Final Project - Attractiveness Bias

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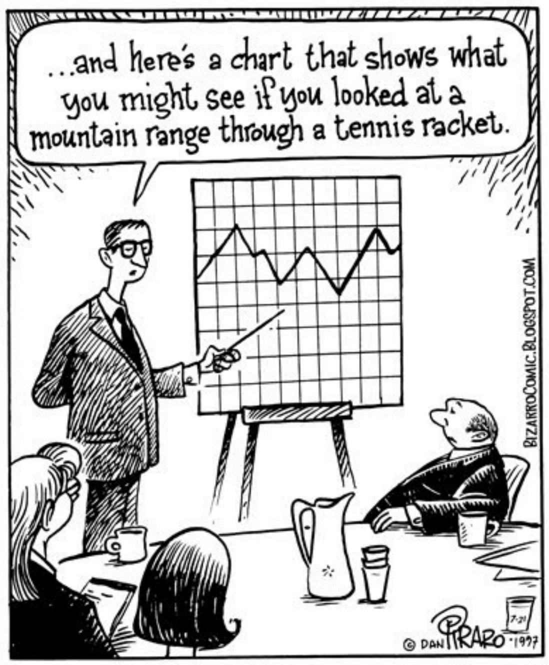


Figure 1: Lets have a look at the data

1. Abstract

Cognitive bias introduces error and reduces efficiency in the decision making process, and can adversely affect the outcomes of those whom it affects.[1] Recently there is a high amount of interest in removing cognitive bias from individual and organization based decisions, especially when the race, gender, or sexual orientation of persons involved may be contributing to the bias.[2] In 2012, it was estimated that workplace discrimination cases alone costs US companies an estimated 64 billion USD annually.[3] This study investigated bias in user interactions on the professional networking site LinkedIn by determining whether the attractiveness of an individual's profile picture affected the rate at which others accepted connection requests. Four otherwise identical profiles were created which had notable education and professional experience, with each having either a male or female and either a more or less attractive profile picture. LinkedIn was able to detect both the more and less attractive male profiles as fake accounts, removing them and their connection information. Among the two female profiles that remained, it was found that the more attractive profile had a connection acceptance rate of 5.5% (± 2.7%) higher than the less attractive profile ($p = 0.046$). Finally, a long tailed distribution was observed in the length of time users responded to connection requests with. To avoid potentially underestimating the ATE, a variable representing the number of connections held by the fake profile was included to condition the estimate to the moment when each request was accepted. Further studies may investigate if this attractiveness bias effect is repeated for different demographics, or in different contexts (e.g. hiring).

2. Introduction

Bias in professional settings has been particularly noted for creating negative consequences for workers as well as companies which must deal with their social and financial costs.[4] Many studies in the past have focused on how members of the general population express or respond to biases in professional contexts by introducing them to artificial scenarios. Studies focused on organic field experiments are more rare, mostly due to difficulties in companies agreeing to have their personnel examined or assembling enough participants from specific backgrounds of interest (e.g. managers, recruiters) to have an unbiased and powered randomized controlled trial (RCT).

One example of the former focused on the role of attractiveness in how women are perceived and treated in professional settings.[5] The study created identical job performance reviews for hypothetical female employees and asked participants how likeable the employee was and if they should be terminated. In addition, attached to the summary report was either a photo of an "extremely attractive, moderately attractive, or unattractive employee". It was found that participants were more often willing to terminate the unattractive employee, and generally rated their profile as more unlikeable compared to participants who received the extremely attractive or moderately attractive profiles.

This study, however, had many features which bring into question its generalizability. Firstly, participants in this case were students from a single Midwestern university, with 73% being either 18 or 19 years old. While general population experiments such as these are the easiest to be carried out in an academic setting, they often rely on student populations who may have important differences in their potential outcomes than populations who would be studied in an ideal experiment (e.g. managers, recruiters). In addition, although the results were found significant with a p-value of less than 0.01, the total sample size of 178 could be enlarged to create a better powered study.

A more recent study specifically investigated the effect of attractiveness of LinkedIn profile pictures on how favorably other LinkedIn users viewed their professional profile information.[6] The study implemented a 3x2 between-subjects factorial design, which included missing, unattractive, or attractive profile pictures along with a low (143 words) or high (409 words) amount of profile information. Unlike the previous study, there was no significant relationship found between attractiveness and professional favorability. While the LinkedIn community making up this sample is better related to professional environments than the previous study's student population, it still could be improved. For example, all participants were specifically recruited for the study and were aware their responses were being used for academic research.

This might have created bias in their responses, especially from demand effects if they became aware of the treatment they were being exposed to. Instead, a single blinded design could have avoided this by taking advantage of the built in social networking functionality of LinkedIn, such as connections and connection requests.

3. Research Question

We are interested in quantifying how large of a role attractiveness plays in accepting a connection from a stranger in a professional network such as LinkedIn. Do acceptance rates of a fake profile with a more attractive picture differ from the otherwise same profile with a less attractive picture?

The experiment will assess the hypothesis that the profile with a more attractive picture will have a statistically significantly higher connection rate than the profile with a less attractive picture.

4. Experimental Design

4.1 Overview

We conducted an audit study, where we created four fake profiles in LinkedIn, two identical women and two identical men, where the only difference was the profile picture. We searched on the web for attractive pictures for our attractive profiles, and used specialized image editing software to distort and "uglicize" the picture for our less attractive profiles. Our study applied a within-subjects, posttest only experiment, following a 2x2 factorial design, which structure can be summarized as in Table 1.

Table 1: 2x2 Factorial Design

Profile	Code	Assignment	Treatment	Measurement
Attractive Woman	A-W	R	X	O
Unattractive Woman	U-W	R	X	O
Attractive Man	A-M	R	X	O
Unattractive Man	U-M	R	X	O

We had four different experimental groups, block randomized based on pre-test covariates. Participants were sourced from the primary connections of the group members in LinkedIn. Our intervention consisted of sending connection requests from the LinkedIn accounts we created specifically for the project. The LinkedIn accounts were exactly the same, except for the profile picture, which could depict either an attractive or unattractive woman, or an attractive or unattractive man. Our outcome measure was the acceptance rate of connections until a cutoff date. In other words, connections accepted over connections requests delivered. We initially connected the four profiles with all of our group project members. The profiles then requested connections from a set of blocked randomly assigned individuals who were primary connections of the group project members. The total number of invitations were similar for all profiles. The profiles did not engage in any other activity than sending connections to the original list they were assigned for. This means they did not accept any potential invite other than the original ones from the group project members, they did not reply to any messages, and they did not interact with any content in the network. During the first weeks of the experiment, our two male profile accounts were banned from LinkedIn (to be discussed in more detail later in the report), which made us to re-design the study to a 1x1 factorial design, with only the two female profiles. At the end of the experiment, we measured and compared the acceptance rate for both profiles in order to reach the conclusions of our study.

4.2 Generalizability

Our study was purposely conducted in a professional social media platform and not any social media platform to try to emulate behaviors and decisions people take in a professional environment. Despite it, we recognize that the decision of accepting or not a connection request in LinkedIn should not be a proxy for other critical decisions taken in a true working environment, like decisions involving the hiring, evaluation or termination of someone. In this sense, we believe the results or our experiment generalize to other social media context, but not necessarily to real working life. Other experiments concerned with appearance-based discrimination in the workplace need to be conducted to get to more generalizable conclusions.

4.3 Participants

We sent a total of 1387 connection requests during 4 weeks of experiment, which ran between March, 5th 2021 and April, 04 2021. 708 connection requests were sent for the attractive profile and 706 connection requests were sent for the unattractive profile. The table below shows the pace of invites sent by day. Apart from the March 21st batch, the pace of connection requests were reasonably similar among the profiles.

Table 2: Total connection requests by day for control (U-W) and treatment (A-W)

Date	U-W	A-W
2021-03-05	48	49
2021-03-06	51	50
2021-03-07	99	78
2021-03-08	0	10
2021-03-14	104	100
2021-03-21	338	102
2021-03-28	60	101
2021-04-02	0	100
2021-04-04	0	97

The participants were sourced from the primary LinkedIn connections of the group project members. They were blocked by gender, source (from which group project member the contact was originally from), and job title groups, and within each block randomly assigned to receive invitations from one of the profiles. It was a single blind design, where users were unaware they were observed. This setting eliminates any risk of demand effects that could bias the experiment results, as participants were actually unaware they were recruited by the experiment. The connection request they received from the fake profiles was not any different from the couple of connections anyone active in LinkedIn receives on a typical week. It's true they came from a stranger, but this is not atypical in LinkedIn as well, on the contrary. And this stranger had a reasonable educational and professional background and at least one connection with a real person they knew.

4.4 Compliance

This setting minimizes the risk of non-compliance as well given that the treatment is passively administered. Provided the user is active on LinkedIn, she has to do no other effort than log-in on the platform in order to receive the connection invite. The subsequent behavior of accepting or rejecting is then our outcome variable of interest. We don't have any measurement to know for sure which subjects did visualize our invitations (either in treatment or control). It's reasonable to assume that some of them were never takers, who did not log-in in LinkedIn during the study and so did not receive the invitation. Those individuals appear for us as having not accepted the invitations, even if they were not exposed to it. As this potential issue would affect both treatment and control groups, and as we properly randomize, we don't think this is a problem that would differentially impact the groups and bias our results.

4.5 Treatments

Apart from the pictures, the profiles had otherwise identical information: name, pronouns, location, professional experience, educational background, skills and interests. This minimizes the risk of any source of extraneous variation. They were based on real profiles to which individuals in the network of the group project members typically connect with, and built in order to sound as credible as possible.

It follows below all the information we used to fill the profiles personal information in LinkedIn and that were visible to the participants receiving a connection request.

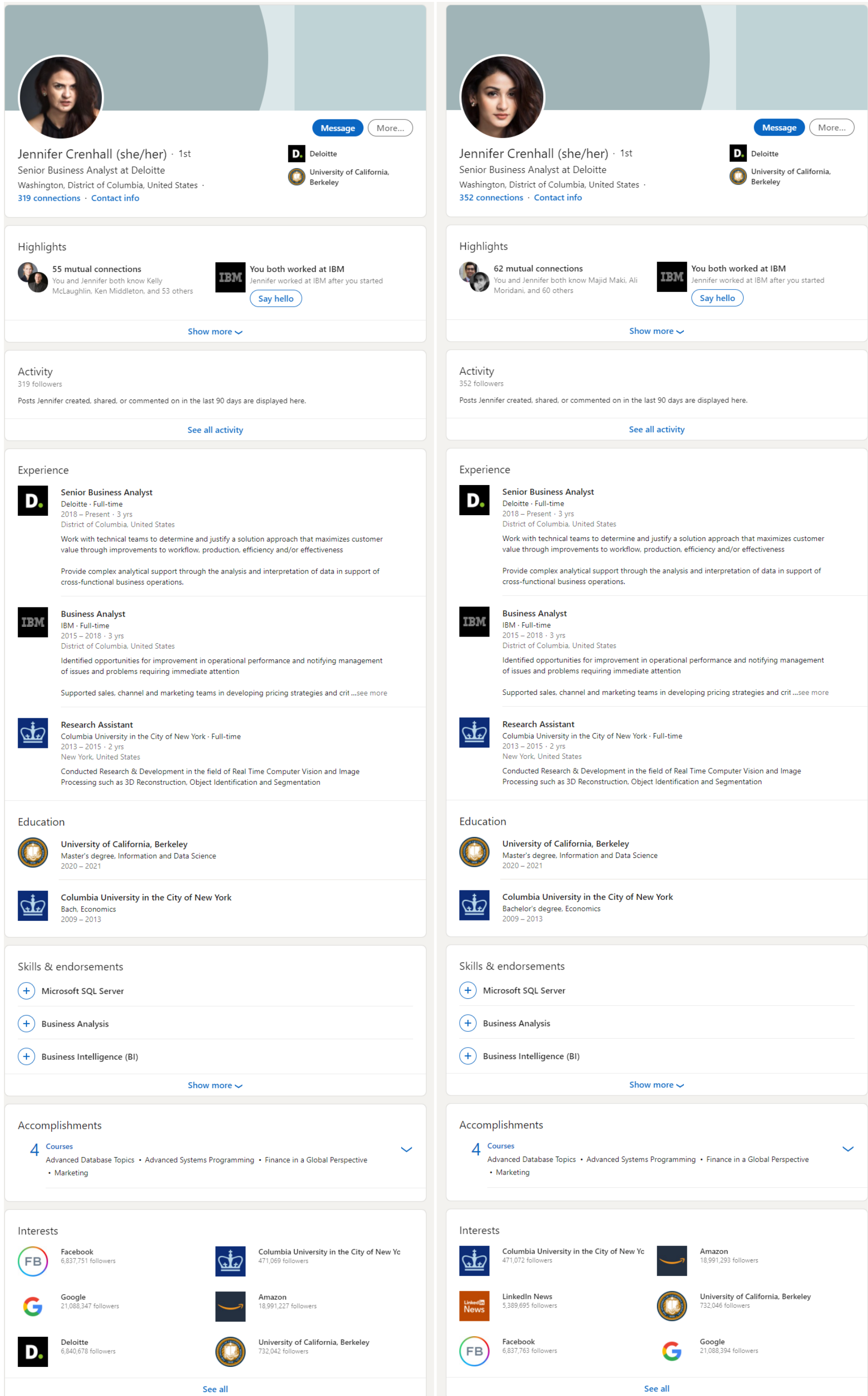


Figure 2: LinkedIn Profiles Side by Side (U-W Left)

The picture used in the attractive profile was sourced from a non-celebrity top-model from the web, and then transformed and distorted using the professional services of a designer, who applied specialized software and techniques to make it less attractive. We opted to exaggerate the distortion effects in order to maximize the dosage of the treatment, and so make it potentially easier to identify and measure the treatment effect.

We opted for using the picture of the same person instead of two different persons to ensure we were meeting the excludability assumption. With this experimental design, we can be sure that the only difference between the profiles to which participants were submitted were the modifications and distortions we applied to one of the pictures. All the rest was exactly the same, and so any treatment effect can only be traced back to this treatment.

If follows below the pictures used for the attractive and unattractive profiles:

Figure 3: Profile pictures, A-W(left) and U-W

4.6 Random Assignment

Participants data were downloaded from LinkedIn by each one of the group project members using a functionality of the network that allows users to download their primary connections basic contact data. This dataset contained first name, last name, company and job title for each one of the primary connections of all group members. We then enriched the dataset classifying names by gender and grouping job titles in 19 different groupings.

We blocked all participants by a combination of gender, source (original connection from which the contact came from), and job title groups. For each one of the blocks, we randomly assigned participants to either receive a connection request from the attractive or the unattractive profile. Participants were also randomly assigned to a weekly timetable as well that indicated when the request should be sent.

Table 3: Participants By Week

Week Number	A-M	A-W	U-M	U-W
09	200	200	200	200
10	350	350	350	350
11	157	158	157	156

Table 4: Participants By Source

Source	A-M	A-W	U-M	U-W
aidan	98	96	100	100
alan	165	164	164	165
lucas	313	315	316	308
piotr	131	133	127	133

Table 5: Participants By Job Title Group

Job Group	A-M	A-W	U-M	U-W
analyst	55	54	54	55
assistant	19	18	19	19
candidate	6	5	3	6
consultant	33	34	33	34
developer	25	24	28	24
director	43	43	44	45
education	24	25	21	23
engineer	36	32	33	34
executive	165	167	165	164
junior	18	20	20	18
manager	77	75	78	79
other	84	83	84	85
partner	32	31	32	31
pharmacist	3	1	2	2
recruiter	1	2	4	2
sales	25	26	25	25
scientist	48	49	46	48
specialist	11	15	14	11
teacher	2	4	2	1

Table 6: Participants By Gender

Gender	A-M	A-W	U-M	U-W
NA	150	141	148	147
f	265	277	266	271
m	292	290	293	288

4.7 Outcome Measurement

The outcome variable is the proportion of connections accepted relative to the number sent. The experiment generally follows an A/B testing framework, where subjects are randomized into receiving connection requests from one of the fake profiles and their potential acceptance of the request is recorded.

$$r = \frac{n_A}{n_T} \tag{1}$$

For each profile, the outcome measurement of interest is the connection rate defined in Eq. 1. As can be seen, the connection rate, r, is equal to the number of accepted connections, n_A, divided by the total number of connections sent out, n_T . From the large sample sizes associated with A/B testing and that are found in this experiment, it is assumed by the central limit theorem that the connection rate for a given profile is normally distributed. The null hypothesis for this experiment states that the connection rate between the profiles should be the same. The alternative hypothesis is that the more attractive profile will have a different connection rate than the less attractive profile, corresponding to a two-tailed hypothesis test. This would be evaluated via linear regression with a significance level of p = 0.05.

4.8 Sample Size And Experiment Power

There are a total of 2,828 potential subjects who are second degree connections of the original accounts of the researchers. With a 2x2 factorial design, there will be 707 potential subjects for each condition. Eliminating the factorial design in favor of a single comparison would result in 1,414 potential subjects each of two conditions.

The statistical power of the experiment is defined as the chance that the null hypothesis is rejected given that the null hypothesis is not true. For calculating statistical power, it was assumed that one account, a "less popular" or "control" account, had a lower conversion rate than the account being compared to it, a "more popular" or "treatment" account

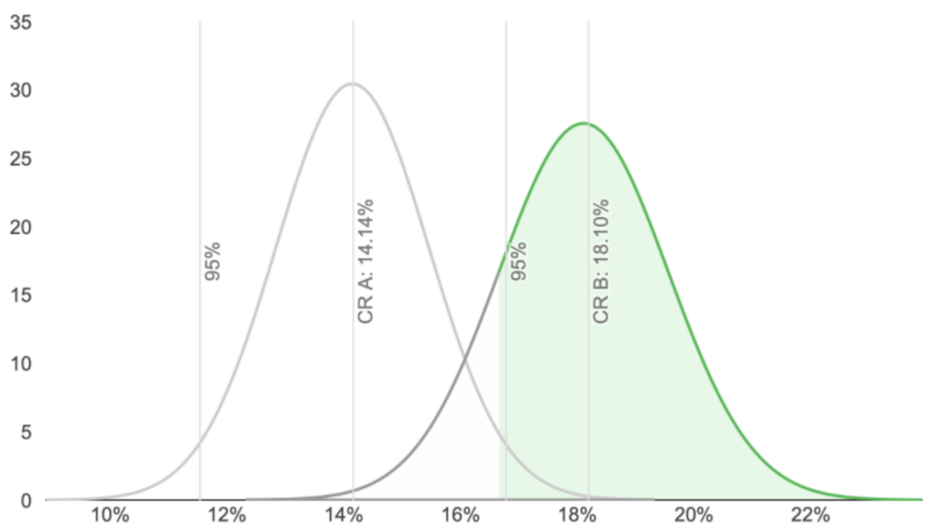


Figure 4: PDF of two hypothetical accounts

Figure 4 gives an example of how statistical power is found from the PDFs of the acceptance rates of the two accounts. The connection acceptance rates are displayed on the x-axis, centered around ~14% for the less popular account and ~18% for the more popular account. Because of the finite bounds (i.e. acceptance cannot be less than 0% or greater than 100%) the variances are not equal. The demarcated tails of the less popular account correspond to a two-tailed rejection of the null hypothesis at 95% confidence. The power of the statistical test is found from the probability that the measurement of the more popular account lies in the area where the null hypothesis is rejected. This is demonstrated by the area of the more popular PDF highlighted in green, and is computed as the green area divided by the total area of the same curve. In the case of this figure, statistical power is ~80%.

In determining statistical power for the experimental design in general, there are two possible methods. The first is to fix the expected ATE of the experiment and calculate how the power would vary under different experimental conditions. The second is to fix the statistical power of the experiment and calculate how the minimum detectable ATE would vary. For each case, the different conditions in this experiment were the number of connection requests that were accepted for the control account. Because there was no a priori knowledge of what proportion of users would accept requests from any fake profile, the latter method was used where statistical power was fixed and the minimum detectable ATE was found. Based on heuristics, statistical power would be no less than 80%.

When calculating power and the minimum detectable ATE, a common metric in A/B testing is uplift. Uplift is defined as the percentage increase in conversions the treatment receives relative to the control. In this experiment, the "conversions" are the number of accepted connection requests. While the final outcome measure in this experiment is connection rate, and not uplift, the latter is useful as a shorthand for comparing different outcome measurements between groups and whether or not a given experiment design will detect them.

Table 7: Detectable uplifts with the 2x2 factorial

Number of connections, less popular account	Minimum Detectable Uplift (%)	Maximum Detectable Uplift (%)
100	28	-
200	17	-
300	13	-
400	10	76
500	7	41
600	5	17
700	1	1

Table 7 lists the minimum and maximum detectable uplifts between two accounts at different levels of accepted connections for the less popular account. The uplifts were determined with the 2x2 factorial design and minimum statistical power of 80%. It can be seen that as the number of connections of the less popular account increases, smaller uplifts are able to be detected. However, when large numbers of users accept the less popular account's connection requests, upper limits emerge to the detectable uplift. The range of the number of connections for the less popular account was determined by the sample size of the 2x2 factorial design, at 707 subjects per profile.

Table 8: Detectable uplifts with no factorial design

Number of connections, less popular account	Minimum Detectable Uplift (%)	Maximum Detectable Uplift (%)
100	29	-
200	19	-

Number of connections, less popular account	Minimum Detectable Uplift (%)	Maximum Detectable Uplift (%)
300	15	-
400	12	-
500	11	-
600	9	-
700	8	-
800	7	76
900	6	57
1000	5	41
1100	4	28
1200	3	17
1300	3	8
1400	1	1

Table 8 shows how the minimum and maximum detectable uplifts would change if the factorial design was eliminated and the entire sample size was split only between two accounts. As can be seen, previous ceilings to the maximum detectable uplift would be increased along with smaller minimum detectable uplifts when the number of control connections is high. At less than 50% of connections being accepted, however, the minimum detectable uplift is slightly higher than when compared to the 2x2 factorial design case. Because it was generally expected that at least half of connections would be ignored or declined, the 2x2 factorial design was chosen because it allowed for more interesting comparisons while retaining the same detectable uplifts at these lower levels.

4.9 Experimental Procedure

For the duration of the experiment, each team member was assigned one of the four accounts to send connections for from the block randomized lists. With 707 connections per account, each team member was to send 50 connections per day for 15 days until all had been sent. This procedure was created under the assumption that there would be no limit to the number of connections sent during this time period, or that the limit wouldn't be reached if one existed.

5. Experiment Implementation

5.1 Pilot Study

We started our pilot study at the beginning of March and planned to use the first week as the pilot study. The four profiles were created with the intended treatments. Each member of the team was assigned a LinkedIn account, and the plan was to send out 50 LinkedIn invitations per day per account. By the end of the pilot study, we would have sent out 1400 connections. However, several unexpected events occurred during the pilot study and we had to scale down our target sample size. We will discuss in more detail in the next section.

5.2 Early Day Challenges and Re-Scoping

Unavailable Automation Tools

At the beginning of our experimental design, we intended to collect a large dataset using automation tools. We explored two options to automate the task of sending connection requests: (1) use LinkedIn API in Python to

execute the experiment (2) use third-party LinkedIn automation tools. After careful evaluation, we decided to not pursue these two options and scaled down our intended sample size for the following reasons:
1. There is a deep learning curve for the Python-based LinkedIn API. We are uncertain if we can master the package and write functioning codes to execute the experiment in a timely manner.
2. The third-party Linkedin automation tools are mostly centered around campaign management and content promotion. Though they do provide functions to automate tasks such as sending connection requests and analyzing connection profiles, we cannot control the randomization process.

LinkedIn Invitation Limits
We also faced the challenge that there was a weekly limit to the number of invitations. After two days of pilot study, we all got notifications from LinkedIn, warning us that we were approaching the weekly limit of 100 invitations which can be seen on Figure 5. This disrupted our original plan to send 50 invitations per day per account and we had to decrease the number of invitations to 100 per week. It appeared that new accounts have stricter restrictions on the number of invitations, but the bar became higher later when we were several weeks into the experiment.

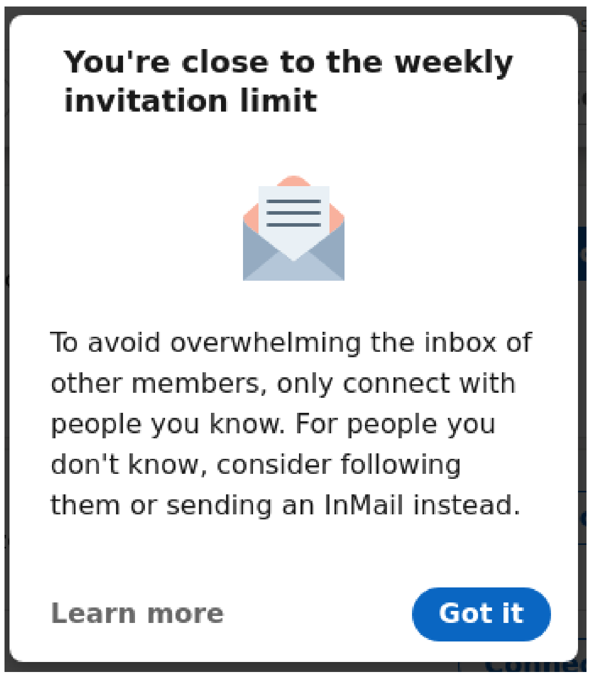


Figure 5: LinkedIn close to limit

LinkedIn Accounts Ban
Another challenge was that the two male profiles were banned by LinkedIn in the pilot study. One account was banned on March 5th as shown on Figure 6. Our hypothesis was that LinkedIn detected the shifting account IP addresses between the US and Brazil (where one of the team members is based). We attempted to solve this issue by creating a fifth account, mimicking the treatment for the banned account. We also started to use a VPN to always log in through an US IP address. However, the newly created account was banned again on March 12th. During this period, the other male profile, with the same name and career experience, was also detected and banned on March 9th by LinkedIn. As a result, we decided to focus only on the two women profiles.

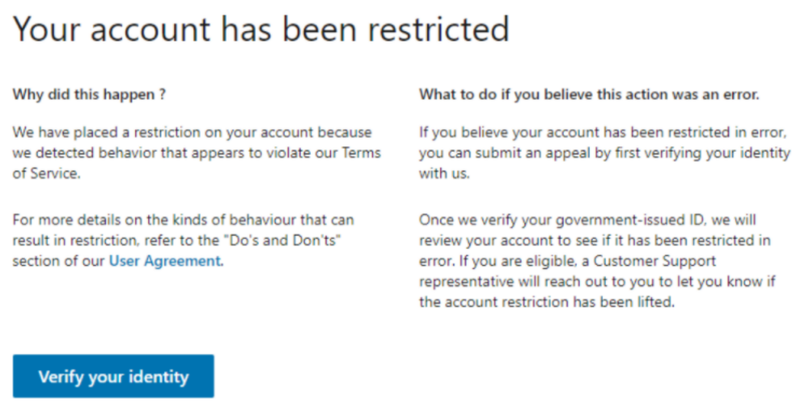


Figure 6: LinkedIn locked account

5.3 Data Collected

We collected the following data points:
- Whether the subject is in treatment group or control group
- Whether the subject accepted the Linkedin invitation
- Gender of the subject
- Job title of the subject
- The source network of the subject

We leveraged the Linkedin connection download functionality to first download the network for all team members. In this data download, we collected the original data points, such as the name of the connection, the job title of the connection and the source of the network. We separated the subjects into four "sources", which represents the four networks belonging to each of the team members. During the experiment, we also documented when we sent invitations, whether the subject accepted invitations, and when the subject accepted the invitation.

The initial data points for gender and job group were created through automatic lookups for first names and job titles. However, early on during the sending of the connections it became apparent that the pictures on profiles did not match the gender that we have predicted based on the first name M/F lookup. The name lookup algorithm did not perform well and subjects ended up having the wrong gender assigned. In order to fix this problem we manually went over the entire dataset and created a new feature gender_corr that stores the corrected value. In total 627 observations required correction. Table 9 contains top 10 examples of names that required correction. This correction does not impact our analysis as we plan to use the corrected gender in our analysis and the only impact would be to our original blocking setup.

Table 9: Gender Correction

First Name	Gender	Gender Corrected	Count
daniel	f	m	14
lucas	f	m	11
michael	f	m	10

First Name	Gender	Gender Corrected	Count
jonathan	f	m	8
diego	f	m	8
robert	f	m	8
emily	m	f	6
jason	f	m	6
chris	f	m	6
andrew	f	m	6

6. Experiment Results

6.1 Observations Tracking

During the experiment we have tracked our subjects in a very detailed manner. Figure 7 demonstrates the tracking of the observations of the course of the experiment. We start the experiment with 2,828 subjects. This list is created by exporting our existing connections from LinkedIn. This export creates a csv file, so we end up with four files that we combine into one list. This entire list is blocked randomized on Source, Gender and Job Type. Source is the name of the exporter, gender and job type is added in manually. The four groups, Unattractive Woman, Attractive Woman, Unattractive Man, Attractive Men. For the Unattractive Woman, Attractive Woman we are unable to contact 27 connections, this is due to email requirements or bad name. For the men account, we have no results as LinkedIn locked the accounts.

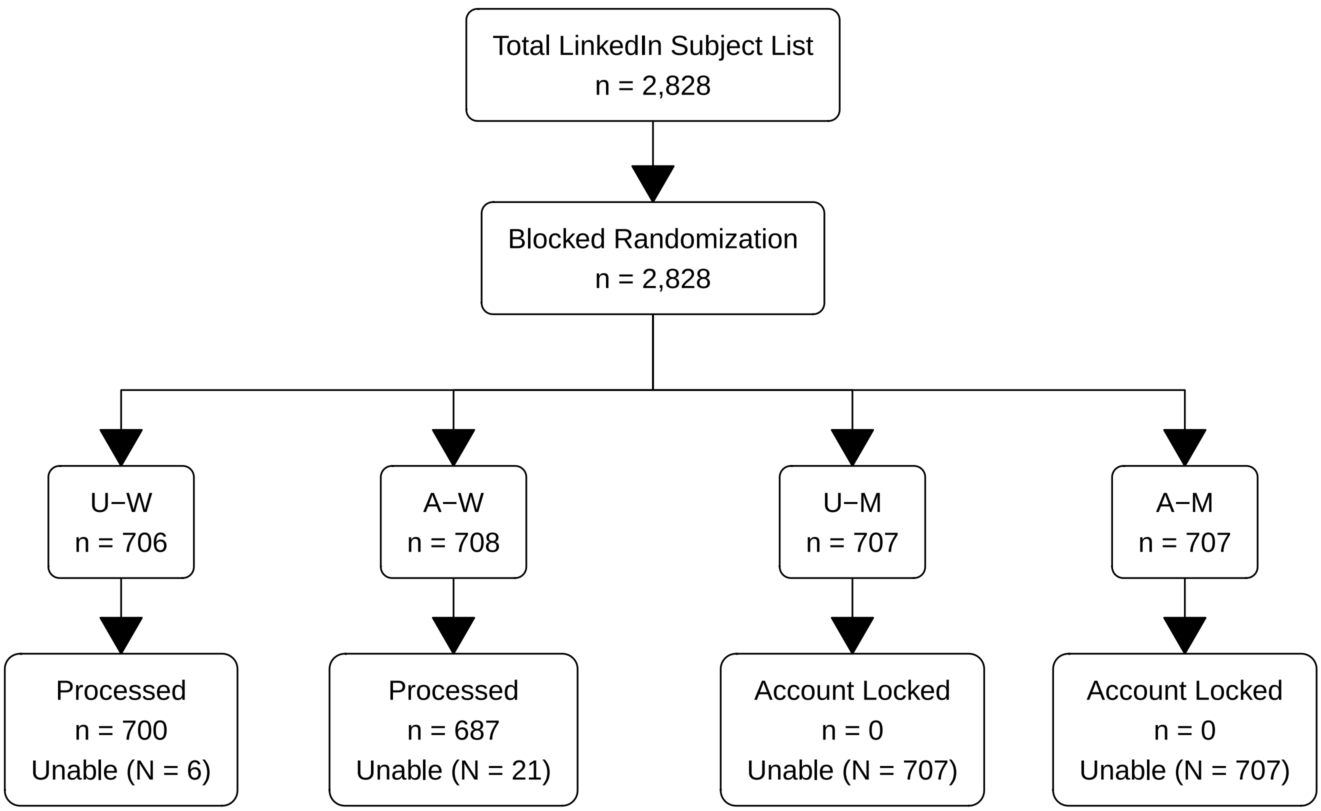


Figure 7: Observation Tracking

6.2 Covariance Balance Check

Table 10 contains regression of our collected covariates VS treatment. The result shows that although we have small differences between control and treatment (U-W VS A-W) the differences are very small and not statistically significant. The covariance balance check passes, we will use these covariates in our final results regression model but they should not impact our treatment effect as they are balanced.

Table 10: Regression Table - Covariance Balance Check

	Dependent variable:		
	treatment		
	Simple-Model	Regular-Model	Full-Model
	(1)	(2)	(3)
gender_corrm	0.006	0.007	0.011
	(0.029)	(0.029)	(0.030)
Sourcealan		0.010	0.015
		(0.046)	(0.048)
Sourcelucas		0.008	0.018
		(0.042)	(0.048)
Sourcepiotr		0.011	0.022
		(0.048)	(0.052)
Constant	0.491***	0.483***	0.468***
	(0.024)	(0.041)	(0.067)
Other Covariate	No	No	job-title-grp
Observations	1,387	1,387	1,387
R^2	0.00004	0.0001	0.003
Adjusted R^2	−0.001	−0.003	−0.014
Note:			*p<0.1; **p<0.05; ***p<0.01

From Figure 8 we can see that our absolute standardized mean differences between control and test are below 0.02. This supports our results from regression Table 10 and indicates that covariates are balanced, and randomization was conducted correctly.

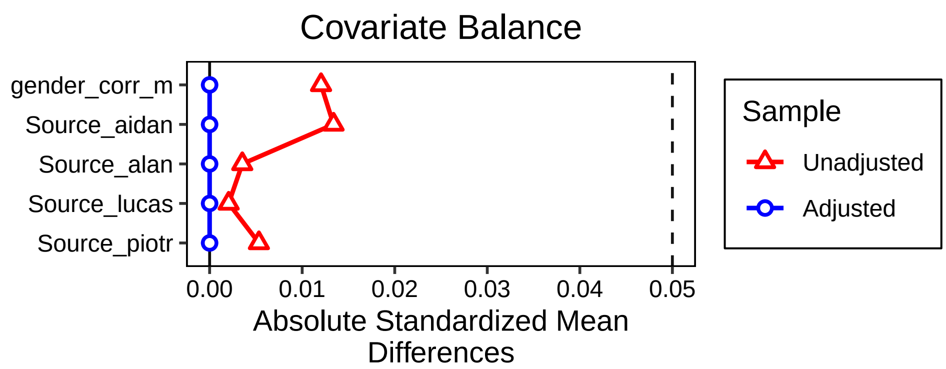


Figure 8: Covariate Balance - Absolute Standardized Mean Differences

6.3 Connection Requests

85.191% of all connections are made within 4 days of sending the request. This can be seen on Figure 8. We can also see that we have a very long tail where in the extreme cases a subject took more than 30 days to accept the connection.

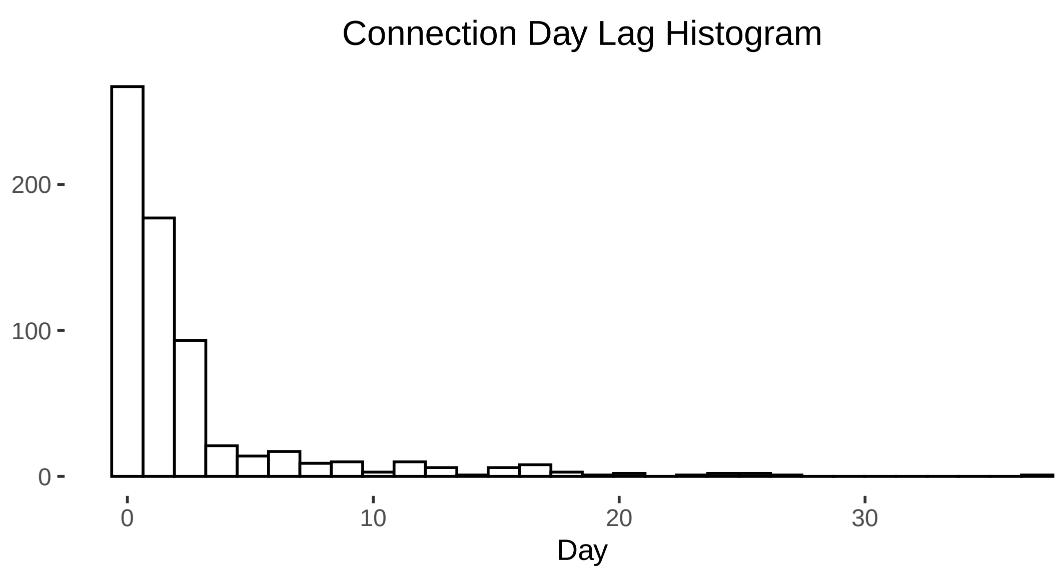


Figure 9: Connection Day Lag Histogram

Looking at connection's processed per day from Figure 10 we can see one large spike on the graph for the control group (U-W). This is the result of sending as many connections as possible as we are under the constant risk of LinkedIn locking the account. The outlier exists in the data where our control profile did not lock us out after sending 100 connections and we were able to send over 300 connections from that account that day. This was done under the assumption that we would be able to also send 300 connections from the treatment profile under the presumption that LinkedIn allows to send more connections after a certain time. However, this was not the case and the treatment account got locked after sending 100 connections. This created a potential problem in the experiment as the control group connections did get processed earlier and therefore have longer time to respond since the experiment closes for both control and treatment on the same day, April-9-2021. ***If no adjustments are made this will cause us to under-estimate the treatment effect since we know from Figure 8 that we do have subjects that take a very long time to accept the connection.*** The solution to this problem is the introduction of new covariates that are described in section 6.4 Additional Covariates, they control for the connection count at the time the request is sent out and for when the connection is sent during the experiment.

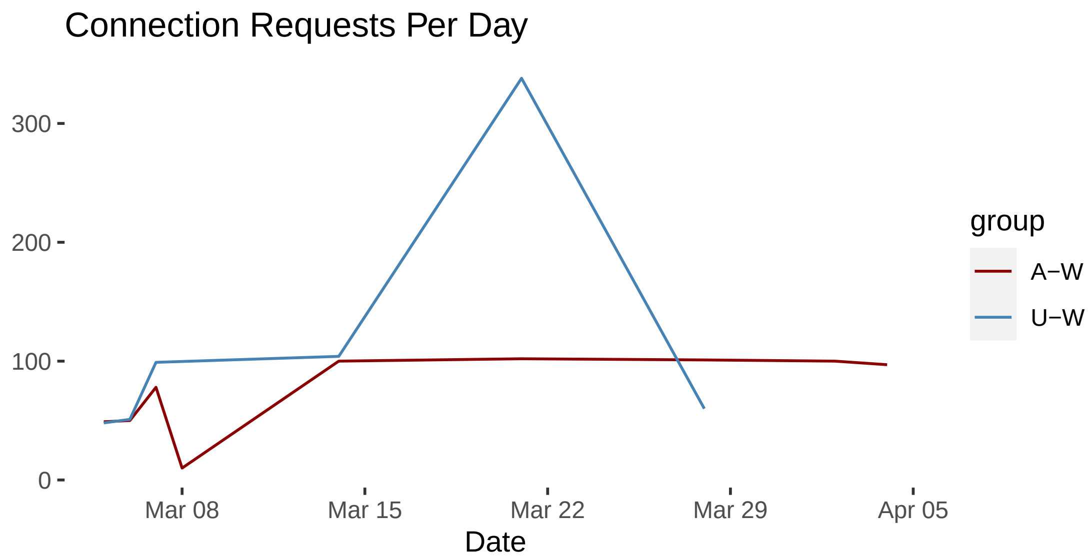


Figure 10: Connection Requests Per Day

6.4 Additional Covariates

After receiving great feedback during our presentation we decided to add the following covariates to the report.

- cdc : an incremental day counter from the beginning of the experiment. The idea behind creating this feature is that it allows capturing possible impacts of sending the connections later vs earlier in the experiment.
- ccon : total accepted connection at the time a connection request is sent out. This would capture the impact of connection count on the acceptance of the connection. Figure 11 graphs the ccon value for A-W and U-W. We can see that due to the spike in sending requests for U-W profile we see an increase in connections acceptance visible by the increase in the U-W slope. A-W profile has received a constant rate of 100 connections per week and the acceptance rate has been constant, only towards the end we see an increase.

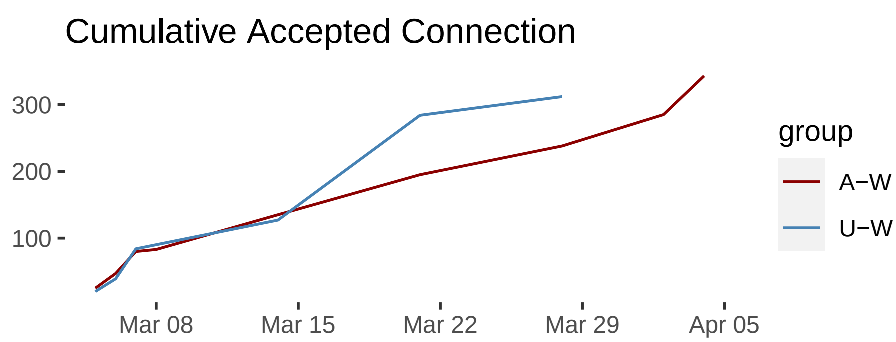
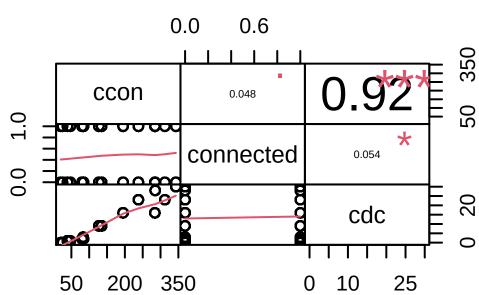


Figure 11: Cumulative Accepted Connection

As we can see in in the Figure below, cdc and ccon are strongly correlated with a p-value below 0.05. Using highly correlated features causes problems in regression models only ccon will used in further analysis. ccon is selected as its use in a regression model solves the issue of sending connection requests at different times as it adjusts for connection count bias towards accepting connection based on the existing connection count.



6.5 Regression Model

The regression model will be used to estimate the treatment effect along with statistical significance. We use heteroskedasticity-robust standard errors when reporting all regression results in the paper.

Table 11: Regression Table - Final Result

	Dependent variable:			
	connected			
	(1)	(2)	(3)	(4)
treatment	0.056^{**}	0.056^{**}	0.055^{**}	0.055^{**}
	(0.027)	(0.027)	(0.027)	(0.027)
ccon	0.0002^{*}	0.0002^{*}	0.0002^{*}	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sourcealan		0.001	0.007	0.009
		(0.045)	(0.045)	(0.048)
Sourcelucas		0.107^{***}	0.100^{**}	0.086^{*}
		(0.041)	(0.041)	(0.047)
Sourcepiotr		-0.023	-0.023	-0.018
		(0.047)	(0.047)	(0.051)
gender_corrm			0.097^{***}	0.093^{***}
			(0.029)	(0.029)
Constant	0.398^{***}	0.356^{***}	0.292^{***}	0.274^{***}
	(0.032)	(0.046)	(0.049)	(0.071)
Other Covariate	No	No	No	job-title-grp
Observations	1,387	1,387	1,387	1,387
R^2	0.005	0.019	0.027	0.045
Adjusted R^2	0.004	0.015	0.022	0.028
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 11 contains the four models we analyze in the regression table. We considered running a test to determine which model is the best however all the models produce a similar treatment effect along with standard errors which renders the test not required. We select model #3 to use to report our findings.

The coefficient of receiving the treatment is 0.055 with a p-value of 0.038. We achieve statistical significance with our p-value < 0.05. Null hypothesis is rejected, we accept the alternative hypothesis that attractiveness plays a role in accepting a new connection on LinkedIn.

- All models treatment coefficient remains relatively constant when adding covariates. The near zero change would indicate that the blocking that was created on gender/source and job-title-grp was executed correctly.
- Interesting observation is that the gender of the subject played a role in connection acceptance. Based on regression results male subject was 0.097 times more willing to accept connection with a p-value < 0.01.
- Observations from Lucas had a coefficient of 0.1 with a p-value < 0.05. As the source variable can be used as a proxy for the country and Lucas connections would be the proxy for Brazil we can make a claim that people

from Brazil are impacted by the treatment more than the USA and Canada.

- As the connection counter grows, we do get a better acceptance rate which can be seen as ccon has a coefficient of 0.0002 with a p-value < 0.1.

6.6 Heterogeneous Treatment Effect

We will analyze the heterogeneous treatment effect across all the collected covariates using a regression model indicator variable. The results are in Table 12 and we do not have any results with a statistically significant result.

Table 12: Regression Table - HTE

	Dependent variable:
	connected
treatment	0.087
	(0.083)
gender_corrm	0.091**
	(0.041)
Sourcealan	0.040
	(0.065)
Sourcelucas	0.101
	(0.062)
Sourcepiotr	−0.001
	(0.068)
ccon	0.0002
	(0.0001)
treatment:gender_corrm	0.003
	(0.058)
treatment:Sourcealan	−0.063
	(0.092)
treatment:Sourcelucas	−0.030
	(0.084)
treatment:Sourcepiotr	−0.035
	(0.096)
Constant	0.258***
	(0.079)
Observations	1,387
R^2	0.045
Adjusted R^2	0.025
Note:	*p<0.1; **p<0.05; ***p<0.01

6.7 Additional Outcome Measure

We can analyze an additional outcome measure that was not part of the original design. The connection lag is measured by the day difference between sending the request and the subject accepting the connection. This can only be done for subjects that accepted the connection. As this was not part of the original design, we are presenting these results as observational results and not a randomized trial result. Table 13 regression table summarizes the results with the following interesting findings:

- Treatment coefficient is negative at -0.219 but not statistically significant, A-W profile treated subjects accepted the connection on average faster than the control U-W profile.
- The connection lag was reduced as the profile had more connections. The coefficient for ccon is -0.009 with a p-value <0.01. This indicates that as participants saw more connection on our profiles, they accepted the connection faster.
- Lucas and Piotr connections accepted the connection faster. Both have a p-value < 0.05.

Table 13: Regression Table - Additional Outcome

	Dependent variable:			
	as.integer(connection_lag)			
	(1)	(2)	(3)	(4)
treatment	−0.219	−0.222	−0.280	−0.280
	(0.342)	(0.343)	(0.351)	(0.350)
ccon	-0.009^{***}	-0.009^{***}	-0.009^{***}	-0.009^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Sourcealan		−0.484	−0.549	−0.549
		(0.751)	(0.818)	(0.640)
Sourcelucas		-1.340^{**}	-1.410^{**}	-1.410^{**}
		(0.629)	(0.685)	(0.608)
Sourcepiotr		-1.430^{**}	-1.480^{*}	-1.480^{**}
		(0.709)	(0.765)	(0.695)
gender_corrm			−0.351	−0.351
			(0.426)	(0.402)
Constant	4.330^{***}	5.340^{***}	5.350^{***}	5.350^{***}
	(0.498)	(0.742)	(0.942)	(0.978)
Other Covariate	No	No	No	job-title-grp
Observations	655	655	655	655
R^2	0.044	0.057	0.083	0.083
Adjusted R^2	0.041	0.050	0.048	0.048
Note:		*p<0.1; **p<0.05; ***p<0.01		

6.8 Attrition

We were unable to send the connection request to 27 subjects. These subjects have been removed from our analysis. The main reason is that we could not find them because the name was corrupted. Name corruption occurs when it contains Unicode characters which are not supported during the file export. The second reason is that some accounts require that we provide an email address to verify that we do know the person we are trying to connect with. As we did not know the email, we were unable to send the connection request. We have conducted two tests to determine if this attrition can result in bias estimates.

We introduce a new feature ***complia*** that represents our ability to send the connection request. Table 14 regression table is a test to determine if we have statistical difference of connections that we were unable to process between the two profiles (U-W and A-W). Results from Table 14 tell us that treatment group has received less connection requests with a p-value < 0.001. The coefficient for treatment is -0.024. As these results indicate a possibility of a problem, we will conduct another test to make sure that the attrition we have is not differential attrition based on the covariates that we have collected.

Table 14: Regression Table - Attrition

	Dependent variable:
	complia
treatment	-0.021^{***}
	(0.007)
Constant	0.992^{***}
	(0.003)
Observations	1,414
R^2	0.006
Adjusted R^2	0.005
Note:	*p<0.1; **p<0.05; ***p<0.01

To test for differential attrition, we regress treatment across all our collected covariates for the attrite subjects to see if we can find any statistical significance. Table 15 presents our findings, none of the observed covariates have statistically significant correlation to complia and the outcome variable. The risk remains of other unobserved covariates that could bias our results, but we feel confident to conclude that based on our collected covariates we do not have differential attrition.

Table 15: Regression Table - Differential Attrition

	Dependent variable:
	treatment
Sourcealan	−0.003
Sourcelucas	0.300
Sourcepiotr	0.124
gender_corrm	−0.121
job_title_grpassistant	−0.697
job_title_grpconsultant	−0.121
job_title_grpdeveloper	0.151
job_title_grpengineer	−0.700
job_title_grpexecutive	−0.362
job_title_grpmanager	0.061
job_title_grpother	0.239
job_title_grppartner	−0.275
job_title_grpsales	−0.000
job_title_grpscientist	−0.000
job_title_grpspecialist	−0.061
Constant	0.821
Observations	27
R^2	0.574
Adjusted R^2	−0.006
Note:	*p<0.1; **p<0.05; ***p<0.01

7 Conclusion

The use of a more attractive profile picture in the female accounts was found to have a significant effect of increasing connection rate by a magnitude of 5.5% via linear regression. Thus, the null hypothesis that relative attractiveness in the profile picture does not affect connection rate is rejected. Instead, the alternative hypothesis that a more attractive profile picture will increase the connection rate is failed to be rejected. No heterogeneous treatment effects on connection rate were found with respect to the gender of the recicpient.

Connection time lag was also a secondary outcome variable investigated in the experiment. Because the time lag could only be investigated for users who accepted connection requests, and not the complete groups based on random assignment, any established relationship between attractiveness and time lag would only be observational and not causal. Unlike the connection acceptance rate, connection time lag was not found to have a significant relationship with the relative attractiveness of the profile photo. This fits with a qualitative understanding of user behavior on LinkedIn, as typically a person will either decide to accept or reject a connection as soon as the request is reviewed. Standard user behavior would not normally involve seeing a request and then taking an extended period of time to deliberate on a decision. Since timestamps of connection acceptances were limited to a daily basis, any connection time lag differences that did exist between the two profiles but were smaller than one day would not have been detected.

In general, the connection rate observed for both profile types was much higher than expected, at 49.9% for the attractive profile and 44.6% for the unattractive profile. Beyond the scope of this experiment, this suggests that nearly up to half of all LinkedIn users would be willing to connect to a person they do not know and in this case does not exist. Since this is a potentially embarassing statistic for LinkedIn as a serious professional networking site, it would be reasonable to assume that the company is not favorable towards field experiments conducted on their platform. This would justify the team's decision to not contact them about the experiment or about the banning of the male accounts, in order to not jeopardize the fulfillment of the study. In the future, it would also be an important consideration for designing further experiments and implementing appropriate protocols to help avoid similar incidents.

The results of this experiment could be further expanded to consider either attractiveness bias in other professional settings or other biased determinants of user behavior on social networks such as LinkedIn. Given the ease at which an online field experiment may be designed and implemented, the latter is generally more favorable. As an immediate starting point, the same experimental procedure could be carried out for male profiles or profiles with other potentially significant changes in the chosen picture, such as race/ethnicity. Potential characteristics about the profiles could also be altered, such as the amount of experience or education they contain. Ultimately, while a chosen outcome such as connection rate is interesting, more serious measures of the effects of bias should also be considered to capture the serious ways it can affect social relationships.

8 References

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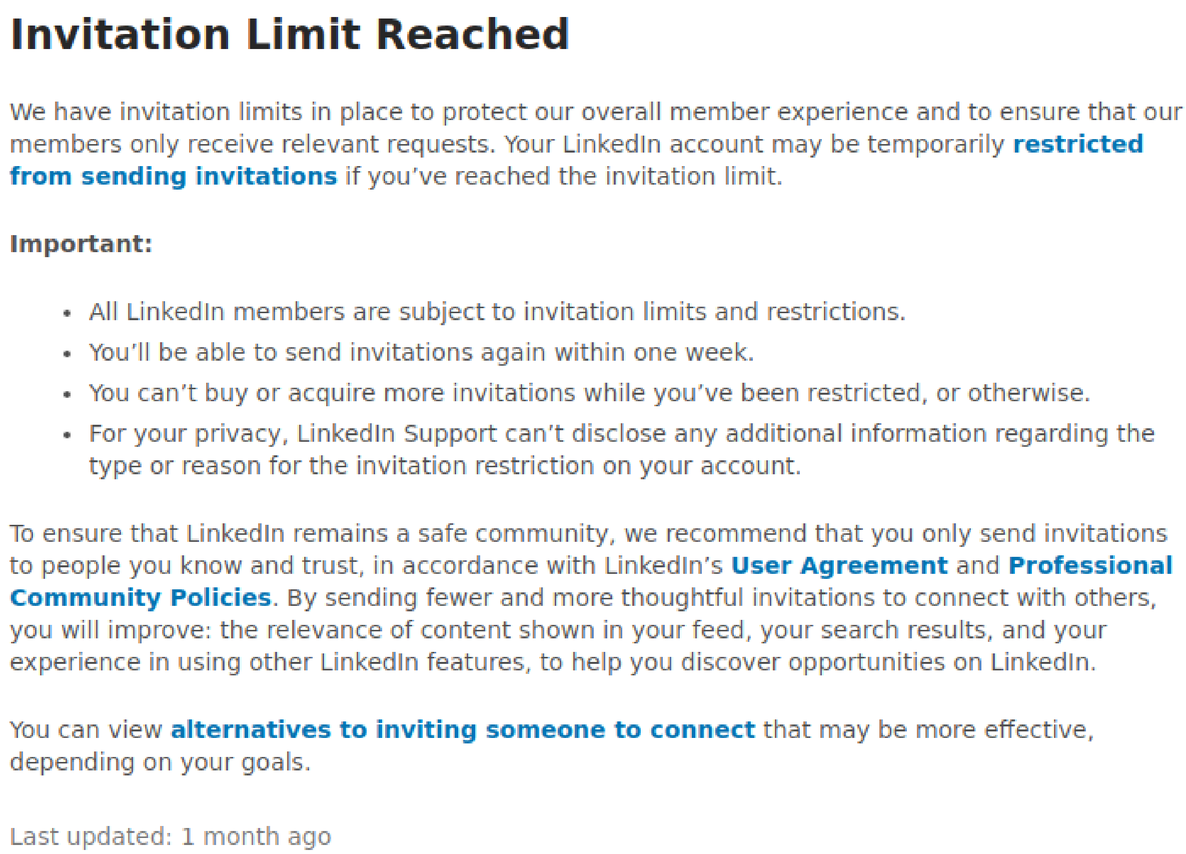
9 Appendix



Invitation Limit Reached

We have invitation limits in place to protect our overall member experience and to ensure that our members only receive relevant requests. Your LinkedIn account may be temporarily **restricted from sending invitations** if you've reached the invitation limit.

Important:

- All LinkedIn members are subject to invitation limits and restrictions.
- You'll be able to send invitations again within one week.
- You can't buy or acquire more invitations while you've been restricted, or otherwise.
- For your privacy, LinkedIn Support can't disclose any additional information regarding the type or reason for the invitation restriction on your account.

To ensure that LinkedIn remains a safe community, we recommend that you only send invitations to people you know and trust, in accordance with LinkedIn's **User Agreement** and **Professional Community Policies**. By sending fewer and more thoughtful invitations to connect with others, you will improve: the relevance of content shown in your feed, your search results, and your experience in using other LinkedIn features, to help you discover opportunities on LinkedIn.

You can view **alternatives to inviting someone to connect** that may be more effective, depending on your goals.

Last updated: 1 month ago

Figure 12: LinkedIn limit reached

Table 16: Connection Rate

Treatment	Connection Rate	Total	Connected
A-W	0.499	687	343

Treatment	Connection Rate	Total	Connected
U-W	0.446	700	312

Table 17: Connection Rate

Gender	Connection Rate	Total	Connected
m	0.507	947	480
f	0.398	440	175

Table 18: Connection Rate

Treatment	Connection Rate Male	Connected	Total
A-W	0.535	471	252
U-W	0.479	476	228

Table 19: Connection Rate

Treatment	Connection Rate Female	Total	Connected
A-W	0.421	216	91
U-W	0.375	224	84

Table 20: Connection Rate

Gender	Connection Rate	Total
lucas	0.537	609
alan	0.429	324
aidan	0.430	193
piotr	0.406	261

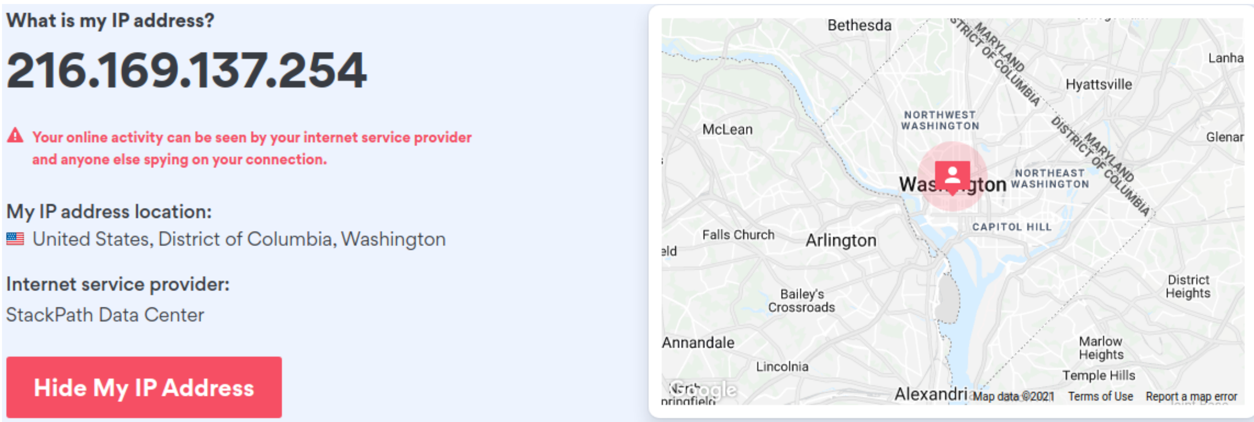


Figure 13: VPN

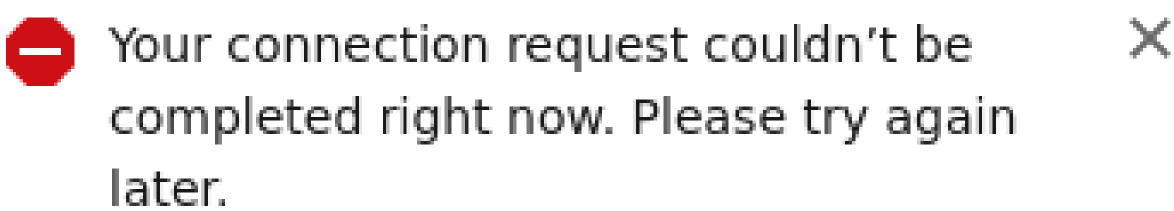


Figure 14: LinkedIn connection limit

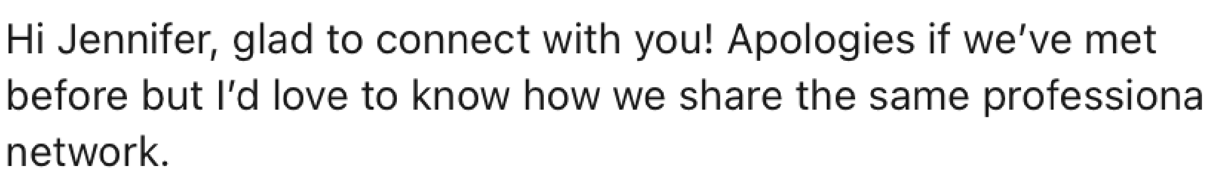


Figure 15: LinkedIn love to connect