64,43%	26,80%	8,65%	0,12%
	Staten Island	64,21%	26,79%	8,88%	0,12%

Segment Analysis of Funnel

Identify Opportunities for Improvement

Neighborhood & Age Analysis summary

Younger generations have got lower drop off rate in search phase, and here we are loosing 50+ genreration.

In Bronx at the age goup of 30-39, 40-49 we have the highest begin_ride %.

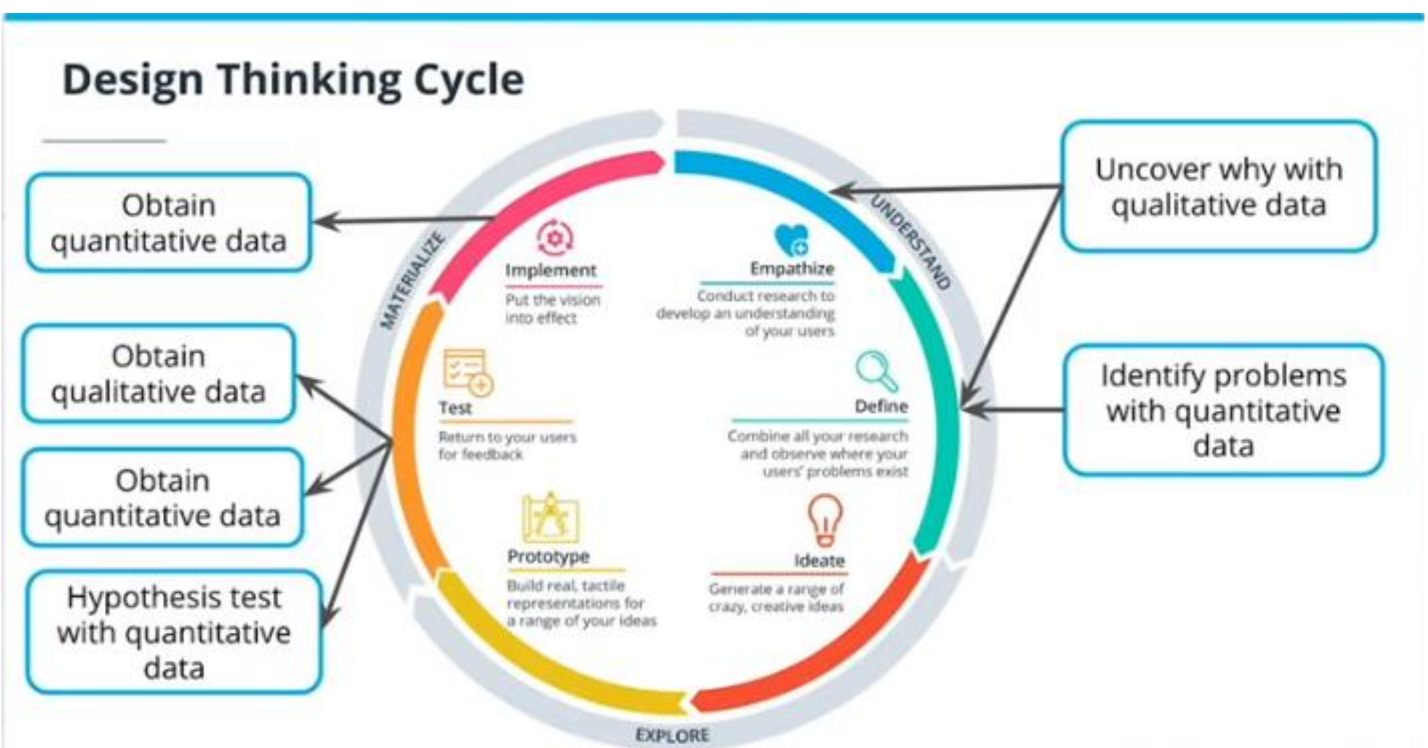
Step 3

Hypothesis & Next Steps

Review Qualitative Data

In this stage I use learnings from Udacity lecture: Integrate Data into Iterative Design (video)

First, analyzing usage data, conversion funnels, and other quantitative data collected can reveal users or areas that are under- and over-performing.
Next, upon seeing areas for improvement via quantitative analysis, product managers then turn to user interviews or other qualitative data techniques to understand why such trends might be occurring.



Review Qualitative Data

Read **user interviews** to understand “why” any funnel under-performance seen in Step 2 might occur

In the user interview log file we can see 50+ age group over represented but it is in line with quantitative data logs (open rate).

Recognized behaviour patterns:

- Calling a service (taxi)
- Use assistant to drive their car
- Tell a phone (voice command) to call a service

Hypothesis behind the patterns:

- poor eyesight in older age | bad UX of the app
- entrenched habits like calling a dispatcher
- uses the phone to make calls and not booking service

Review Qualitative Data

List your hypothesis for what customer need is being under-served

In this stage I use learnings from Udacity lecture: **Jobs to Be Done Framework**

The Jobs to Be Done Framework pushes product managers to consider what job people are hiring their product to do. This job goes beyond the simple actions a user takes and instead examines the motivations and goals a customer is trying to achieve.

Core functional job: this is the direct result that job executor is trying to achieve by using a product. Note: it should be motivations and goals a customer is trying to achieve, regardless of what tools they use. ➔ Being from A to B as fast as possible fast and safe (detailed in the next slides)

Related jobs: these are jobs done either before, during, or following the execution of the core functional job. By understanding related jobs, you can find opportunities to add additional features to the product that helps customers.

Emotional job: this is how the job executor wants to feel or be perceived after finishing the core functional job. ➔ super cool to fly and arrive to destination, gives credits in society

[video]

Review Qualitative Data

List your hypothesis for what customer need is being under-served

Step 1: Define: defines goals and the resources needed for achieving goals.
In this step, product managers can improve their product by making planning simpler for the user.

➔ flyber user realizes she needs to be in Manhattan in 25 minutes for the next meeting. She wants to avoid traffic jam.

➔ feature makes planning simpler: syncronize user calendar with flyber app and give signals when to start trip based on traffic. Save user addresses and favourite places make planning easier.

Step 2: Locate: gathers everything needed to accomplish a job, whether physical tools or information.
A product manager can innovate in this step by making it easier for a user to gather everything they need in one place.

➔ user checks the traffic situation, calls his cab service for estimated time to arrive, check google maps

➔ feature makes easier gathering information: comparing ETA and costs based on taxi, uber, own car and flyber

Step 3: Prepare: sets up the environment to do a job.
To make improvements, product managers can reduce required set up or provide guidance that allows users to prepare more quickly.

➔ user prepares his mobile for booking, his car for driving

➔ feature helps to prepare more quickly: voice command for route planning, virtual assistant for complete execution

Review Qualitative Data

List your hypothesis for what customer need is being under-served

Step 4: Confirm: a final check to make sure the job is ready to do.
Product manager can innovate by giving users easy ways to confirm their readiness for a job.

➔ user checks things before starting her trip: meeting notes, laptops, her children present, clothes…

➔ feature helps this phase: Based on the user's calendar entry, the app analyzes the type of appointment and gives a forecast of what tools are needed for the appointment. Eg. if she has a business meeting the app will remind the user to bring her laptop and notes.

Step 5: Execute: begins to carry out a job.
A product manager improves this step by removing blockers and ensuring their product is intuitive to use.

➔ user call the service or book the trip

➔ features: voice command, ‚press one button', clear instruction (visible)

Step 6: Monitor: checks whether the job is being successfully carried out.
For this step, product managers can innovate by giving users more information about progress towards their goal.

➔ user monitor the progress: in time?, no danger?, traffic changed?..

➔ features: show the ETA, progress on map vs cab & uber, show traffic changes

Review Qualitative Data

List your hypothesis for what customer need is being under-served

Step 7: Modify: make changes or adjustments to improve the outcomes of the job.
To improve a product in this step, a product manager should reduce the number of modifications a user has to make when executing a job.

- ➔ user can change the destination or stop picking up her partner
- ➔ feature: options if destination changed (next flyber drop off station with continuing uber pick up)

Step 8: Conclude: finishes executing the job.
To improve a product in this step, product managers can decrease the work needed to conclude a job.

- ➔ user arrives her destination in good mood, fresh with pride
- ➔ features: payment without delay (not transactional one)

Emotional Needs Served

A flyber user has emotional need for feeling safer and winner. Showing others that they are rich, tech-driven people.

Case Studies: Customer Empathy with Jobs to Be Done: The UBER Case, Build Products That Solve Real Problems With This Lightweight JTBD Framework

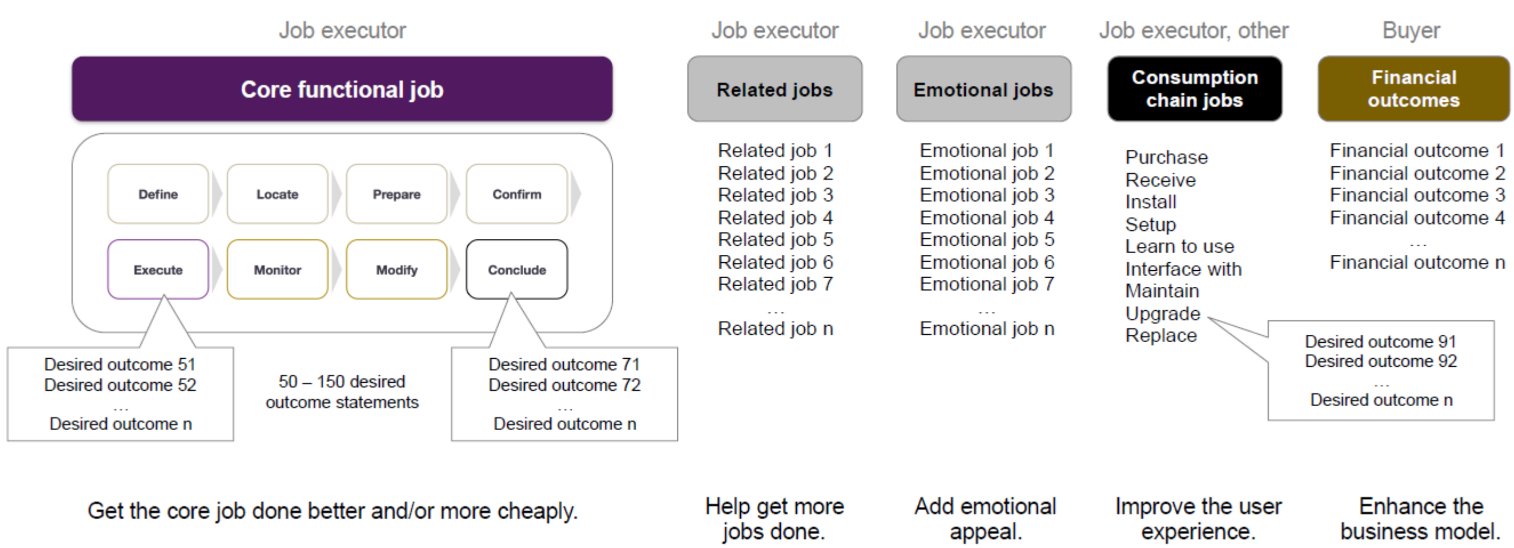
Tony Ulwick – Put Jobs-To-Be-Done Theory Into Practice With Outcome-Driven Innovation

Review Qualitative Data

List your hypothesis for what customer need is being under-served

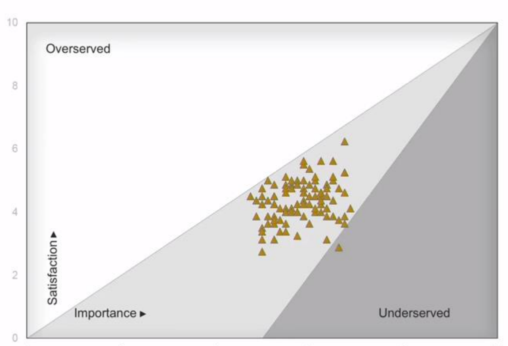
Tony Ulwick – Put Jobs-To-Be-Done Theory Into Practice With Outcome-Driven Innovation

THE JOBS-TO-BE-DONE NEEDS FRAMEWORK



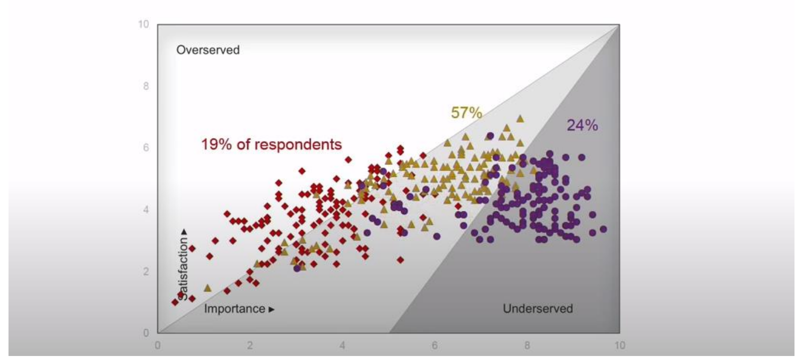
ON AVERAGE A MARKET MAY APPEAR WELL SERVED

But the average customer does not exist. There are always segments of customers with different unmet outcomes.



DISCOVER HIDDEN SEGMENTS OF OPPORTUNITY

Outcome-Based Segmentation reveals under- and overserved segments, their size, and which outcomes to target for growth.



Review Qualitative Data

List your hypothesis for what customer need is being under-served

Simple planning: syncronize user calendar with flyber app and give signals when to start trip based on traffic. Save user addresses and favourite places make planning easier.

Makes easier gathering information: comparing ETA and costs based on taxi, uber, own car and flyber

Prepare the trip more quickly: voice command for route planning, virtual assistant for complete execution

Booking : voice command, ‚press one button’, clear instruction (visible)

Prioritization

RICE framework
R (Reach): the number of people or customers a feature is expected to be used by, in a set time period. (Qualitative log data 50+ age / location)
I (Impact): measures the effect a new feature is expected to have on KPIs such as conversion rate or customer satisfaction. (data log conversion funnal drop off)
C (Confidence): describes how sure you are that your estimates are correct. The more data you have about reach, impact, and effort, the more confident you would be.
E (Effort): the amount of time it will take to make a feature go live, from design to engineering to QA and launch. The effort can be measured in person-mor
which means the work one person can do in a number of months.
How to do it: link

```
RICE Score = (R * I * C) / E
```

Review Qualitative Data

Provide 3 or more quotes as evidence for this hypothesis

'Honestly, I thought about using Flyber to suprise my grandson or granddaughter with a visit to one of their sporting games. Luckily my daughter was around to help me book the ride. I usually just use **Uber because it remembers my addresses and has all my favorite places saved, so I guess I always just open that up since it is so convenient and saves me time**. Though now that I say that, I really should use Flyber again since it would save more time when it comes to fighting traffic!'

‚If the timing isn't different, I'll take a taxi or uber to save money. ,

‚I just hail a taxi or tell my phone to call a cab to go to a certain address (I'm always on the phone, so I just use voice commands with my phone most of the time)'

‚I have a personal car service on call. My assistant books Flyber whenever I'd be travelling during peak NYC traffic hours. Time is money and Flyber saves me time! But I let my assistant actually book the Flyber because the first few times **I tried booking, the instructions were too small.'**

Suggested Features & Experimentation Plan

Share **your hypothesis** using the following format:

We believe [observed quantitative effect] Because [hypothesized user “why”] And that by [general change/opportunity for Flyber to improve] for [targeted cohort] we will see [expected effect]

We believe the age 50+ user group high drop off rate in booking (search) phase because difficult for them to use our app’s booking feature and by voice control (voice to text and auto-fill feature) for this age group we will see the same drop off rate as younger age groups.

Suggested Features & Experimentation Plan

Suggest 2 or more features that would match your hypothesis and determine a plan for multivariate testing, including describing the control and experimental conditions

- Voice control (voice to text)
- Auto-fill function

Suggested Features & Experimentation Plan

Determine who should be exposed to the experimental changes

‚on the next slides’

List any additional metrics that would be helpful to collect from your suggested features

‚on the next slides’

Suggested Features & Experimentation Plan

Instrumentation

Product managers do not always run experiments on all users, but may *focus on a particular type of users*. This means you need to instrument and collect information on the right type of users and ensure that they are part of the experiment.

- It is vitally important to track *which test state a user is assigned.* This enables you to analyze the difference in results among experiment groups and to ensure the same test state is shown to the same user until the experiment is over.

- The final thing to track during an experiment is the *conversion rate*. It is the percentage of users who successfully performed the desired action in each experiment group. The key to choosing the correct conversion rate is to choose one that relates to the important, long term impact you wish your experiment to drive. This may often be a product or feature KPI.

Suggested Features & Experimentation Plan

Track User Actions During Testing

- We need to track the number of unique visitors to the page where they will be testing the new design.
- We will need to track whether a user sees the control or the experimental design on the page.
- We will also likely want to track the device and browser that the visitor is using in case the designs perform differently across device types.
- Finally, to know which page is more effective, they will need to track whether the visitor takes the desired action of using the social linking feature

Suggested Features & Experimentation Plan

Ensure Unbiased Control & Test Groups

- When running experiments, you must make sure that users in the control and the test/experiment group share the same characteristics. That way, you can ensure the differences among experiment groups is caused by the change of the product, not by different user characteristics. ➔ in our expirement we should be careful with demographic (age 50+) and locations characteristics.

- First, you need to determine what type of user you are testing and make sure these target users are put into both the control and experiment groups. ➔ age 50+

- In addition to everyone being a target user, you need to make sure other user characteristics such as age, race, income are balanced between the control and experiment groups.

- A great way to get a balance of user characteristics among the groups is **to randomize** who is in the control and who is in the experiment group.

Suggested Features & Experimentation Plan

Calculate & Respond to Test Results

The results experiments can be evaluated by a **T-Test.** A T-test compares the means of two groups to see whether the difference in the means is large enough that it is probably not due to random chance. In the case of an A/B or multivariate test, the T-test helps us understand whether any differences observed in the conversion rate are significant and are likely due to the change we made.

- **Step 1: state the null hypothesis.** The null hypothesis represents the idea that the control state is not different from a test state, which is what we want to *reject*. A generic null hypothesis would be: customers *convert the same* with the test state compared to the control state. ➔ **In our case in this will be the control state. No changes will be added here that is the current product state.**

- **Step 2: state the alternative hypothesis.** The alternative hypothesis is the one you want to *accept*. A generic alternative hypothesis would be: customers will *convert differently* with this change. ➔ **Here we will add the two new features with several experiments**

- **Step 3: set a confidence threshold.** Product managers almost universally user a *95% confidence level*, which means a 95% chance that the result appears statistically valid and a 5% chance that the result is an error.

- **Step 4: run the A/B or multivariate experiment.**

- **Step 5: perform a T-test.** After you get the result from your experiment, you need to perform a T-test to see if the differences you see in the experiment are significant. To perform a T-test, you will need to know:

    - The number of users in the control group and in each test group

    - The number of conversions in each group

    - The confidence threshold from step 3

    - Decide if the T-test is a one-tailed or two-tailed test. A two-tailed test means you assume the experiment conversion rate is different from the control, maybe *worse OR better*.

Appendix

Raw Data

Additional Info

You could include supporting or additional information that can support your previous slides but isn't necessary for every person to see that looks at your slides.