Does Humor Impact Dating Success?

12/11/2023

1 Abstract

This study examines how varying personality portrayals in dating app profiles – independent of accompanying photos – affect user interactions and engagement. We investigate the user personalities displayed on dating app profiles and their subsequent engagement levels by comparing the effects of creating a neutral personality profile with a highly humorous one. Our experiment generated the following results: dating profiles with amusing textual cues received more likes and matches than the same dating profiles without funny textual lines with statistical significance. These results can benefit online dating app users as they evaluate where to spend their time developing attractive dating profiles.

2 Introduction

Humor is a universal human experience that promotes bonding and positive social interaction. Historically, humor has been shown to decrease social tension and increase likability. The treatment involving humor in the description is expected to change the measured behavior of humans who receive it. In the context of dating, where first impressions are critical, a humorous profile may pique interest by presenting someone as relatable, fun, and approachable, thereby increasing the chances of having dating success.

Our team is interested in investigating whether humorous expressions through textual cues affect dating success on a dating app. Current academic literature has evaluated this concept in similar, yet different, ways. First, a research study has evaluated how messages with varying levels of humor impact a person's perceived attractiveness (Garove & Farley, 2015). Second, a research study evaluated how live humor and laughter in discourse are associated with perceived attractiveness (Hall, 2015). Lastly, a few research studies have evaluated attractiveness (Fiore et al., 2008) or first impressions (Zanden, 2021), specifically within dating apps. However, none of these studies evaluate whether humorous textual cues within a dating app affect a person's attractiveness when primary cues like photographs and demographic information remain constant.

3 Experiment Concept

People spend hours daily on dating apps looking for potential partners. The selection process gets more complicated with the increase in the abundance of options available to them. While the superficial qualities and end goals are highly esteemed, a profile with a humorous caption tends to stand out among the numerous mundane ones as it indicates a witty personality, which is not captured through pictures and usual descriptions easily.

Our intervention variable is the textual differences between the two categories of Hinge dating profiles. Some users will experience a dating profile that is humorous and fun (treatment), and others will experience a plain and unimaginative dating profile (control). To reduce noise driven by confounding variables, we ensure both profiles have the same characteristics and content apart from responses to question prompts. Controlling for these other factors is an essential feature of this experience because while studies have shown that photos and demographics heavily influence dating profile experiences, this experiment focuses on the causal effect of personality traits expressed through text on someone's dating success on Hinge.

Due to limitations in timing and resources, we are utilizing only the Hinge application. However, we would likely see similar results if we replicated the results on other dating apps, such as Tinder or Bumble.

4 Experiment Design

This experiment aims to explore the impact of incorporating a humorous personality into dating app profiles on user engagement. Specifically, we compare the effects of creating a neutral personality profile with crafting a highly humorous and intriguing personality description on user interactions and engagement. We targeted the fake users as a narrowly diverse group of white males aged 25-33. Each team member created fake profiles for control and treatment groups with the same pictures and virtues. In the control group, the profile is neutral, while in the treatment group, the profile is highly humorous and intriguing. The fake profiles were launched at the same time on the dating app for a specified period of time. The number of likes and matches is the key metric for measuring the causal effect.

We chose two locations in the United States— New York City and San Francisco to introduce the fictitious dating profiles. The underlying assumption is that users of the dating app from these two U.S. locations exhibit similar reactions regardless of whether a humorous personality is presented. Additionally, we deliberately launched identical profiles in different locations to prevent a single participant from encountering two identical profiles simultaneously. For every treatment profile launched in New York, a control profile was launched in San Francisco and vice versa.

The following variables are measured to assess the impact on user engagement: Number of profile likes: How many users have liked the profile in a given day Number of matches: How many users have matched with the profile

Dating apps necessitate mutual likes for a match to occur; for example, if one profile "swipes" right on five people, their maximum potential matches are limited to five. In the context of this experiment, we refer to "swipes" as a team member's action to actively like another profile, while "like" refers to the number of likes our user profiles receive in a given day. To ensure that the created profile's actions (how much time we swipe right) do not unduly influence the effectiveness of our "match" measures, we analyze this data at the swipe level (i.e., one swipe is one sample). This is described in more detail in the Data Cleaning section below.

5 Data Cleaning

The provided dataset records essential metrics—swipes, likes, and matches —for various user profiles, classified into control and treatment groups on distinct dates. It encompasses information about user profiles within a dating application (refer to the Appendix for a detailed description of the table columns).

We employ two main tables for our data analysis. The primary focus is on the 'exp_d' table for evaluating the metric of matches, which is our key criterion. In this table, we expand the daily swipes into individual samples, creating one swipe per row. This expansion is justified by the fact that matches can only occur when swipes take place. Consequently, we have a total of 2752 samples for the evaluation of the matches metric.

Regarding the metrics of likes, given that they are not strictly contingent on individual swipes, individuals using Hinge might express their interest by liking the profile descriptions we have created. In this context, our unit of measurement for one sample will be based on the date of our experiment. This spans 36 days, from October 19th to November 14th, yielding 284 samples.

6 Randomization Check

A randomization check was performed to evaluate whether our treatment and control groups made up representative samples. To perform this check, two regression models were developed. The first model, null_mod, is the simplest and captures the intercept. The second model, full_mod, is more complex and includes profile characteristic variables such as who created the profile (Owner), the profile's name (Profile), the location where the profile is active (City), the day the sample was collected (Day), and the number of swipes taken on the profile (Swipes).

For the 'Matches Experiment', the first simple model illustrates a 0.502 intercept to support the assumption that both treatment and control groups comprise representative samples. The second complex model with five covariates illustrates a 0.412 intercept and captures a small pattern; The City variable has a statistically significant correlation with treatment outcomes. This suggests that different profile locations (San Francisco or New York) contribute to sample differences between the treatment and control groups. An ANOVA test confirms this difference between the treatment and control groups based on city location with a p-value of less than 0.001. However, while the City variable is statistically significant, the impact seems impractically significant at 0.167.

% Table created by stargazer v.5.2.3 by Marek Hlavac, Social Policy Institute. E-mail: marek.hlavac at gmail.com % Date and time: Mon, Dec 18, 2023 - 02:50:32 AM

```
## Analysis of Variance Table
##
## Model 1: Treat_binary ~ 1 + OwnerNum + ProfileNum + City + ExpDay_profile +
##     Swipes
## Model 2: Treat_binary ~ 1
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1   2736 666.29
```

Table 1:

	Dependent variable:	
	Treat_binary	
	(1)	(2)
Owner		0.002
		(0.009)
Profile		−0.0002
		(0.007)
City - San Francisco		0.167***
		(0.019)
Day		0.001
		(0.001)
Swipes		−0.001
		(0.003)
Intercept	0.502***	0.412***
	(0.010)	(0.039)
Observations	2,742	2,742
R^2	0.000	0.028
Adjusted R^2	0.000	0.026
Residual Std. Error	0.500 (df = 2741)	0.493 (df = 2736)
F Statistic		15.773*** (df = 5; 2736)
Note:		*p<0.1; **p<0.05; ***p<0.01

```
## 2   2741 685.49 -5   -19.206 15.773 2.428e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For the 'Likes Experiment,' the first simple model illustrates a 0.502 intercept to support the assumption that both treatment and control groups make up representative samples with a p-value of <.001. The second complex model with five covariates illustrates a -10.347 intercept with a p-value of .4369. The large shift in the two models' intercept suggests there may be material differences between treatment and control groups for our like experiment data. We suspect our low sample size is contributing to our inability to achieve statistically significant results.

One covariate is the main driver for sample group differences: City Location. With a p-value of 0.01, the City covariate correlates with treatment or control group assignment. However, an ANOVA test cannot confirm whether this difference is material because the p-value is 0.439.

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Table 2:

	Dependent variable:	
	Treat_binary	
	(1)	(2)
Owner		0.012
		(0.146)
Profile		−0.008
		(0.116)
City - San Francisco		0.131**
		(0.060)
Day		0.001
		(0.004)
Swipes		0.00001
		(0.011)
Intercept	0.502***	−10.347
	(0.030)	(68.817)
Observations	283	283
R^2	0.000	0.017
Adjusted R^2	0.000	−0.001
Residual Std. Error	0.501 (df = 282)	0.501 (df = 277)
F Statistic		0.969 (df = 5; 277)
Note:		*p<0.1; **p<0.05; ***p<0.01

```
## Analysis of Variance Table
##
## Model 1: Treat_binary ~ 1 + OwnerNum + ProfileNum + City + Date + Swipes
## Model 2: Treat_binary ~ 1
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1    277 69.533
## 2    282 70.749 -5   -1.2165 0.9693 0.4369
```

7 Data Exploration & Analytics

7.1 Design Assumptions

Our experiment design for the dating profiles consists of multiple assumptions. We limited our experiment profile features to 25-33-year-old white heterosexual males in two of the biggest cities in the country, New York and San Francisco, to ensure consistency in our results. While most of the factors were consistent across all the accounts, some were more prone to affect the potential outcomes. So, we measured the variance of outcomes across the following factors to justify our assumptions.

7.1.1 Variance within Treatment and Control

The six sets of treatment and control accounts are distributed equivalently across the two selected cities. The vitals and virtues are kept the same across each set except for the prompt and the location. While the difference in the prompt is the treatment, the location of the accounts was blocked to ensure randomizations that keep treatment and control similarly. Moreover, this reduced non-compliance, meaning someone liking or matching a control account, is unlikely to come across the treatment and vice versa. Before interpreting the statistical analysis results of the datasets, we looked at the variances between the control and treatment accounts. So far, the following values are similar enough to support our assumption that they will allow for a more confident interpretation of the differences in means of control and treatment. accounts.

```
##        Treat        V1
## 1:   Control 0.7276596
## 2: Treatment 1.7115673
```

```
##        Treat       V1
## 1:   Control 6.049949
## 2: Treatment 9.866996
```

```
##        Treat        V1
## 1:   Control 0.1517730
## 2: Treatment 0.6755069
```

7.1.2 Variance within Locations

We have three treatment accounts three control accounts in New York, and three treatment accounts and three control accounts in San Francisco. We assumed that both cities are similar in terms of the popularity of the Hinge app and should attract subjects similarly. However, to ensure the dispersion of values within each dataset is comparable, we calculated the variance per treatment and control, and the results show some disparity between the two cities.

```
##             City       V1
## 1: San Francisco 12.49858
## 2:      New York  6.61449
```

```
##             City       V1
## 1:      New York 9.377215
## 2: San Francisco 1.479235
```

```
##             City        V1
## 1: San Francisco 0.3276899
## 2:      New York 1.0936013
```

```
##             City         V1
## 1:      New York 0.09113924
## 2: San Francisco 0.22185792
```

```
##             City       V1
## 1: San Francisco 1.847468
## 2:      New York 1.563458
```

```
##             City        V1
## 1:      New York 0.8213608
## 2: San Francisco 0.6158470
```

7.1.3 Variance within Profile Owners

While similar in most aspects, the six sets of profiles differ in a few ways, such as names, ages, profile pictures, types of humor, and prompts. Since these play a crucial role in determining the likelihood of a profile being liked or matched, we computed and compared the variance of the dataset from each owner before adding them to the same group for further analysis.

```
##          Owner        V1
## 1:      Brian 17.113978
## 2:      Quazi 11.628571
## 3: Erin Smith 10.357143
## 4:         KT  1.328042
## 5:       Luka  3.092803
```

```
##          Owner         V1
## 1:      Brian  3.4946237
## 2:      Quazi 14.5571429
## 3: Erin Smith  2.0640394
## 4:         KT  1.4761905
## 5:       Luka  0.9667339
```

```
##          Owner        V1
## 1:      Brian 0.1612903
## 2:      Quazi 0.6333333
## 3: Erin Smith 1.8916256
## 4:         KT 0.1944444
## 5:       Luka 0.2178030
```

```
##          Owner         V1
## 1:      Brian 0.13978495
## 2:      Quazi 0.09047619
## 3: Erin Smith 0.26108374
## 4:         KT 0.03571429
## 5:       Luka 0.19354839
```

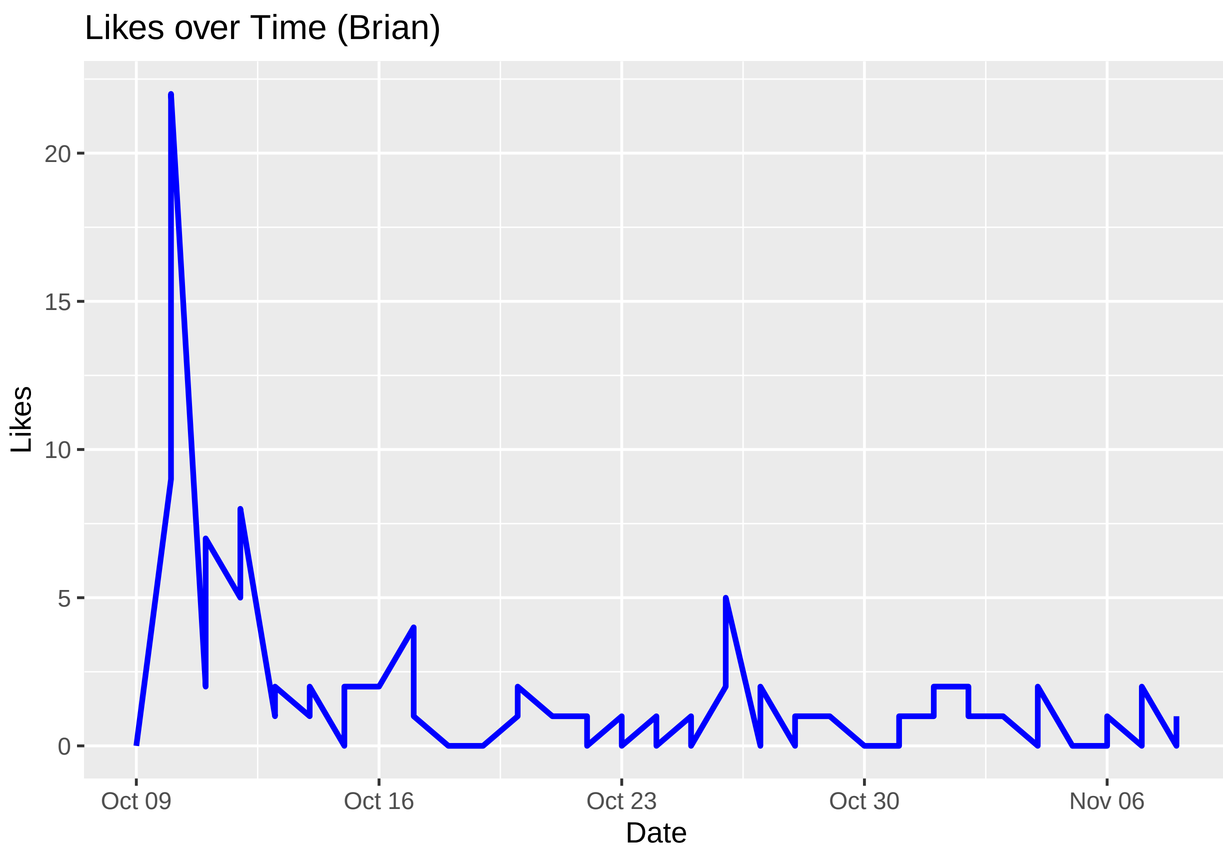
```
##          Owner       V1
## 1:      Brian 1.692473
## 2:      Quazi 1.228571
## 3: Erin Smith 1.544335
## 4:         KT 1.941799
## 5:       Luka 1.530303
```

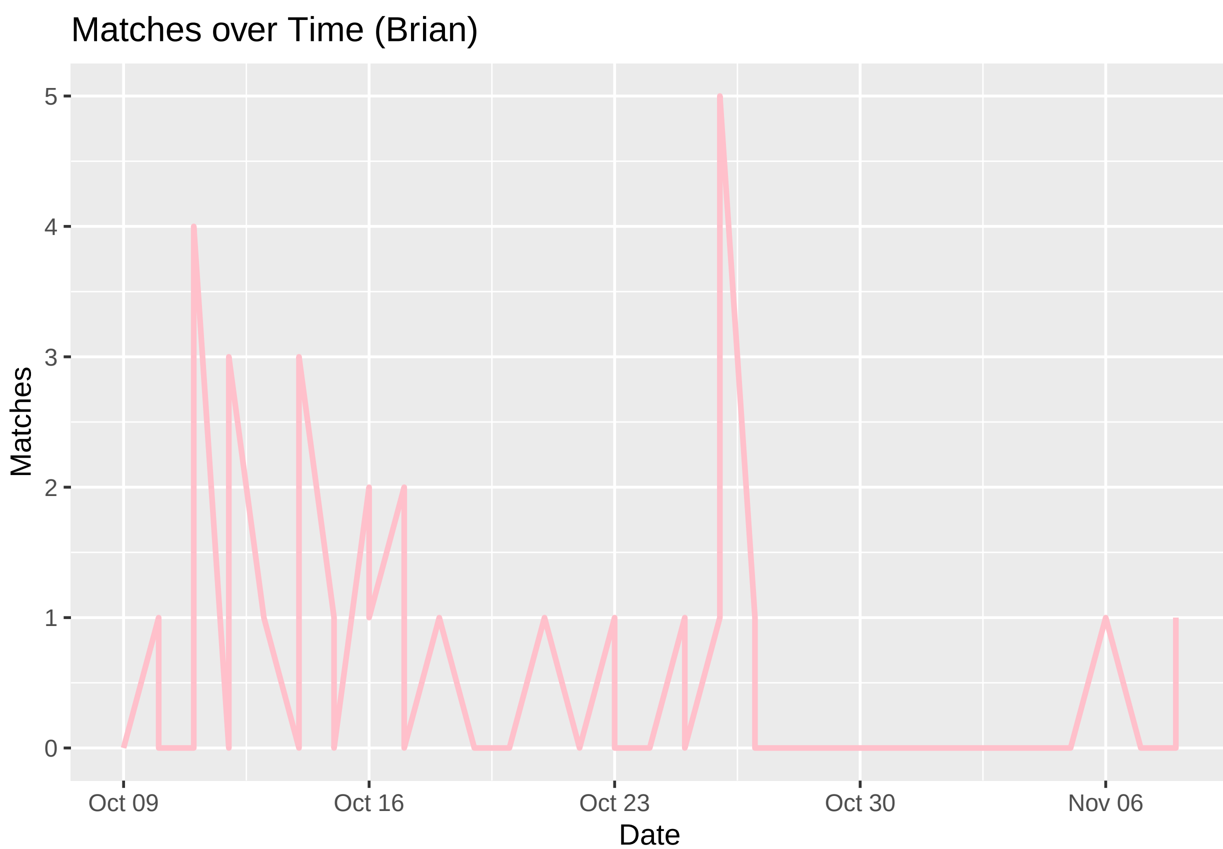
```
##          Owner        V1
## 1:      Brian 0.3892473
## 2:      Quazi 0.8476190
## 3: Erin Smith 0.5344828
## 4:         KT 1.0621693
## 5:       Luka 0.6925403
```

7.1.4 Variance within Humor Type

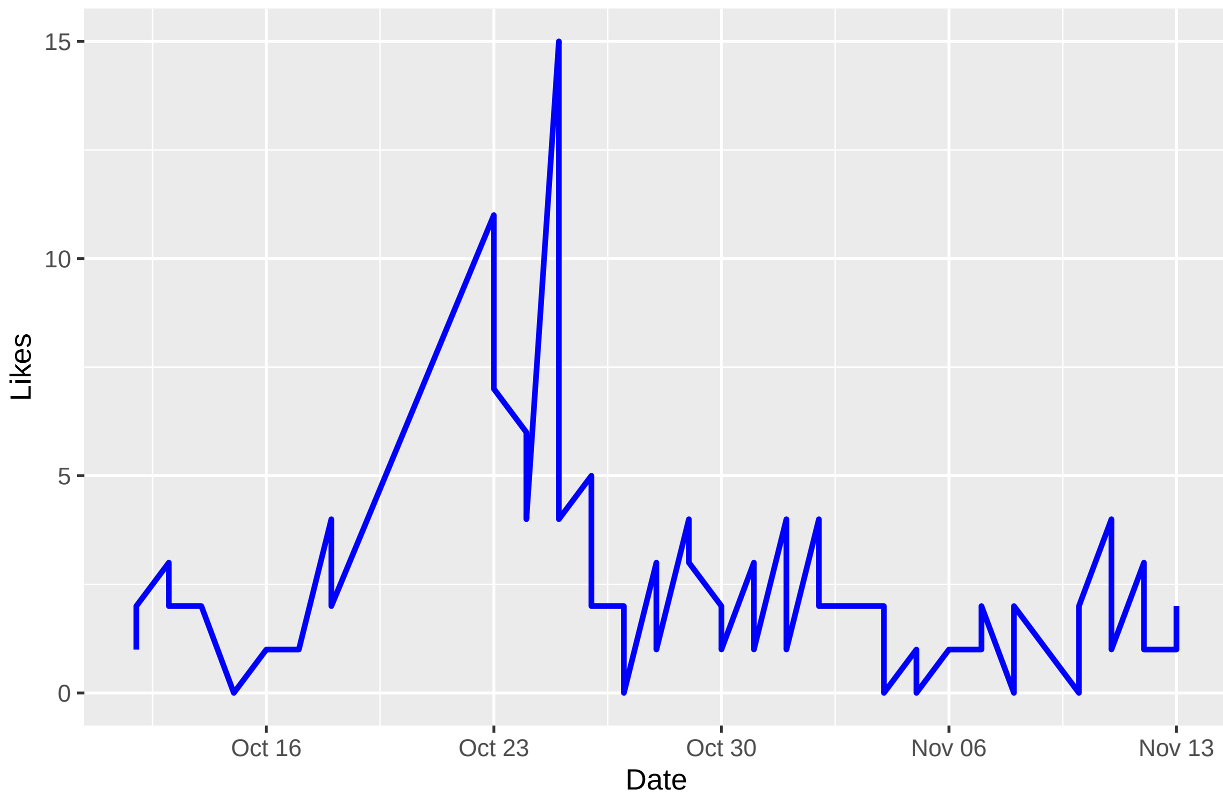
Most of the profiles used humor generated by AI tools like ChatGPT. However, two sets of profiles did not: Owner = "KT" and Owner = "Erin". In order to ensure consistency, the above variance comparisons among the owners also ensure the assumption that the humor types in the prompts, regardless of the source, are similar enough to be grouped.

The graphs below show the trend of likes and matches across each profile owner throughout the experiment.

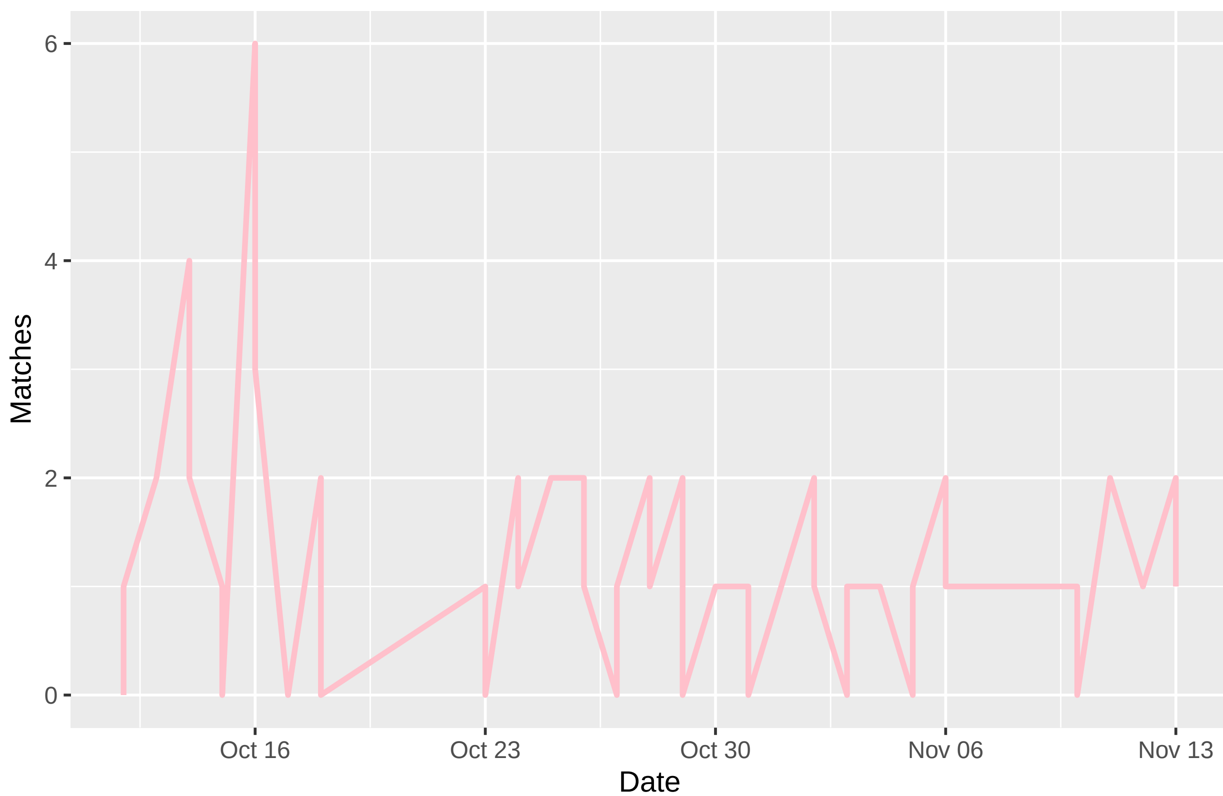

Likes over Time (Brian)
Likes
20
15
10
5
0
Oct 09
Oct 16
Oct 23
Oct 30
Nov 06
Date

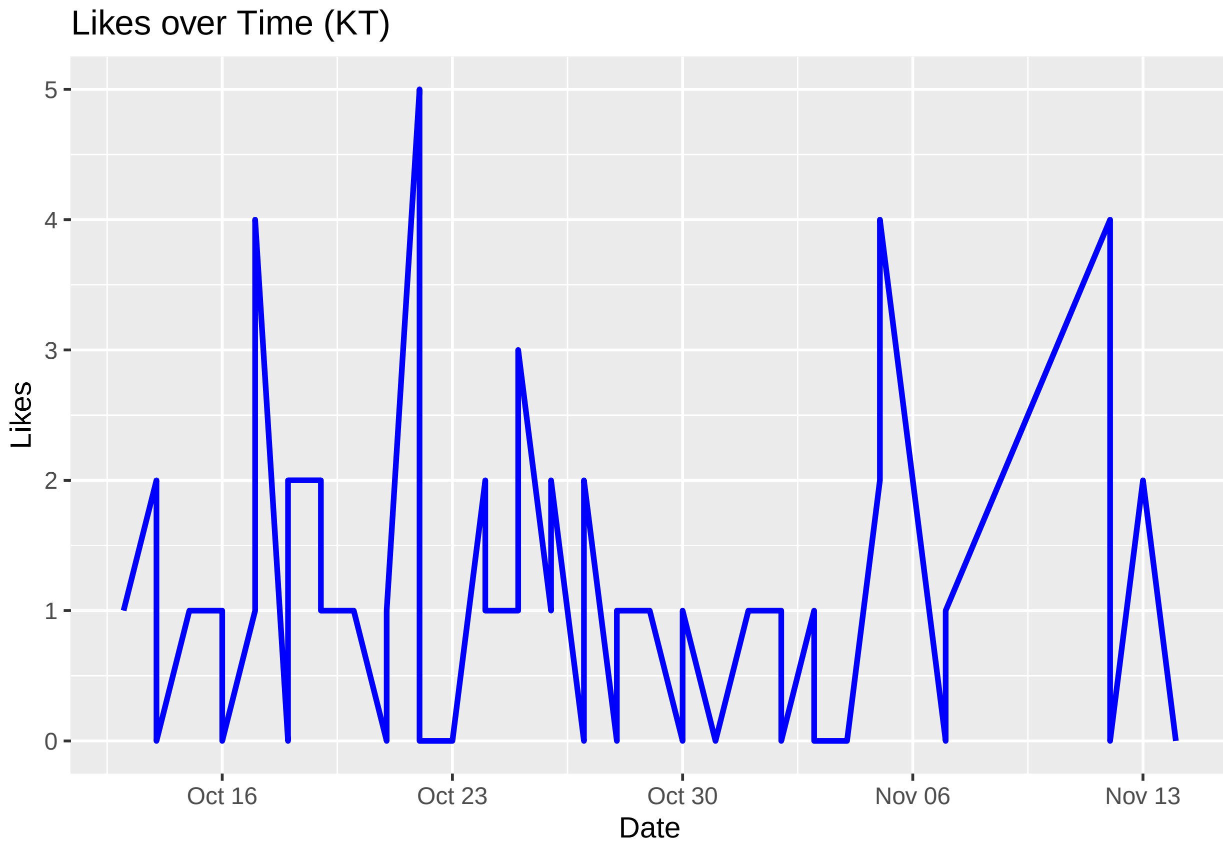

Matches over Time (Brian)
Matches
5
4
3
2
1
0
Oct 09
Oct 16
Oct 23
Oct 30
Nov 06
Date

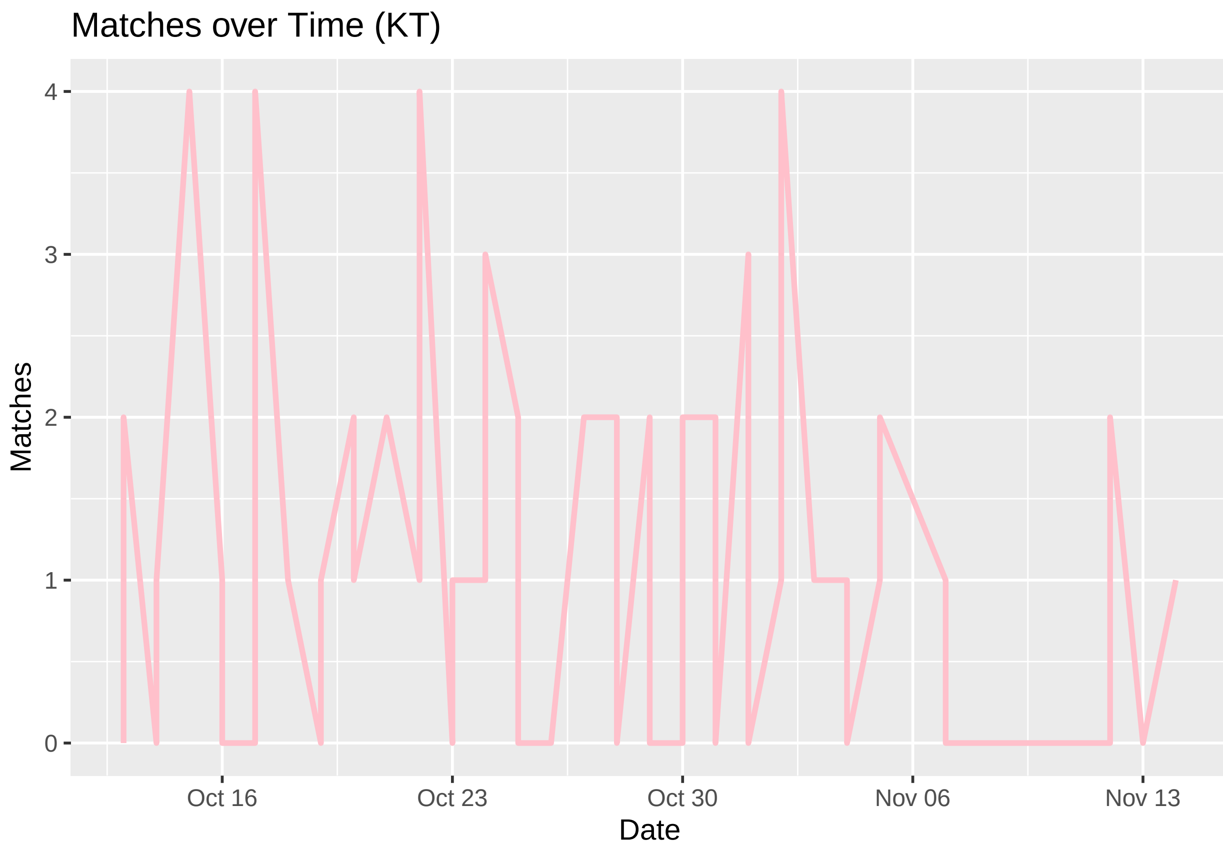
Likes over Time (Erin)

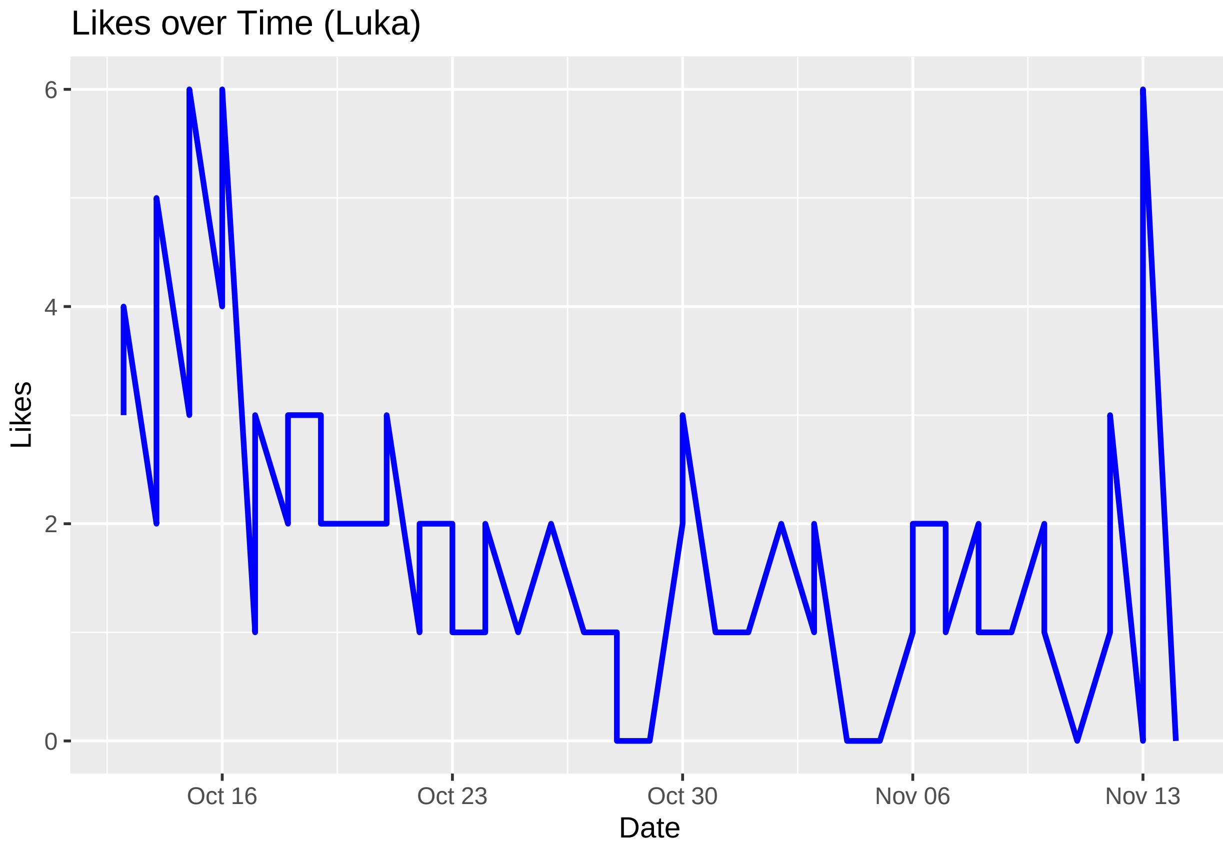


Matches over Time (Erin)

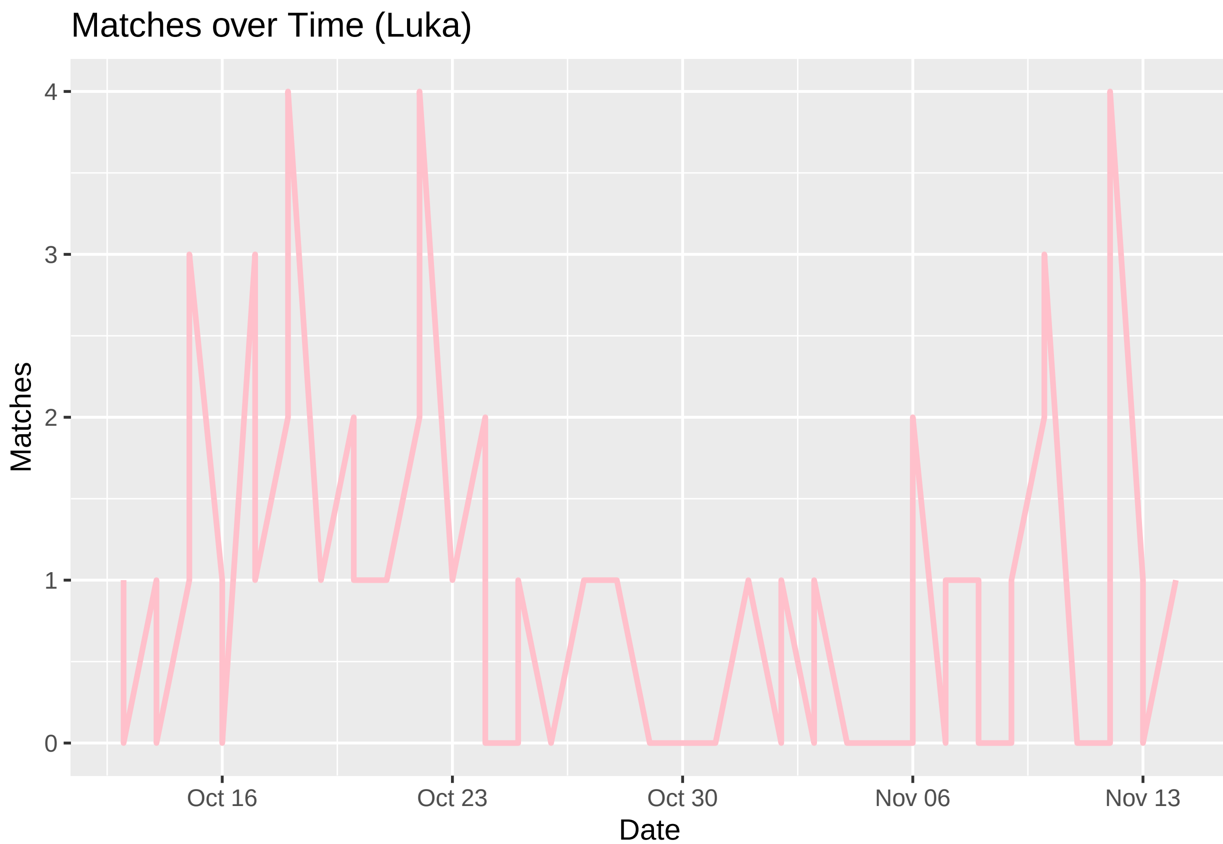



Likes over Time (KT)
Likes
Date
0
1
2
3
4
5
Oct 16
Oct 23
Oct 30
Nov 06
Nov 13

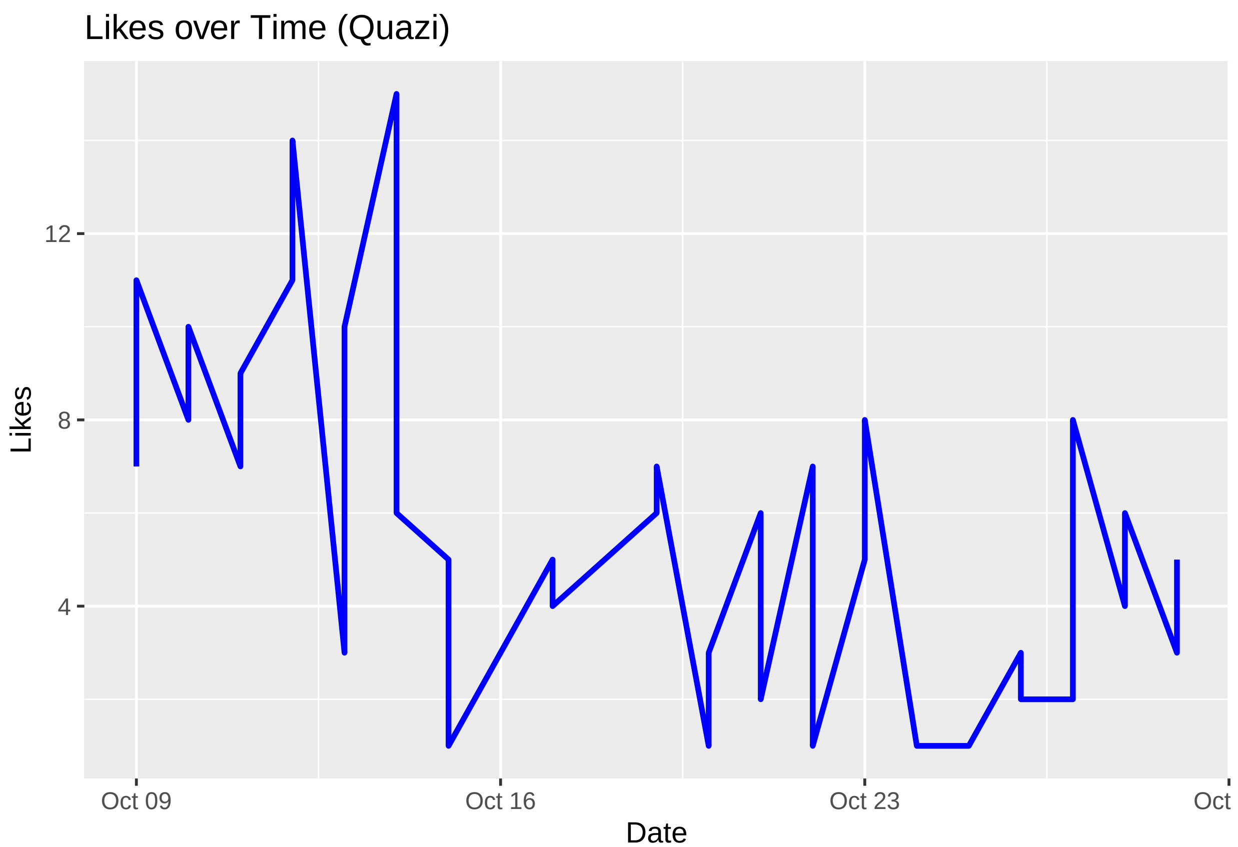

Matches over Time (KT)
Matches
Date
0
1
2
3
4
Oct 16
Oct 23
Oct 30
Nov 06
Nov 13

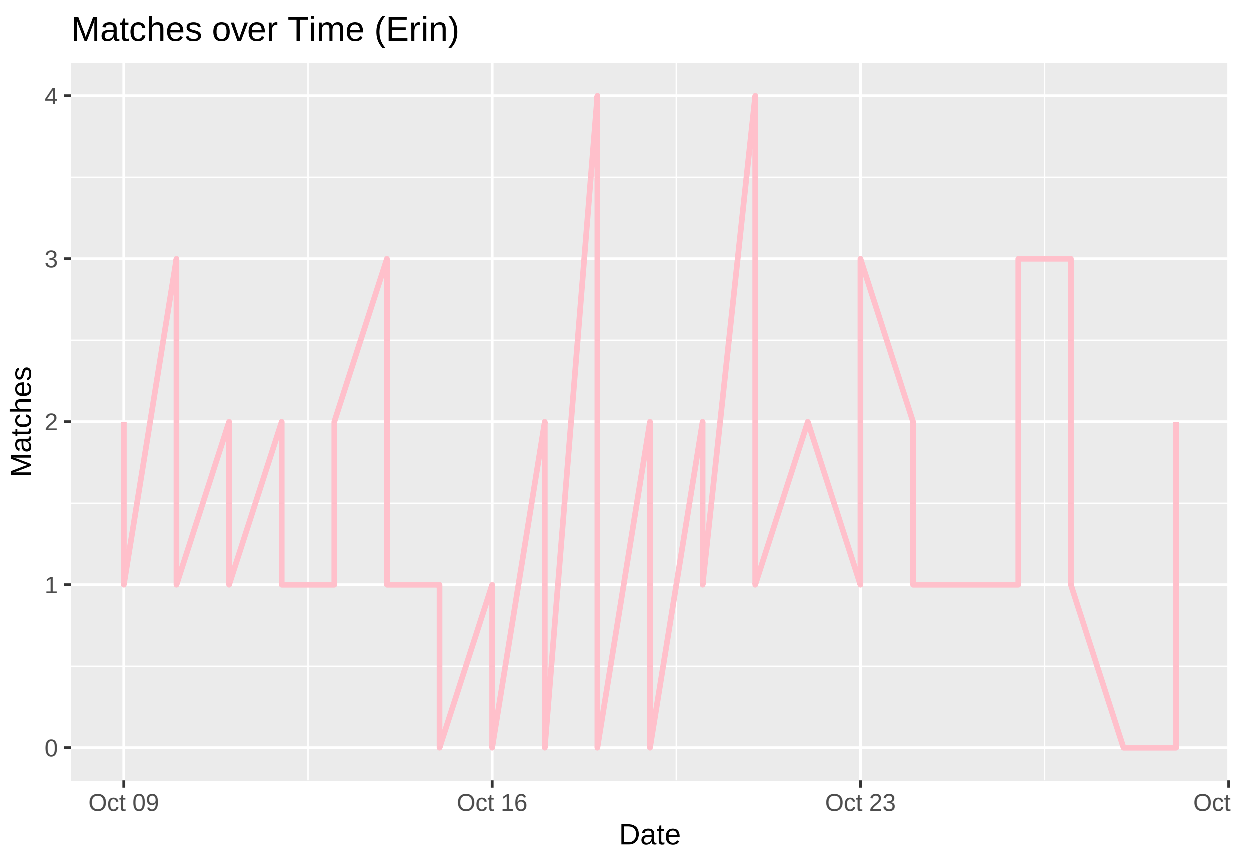


Likes over Time (Luka)
Likes
6
4
2
0
Oct 16
Oct 23
Oct 30
Nov 06
Nov 13
Date



Matches over Time (Luka)
Matches
4
3
2
1
0
Oct 16
Oct 23
Oct 30
Nov 06
Nov 13
Date





The trend shown across the likes and matches each owner receives in the above graphs shows an approximate similarity to validate our final hypothesis.

7.2 Challenges and Limitations

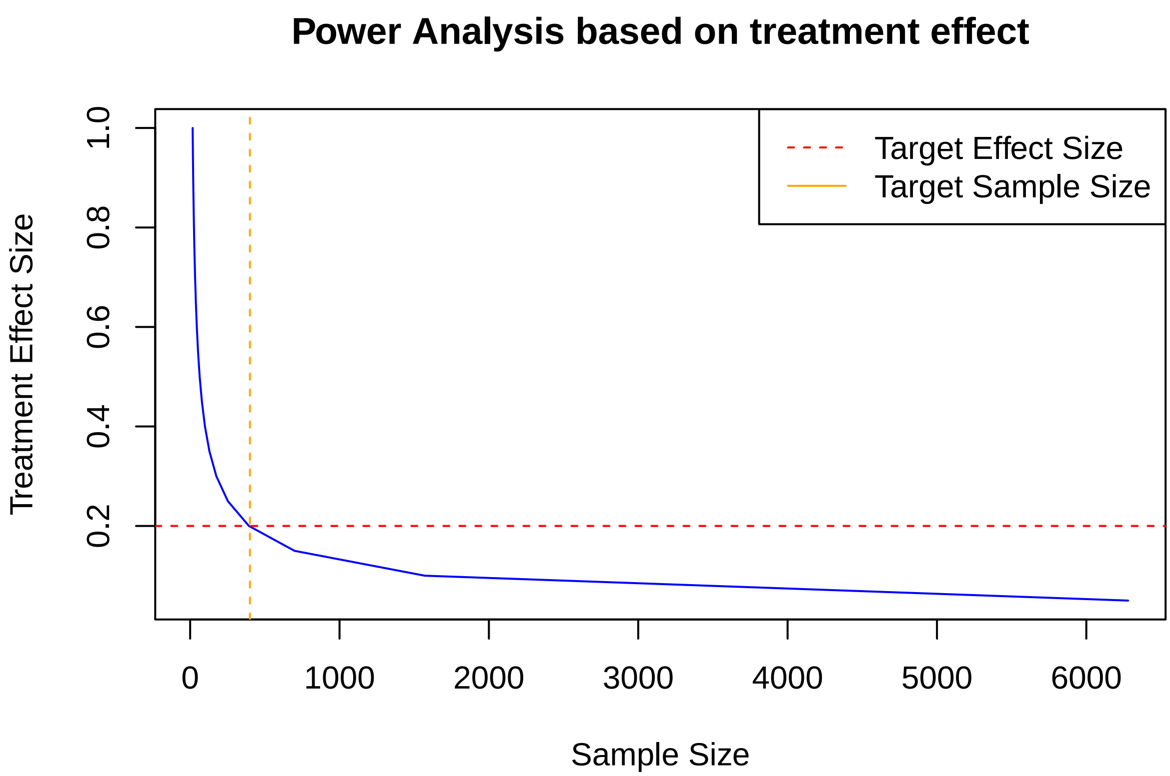
We resorted to using artificial intelligence-generated pictures for profile owners to avoid any privacy invasion of an actual person or possible accusation of catfishing. As advanced as AI is, almost half of our accounts got flagged at one point due to Hinge Trust & Service policy violation during the four-week duration of the experiment. Some comments indicated that users could tell that the accounts were counterfeit. The first set got deleted on day 2, so we re-created similar accounts. The second set got flagged around day seven, and again we followed a similar recovery plan. The third set got banned on week three and demanded ID proof of the fake profile owner, so that one could not be recovered.

Our only interaction on the profiles was to swipe on 10 accounts in a row per day. This limited interaction reduced our chances of getting more matches and likes as the profile visibility depends on how interactive the users are. Other than swipes, it isn't easy to maintain consistency of interactions between each user.

8 Experimentation

In this section, we dive deeper into the analysis of our experiment, aiming to elucidate the impact of incorporating a humorous personality into dating app profiles while accounting for various control variables. Our primary objective remains consistent: to assess the effect of the treatment variable, denoting the presence of a highly humorous and intriguing personality description within the profile, on user engagement metrics, specifically, the number of likes and matches.

We performed a power analysis simulation before the experiment to ensure a high probability (80%) of detecting a treatment effect of 20%. In this case, a treatment effect of 20% suggests that the study is designed to detect a 20% difference between groups, such as a treatment group and a control group. A sample size of 400 is recommended for conducting the statistical test.



This experiment was conducted for 45 days. However, due to unforeseen issues with profiles being removed unexpectedly, we could not collect data for all of those days. We got a total of 283 samples in terms of unique profiles collecting data per day. To analyze the number of matches each profile received, we expanded the data for that model so that each sample is a single "swipe" or "like" that the profile sent in a day. This means that the outcome variable for each sample is a binary key for indicating whether or not that swipe garnered a match. The total number of samples for our match model is 2742.

We analyzed the likes that a profile received is a bit more complicated than that. It is unclear exactly how Hinge shows certain profiles to users, so it is impossible to determine the total number of users actually encountered our profiles in a given day. Therefore, we will analyze the likes on a per-day sample. That is to say that a single sample represents a single day in our experiment, and the outcome variable is the number of likes that a profile receives. The total number of samples for our likes model is 283.

8.1 Number of Matches Experiment - Simple

Using a t-test, we compared the mean matches between the two groups. The t-value is approximately -3.3309, and the p-value is 0.0008773. The results suggest a statistically significant difference in means between control and treatment, as indicated by the small p-value and the confidence interval(-0.06248673 -0.01617828) that does not include zero. The negative t-value suggests that the mean in treatment is higher than the mean in control."

```
##
##  Welch Two Sample t-test
##
## data:  match by Treat_binary
## t = -3.3309, df = 2676.3, p-value = 0.0008773
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  -0.06248673 -0.01617828
## sample estimates:
## mean in group 0 mean in group 1
##      0.08784773      0.12718023
```

We conducted a regression analysis to examine the impact of treatment 'match'. The 'Treat_binary' coefficient (0.039) indicates an average 0.039-unit increase in the 'Match' variable for the treatment group, which is 'Treat_binary'= 1. The p-value associated with 'Treat_binary' is highly significant (***p<0.01), suggesting that 'Treat_binary' is a significant predictor of 'match.' Since we are exploring whether there is a significant difference between control and treatment groups in matches, the t-test and a simple linear regression produce a very similar result.

Table 3: Simple Regression Resutls - Matches

	Dependent variable:
	match
Treat_binary	0.039***
	(0.012)
Constant	0.088***
	(0.008)
Observations	2,742
R^2	0.004
Adjusted R^2	0.004
Residual Std. Error	0.309 (df = 2740)
F Statistic	11.082*** (df = 1; 2740)
Note:	*p<0.1; **p<0.05; ***p<0.01

The 'Treat_binary' coefficient (0.039) indicates an average 0.039-unit increase in the 'match' variable for the treatment group, which is 'Treat_binary'= 1. The p-value associated with 'Treat_binary' is highly significant (***p<0.01), suggesting that 'Treat_binary' is a significant predictor of 'match.' Since we are exploring whether there is a significant difference between control and treatment groups in matches, the t-test and a simple linear regression produce a similar result.

8.2 Number of Matches Expriment - Comphrehesive

To further enhance the analysis of the impact of humor on dating app matches, we include additional variables, such as dating app profile, which can capture and account for potential influence on the number of matches, and the city or days of the week. I believe that this helps to isolate the true effect of treat_binary (humor) on matches, reducing extraneous noise and improving the accuracy the estimates. Additionally, including more variables allows you to understand how different factors interact and contribute to the outcome. This creates a more nuanced picture of the relationships between humor and matches, rather than just a single, isolated effect. Lastly, we will be able to reduce the risk of omitted variable bias and obtain more reliable results.

Table 4: Regression Results - Matches

	Dependent variable:			
	match			
	(1)	(2)	(3)	(4)
Treat_binary	0.039***	0.040***	0.040***	0.040***
	(0.012)	(0.012)	(0.012)	(0.012)
CityNum	0.001	0.001	0.001	0.001
	(0.012)	(0.012)	(0.012)	(0.012)
factor(ProfileNum)2		0.108***	0.107***	0.079**
		(0.033)	(0.033)	(0.034)
factor(ProfileNum)3		0.067***	0.067***	0.065***
		(0.017)	(0.017)	(0.017)
factor(ProfileNum)4		0.034**	0.035**	0.037**
		(0.015)	(0.015)	(0.015)
factor(ProfileNum)5		0.089***	0.088***	0.076***
		(0.020)	(0.020)	(0.020)
factor(ProfileNum)6		0.080***	0.080***	0.069***
		(0.021)	(0.021)	(0.021)
factor(weekday)1			0.001	0.001
			(0.019)	(0.019)
factor(weekday)2			0.029	0.027
			(0.022)	(0.022)
factor(weekday)3			0.018	0.016
			(0.022)	(0.022)
factor(weekday)4			0.013	0.009
			(0.020)	(0.020)
factor(weekday)5			0.026	0.021
			(0.022)	(0.022)
factor(weekday)6			0.024	0.027
			(0.021)	(0.021)
ExpDay_profile				−0.002***
				(0.001)
Constant	0.087***	0.036***	0.021	0.060***
	(0.011)	(0.013)	(0.018)	(0.022)
Observations	2,742	2,742	2,742	2,742
R^2	0.004	0.017	0.018	0.022
Adjusted R^2	0.003	0.014	0.013	0.017
Residual Std. Error	0.309 (df = 2739)	0.308 (df = 2734)	0.308 (df = 2728)	0.307 (df = 2727)
F Statistic	5.541*** (df = 2; 2739)	6.556*** (df = 7; 2734)	3.798*** (df = 13; 2728)	4.315*** (df = 14; 2727)
Note:				*p<0.1; **p<0.05; ***p<0.01

8.3 Matches Model Interpretation

Model 1: We included city data (limited to San Francisco and New York City) to assess its potential influence on dating app matches. As anticipated, incorporating humor into profiles significantly increased matches, regardless of city location, which aligns with our assumption that individuals in these two major cities would exhibit similar behavior regarding online dating preferences.

Model 2: By incorporating "profile_id" as a categorical variable in our analysis, we demonstrated that all six profiles exhibited statistically significant differences in their average number of matches compared to the control group. This finding provides valuable insights into how individual profile characteristics influence dating app success and highlights the importance of considering individual variability in such research.

Model 3: This model further expands by incorporating the day of the week the user profile was active (coded as a factor with seven levels). Consistent with the previous model, the results reaffirm that incorporating humor significantly increases the number of matches received, and individual profile characteristics remain influential factors in dating app success. However, like city location, weekdays do not significantly impact match count statistically.

Model 4: This model expands upon previous iterations by incorporating "ExpDay_profile," which signifies the duration since a profile's creation. This addition enables us to examine the relationship between the number of days a profile is active on the app (exposure days) and the number of matches received. The negative coefficient (-0.00238) associated with ExpDay_profile reveals that the average number of matches received decreases as the exposure days increase. This finding suggests the potential presence of a decay effect, where the initial boost experienced by new profiles gradually diminishes over time. Consequently, the importance of profile refresh or update strategies to sustain user engagement and maintain match potential is highlighted.

8.4 Number of Likes Experiment - Simple

We conducted a t-test to compare the mean matches between the treatment and control groups. The resulting t-value was approximately -1.6386, and the corresponding p-value was found to be 0.1025. These outcomes suggest no statistically significant difference in the number of matches between the two groups.

```
##
##  Welch Two Sample t-test
##
## data:  Likes by Treat_binary
## t = -1.6386, df = 266.54, p-value = 0.1025
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal to 0
## 95 percent confidence interval:
##  -1.2094231  0.1107316
## sample estimates:
## mean in group 0 mean in group 1
##        1.992908        2.542254
```

Furthermore, the 95% confidence interval for the difference in means (-1.2094231 to 0.1107316) encompasses zero. This observation signifies that we do not have sufficient evidence to establish any statistical significance in comparing mean matches between the treatment and control groups.

We conducted a regression analysis to examine the impact of treatment on the number of 'Likes' received in dating app profiles. The coefficient for the treatment variable is 0.549, indicating that profiles with a humorous personality description (in the treatment group) tend to receive approximately 0.549 more 'Likes' compared to profiles without such descriptions (in the control group). However, this result does not reach statistical significance ($p > 0.1$), suggesting that the effect of the treatment on 'Likes' is not statistically conclusive.

The constant term in the model is 1.993, representing the estimated number of 'Likes' for profiles in the control group. The overall model explains a small portion of the variability in 'Likes' (R-squared = 0.009) and cannot predict the number of 'Likes' based on the treatment variable. The F-statistic is 2.680, with a p-value more significant than 0.1, indicating that the model does not provide strong evidence for the relationship between the treatment variable and 'Likes.'

In summary, while there is a positive association between the treatment and the number of 'Likes,' our results do not demonstrate statistical significance. Therefore, the impact of a humorous personality description on the number of 'Likes' in dating app profiles remains inconclusive based on this analysis.

Table 5: Simple Regression Results - Likes

	Dependent variable:
	Likes
Treat_binary	0.549
	(0.336)
Constant	1.993***
	(0.208)
Observations	283
R^2	0.009
Adjusted R^2	0.006
Residual Std. Error	2.822 (df = 281)
F Statistic	2.680 (df = 1; 281)
Note:	*p<0.1; **p<0.05; ***p<0.01

8.5 Number of Likes Expriment - Comphrehesive

Building upon the foundation in the earlier section, where we examined the sample relationships between the treatment variable and our outcome variables, Likes and Matches, we recognize the need to consider a broader context. By doing so, we aim to control for potential confounding variables that might otherwise obscure the true impact of the treatment variable. These control variables encompass demographic and contextual factors, allowing us to explore how the humorous personality description affects user engagement while holding other relevant factors constant.

The coefficient for our binary treatment variable varies between 0.549 and 0.598 across different models, suggesting that profiles featuring a humorous description tend to attract more "Likes" compared to profiles without humor. However, it is worth noting that not all p-values across the models consistently reach statistical significance, with only 3 out of 5 falling below the 0.05 threshold.

The profile owner variable indicates the individual who created the profile (i.e., the group member responsible for the user's creation). Notably, profiles owned by Quazi consistently exhibit positive coefficients ranging from 3.290 to 3.665 across models. This implies that Quazi's profiles have a statistically significant impact on the number of "Likes" received in these models at the 0.01 significance level.

Time also emerges as a significant factor in this experiment. In models considering the day of the week, Thursday demonstrates a coefficient between 0.932 and 0.984, achieving statistical significance at 0.05. Furthermore, the day of the experiment proved to be highly significant at the 0.01 level, with a coefficient of -0.057. This suggests a negative effect on the number of 'Likes' a profile receives on later days during the experiment.

In summary, the inclusion of humor in dating app profiles is linked to an increase in the number of "Likes" and is statistically significant. Additional factors, such as specific profile identifiers and the timing of the experiment, including the day of the week and the day of the experiment, also influence "Likes." However, the impact of factors like the day of the week, the user's city location, and the number of daily swipes often appeared less pronounced and frequently fails to reach statistical significance in the presented models.

8.6 Experimentation Results

The matches and likes analysis results indicate that having a humorous personality description significantly influences user engagement on dating apps, mainly through increased matches and likes. The control variables in these models do not exhibit significant effects on being in the treatment group, reinforcing the importance of personality traits expressed through text in shaping user interactions and experiences on dating apps.

8.7 Heterogeneous Treatment Effects (HTE)

There are three groups for our experiment to break down: treatment effects by Owner, City, and Time. The owner will measure any disparate impacts by the different team members, looking for if any owners are more humorous than others. The city will measure if the selection of New York as the treatment or control impacted the results. Time will measure any

Table 6: Regression Results - Likes

	Dependent variable:				
	Likes				
	(1)	(2)	(3)	(4)	(5)
Treat_binary	0.549	0.589*	0.593**	0.590**	0.598**
	(0.337)	(0.321)	(0.290)	(0.292)	(0.283)
Swipes	0.023	0.023	0.028	0.031	0.016
	(0.038)	(0.038)	(0.027)	(0.029)	(0.022)
CityNum		−0.030	−0.031	−0.030	−0.031
		(0.032)	(0.029)	(0.029)	(0.028)
factor(Owner)Erin Smith			0.695	0.714	1.032**
			(0.528)	(0.522)	(0.492)
factor(Owner)KT			−0.638	−0.590	−0.377
			(0.443)	(0.452)	(0.410)
factor(Owner)Luka			0.037	0.082	0.415
			(0.450)	(0.442)	(0.366)
factor(Owner)Quazi			3.647***	3.665***	3.290***
			(0.700)	(0.697)	(0.684)
factor(DOW)Monday				0.475	0.522
				(0.446)	(0.445)
factor(DOW)Saturday				0.122	0.156
				(0.422)	(0.401)
factor(DOW)Sunday				−0.067	0.086
				(0.392)	(0.405)
factor(DOW)Thursday				0.984**	0.932**
				(0.498)	(0.468)
factor(DOW)Tuesday				0.710	0.765
				(0.638)	(0.606)
factor(DOW)Wednesday				0.532	0.511
				(0.523)	(0.498)
ExpDay					−0.057***
					(0.013)
Constant	1.770***	2.502**	1.894**	1.449*	2.753***
	(0.410)	(1.005)	(0.775)	(0.824)	(0.796)
Observations	283	283	283	283	283
R^2	0.010	0.013	0.242	0.258	0.321
Adjusted R^2	0.003	0.002	0.223	0.222	0.285
Residual Std. Error	2.827 (df = 280)	2.828 (df = 279)	2.495 (df = 275)	2.496 (df = 269)	2.393 (df = 268)
F Statistic	1.408 (df = 2; 280)	1.201 (df = 3; 279)	12.571*** (df = 7; 275)	7.204*** (df = 13; 269)	9.035*** (df = 14; 268)

Note: *p<0.1; **p<0.05; ***p<0.01

impact by weeks since opening the account (there is an internet theory that Hinge will boost the likes you receive when opening an account).

```
## `summarise()` has grouped output by 'Profile_Name', 'City'. You can override
## using the `.groups` argument.
## `summarise()` has grouped output by 'Owner', 'Profile_Name', 'Date'. You can
## override using the `.groups` argument.
```

9 HTE by Owner

From a simple average treatment effect by the owner, there is a significant discrepancy between owners. For likes, Quazi's treatment had a negative impact, while Erin's treatment had the highest impact. Interestingly, Quazi's treatment had the highest impact on matches, indicating some complexity to Quazi's humor.

```
## # A tibble: 5 x 3
##   Owner      average_effect_likes average_effect_matches
##   <chr>                     <dbl>                  <dbl>
## 1 Brian                     1.03                   0.226
## 2 Erin Smith                1.28                   0.517
## 3 KT                        0                      0.25
## 4 Luka                      0.606                  0.273
## 5 Quazi                    -0.429                  0.810
```

Performing an ANOVA on likes and matches, the ANOVA test for likes is almost statistically significant, with a p-value of 0.0783. The p-value suggests differences in the average number of likes between different owners, but these differences are not statistically significant at the 5% level (though they are close). While some variation in likes is attributable to the different owners, this variation may be due to chance.

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## Owner         4   51.1  12.787   2.147 0.0783 .
## Residuals   137  815.8   5.955
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## Owner         4    6.0   1.501   0.762  0.552
## Residuals   137  269.7   1.969
```

The ANOVA test for matches is not statistically significant, with a p-value of 0.552, indicating any differences are probably due to chance.

10 HTE By City

We next want to investigate whether the city significantly impacted treatments. While the last test was interesting to measure which owner was the most humorous, this is the most crucial test for our team. We made a significant assumption that city selection would not impact the likes or matches received, so now we must confirm this.

```
## `summarise()` has grouped output by 'City_Control'. You can override using the
## `.groups` argument.
```

```
## # A tibble: 3 x 4
##   City_Control  City_Treat    average_effect_likes average_effect_matches
##   <chr>         <chr>                        <dbl>                  <dbl>
## 1 New York      San Francisco                0.288                  0.388
## 2 San Francisco New York                     0.934                  0.377
## 3 <NA>          New York                     0                      1
```

We can immediately see that selecting New York as the treatment city provided approximately 0.6 more likes per day than picking San Francisco as a treatment. There is slight variation in the average effect on matches. There is an additional row here that indicates a data defect. There was a row that did not have the control city marked.

Let us see if the treatment city is statistically significant.

```
##
##  Welch Two Sample t-test
##
## data:  treatment_effect_likes by interaction(City_Control, City_Treat)
## t = 1.6065, df = 138.45, p-value = 0.1105
## alternative hypothesis: true difference in means between group San Francisco.New York and group New York.S
## 95 percent confidence interval:
##  -0.1493147  1.4431672
## sample estimates:
## mean in group San Francisco.New York mean in group New York.San Francisco
##                            0.9344262                            0.2875000
```

```
##
##  Welch Two Sample t-test
##
## data:  treatment_effect_matches by interaction(City_Control, City_Treat)
## t = -0.045581, df = 138.66, p-value = 0.9637
## alternative hypothesis: true difference in means between group San Francisco.New York and group New York.S
## 95 percent confidence interval:
##  -0.4637907  0.4428891
## sample estimates:
## mean in group San Francisco.New York mean in group New York.San Francisco
##                            0.3770492                            0.3875000
```

The t-test for likes has a p-value of 0.11, which is not statistically significant. Similar to the owner analysis, it implies that while there is some variation in likes attributable to the treatment city, this variation may be due to chance. As expected for our matches t-test, there is a very high p-value of 0.96, indicating that the variation is most likely due to chance.

11 HTE by Weeks

When creating our hinge accounts, we noticed that the number of likes was very high initially and then tapered off. We want to confirm if this has any impact on our treatment.

```
## # A tibble: 6 x 3
##   weeks_since_start average_effect_likes average_effect_matches
##               <dbl>                <dbl>                  <dbl>
## 1                 1               1.25                   0.333
## 2                 2               1.18                   0.7
## 3                 3               0.257                  0.314
## 4                 4              -0.0625                 0.0312
## 5                 5               0.375                  0.25
## 6                 6               0.714                  1
```

Interestingly, the average effect of likes steadily declines but then rises back up, creating a U-shape. The matchs' behavior does not have any discerning pattern.

```
##                    Df Sum Sq Mean Sq F value Pr(>F)
## weeks_since_start   1   16.7  16.706   2.751 0.0994 .
## Residuals         140  850.2   6.073
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##                    Df Sum Sq Mean Sq F value Pr(>F)
## weeks_since_start   1   0.82  0.8191   0.417  0.519
## Residuals         140 274.88  1.9634
```

Performing an ANOVA shows a p-value of .0994 for likes and a high p-value of .519 for matches. Again, similiar to the other HTEs, it implies that while there is some variation in likes attributable to the week since the account opened, this variation might be due to chance.

12 Conclusion

Our experiment reveals a clear uptick in user engagement when profiles incorporate humor compared to those lacking this element. Notably, we detected a statistically significant impact of humor on the number of matches received by a profile. Additionally, external factors, such as the duration a profile has been active, significantly influence user engagement. Intriguingly, profiles experience the highest engagement during their initial weeks online, followed by a gradual decline over time. This trend may be attributed to the algorithms employed by Hinge for profile visibility.

Additional research is needed to explore the ramifications of a humorous personality on profile users with diverse demographic attributes, including gender, race, and age. Furthermore, future investigations may involve the following upgrades: actual profile users, incorporating various interventions like interactive engagement through platform chat features and assessing a broader spectrum of outcome variables, such as the impact of engagement on actual dates.

13 Appendix

Summary of the data columns:

- Owner: The team member who owns the profile.
- OwnerNum (Categorical): Owner variable transformed into an integer variable
- Profile_Name: The name associated with the profile.
- ProfileNum(Categorical): Profile Name variable transformed into an integer. We have 6 profile name.
- City: The city where the profile is located.
- CityNum:Integer of city, San Francisco = 0, NYC = 1
- Treat: Indicates whether the profile is in the control group or the treatment group.
- Treat_binary: Logical condition into binary values (0 for "Control" and 1 for "Treatment"). Indicator for the treatment group (humorous profile).
- Date: The date of the recorded data.
- Swipes: The number of times the profile was swiped.we carry out a daily random allocation of 10 swipes in the profiles, both in the control and treatment groups. This measure serves a dual purpose: first, it keeps our profiles actively participating in the app, and second, it facilitates interaction with other profiles, increasing the visibility of our profiles to other users.
- Likes: The number of likes received by the profile.
- ExpDate_Profile: Date variable transformed into an integer based on the day number in the experiment by profile. Starting from one.