Body Type Prediction

Okcupid Project Report

Team 21

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1. Executive summary

The past decade has shown a rise in popularity for online dating platforms, and now there are many different applications that match a variety of diverse lifestyles. Each platform has their own algorithm for making matches and connections; therefore, there is a lot of competition between sites. Although there are differences in each platform, the online dating scene usually follows a similar format. At signup, users are asked a series of questions such as age, location, level of education, income, hobbies, etc. in order to find compatible and similar individuals. Users are able to parse through matched profiles one at a time and choose whether or not they are interested in that person. Once both users match, they have the ability to send a direct message to the other person and begin connecting with them. After the connection is made, the application serves as the primary means of communicating until the users have a few conversations and decide to move further. In theory, this is a seamless process that allows people to meet and connect with a variety of people with ease and efficiency; however, one of the main problems with online dating is the possibility that a user is interacting with a fraudulent person. This can take form as someone that has put false information about themselves in their profile or even as users that are complete imposters. This issue has proved to be one of the main deterrents to the online dating scene and serves to be the topic that we hope to improve.

2. Explain the business idea, why it's important, and the data source

Due to the pandemic, people are unable mingle at social gatherings and meet new people. As a result, people are becoming lonelier and more isolated; therefore, the demand for companionship has been on the rise. In the past eight months, there has been an increased amount of signups and user traffic on these online dating platforms. Since there are many alternatives and substitutes available for consumers, it is important for companies to have their users keep coming back. Therefore, we are proposing this topic because it now a priority to capture this influx of users by improving the quality of the connections and interactions on the applications. If a user has a good experience with a specific dating platform, they are likely to spread their positive experience to their friends, online audience, or as a review which will prompt more potential users to use the platform. Finding data that can be helpful in answering these questions will allow us to depict and propose novel ways to improve the customer experience in online dating. Ensuring that the user has an enjoyable experience throughout the whole process will be imperative to the success of the online dating platform. By collecting, analyzing, and interpreting the data from the user experience, we hope to propose a solution that can allow users to connect with peace of mind. The data source was Kaggle and the dataset we acquired was comprised of 59,946 people and their okcupid profiles. We included variables that would give good insights into the habits and personality of the user. Looking into the dataset through machine learning would provide a good way to improve the online dating platform itself.

3. Data summary, description, visualization.

Data Source: Kaggle

Organization: Okcupid

The data has 59946 rows and 31 columns.

The data has demographic information of customers like age, sex, location, job income and habits information such as drinks, drugs and smoke, also there is text data that where customers give brief information about them.

Here is the brief description of the columns:

Except the age, income and height, all the columns are categorical variables with overlapping values hence needs to be grouped into appropriate categories.

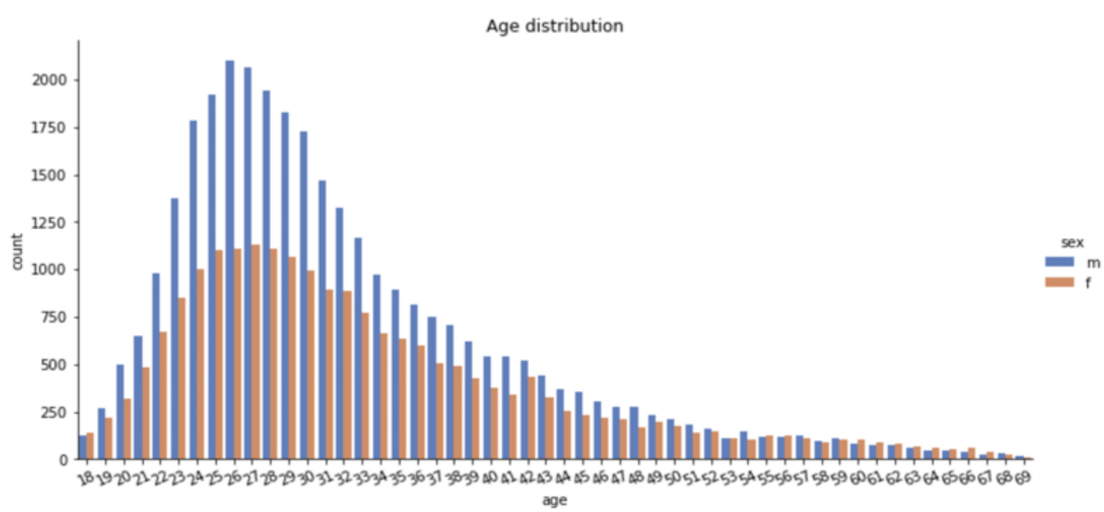
Tools used:

Python: Data processing and modeling.

Tableau: Visualization.

Column	**Description**
age	age of the customer
status	status of the customer
sex	sex of the customer
orientation	orientation of the customer
body_type	body type of the customer
diet	diet of the customer
drinks	customer drinking information
drugs	information if the customer consumes drugs
education	education of the customer
ethnicity	ethnicity of the customer
height	height of the customer
income	income of the customer
job	job of the customer
last_online	last online date and time of the customer

location	location of the customer
offspring	offspring of the customer
pets	pets of the customer
religion	religion of the customer
sign	sign of the customer
smokes	information if the customer smokes
speaks	language of the customer
essay0	introduction of the customer
essay1	introduction of the customer
essay2	introduction of the customer
essay3	introduction of the customer
essay4	introduction of the customer
essay5	introduction of the customer
essay6	introduction of the customer
essay7	introduction of the customer
essay8	introduction of the customer
essay9	introduction of the customer



Count and percentage of missing values in the data:

column	obs	Percent
offspring	35561	59.30%
diet	24395	40.70%
religion	20226	33.70%
pets	19921	33.20%
essay8	19225	32.10%
drugs	14080	23.50%
essay6	13771	23.00%
essay9	12603	21.00%
essay7	12451	20.80%
essay3	11476	19.10%
sign	11056	18.40%
essay5	10850	18.10%
essay4	10537	17.60%
essay2	9638	16.10%
job	8198	13.70%
essay1	7572	12.60%
education	6628	11.10%
ethnicity	5680	9.50%
smokes	5512	9.20%
essay0	5488	9.20%
body_type	5296	8.80%
drinks	2985	5.00%
speaks	50	0.10%
height	3	0.00%

orientation	0	0.00%
status	0	0.00%
sex	0	0.00%
income	0	0.00%
last_online	0	0.00%
location	0	0.00%
age	0	0.00%

Distribution of class variable without preprocessing:

body_type	**obs**
thin	4711
skinny	1777
a little extra	2629
average	14652
curvy	3924
full figured	1009
rather not say	198
used up	355
overweight	444
athletic	11819
fit	12711
jacked	421

4 Analysis, Benchmark accuracy without pre-processing data.

Predicting **Body Type** using habits and demographic data

Decision Tree

- Best accuracy = 0.29
- Best Depth = 5

Random Forest

- Accuracy = 0.23

K Nearest Neighbor

- Best Accuracy = 0.27
- Best Neighbor Amt. = 35

Data processing and cleaning: all the categorical columns having similar values have been grouped into one category. All the numerical variables remain as is except the income column where the –1 which stands for missing values has been treated to remove those values

Status before: **single** and **available** values are grouped into **single** category.

Status	**Obs**
single	55697
available	1865
seeing someone	2064
married	310
unknown	10

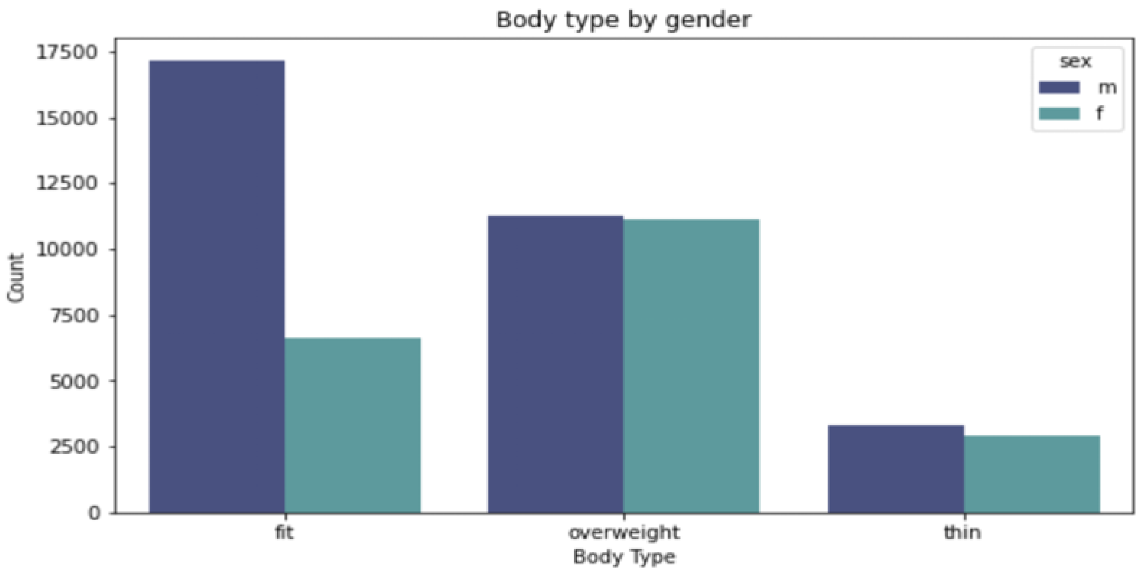
Status after:

Status	**Obs**
single	57562
seeing someone	2064

married	310
unknown	10

Sex : no categorization of the values in this column

Sex	**Obs**
m	35829
f	24117



Categorization used for **Body Type**:

body_type	**obs**	**new category**
thin	4711	thin
skinny	1777	thin
a little extra	2629	overweight
average	14652	overweight
curvy	3924	overweight
full figured	1009	overweight

rather not say	198	overweight
used up	355	overweight
overweight	444	overweight
athletic	11819	fit
fit	12711	fit
jacked	421	fit

Body type after:

Body Type	**Obs**
fit	24951
overweight	23211
thin	6488

Categorization used for **Diet**:

diet	**obs**	**new category**
strictly other	452	anything
other	331	anything
mostly other	1007	anything
strictly anything	5113	anything
mostly anything	16585	anything
anything	6183	anything
strictly halal	18	kosher/halal
mostly halal	48	kosher/halal
halal	11	kosher/halal

strictly kosher	18	kosher/halal
mostly kosher	86	kosher/halal
kosher	11	kosher/halal
vegan	136	vegan
strictly vegan	228	vegan
mostly vegan	338	vegan
vegetarian	667	vegeterian
strictly vegetarian	875	vegeterian
mostly vegetarian	3444	vegeterian

Diet after:

Diet	**Obs**
anything	29671
vegetarian	4986
vegan	702
kosher/halal	192

Categorization used for **Drinks**:

drinks	**obs**	**new category**
socially	41780	yes
often	5164	yes
very often	471	yes
desperately	322	yes
not at all	3267	no
rarely	5957	no

Drinks after:

Drinks	Obs
yes	47737
no	9224

Categorization used for **Drugs**:

Drugs	obs	new category
never	37724	no
sometimes	7732	yes
often	410	yes

Drugs after:

Drugs	Obs
no	37724
yes	8142

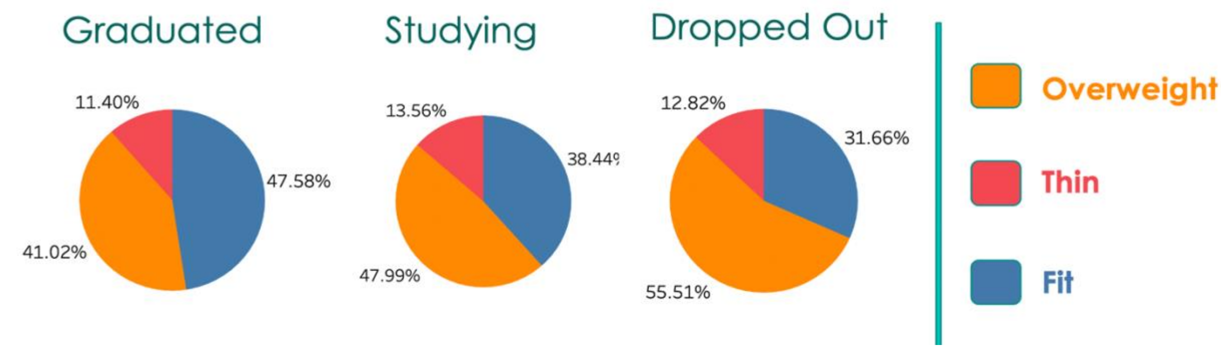
Categorization used for **Education**:

education	obs	new category
college/university	801	graduated
graduated from college/university	23959	graduated
graduated from high school	1428	graduated
graduated from law school	1122	graduated
graduated from masters program	8961	graduated
graduated from med school	446	graduated
graduated from ph.d program	1272	graduated
graduated from space camp	657	graduated
graduated from two-year college	1531	graduated

high school	96	graduated
law school	19	graduated
masters program	136	graduated
med school	11	graduated
ph.d program	26	graduated
space camp	58	graduated
two-year college	222	graduated
dropped out of college/university	995	dropped out
dropped out of high school	102	dropped out
dropped out of law school	18	dropped out
dropped out of masters program	140	dropped out
dropped out of med school	12	dropped out
dropped out of ph.d program	127	dropped out
dropped out of space camp	523	dropped out
dropped out of two-year college	191	dropped out
working on college/university	5712	studying
working on high school	87	studying
working on law school	269	studying
working on masters program	1683	studying
working on med school	212	studying
working on ph.d program	983	studying
working on space camp	445	studying
working on two-year college	1074	studying

Education after:

Education	Obs
graduated	40745
studying	10465
dropped out	2108



Ethnicity : Ethnicity column was split with space as separator and the first part of the string was used to get the ethnicity value. Similar values are grouped into one category.

ethnicity	obs	new category
black	2,008	black
black,	1,063	black
indian	1,077	indian
indian,	119	indian
other	1,706	other
middle	811	other
pacific	717	other
native	709	other
hispanic	4,379	hispanic
asian	6,134	asian
asian,	2,071	asian
white,	641	white

white	32,831	white

Ethnicity after:pet

Ethnicity	**Obs**
white	33472
asian	8205
hispanic	4379
other	3943
black	3071
indian	1196

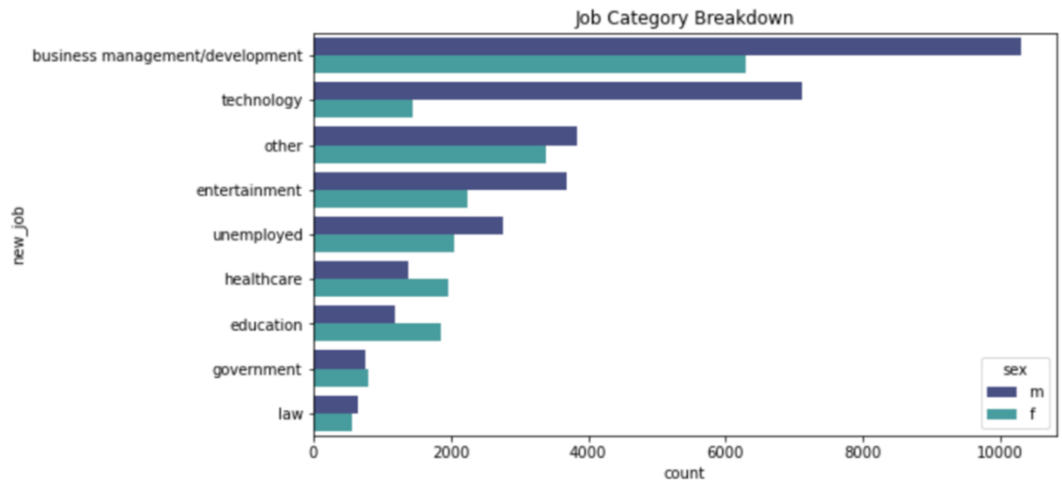
Categorization used for **Job**:

job	**obs**	**new category**
executive / management	2373	Business Management
sales / marketing / biz dev	4391	Business Management
hospitality / travel	1364	Business Management
banking / financial / real estate	2266	Business Management
transportation	366	Business Management
construction / craftsmanship	1021	Business Management
computer / hardware / software	4709	Technology
science / tech / engineering	4848	Technology
entertainment / media	2250	Entertainment
artistic / musical / writer	4439	Entertainment
student	4882	Unemployed
retired	250	Unemployed
unemployed	273	Unemployed

education / academia	3513	Education
medicine / health	3680	Medical
law / legal services	1381	law
other	7589	other
rather not say	436	other
political / government	708	govt
clerical / administrative	805	govt
military	204	govt

Job after:

Job	**Obs**
business management/development	11781
technology	9557
other	8025
entertainment	6689
unemployed	5405
healthcare	3680
education	3513
government	1717
law	1381

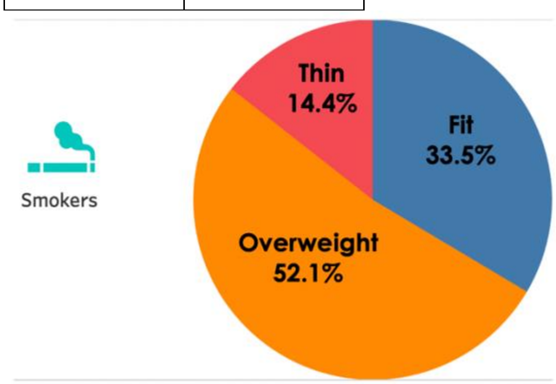


Categorization for **Smokes**:

smokes	**obs**	**new category**
no	43896	no
sometimes	3787	yes
when drinking	3040	yes
yes	2231	yes
trying to quit	1480	yes

Smokes after:

Smokes	**Obs**
no	43896
yes	10538



Data cleaning:

The raw data was subset to consider only the columns that we are going to use for the model which are: age, sex, height, income, status, body_type, diet, drinks, drugs, education, ethnicity, job, smokes. The data used for model has 52318 rows and 13 columns

- Removed the null values from the class variable body_type. Distribution of the class variable:

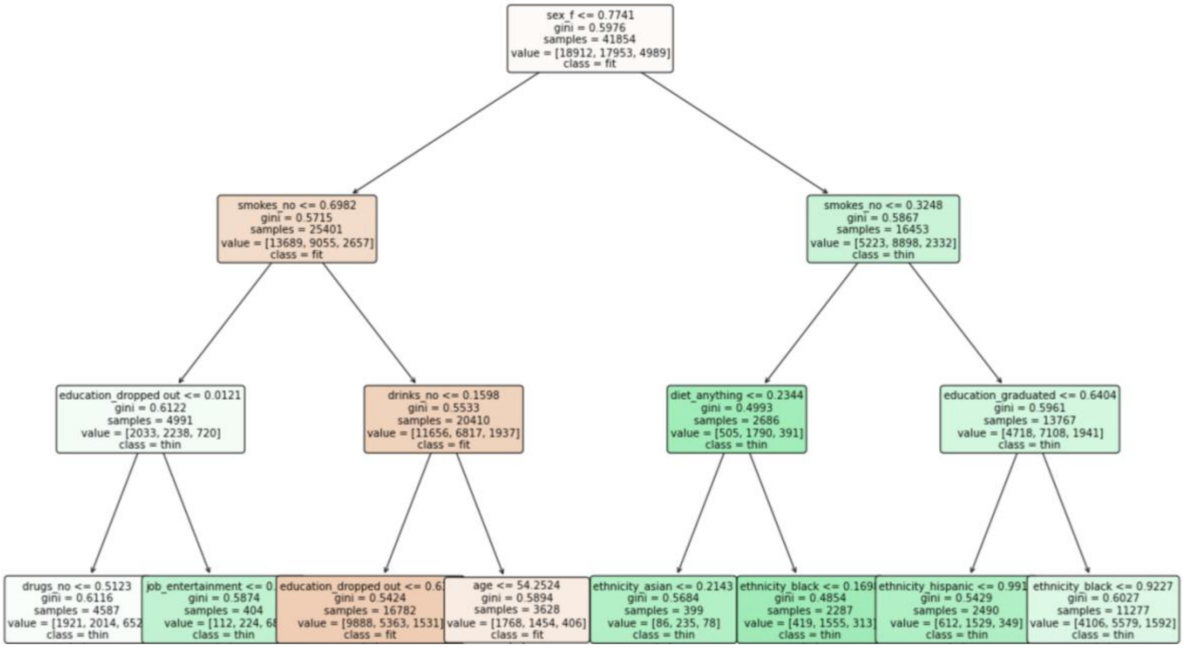
body_type	**obs**
overweight	22381
thin	6193
fit	23744

- Removed the null values from the drinks column which has less than 5% missing values
- Treated all the categorical variables with the most occuring value
- Treated the –1 values in the income column with median values by each job type
- Removed the pets and offspring columns since they had missing values more than 30%
- Rest of the columns were removed because of less relevancy to the class variable and no variance in the values

Modeling:

- Converted the class variable using label encoder
- Converted all the categorical variables into binary
- Split the data into training and test using 80-20 split

Decision Tree: ran the decision tree in python in loop for depth from 1 to 20 to get the depth with the best accuracy. The accuracy is 55% with max depth of 7.



Random forest classifier: ran the random forest classifier in python with the 1000 as estimators which gave the accuracy of 50%.

K nearest neighbors: ran the KNN in loop to get the neighbors with highest accuracy from 1 to 100. The nearest neighbors were 88 and with the maximum accuracy of 54%.

Decision tree had the best accuracy hence ran the tree keeping the max depth parameter as 7 on the training data. Ran the confusion matrix on the test data and below is the classification report. The precision and recall for the **Thin** category are the lowest due to uneven distribution of the observations.

```
Classification report -
              precision    recall  f1-score   support

          0       0.58      0.64      0.61      4832
          1       0.52      0.60      0.56      4428
          2       0.33      0.01      0.01      1204

avg / total       0.52      0.55      0.52     10464
```

Decision tree was run in Weka using J48 classifier with the 10 fold cross validation which gave the accuracy of 54% . Below are the results:

```
Number of Leaves  :     2146

Size of the tree :      3599


Time taken to build model: 6.72 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances       28375               54.2356 %
Incorrectly Classified Instances     23943               45.7644 %
Kappa statistic                          0.1879
Mean absolute error                      0.3705
Root mean squared error                  0.4508
Relative absolute error                 93.0982 %
Root relative squared error            101.0584 %
Total Number of Instances            52318

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.546    0.350    0.538      0.546    0.542      0.196    0.608     0.512     overweight
                 0.022    0.018    0.144      0.022    0.038      0.011    0.570     0.145     thin
                 0.674    0.443    0.559      0.674    0.611      0.232    0.634     0.544     fit
Weighted Avg.    0.542    0.353    0.501      0.542    0.514      0.190    0.615     0.483

=== Confusion Matrix ===

     a     b     c   <-- classified as
 12223   426  9732 |     a = overweight
  3137   137  2919 |     b = thin
  7343   386 16015 |     c = fit
```

Takeaways

Factors for improvement of accuracy:

- The data used for analysis was similar to a survey data because there is no way to validate if the customers entered the correct information
- The categorical variables if grouped differently might increase the accuracy
- The availability of the columns such as weight, BMI might increase the accuracy .
- The missing value treatment if done differently might lead to an increase in the accuracy.

(b) Interpret and analyze your results to help business managers understand the implications and actions that follow from the analysis.

From this analysis, we take away a few key points:

The number of missing values must be reduced in order to improve accuracy.

- The more data we lose, the worse it will be for the matching algorithms that this online dating platform relies on. To improve the algorithm would be to improve the bottom line. Therefore, it is important to acquire these precious missing data points.

The number of categorical choices must be increased in order to improve accuracy

- This will allow for more data points that are accurately grouped and categorized. Allowing for better matching of the detailed variables that users value.

Business implications

To improve the matching algorithm is to improve the bottom line. In order to improve the connections of the users, there must be a machine learning algorithm that can learn how to match users efficiently and with an exponential increase in learning. In order for this to happen, there must be more data to analyze. This is not only referring to the number of rows/instances, but also the column/attributes of the person. This will therefore give better insights of the tangible connection points for the users. This means that users will like going on dates, and those users will make a true connection. Improving the customer satisfaction would lead to a positive review or a user recommending okcupid to another friend, stimulating more customers to join this online dating platform.

(c) Other recommendations.

Finding data that can be helpful in answering these questions will allow us to depict and propose novel ways to improve the customer experience in online dating. Ensuring that the user has an enjoyable experience throughout the whole process will be imperative to the success of the online dating platform. By collecting, analyzing, and interpreting the data from the user experience, we hope that can allow users to connect with peace of mind.