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Measuring First Impressions

Does knowledge of someone's history of criminal drug use affect your first impression of them?

INTRODUCTION

One setting in which first impressions can be easily measured is within the context of dating apps. Users look at photos on a profile and some limited information about a person, and then make a split second decision on whether to swipe left or right. Existing research shows us that there is a lot of bias at play within dating apps themselves. Discrimination is made based on race, which is rationalized by users as personal preference (Conner, 2022). Even further, a causal effects study done by Emilce Santana (2024) found that the depth of the skin tone on the profile, without regards to gender, also had a significant effect on the impressions that they made and how people responded to their profiles. This naturally leads to questions about how other types of bias are represented in dating apps. A type of stigma that is commonly seen is those against people who use drugs and people who have gone to jail, particularly people who went to jail for drug use. Using a dataset containing initial reactions to the dating profiles with and without a history of criminal drug use, matching can be used in order to see if that bias is prevalent among online dating. There is literature that suggests that the stigma associated with drug use differs among different subgroups. One review suggests that within qualitative studies of drug use stigma, women face more bias against them for their history of drug use than men do (Meyers et. al., 2021). Does this difference among subgroups extend to drug use bias in online dating as well? And are there other subgroups that could have differences? To check for this I will do a subgroup analysis after my initial matching. This will expand the existing literature on bias in online dating and first impressions, of which there is very little outside of a few articles exploring the effects of racism.

DATA AND METHODS

The data used for this analysis was found on the OpenICPSR database, titled "Evaluations of online dating profiles by race, gender, and history of incarceration," featuring data collected in surveys done by Frankie Kennedy et. al. from Syracuse University. There were two separate surveys and their responses in this dataset, and I used the results from Survey 1. In this, 1032 people were paid to take a survey on Amazon Mechanical Turk in 2018 in which they were presented with a dating profile and asked to respond to questions about their impressions of the person on the profile. Many questions had an N/A option, and there was a question at the end of the survey that asked if the survey taker had answered any questions jokingly. After filtering out the people who answered yes to that question or had N/A responses, there were 944 usable responses. Each person taking the survey had a 50% chance of receiving the treatment, which was the person on the randomly generated dating profile disclosing a past history of criminal drug use by saying "Four years ago, I spent a year in prison for a drug charge, but that's behind me now. I am focused on reframing my life from here on out." If someone was presented with this form of the dating profile, they have a "yes" value in the *formerly_incarcerated* variable in my dataset.

The dataset itself required a lot of data cleaning in order to be usable for my analysis. First, every column name was written in the form of a question number, and there were a lot of columns that were unnecessary to my analysis, especially those regarding the timing of the person taking the test. All of the unneeded variables were removed, and the rest of the columns were renamed in order to easily and correctly represent what they mean without flipping back and forth from the survey questions. With this, every question pertaining to the characteristics of the survey taker started with “p_” in order to be distinct from the same characteristics in the dating profile. The data itself had “-99” as the value representing N/As, so the next step was to remove all rows which had that as a value somewhere. Next, all of the survey responses were coded as character type variables, so I had to go through and sort them and either numeric or categorical and refactor each of those so that the matching models ran correctly. There were also a few variables which needed to be cleaned individually, like *p_gender* and *p_race,* and some variables I created through combining other variables, like the *p_comfort_drugs_combined* variable and my outcome, *first_impression.*

Running through these variables that earned extra attention from me, the first one was the gender of the survey taker. On the survey itself, the question asking the person taking the survey their gender was a textbox, so every different typo, capitalization, and spacing resulted in a different category in the *p_gender* variable, resulting in 28 different genders in the initial dataset. After removing 2 N/A answers and 3 people who answered with some form of nonbinary (as this wasn’t enough to justify making another category), I was left with only male and female. *p_race* also required a lot of care and deliberation, as on the survey there was a very comprehensive question asking race, with 10 different options and the ability to select more than one, and left 29 different races on my survey, many of them only having one or two people selecting that particular combination. After some research including going to see what the categories are for race in the U.S. Census, I decided to make four groups: “white,” “black,” “mixed,” and “aapi,” which stands for Asian American Pacific Islander. Even after doing this, the groups were still very disproportionate, with 720 people in the “white” category, 105 in “black,” 85 in “aapi,” and 31 in “mixed,” however, this successfully dealt with all of the categories with only a few people in them. The final variable that needed a lot of attention in order to be usable was the one representing the survey taker's comfort level with recreational drugs. I took their responses to three questions about their comfort with recreational drugs in general, their comfort with friends using recreational drugs, and their comfort with their partners using recreational drugs and found the mean response to those in order to represent their comfort with recreational drugs in one variable.

In the original dataset, there were 34 questions about the survey takers reactions to the dating profile they saw. In order to do this analysis, I had to pick which one of these would represent their first impression of the dating profile. I decided to use the answers to the first question that people got after seeing the profile, but that question was in three parts, having the survey takers rate the person they just saw on a sliding scale from 0-100. On the first part, you rated from negative to positive, on the second, unfavorable to favorable, and the third, cold to warm. Using the same approach as with the survey taker's comfort with recreational drugs, I found the mean value of each of these three variables and created a new variable called *first_impression.* If you see Figure 1, there is a clear difference in the distribution of first impression scores for the profiles who did have a history of criminal drug use and those who didn't. To investigate this difference, I will use matching.

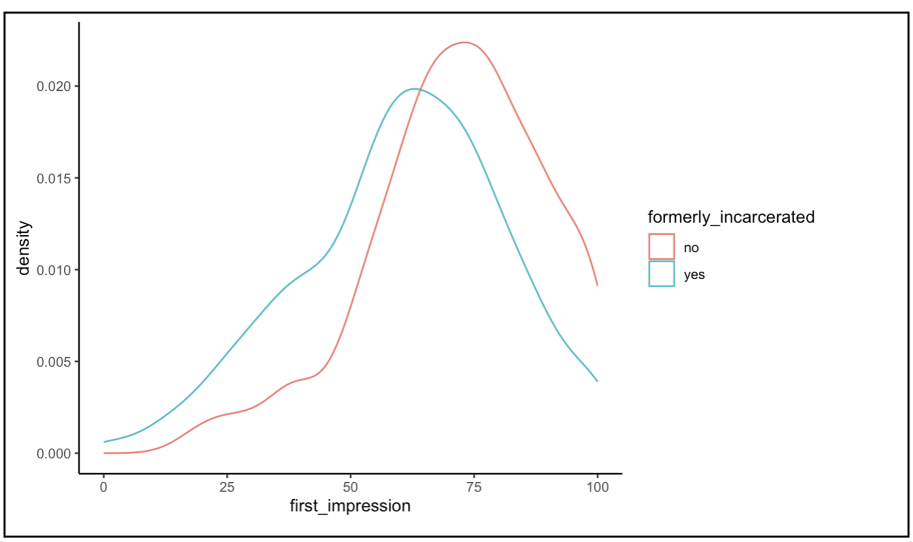


Figure 1. Density plot of first impression scores, colored by history of criminal drug use

From there, I needed to decide what variables to include in my analysis. To do so, I made a causal graph in order to better understand the connections between my treatment, *formerly_incarcerated*, and my outcome *first_impression.* Figure 2 shows the causal graph that I made originally describing the scenario. There are three main noncausal paths that I identified: one through the race on the profile, justified through racism in the criminal justice system and everyday life, one through the gender on the profile, justified similarly using sexism, and one through the drug attitudes of where the survey taker lives. This last one makes sense under the context that the local drug laws will both affect how likely it is for the person on the dating profile to go to jail for drug use, but also there is a connection between the personal drug attitudes of the people living in those areas and their laws, as people have to elect officials who make those decisions. Thus, the area's drug attitudes for where the survey taker lives has a connection to their personal drug attitudes as well. Finally, other characteristics of the survey taker could also impact their first impressions of the dating profiles, like the gender, race, and opinions of the survey taker. However, because the data on here was collected with the treatment being given via random assignment, any arrows pointing towards the treatment can be removed and instead replaced with a random number generator (see fig. 3). This means that there are no noncausal paths that need to be blocked, but in order to remove confounders anything that is pointing at the first impression outcome will need to be matched on. From these causal graphs, the variables I matched on were the gender and race on the profile, the gender and race of the survey taker, the personal drug attitudes of the survey taker as represented by *p_comfort_drugs_combined*, how religious the survey taker is, and their political leanings, defined by either liberal or conservative.

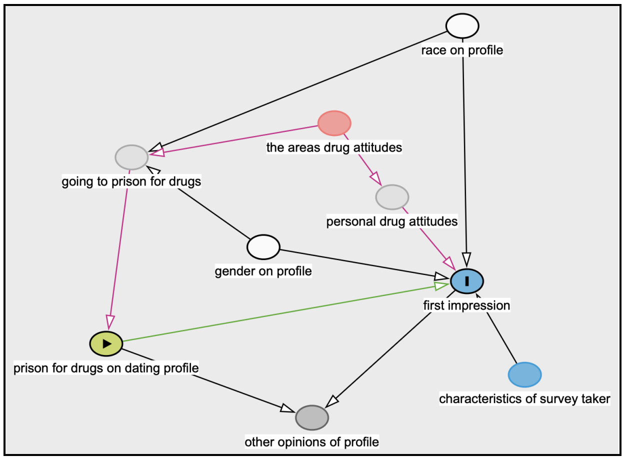


Figure 2. Original Causal Graph

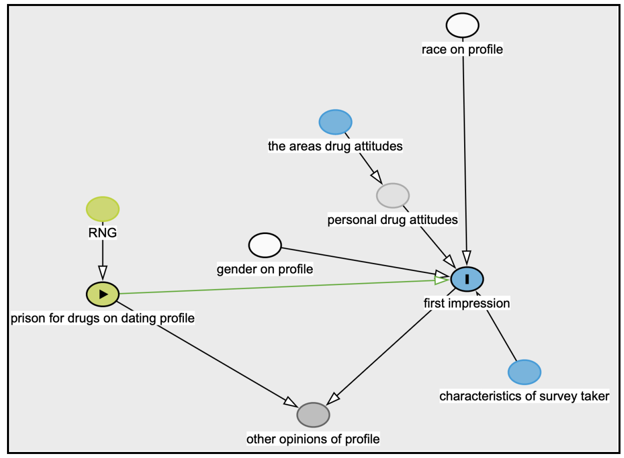
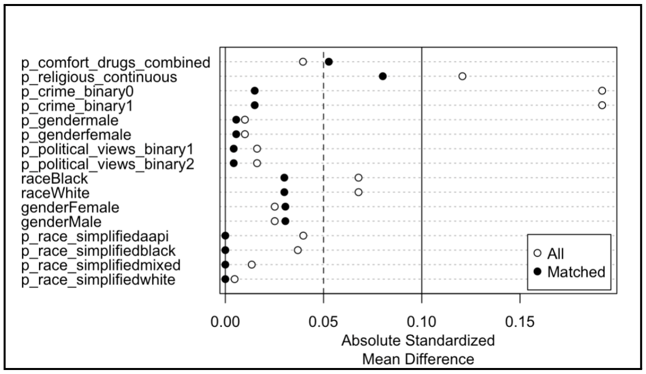


Figure 3. Adjusted for Random Treatment

The next step was to find the best matching method in order to minimize the differences between treatment groups. I decided to use full matching as it works well with categorical variables, and then experimented with different distance measures. My top two were mahalanobis and glm distance, and the best model came from using the glm distance measure. You can see in Figure 4 that this resulted in an absolute standardized mean distance of less than 0.1 for each of the variables. The figure does not contain the interaction terms in order to be legible, but all of the interaction terms also have an absolute standardized mean distance of less than 0.1. Many of the variables actually have a very small difference between treatment groups to begin with, which makes sense because of the random assignment of the treatment. Any difference between treatment groups falls purely to chance, and does not occur as a result of a systemic difference in who does or does not receive the treatment. This symptom of random treatment assignment is also seen in my common support plots (fig. 5). The true propensity score for any one person to receive treatment was 0.5, which looks to be the mean of both treatment groups. There is of course some random variation, but each treatment group covers approximately the same range of possible propensity scores, so there is no issue with common support in my model.



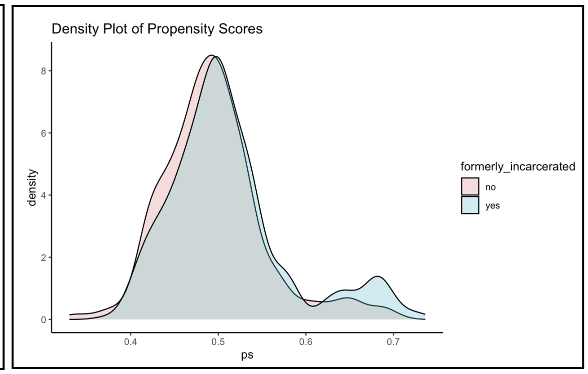


Figure 4. Checking difference between groups *Figure 5. Common Support Plot*

After doing the initial matching of the whole group, I proceeded to do subgroup analysis on a variety of variables using the methods outlined by Noah Greifer (2022). The variables I did this with included the gender of the survey taker, the gender and race on the dating profile, the political leanings of the survey taker, and how religious the survey taker is. In order to do the last one, I converted the ranking of how religious someone is on a scale of 1-9 into a categorical variable instead, with 1-2 representing "not religious," 3-6 representing "somewhat religious," and 7-9 representing "very religious." I attempted to do a subgroup analysis of the different races of survey takers using *p_race_simplified*, however, some of the subgroups were just too small to get good matches for.

RESULTS

Estimate <chr>	**Std. Error** <chr>	**z** <chr>	**Pr(>|z|)** <chr>	**S** <chr>	**2.5 %** <chr>	**97.5 %** <chr>
-10.9	1.43	-7.61	<0.001	45.1	-13.7	-8.11

Figure 6. Initial Matching Results

The estimate in Figure 6 is for the average treatment effect (ATE), which is the average effect that the treatment has (or would have) on every first impression of a profile in the trial. By this, we see that the ATE is -10.9. This means that on average, knowing that someone has been formerly incarcerated on drug charges will decrease someone's first impression of them by approximately 11 points on a 0-100 scale. As the confidence interval from (-13.7, -8.11) does not pass zero, we can say that knowing someone is formerly incarcerated does indeed have a negative impact on first impressions. In Figure 7, there are all of the results of the subgroup analysis. If you look in the Value column, all of the rows with "COMPARISON" in them are checking for the difference in ATE between subgroups, so for example, the third row in the the *p_gender* subgroup analysis is saying that there was a 3.71 difference in the ATE between female and male survey takers. This means that the women taking the survey, had they all received the treatment, put first impressions about 4 points higher than the men would have. However, the confidence interval for this comparison is from (-1.4, 8.81), which contains zero. This means that we can't reject the idea that there is no difference between subgroups, in this case, male and female survey takers. The confidence intervals for all of my comparisons contained zero, so there was no significant difference in the effect of the treatment on first impressions in any of the subgroups.

Subgroup	Value	Estimate	Std. Error	z	Pr(>|z|)	S	2.5%	97.5%
p_gender	female	-8.3	2.03	-4.09	<0.001	14.5	-12.3	-4.32
	male	-12.0	1.63`	-7.38	<0.001	42.5	-15.2	-8.82
	COMPARISON	3.71	2.6	1.42	0.154	2.7	-1.4	8.81
p_political_views_binary	liberal	-11.3	1.59	-7.12	<0.001	39.7	-14.4	-8.19
	conservative	-12.0	2.04	-5.91	<0.001	28.2	-16.0	-8.05
	COMPARISON	0.738	2.58	0.29	0.775	0.4	-4.32	5.8
p_religious_categorical	not_religious	-11.30	2.00	-5.66	<0.001	25.9	-15.2	-7.38

	somewhat_ religious	-12.09	2.30	-5.26	<0.001	22.7	-16.6	-7.58
	very_religious	-9.06	3.18	-2.85	0.00443	7.8	-15.3	-2.82
	COMPARISON (not - somewhat)	0.738	3.05	0.26	0.796	0.3	-5.18	6.75
	COMPARISON (not - very)	-2.243	3.76	-0.60	0.551	0.9	-9.61	5.12
	COMPARISON (somewhat - very)	-3.028	3.93	-0.77	0.440	1.2	-10.72	4.67
race	Black	-9.84	1.8	-5.46	<0.001	24.3	-13.4	-6.31
	White	-13.06	1.7	-7.69	<0.001	45.9	-16.4	-9.73
	COMPARISON	3.22	2.38	1.3	0.194	2.4	-1.64	8.07
gender	Female	-11.2	1.79	-6.26	<0.001	31.3	-14.7	-7.72
	Male	-12.0	1.72	-6.99	<0.001	38.4	-15.4	-8.65
	COMPARISON	0.798	2.48	0.32	0.748	0.4	-4.07	5.67

Figure 7. Subgroup Analysis Results

DISCUSSION

The most key result of this is that knowledge of someone's history of criminal drug use truly does have a negative impact on your first impression of them on dating apps, and likely extending into daily life as well. Following my research on existing literature, this is an expected outcome. An unexpected outcome is that all of the subgroup analysis showed that there was no significant difference in someone's first impressions of people with a past history of criminal drug use within different subgroups. After reading journal articles about the difference in drug stigma between men and women and skimming many others about differences in bias between groups, I didn't expect this to be the case. In the future with proper resources, I would do an analysis like this again with the different subgroups, and see if there were any significant differences between them. That would require a larger dataset with better diversity than this one, which did not have equal representations of every subgroup. This would also allow me to do a subgroup analysis of the race of the survey taker as well, which was one of the results I was most interested in but was unable to do. Besides limitations with the size and diversity of the dataset, there are also concerns that because the information was collected on Amazon Mechanical Turk in exchange for money by workers who fill surveys and things like this out to support themselves, that they could be just clicking through the survey as fast as possible in order to make money as quickly as possible. In collecting another dataset, I would use a different method in order to reduce the possibility of this happening. Although I would love to be able to generalize this result to people you meet in person, the questions about first impressions were all answered through the guise of dating apps and, theoretically, your response to the idea of dating this person, so it can only be generalized to bias making a difference in first impressions on dating apps. In another survey, care could be taken in order to make this generalizable to the entire population and first impressions in general.

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