To be or not to be on social media: How social media content impacts recruitment *

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Abstract

This paper extends the literature studying the effect of social media content on the evaluation of job candidates. In a large-scale online experiment that resembles real-life screening of candidates for a basic managerial position in the hospitality sector, we find that information available on social media through hashtags and liked pages can have a substantial and significant effect on a candidate's chances of obtaining a good rating. Candidates with social media content indicating mental health problems receive lower ratings by an amount equivalent to the effect of having three years on-the-job experience. Interestingly, candidates with no social media profile receive even lower ratings than candidates with mental health problems. In addition, unappealing social media content leads to the strongest reduction in ratings, equivalent to the value of nine years of on-the-job experience. These findings persist across participant pools, including both the general public and experienced recruiters, highlighting social media's substantial and likely increasing role in the hiring process.

JEL Classification: D83, J64, J79

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1 Introduction

Employers are increasingly using content from social media in recruitment processes. A little over 10 percent of employers used social media to screen job candidates in 2006 and more than 90 percent of employers do so today.[1] In a recent survey (Careerbuilder 2018), more than 50% of employers answered they rejected a job-candidate based on what they found on their social media. In addition, more than 80 percent of labour-market-age US Americans have a social media account, often revealing information about personal characteristics, health, political orientation, and much more (Zhang et al. 2020). While survey experimental evidence indicates managers indeed use social media for screening, evidence is still scarce about how they treat the content they find or do not find and how this translates to the evaluation of job candidates.

To examine how social media content influences the assessment of job applicants, we enlisted 1,500 individuals from the overall U.S. populace and 500 participants with substantial managerial and hiring experience through two crowd-sourcing platforms. These individuals served as evaluators for a recruitment decision. Their task was to evaluate candidates for a job in the hospitality sector. For each candidate, evaluators received a fictitious CV and some social media content. After the evaluation of six candidates, they answered a short questionnaire. For our experiment, we randomly created a large number of CVs for evaluation from a matrix containing combinations of experience, education, skills, and interests. We created the social media content such that it revealed something about each of the six candidates. We chose content that was previously unavailable in a standard recruiting process but now can be commonly found on social media profiles. These include an (undisclosed) employment gap, mental health problems, and generally unappealing personal characteristics. For some candidates, we did not provide any social media content, and as a control, we provided reasonably appealing social media content.

In both participant pools, we find substantial and similar effects of social media content on candidate rating and, therefore, presumably on the chances of obtaining a job. The magnitude of the effect is equivalent to traditional information revealed on the CV. On a scale from 0 to 10, candidates with unappealing social media content received on average, 1.94 [Recruiters sample: 1.65] fewer points than candidates from the control group. For comparison, this is equivalent to the effect we find for having around 9 fewer years of on-the-job experience. Most surprisingly, candidates cannot avoid the negative effects of social media content by being undetectable on social media. Unavailable social media content harms the candidate rating by 0.88 points (same for both participant pools). This is equivalent to the value we find for a bachelor's degree, and worse than the value we find for an indication of mental health problems (-0.68, Recruiters: -0.54) or a recent two-year unemployment gap (-0.29, Recruiters: -0.32). Finally, candidates whose employment gap was only revealed on social media, thus unmasking the employment part of the CV as incorrect, were not ranked differently from candidates with an employment gap honestly revealed on both social media and CV.

Beyond the insights on treatment effects, we combine rich data on evaluators' characteristics and opinions with the experimental variation in candidates' characteristics, to explore the heterogeneity in treatment effects. Qualitatively, the relative effect of the treatments is similar across candidates and evaluators. However, we still identify some heterogeneity. For example, evaluators who are themselves active on social media are more likely to penalise candidates without a social media account. Those without social media experience also penalise, but less.

The robust replication of results across participant pools and time periods significantly reinforces

[1]See Figure A.1 in the appendix, based on CareerBuilder (Careerbuilder 2018) and The Manifest surveys (Mckeon 2020).

the internal and external validity of the findings. The experiment was carried out in two phases: the first wave involved 1,500 participants on Amazon MTurk and took place between February and April 2022, while the second wave involved experienced recruiters on Prolific and occurred between October to December 2023. Each wave was separately pre-registered, as we conducted the second wave to validate the results of the first one.

Our paper bridges the gap between two strands of the recruitment literature, correspondence studies, and lab or online experiments. As in correspondence studies (and different from lab and online experiments), our evaluators are paid to make choices without being explicitly informed that they are participating in an experiment or being incentivised to make the "best" choice. As in lab experiments (and different from correspondence studies), we can collect a rich data set of evaluator characteristics, ratings, and behaviour. While our design is not a natural field experiment like correspondence studies are, it strongly resembles a real-life recruitment task.

Our approach allows us to make several unique contributions to the literature on job-market recruitment. First, to the best of our knowledge, this is the first paper to reveal the negative effect of not having a social media profile on the evaluations of job-candidates (Roth et al. 2016, thoroughly emphasise this gap in the literature). John, Barasz, and Norton (2016) use lab experiments to show that participants judge hiding information (in dating apps or on a CV) worse than revealing some negative information. They suggest revealing contributes to creating trust and thus leading to positive evaluation. Our text analysis supports the hypothesis that evaluators perceive not having a social media account as a negative signal. This is plausible, given that 80 percent of the labour-market-age US Americans have one. Still, additional research is required to fully clarify the mechanism behind this effect. In line with this interpretation, having a social media profile is already a common recommendation to job-seekers (see, for example, White 2015).

Second, we expand and strengthen the findings that information revealed on social media can negatively impact candidate rating and job-market opportunities. Acquisti and Fong (2020), Baert (2018a), and Manant, Pajak, and Soulié (2019) use correspondence studies to provide evidence that information on ethnicity and appearance revealed on social media affects employers' callback rate. We also show that mental health problems revealed through social media — such as hashtags and liked pages — have a significant negative impact on the job candidates' chances of employment. This creates a new channel for job market discrimination, contributing to the extensive literature on job-market discrimination, recently surveyed in Baert (2018b), Bertrand and Duflo (2017), and Neumark (2018). From another perspective, Becton et al. (2019), Bohnert and Ross (2010), Tews, Stafford, and Kudler (2020), and Zhang et al. (2020) use lab experiments to show that alcohol orientation, self-absorption, and unprofessional social media profiles have a significant negative effect on job candidates' ratings. We expand this strand by using an environment that is contextually closer to the environment of the recruitment decision and a more moderate "unappealing profile". Our more natural environment reinforces the external validity of our findings. Our moderate "unappealing profile" makes the results relevant to many social media users who might be interested in gaming, enjoy jokes about their job and are not always polite.

Third, and lastly, we are able to show how treatment effects change with the characteristics of the candidate and the evaluator. Most correspondence studies focus on the average treatment effect of one or two variables of interest. A few recent studies further examine the heterogeneity in recruitment behaviour across recruiters' gender and ethnicity, which they extract from the name of the recruiter in the contact information (Edo, Jacquemet, and Yannelis 2019; Erlandsson 2019) or using post-experiment interviews with recruiters (Carlsson and Rooth 2007). From the candidate side, Oreopoulos (2011) vary a large number of candidate ethnicity characteristics to better understand the variation in ethnic discrimination. The nature of correspondence studies makes any deviation from these minor variations challenging. We contribute to this literature by expanding the scope of heterogeneity analysis. Our design allows us to measure the correlation between the treatment effect size and different candidate and evaluator characteristics. With a large variation in candidate characteristics and rich data on the evaluators, we show that on the one hand, the negative effects of the unappealing profile, mental health problems, employment gaps and lack of social media profile are persistent for various characteristics of candidates and evaluators. On the other hand, some evaluators are more sensitive to some treatments than others.

The paper is organised as follows: Section 2 explains the design, Section 3 presents the research questions, Section 4 depicts and discusses the results and Section 5 concludes.

2 Design & Data

To study the effect of social media content on a candidate's chance of employment, we recruit 1,500 participants (evaluators) on Amazon Mechanical Turk and 500 participants with managerial and hiring experience from Prolific for a task of candidate screening. Each evaluator rates six fictitious candidates after viewing a CV and social media content. The evaluation is followed by a short questionnaire. The experiment was conducted using oTree (Chen, Schonger, and Wickens 2016).

2.1 Design

Figure 1: Stages of Experiment

Notes: See Appendix C.1 for a detailed screenshots of the experiment stages.

Evaluators The evaluators in the first participant pool, who participated between February and April 2022, are US residents, recruited from the online platform Amazon Mechanical Turk, which specialises in recruiting anonymous workers for small online tasks. Each evaluator received $ 7.50 for their participation. We chose this platform over survey companies to support the credibility of the design. To filter out non-US residents who could be accessing the platform through a VPN, and to verify the evaluator's attention, the process starts with a small English assignment. This assignment is easy for native speakers, but selects out non-native speakers and low-effort participants who just automatically click "continue". To avoid spillovers of evaluators from the same household, we exclude those with a similar IP address and geographic location. In total, 4390 evaluators accessed the task, 1638 passed the English assignment and saw the instructions for the task, and 1500 completed the task.[2] As Appendix Table B.1 shows, the sample includes enough variation to represent the general US population. We will refer to this sample as *"General Public"*.

The evaluators in the second participant pool, who participated between October and December 2023, are US residents who speak English as their first language, possess prior managerial experience

[2]Of those who did not continue to the task, 544 were rejected for having the same IP or location, 149 gave up on the first screen that announces this is a long HIT (see Appendix Figure C.1a), 388 gave up after seeing the English task, 931 clicked continue without attempting the task, and 740 failed the English assignment.

overseeing at least three subordinates, and have hiring experience. These evaluators were recruited from the online platform Prolific, which specialises in recruiting anonymous research participants. Each evaluator received $ 7.50 for their participation. To validate the quality and the recruitment and managerial experience of the participants, we first invited all the participants who qualified for our conditions based on the Prolific participant data to a short survey. The survey included an English task, identical to the task from MTurk described above, and an additional question that asked them how much experience they had in a few tasks (See Appendix Figure C.1c). Among them, unrelated tasks such as "translation from German to English" or "Social Media product management", and our tasks of interest, "Screening job applicants" and "Managing a project". We also included "programming in Qualtro," which is a programming language that does not exist. This allowed the exclusion of participants who did not validate the Prolific data on hiring experience or were not honest by saying they had experience in Qualtro. Reassuringly, more participants claimed to have 'some' or 'a lot' of experience in 'Screening job applicants' (93%) and in 'Managing a project' (93%) than claimed to have experience in the other tasks (an average of 32%)[3]. Of about 3,200 active participants who qualified for the first survey, 1,868 completed the survey, 1176 qualified for the evaluation task, and 500 completed the evaluation task. We will refer to this sample as *"Recruiters"*.

Setting After the participants' validation stage, we inform our evaluators that their task is to pre-screen candidates for a job in the hospitality sector. Similar to correspondence studies, we did not inform the evaluators this is an experiment.[4]

To make the task persuasive, we create an online platform that presents the position requirements and six different fictitious candidates to be rated. The recruiter views the candidates who each have a CV and an information table scraped from social media. The rating of the candidates is done on a scale of 0-10, specifically asking them not to rate two candidates exactly the same.[5] After completing the rating, the evaluators answer a short follow-up questionnaire.

CV design and content Our CVs have four parts: experience, education, skills, and interests. An individual CV is created by randomly selecting from six possible values for each of these categories and inserting them into one of six templates. Therefore there are 7776 possible CVs. This random assignment allows us to evaluate treatment effects across common qualifications characteristics. Figure C.1i in the appendix presents an example of a CV, and Table C.1 in the appendix presents all possible values. Experience ranges from 4 to 18.5 years and a greater number of years also implies a more senior job title.[6] Education ranges from candidates who have a qualification equivalent to a high school diploma to having a bachelor's degree and an additional professional qualification. Skills and interests are randomly assigned from 6 different clusters (see Table C.1 for more details).

The only treatment that required a change in the CV is the **Employment Gap Treatment**

[3] 52% of participants claimed to have 'a lot' of experience in 'Screening job applicants'; 54% in 'Managing a project'; 20% in 'Create content'; 15% in 'Data analysis project'; 2% in 'Writing code for games'; 1% in 'Programming in Qualtro'; 6% in 'Renovation of apartments'; 7% in 'Social Media Product Management'; 1% in 'Translation from German to English'

[4] As Baker, Grimm, and Ofek-Shanny (2021) show, discriminatory behaviour can change when evaluators know they are participating in an experiment. For the evaluators in the MTurk participant pool, we explicitly informed them that "*We help companies fill job vacancies. There are many candidates so we outsource part of the evaluation*". In contrast, participants on Prolific are already cognizant of their engagement in research; therefore, we did not explicitly state the purpose but simply wrote, "*In the following pages, you will be shown the résumés of six job candidates as well as some further information. Your task is to read them and pre-screen them by scoring them on a scale of one to ten*".

[5] This approach is realistic in a recruitment context, where the decision maker is often required to choose one candidate from a pool, even if two candidates appear equally qualified.

[6] One could also try to compare candidates with many years experience in a junior job, but this was not the focus of our study.

(Gap) (second row of Table 1). After randomly determining all the contents of a CV, we add a two-year unemployment gap lasting until the present while keeping the total number of years worked constant. All the other treatments are implemented through the social media content.

Social media design and contents The evaluator sees the social media content in a table that simulates data scraped from social media profiles (see Figure C.1i of the appendix for an example).[7] We answer the research questions by systematically modifying the social media content. Table 1 presents the change in content across treatments for experience, commonly used hashtags, "most active groups/pages on Facebook" and an automatic report on the grammar and tone of interactions. All six content variations were registered at the AEA Registry for both waves of the experiment.

As a **Control Treatment** (first row of Table 1), we use candidates, where neither the CV nor the social media content indicates an employment gap, and social media content features common and positive hashtags, groups and behaviour. For the control treatment, social media information is designed such that it does not give any reason to suspect that the candidates are not suitable for the job.

For our **Employment Gap Treatment (Gap)** (second row of Table 1), we add an additional entry lasting for the last two years stating "seeking employment". In the **Employment Gap and Lying About It Treatment (Gap+Lie)** (third row of Table 1), we add this entry only on social media, thus creating a contradiction between the CV and the social media content.[8]

For the **Mental Health Problems Treatment (Mental Health)** (fourth row of Table 1) mental health problems are indicated using hashtags and liked groups and pages. The items in the most used hashtag section include #recovery and one from #therapy, #bipolar, or #bipolardisorder. Two of the most active groups/pages are mental health groups such as "Defeat Depression", "Anxiety and Depression Support Group", etc. The other hashtags and groups are identical to the control treatment.

For the **Unappealing Social Media Treatment (Bad SM)** (fifth row of Table 1) we create the impression of someone with an interest in gaming rather than enthusiastic about work. To make the results relevant for a larger part of the population, we avoid mentioning anything obviously offputting such as alcohol use, drug use, violence, and racism. This treatment includes common hashtags such as #gaming or #fuckmylife. The active groups include popular groups of video games and funny groups like "I Hate Monday Mornings". The automatic report says the grammar is bad, and the language is generally neutral but sometimes negative or rude.

For the **No Social Media Treatment (No SM)** (last row of Table 1), we include the statement "no social media account found" in the social media content table.

Follow-up questionnaire To understand the underlying mechanisms and to allow heterogeneity treatment analyses, we ask the evaluators to fill out a short follow-up questionnaire, in which we ask them (1) about their characteristics, (2) whether they noticed any inconsistencies, and (3) some opinions. The first includes their demographic characteristics, social media usage frequency, and political orientation. The second includes whether they noticed any health problems, work experience inconsistencies, criminal activity, etc, in the applications. We use these questions to see whether the evaluators noticed the treatment variation. The third includes questions about the evaluators' opinions about what skills are important in the recruitment decision and about the role of social

[7] Similar to reports created by social media screening firms (see `https://www.accurate.com/employment-screening/social-media-searches/` for example). Chamorro-Premuzic et al. (2016) describe the potential of this practice in detail.

[8] The period of the last work experience entry on the CV simply continues to present. Guillory and Hancock (2012) show that people tend to use less deception on LinkedIn compared to a traditional CV, so this supports the possibility that a candidate will manipulate CV experience but not the experience on social media.

Table 1: Treatments

Treatment	CV	Social Media			
	Employment Gap	Employment Gap	Hashtag Examples	Groups/Pages Examples	Automatic Screening
Control	No	No	#teamwork #Nature #fitness	-Walking and talking -NowThis -Adele	-Positive language -Positive interactions -Good grammar
Gap	Yes	Yes	-	-	-
Gap+Lie	No	Yes	-	-	-
Mental Health	-	-	#therapy #bipolar #recovery	-Defeat Depression -Anxiety Lounge -Depression and Anxiety Talk	-
Bad SM	-	-	#tgif #tired #xbox	-I hate Monday mornings -grand theft auto V -call of duty	-Neutral language -Some negative interactions -Bad grammar
No SM	None	None	None	None	None

Notes: The table shows the variation in the information available on each candidate for each treatment. A '-' sign in the cell indicates that content is identical to the control treatment. For Hashtags and Groups/Pages the table shows three examples from a larger set of similar elements. For a full set content see Table C.2 in the appendix.

media in recruitment. To justify the questionnaire, we inform the evaluators that using social media in recruitment is a new component that we would like to evaluate. Where possible, we used existing questions already used in the literature to allow comparison with the US population. Appendix C.1 shows screenshots of all the questionnaire parts and Table B.2 lists the sources of the questions.

2.2 Data

This section describes the data we obtain from the experiment in detail. We divide our explanatory variables into four groups: (1) candidate variables, (2) evaluator characteristics, (3) evaluator opinions, and (4) evaluator engagement measures.

The *candidate variables* comprise working experience, education, CV skills, CV interests, candidate gender, the order in which the candidate appeared, and five LinkedIn endorsement variables. The *evaluator characteristics* comprise the evaluator's age, ethnicity, education, marital status, employment status, self-declared political orientation, and activity on selected social media platforms (Twitter, Instagram, Facebook, Snapchat, LinkedIn, and TikTok). The *evaluator opinions* comprise answers to three post-experiment survey questions measuring attitudes toward social media, three questions measuring attitudes toward privacy, questions asking whether the evaluator noticed particular features of the candidates, and lastly, questions asking what the evaluator values in a candidate. The *evaluator engagement* measures comprise the amount of time the evaluator spent reading the instructions, the mean number of times they clicked on a candidate, the mean number of characters they wrote in the provided notes section, and the minimum amount of time an evaluator spent looking at an individual candidate. A more detailed description of each variable can be found in Table B.2 in the appendix. All variables apart from the dummy variables are mean normalised. That is, they are demeaned and scaled by the range so that all elements of the vector lie between -0.5 and 0.5.

3 Research Questions

Our research questions are rooted in previous studies on general recruitment screening decisions and aim at extending or deepening insights. We specifically focus on information that was private prior to the social media period and has now become more accessible to employers. Specifically, the effect of employment gaps, lying about them, as well as the impact of mental health issues on recruitment, have previously been studied, with inconclusive results. The impact of the absence of social media content has not yet been studied.

The general effect of social media information Becton et al. (2019) and Tews, Stafford, and Kudler (2020) find that *unappealing profiles* indicating self-absorption, opinionatedness, rude behaviour, and alcohol or drug use, significantly reduce that candidate rating. Stuart (2006) reviews the broad literature on employment-related stigma and discrimination experienced by people with *mental health problems*. Recent experimental evidence also shows negative effect. Baert et al. (2016), Bjørnshagen (2021), and Hipes et al. (2016) all find lower callback rates for candidates indicating mental health problems in their job-application documents. For design reasons, all these studies analyse the combined effect of an employment gap and mental health problems. We study their effect separately. Ridley (2022) uses an online experiment to show workers with mental health problems are discriminated against even though they perform the task no worse than other workers. Kroft, Lange, and Notowidigdo (2013) find that *employment gaps* over nine months have a significant negative effect, but this effect does not increase further as the gap increases. Eriksson and Rooth (2014) find that the effect of a nine-month employment gap is equivalent to the difference between one and four years of occupational experience. Conversely, Farber, Silverman, and Von Wachter (2016) do not find an employment gap effect. Our main research question focuses on the effect of revealing these pieces of information on social media:

Research Question 1 (General effect) *What is the effect of social media content on candidate rating?*

The absence of social media To the best of our knowledge, the effect of lacking a social media profile has not yet been empirically studied. In a more general framework, several studies find a negative effect of missing information (Roth et al. 2016). The channels those studies refer to are either increased uncertainty or a signal for "having something to hide". From another perspective, lacking a social media presence can also indicate lower proficiency in the use of digital media. On the other hand, it can also be a positive indication of people who do not waste time on social media because they are more dedicated to work. Building on this discussion, we formulate the second question:

Research Question 2 (No SM profile) *What is the effect of the absence of social media profiles on candidate rating?*

Lying on CVs This is a widespread practice, usually involving small improvements in education or experience (Babcock 2003; Guillory and Hancock 2012). However, evidence of the effect of these lies is scarce (Henle, Dineen, and Duffy 2019). Wood, Schmidtke, and Decker (2007) find that overt misrepresentations reduced hiring intentions in the lab. Another paper, by Kuhn, Johnson, and Miller (2013), finds that minor embellishments had little effect on favoured candidates but a significant effect on less desirable candidates. We contribute to this strand by exploring the effect of a common minor misrepresentation:

Research Question 3 (Lie on CV) *What is the effect of an employment gap on social media but not on the CV indicating that the candidate is trying to conceal it?*

Evidence on heterogeneity The evidence on heterogeneity in treatment effects across candidate and evaluator characteristics is scarce. The treatment effect is usually studied using correspondence studies, which are limited in both dimensions. First, in order to guarantee sufficient statistical power, they usually vary only the treatment, holding all other candidate characteristics constant. Second, the identity and characteristics of the evaluator are usually unknown.[9] The scarcity of evidence motivated us to explore three additional questions:

Research Question 4 (Robustness) *Is the effect of social media content robust across candidate and evaluator characteristics?*

Research Question 5 (Heterogeneity) *Is there heterogeneity in the effect of social media information across candidate and evaluator characteristics?*

Research Question 6 (Evaluator opinions about social media) *Are the ratings of the evaluators guided by their opinions about the use of social media in recruitment?*

4 Results

In this section, we present and discuss the experimental results. Section 4.1 presents our main results on the significant and large effects of information revealed on social media. Section 4.2 presents the variation of our treatment effects across evaluator and candidate characteristics. Sections 4.3 and 4.4 discuss the internal and external validity of our results.

4.1 Effects of social media content

To estimate the effect of information revealed on social media on the rating of job candidates, we use OLS regression analysis. For the main results, our specification is

$$Rating_i = \beta_0 + T_{ki}\beta_k + X_i\gamma + \epsilon_i,$$

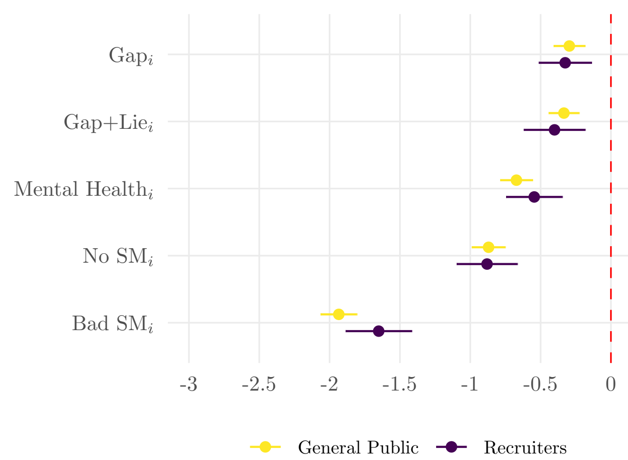
where $Rating_i$ is the score of candidate i, T_k are five treatment dummies (*Mental Health, Gap, Gap+Lie, Bad SM, No SM*) set to 1 when the candidate is part of the specific treatment and 0 otherwise. β_0 represents the control. The value of the other β's represents the difference in treatment effect compared to the control. X_i is a vector of candidate characteristics (*Experience, Education, Skills, Interests, Cand. Female, Order, and Endorsements*), and ϵ_i is the error term. All the regression and analysis are done separately for the and the recruiter's samples.

Figure 2 and Table B.3 present the effect of different treatments compared to the control treatment. Candidates with unappealing social media received, on average, the lowest ratings, 1.94 [Recruiters sample: 1.65] points lower than the candidates in the control treatment (on a scale of 0 to 10). The second worst were the candidates with no social media content (-0.88 on both samples). Evidence on social media indicative of mental health problems had a somewhat lower negative effect on candidate evaluation (-0.68, Recruiters: -0.54). The employment gap+lie (-0.33, Recruiters: -0.40), and employment gap (-0.29, Recruiters: -0.32) had the smallest average effects. All these results are significantly different from the evaluation of the control treatment and from each other based on the OLS results,

[9] A few exceptions: Edo, Jacquemet, and Yannelis (2019) and Erlandsson (2019) use the name of the recruiter in the contact information to identify gender and ethnicity; Carlsson and Rooth (2007) also add interviews with the recruiters and administrative data on firm characteristics; and Oreopoulos (2011) vary a large number of candidate ethnicity characteristics.

with the exception of the comparison between the two employment gap treatments. These results also qualitatively persist in a pairwise non-parametric test (Wilcoxon signed-rank) with Bonferroni corrections, (see Tables B.4a and B.4b in the appendix for a full summary). These findings allow us to answer our first three research questions.

Figure 2: Treatment Effects - General Public and Experienced Recruiters



Notes: Treatment effects relative to the control treatment. Treatment effect coefficients from an OLS regression (error bars indicate 95% confidence intervals). The dependent variable is the candidate score from 0 to 10. With evaluator fixed-effects and standard errors clustered on the evaluator level. Control variables include candidate characteristics - experience, education, skills, interests, LinkedIn endorsements, gender, and candidate order on the screen. Treatments are Gap - two-year employment gap indicated in the employment section of the CV and the social media; Gap+Lie - two-year employment gap indicated in the employment section of the social media and not on the CV, creating contradiction; Mental Health - hashtags and groups in the social media content indicate mental health problems; No SM - social media table indicates no social media account found; Bad SM - hashtags include #gaming, #fuckmylife, groups include - "I Hate Monday Mornings" and automatic screening report indicates "grammar is bad, language is generally neutral but sometimes negative or rude".

General effect of social media information Information from social media has an effect on candidate evaluation throughout all treatments. The 0.68 [Recruiters sample: 0.54] points difference between candidates with social media content that indicates mental health problems and the control treatment is equivalent to the effect we find for 3.3 [Recruiters: 2.8] years of on-the-job experience. While the negative effects of information on mental health problems on recruitment decisions are well known, our results show that the revelation of those aspects on social media could contribute to revealing these problems to employers, with the corresponding negative effect on labour market success. Given the increase of information on social media on the mental health status of users (Strano 2022), new artificial intelligence methods to identify the mental health condition of users (Kopel 2021) and match the information to a particular person, and the increase in the use of social media by employers, these results are likely to lead to an increase in mental health labour market discrimination.

Having an unappealing social media profile can dramatically reduce evaluations, thus impacting recruitment chances. A 1.94 point difference [Recruites: 1.65] between the candidates in the control treatment and those with unappealing social media profiles is equivalent to the effect we find for 9.4 [Recruites: 8.6] years of on-the-job experience. Previous studies that showed negative effects of social media content used extreme personality characteristics and content showing drug and alcohol use. Our findings show that even "normal" people, who like gaming, are sometimes in a bad mood and are able to joke about their work, can suffer from strong negative effects on their rating.

Result 1 (General effect): *Information revealed through social media content has a large and significant effect on candidate rating. Unappealing content has the largest effect (1.94 compared to control, Recruiters: -1.65) followed by mental health problems (-0.68, Recruiters: -0.54) and an employment gap (-0.29, Recruiters: -0.32).*

No Social Media profile Not only people with social media profiles are affected by employers' use of social media for screening. Surprisingly, candidates with no social media content scored 0.88 points lower than the control treatment, equivalent to the effect we find for 4.3 [Recruiters: 4.6] years of on-the-job experience. This effect is larger than the impact of a two-year employment gap (on both treatments), and the impact of mental health problems revealed on social media. The negative effect of not having a profile means that a job seeker cannot avoid the effects of social media simply by not being present.

Low ratings for candidates without social media may have several causes (Roth et al. 2016). First, less information could simply mean more risk to the employer due to uncertainty. Second, a lack of information could indicate that a candidate has something to hide.[10] Third, it can indicate low computer or social media skills that might be of value to the hospitality sector. Lastly, it could also indicate that the candidate is unaware of job-seeking recommendations and norms, which could be seen as a sign of lower candidate quality.

An analysis of the evaluators' notes provides evidence that all of these played at least some role. One evaluator notes the good experience of the candidate but regrets that "there is no social media activity to corroborate his claims" and concludes that "verification of written credentials would be a good idea". Another evaluator speculates that "they may have something to hide". A third notes that the lack of social media "may mean they aren't tech savy (sic)". Finally, one notes that the lack of "social media data is a bit odd. Maybe they're very introverted". Quantitatively, 'corroborate', 'hiding', 'tech', and 'introvert' all featured highly in the notes of the no social media treatment relative to their frequency in the notes of the other treatments (see Appendix Figures A.2 and A.3).

A closer examination of the notes suggests two primary concerns raised by the evaluators: increased uncertainty due to less information and the perception that lacking a social media presence is odd and potentially negative. To quantify the prevalence of each suggested cause, we manually examined all notes on candidates without social media profiles and categorized them. Among the 2000 candidates evaluated without social media, 79.8% [Recruiters: 66.6%] had notes with meaningful content (defined as more than 10 characters). Of those with meaningful notes, 55% [Recruiters: 59.7%] explicitly mentioned the absence of social media content. Within the evaluators that mentioned the absence of social media, 11.3% [Recruiters: 13.5%] referenced the lack of information, either required to assess the content of the resume or to provide some insight into the personality of the candidate. 12.8% [Recruiters: 12.6%] considered the absence of a social media profile as a "red flag," odd, or indicative of the candidate hiding something. Additionally, 3.9% [Recruiters: 2.5%] suggested that not having a profile could imply lower relevant skills, typically computer or social skills. The remaining comments generally mentioned the absence negatively, with 4.7% [Recruiters: 6%] suggesting overcoming this by asking for references or collecting soft information through the interview. On the other side of the

[10] John, Barasz, and Norton (2016) use a lab experiment to disentangle the first two causes and show they both have an effect. When rating hypothetical partners for dating, the partners that revealed information on desirable behaviours such as donating blood or money to charity were ranked highest (7.5 of 10). Partners for which the information was technically not available were ranked second (6.5) and those who refused to answer were ranked the lowest (6). This suggests a combined effect of missing information and the decision not to answer.

spectrum, 8.7% [Recruiters: 9.4%] viewed not having a social media presence as a positive attribute. Table XXX presents a few examples of the notes that relate to each category.

Summarising the answer to the second research question:

Result 2 (No SM profile): *The absence of social media content has a significant negative effect (-0.88 in both participant pools), which is larger than the effect we find for mental health problems (-0.68, Recruiters: -0.54), or an employment gap (-0.29, Recruiters: -0.32).*

Lie on CV The third result we derive from the treatment effects concerns the impact of dishonesty in the CV. Interestingly, candidates who lie about their employment history are rated similarly to those who are honest about it. Specifically, candidates who disclose an employment gap both in the CV and in social media data, score on average 0.29 [Recruiters: 0.32] points lower than the control treatment. Likewise, candidates who reveal the gap on social media while denying its existence in the CV, indicating deception, score on average 0.33 [Recruiters: 0.4] points lower. The difference between the two treatments is not statistically significant.

This effect of a two-year employment gap is equivalent to the effect we find of 1.4 [Recruiters: 1.7] years of on-the-job experience (1.6 and 2.1 for Gap+Lie treatment). Slightly smaller than the findings of Eriksson and Rooth (2014), who evaluate a 9-month gap as equivalent to the difference between one and four years of experience. Having extended unemployment for hospitality workers during the corona period is common and could explain the difference in effects. This played a role, at least with some evaluators. For example, one evaluator writes in the provided notes box that the candidate has not "worked in two years, but given covid that is understandable".[11]

The effect of a lie on the CV could go in both directions. On the one hand, some evaluators might not notice the gap in information in social media, making the gap+lie candidates identical to the control treatment candidates. On the other hand, evaluators who notice the lie on the CV could rate the candidate worse than those who were honest about the gap. If this were the case, we would expect a bimodal distribution of residualised candidate ratings and a significantly lower rating of evaluators who say they noticed work inconsistencies. We do not find evidence to support this.[12]

There are a few possible explanations for these results. In the post-evaluation questionnaire, approximately half of the evaluators explicitly mentioned observing work experience inconsistencies, so the effect could be masked by those who did not notice. Another plausible explanation is that individuals may have recognized the inconsistency but did not view it as a significant issue, possibly due to the expectation of minor discrepancies on CVs. Even when analyzing the Gap and Gap+Lie coefficients exclusively for evaluators who noticed work experience inconsistencies, the observed difference remains statistically insignificant. This explanation is also supported by Wood, Schmidtke, and Decker (2007), who found HR professionals did not perceive small misrepresentations as lies, and by the survey evidence that 78 percent of job candidates admit they lie on their job applications.[13] To conclude, the answer to our third research question is:

[11] The coefficients for the Recruiters' sample are slightly (and not statistically significant) larger. This aligns with the Recruiters' wave of the experiment, occurring a year later, making it more distant from the lockdowns and recessions associated with the initial impact of the coronavirus.

[12] According to Levene's test, the variance of candidate ratings in the Gap+Lie treatment group is not significantly different from the variance in either the control or gap treatment groups. A dip statistical test (J. A. Hartigan and P. M. Hartigan 1985) on the residuals from regressing candidate score on candidate characteristics for the Gap+Lie treatment group cannot reject the null hypothesis of unimodality.

[13] Liu, J. (2020, February 20). 78 percent of job seekers lie during the hiring process-here's what happened to 4 of them. CNBC. Retrieved April 25, 2022, from https://www.cnbc.com/2020/02/19/how-many-job-seekers-lie-on-their-job-application.html

Result 3 (Lie on CV): *The difference between the effect of having a two-year employment gap and being honest about it, and the effect of having the same gap and lying about it in the CV is not statistically significant.*

4.2 Heterogeneity and robustness of the effect of social media content across candidate and evaluator characteristics and opinions

Our setting provides a large variation in the candidate characteristics and rich data on our evaluators that allow us to explore the robustness and heterogeneity of the treatment effects. Qualitatively, the relative effect of the treatments is similar across groups and estimation methods. In all groups, the unappealing content on social media has the largest effect on recruitment, while a gap in employment years has the smallest effect. Despite the similar broad trends, we still find evidence for heterogeneity in the effect of several treatments. For example, female evaluators are more stringent toward the unappealing social media candidates, and perhaps unsurprisingly, evaluators who are active on social media are more likely to penalise candidates without a social media account.

Robustness The findings from the second wave of the experiment (Recruiters sample) provide substantial support for the robustness of our results. The main findings and most of the heterogeneous effects are replicated, indicating consistency a year later within a population possessing distinct hiring and managerial experience. To further investigate the robustness of our findings, we use three techniques. First, we evaluate treatment effects for subgroups of our sample. Second, we examine the statistical significance of our main results with non-parametric tests. Third, we reproduce our main results from the sample with weights assigned to the evaluators such that the weighted sample is comparable to the US population.

Figure 3 depicts the treatment effect for each subgroup of interest, evaluated by estimating separately and controlling for all other characteristics. The treatment effect sizes and the different treatments' rankings are consistent. The negative effect of an unappealing social media profile remains the strongest, around -2 points, and the negative effect of an employment gap remains the smallest, around -0.3 points for all subgroups. While the stability of the treatment effects strengthens the validity of the mean effect size, we also consider it to be an important contribution on its own. Usually, in the hiring literature, there is only limited information on the identity of the evaluator and small or no variation in the candidate characteristics in a way that does not allow such a wide examination of the robustness of the effects across evaluator and candidate characteristics. This answers RQ 4:

Result 4 (Robustness): *Treatment effects are robust to variation in candidate and evaluator characteristics. The relative effect of the treatments is similar across candidates and evaluators. In all sub-groups, unappealing social media content has the largest effect on rating, while a gap in employment years has the smallest effect.*

To examine how sensitive our results are to the parametric statistic assumptions, we also examine them using a non-parametric Wilcoxon signed-rank test with Bonferroni adjustment for multiple hypotheses. In the General Public sample, the effects for all treatments remain significantly different from each other at the 1% significance level with a few exceptions. The difference between the Gap and the Gap+Lie treatments remains insignificant, and the difference between the No Social Media treatment and the Mental Health treatment is significant only at the 5% significance level. In the Recruiters sample, Gap, Gap+Lie, and Mental Health treatments are not significantly different from

Figure 3: Treatment effects are robust to different types of candidates and evaluators

Notes: Treatment effect coefficients (with 95% confidence intervals) from regressing candidate scores onto treatment variables and candidate and evaluator characteristics for various subgroups of candidates and evaluators. The top three graphs show data partitioned by candidate characteristics: work experience level, education level on CV, and the candidate's gender as revealed by social media data. The bottom two graphs show self-reported evaluator characteristics: gender, and age.

each other, and Mental Health is also not significantly different from No SM. Tables B.4a and B.4b in the appendix present the detailed results.

To examine how sensitive our results are to the composition of the evaluators, we use entropy balancing (Hainmueller 2012) to assign weights to each evaluator in the General Public sample in a way that makes our evaluator population comparable to the US population. Specifically, the weighted sample is similar to the US population in age, gender, ethnicity, education, marital status, employment status, level of conservatism, and social media usage on Twitter, Instagram, Facebook, and Snapchat. The mean values for all these variables are presented in Appendix Table B.1. The balanced average treatment effects (differences from the control treatment) are slightly smaller but not significantly different than the baseline coefficients: -0.79 compared to -0.88 for the No Social Media treatment, -0.60 compared to -0.68 for Mental Health, -0.30 compared to -0.33 in the Gap+Lie and -0.24 compared to -0.29 in the Gap Treatment. There is no difference in the Bad Social Media treatment: both are -1.94. Figure A.4 and Table B.3 in the appendix, present the detailed results.

Heterogeneity While overall, Figure 3 indicates treatment effects are quite persistent, Table 2 reveals some interesting heterogeneity in the size of the effects. If not mentioned otherwise, the values reported in this section represent the average effect of moving from one extreme to the other (1 to 7 on a likert scale).

Considering the gender of the evaluators, we find that female evaluators are less tolerant of candidates with unappealing social media content, rating it 0.46 [Recruiters: 0.74] points lower than male evaluators. We did not find previous studies investigating which gender is harsher toward this kind of information about the job candidate. One possible interpretation of this finding is that women are more sensitive to toxic working environments (Spoon et al. 2023). A correlation could potentially exist between negative social media behavior and the perpetuation of such detrimental workplace atmospheres.

Result 5a (Heterogeneity): *Female evaluators rate candidates with unappealing social media content lower than male evaluators.*

Evaluators who are highly active on social media rated the candidates with no social media 0.61 [Recruiters: 0.96] points lower than evaluators who are less active on social media. With the increase in social media use in the last decade, the likelihood of having an active evaluator increases, amplifying the negative effect of not having a social media presence on job candidates even further.

Result 5b (Heterogeneity): *Evaluators who are more active on social media themselves rate candidates with no social media particularly harshly.*

Most candidate characteristics do not change the treatment effects (see Appendix Table B.6). However, the experience level of candidates significantly affects the size of the treatment effect. Specifically, the negative impact of lacking social media presence is reduced by 0.42 [Recruiters: 0.41] for candidates with extensive experience (although the coefficient is nearly the same, it lacks statistical significance in the Recruiters' sample). This supports the explanation that part of the no social media effect comes from increased uncertainty about the candidate. More experience (and education, though not statistically significant) reduces some uncertainty. In contrast, strong work experience does not ameliorate the effect of bad social media content – in fact, for the General Public sample, it even amplifies it.

Result 5c (Heterogeneity): *Candidates with more experience are less affected by the no social media content.*

Evaluators Opinions The opinions of our evaluators regarding employers' use of social media content are aligned with the candidates' rating choices. Evaluators who stated *employers should use social media to make recruitment decisions* rate unappealing social media candidates 1.47 [Recruiters: 1.9] points lower than those who state employers should not use social media.

Evaluators that strongly agreed with the statement that *social media content is important for recruitment* rated the unappealing social media profile 2.44 [Recruiters: 2.13] points lower, the candidates with no social media 1.15 [Recruiters: 1.18] points lower, and the mental health candidates 0.74 [Recruiters: 0.75] points lower than evaluators that strongly disagreed with the statement.

Evaluators that strongly agreed with the statement that *it is important to have a professional social media* rated the unappealing social media candidates 0.6 [Recruiters: 1.63] points lower, and the no social media candidates 0.6 [Recruiters: 1.05] points lower than evaluators who strongly disagreed with the statement.

Result 6 (Evaluator opinions about social media): *Evaluators who are positive about the importance of social media content and employer use of it are more affected by social media content.*

This evidence suggests that the choices of the evaluators are guided by their beliefs and preferences, and strengthen the validity of our results. We further discuss this in the next section.

4.3 Descriptive statistics support internal validity

Several measures taken during the experiment indicate that the evaluators took the task seriously and meaningfully. First, the effects of covariates are in the expected direction. Experience, education, and skills endorsements on LinkedIn positively affect the rating (see Appendix Figure A.3). Second, the response patterns indicate high engagement with the candidate's content. Evaluators took, on average, 163 [Recruiters: 130] seconds to review the information about each candidate, and 87 [Recruiters: 76] percent of them also voluntarily added notes to at least one candidate. Lastly, we also see a meaningful treatment effect on these response patterns. Evaluators spent the least on candidates with no social media data and made the longest notes on candidates with mental health problems or unappealing content.

The effects of the experiment's covariates indicate that the evaluators used all the available information for the evaluation. In line with common knowledge on the importance of experience, it has the strongest positive effect on the candidate rating followed by education and LinkedIn endorsements. Figure A.3 shows the effect of each covariate on the candidate rating. The values are standardised such that the coefficient value represents the average effect of moving from the lowest to the highest value. An increase from four years of labour market experience to 18.5 years increases the average rating by 2.97 [Recruiters: 2.78] points on a zero to ten scale. An increase from having a GED certificate to having a BA in business administration and a certificate in hospitality management increases the rating by 0.99 [Recruiters: 0.78] points. An increase from an average of five LinkedIn endorsements to 25 increases the rating by 0.60 [Recruiters: 0.61] points.

Time per candidate and note length also suggest that the evaluators took the task seriously. Figure 4a shows a histogram of the time the evaluators took to review each of the six candidates. The average and median time per candidate was 163 and 121 seconds, respectively [Recruiters: 129 and 91]. Less than five percent of the candidates were viewed for 30 seconds or less. While not specifically requested to add notes, 87 [Recruiters: 76] percent of the evaluators made at least one note. Figure 4b shows a histogram of the note length the evaluators wrote about each candidate. The mean and median note

Table 2: Interactions between evaluator characteristics and treatment

	Gap	Lie+Gap	Mental Health	No SM	Bad SM
General Public					
Eval. Female	-0.02	-0.08	-0.11	0	**-0.46*** **
Age	0.03	0.09	**-0.36***	0.05	-0.23
Eval. 'Conservative'	-0.23	0.06	**-0.42****	0.19	-0.09
Active on SM	0.11	-0.13	0.14	**-0.61*****	0.1
Graduate	**-0.22***	-0.15	0.03	0.03	0.13
SM Approval	0.26	0.17	-0.04	**-0.32***	-0.09
Employers should use SM.	-0.1	0.06	**-0.37***	**-0.45***	**-1.47*****
Professional SM Imp.	0.06	0.05	-0.33	**-0.6*****	**-0.6*****
Privacy	0.2	-0.02	-0.05	-0.09	**-0.5****
SM Contents Imp.	**-0.45***	-0.29	**-0.74*****	**-1.15*****	**-2.44*****
Recruiters					
Eval. Female	-0.09	-0.34	-0.12	0.11	**-0.74*****
Age	0.34	0.53	0.48	0.15	-0.17
Eval. 'Conservative'	0.05	**0.69****	-0.18	0.22	**0.93*****
Active on SM	0.03	0.29	**0.48***	**-0.96*****	0.51
Graduate	-0.11	-0.16	-0.22	**-0.59****	0.05
SM Approval	0.07	0.4	-0.02	**-0.64****	-0.16
Employers should use SM.	**-0.6***	**-0.87****	**-1.33*****	**-0.94****	**-1.9*****
Professional SM Imp.	-0.29	-0.4	-0.57	**-1.05*****	**-1.63*****
Privacy	0.47	0.08	**0.72****	0.27	**-0.76****
SM Contents Imp.	**-0.66***	-0.61	**-0.75***	**-1.18****	**-2.13*****

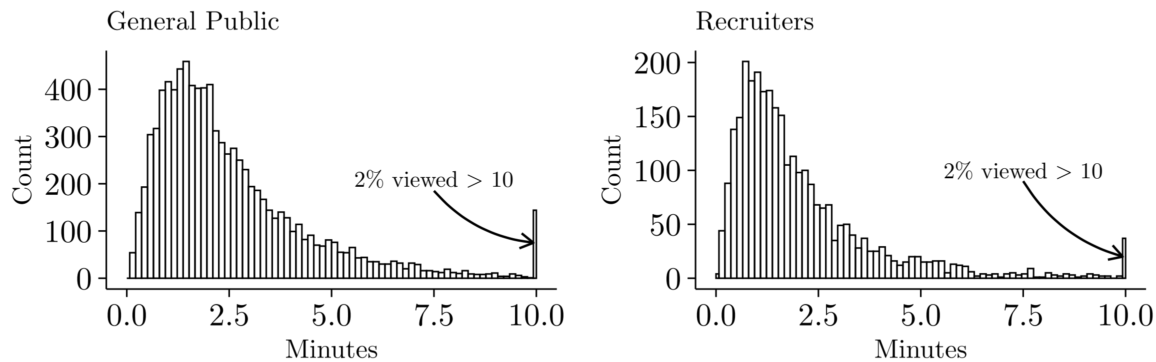
Notes: Table of coefficients of application characteristics interaction terms. Obtained by regressing application score on application characteristics, treatment variables, and the covariate in question interacted with each of the treatment variables. Explanatory variables are demeaned and standardized such that the coefficient value represents the effect of moving from the fifth to the ninety-fifth percentile apart from dummy variables (Eval. Female and Cand. Female). See detailed description of the variables in appendix Table B.2. *p<0.1; **p<0.05; ***p<0.01.

length was 113 and 89 characters, respectively [Recruiters: 80 and 56], equivalent to one sentence.

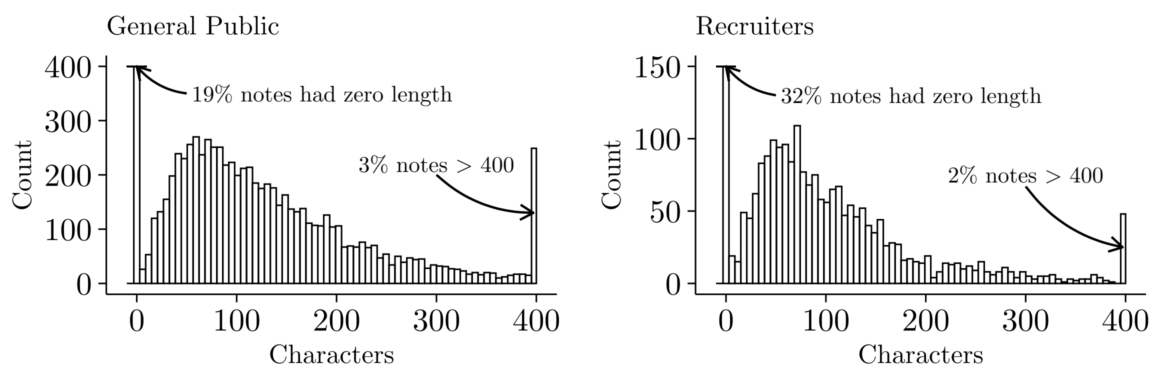
Figure 5a presents the time spent by treatment and Figure 5b does the same for note-length. On average, evaluators spent 22 seconds less on candidates with no social media content. The no social media candidates also had the shortest note length, similar to the note length of the control treatment candidates. We find this plausible since both candidates did not contain "additional" interesting information. The gap candidates had a slightly higher note length, followed by the gap lie, mental health, and the unappealing social media content with the longest notes, 22 characters longer than the control (these findings are very similar to both evaluator samples).

Figure 4: Evaluators spent time and effort rating the candidates

(a) Time per Candidate



(b) Note Length

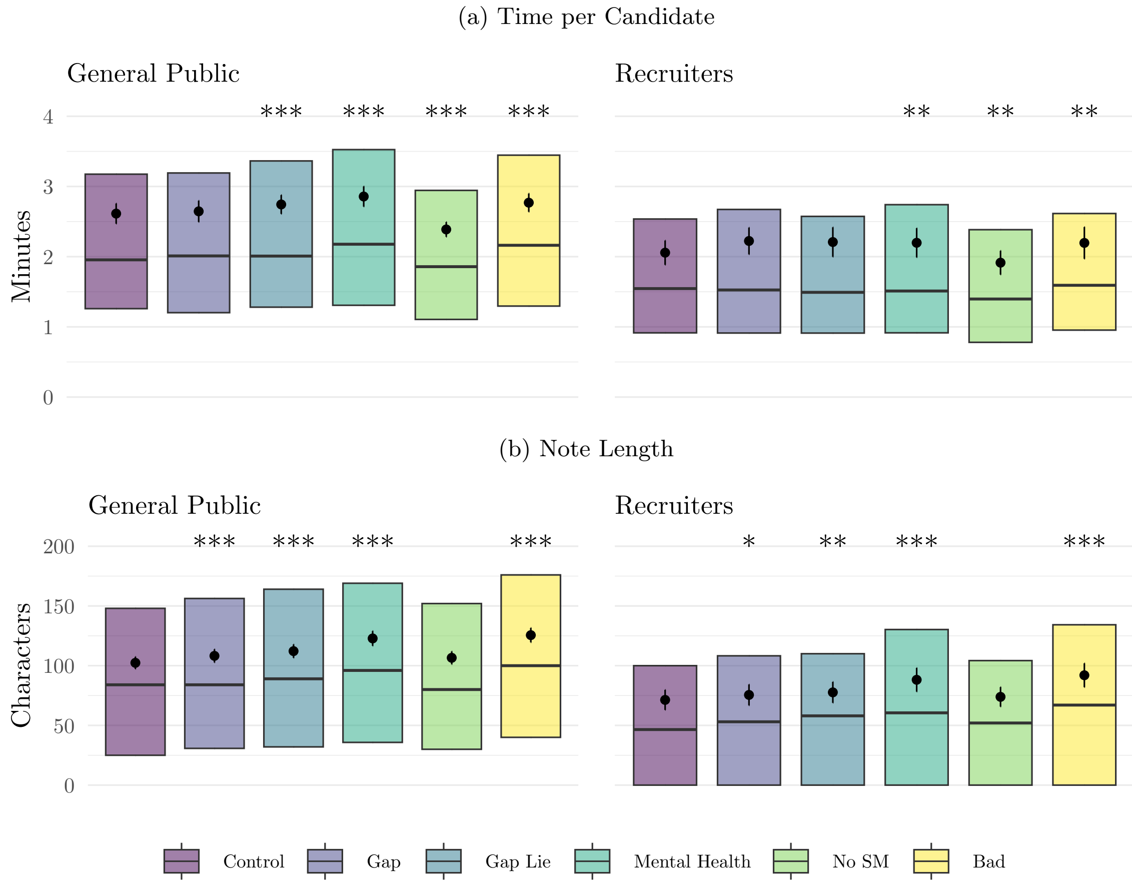


Notes: Histogram of time spent on each candidate and on the note length for each candidate. Two percent of candidates were viewed for more than 10 minutes. 19 percent of the candidates in the General Public and 32 percent of the candidates in the Recruiters sample had a zero note length, and three and two percent had a note length of longer than 400 characters, respectively.

4.4 External Validity

While our design is not a natural field experiment as the correspondence studies (recently surveyed in Baert 2018b), we incorporated various elements to enhance the external validity of the results. It strongly resembles a real-life recruitment task with either real workers on an online platform or experienced recruiters on a survey platform, paid to perform the task, and it allows us to collect a rich data-set to support the engagement of the evaluators. After providing evidence that our evaluators take their task seriously, we expand in this part, on the possible effects of the job type and the robustness of our results to the identity of the evaluators. In addition, we compare the strengths and weaknesses

Figure 5: Treatment Effects on Attention Measures



Notes: The figure presents the time the evaluators used to read the available information on each candidate and the length of the notes they wrote. The dots and error bars represent mean and 95% confidence intervals. The middle horizontal line is the median, and the top and bottom are the 25^{th} and 75^{th} percentiles, respectively. Asterisks denote significance from a Wilcoxon signed-rank comparison with the control treatment *p<0.1; **p<0.05; ***p<0.01.

of our and two other common methods.

Job type We chose a job of an office manager in the hospitality sector because it is relatively general with no unique qualifications. In particular, it does not require any social media use or skills. The job-description included requirements for hard-working, organised, and reliable worker with excellent customer service skills. We suggest our results are externally valid for the range of jobs with similar skill requirements. The effects of mental health problems and unappealing social media might be smaller for jobs without customer contact and might be larger for jobs with more managerial responsibilities. Also, since the experiment was conducted after a two-year corona period when many workers in the hospitality sector were unemployed, it might diminish the effect of an employment gap.

Identity of evaluators Our evaluators come from two participant pools - evaluators with managerial and hiring experience recruited through Prolific, and evaluators from the general public recruited from Amazon Mechanichal Turk. The results remain strong and significant across all the specifications. The two samples are diverse enough to allow robustness tests for different evaluators' distributions. Given that the results remain nearly unchanged for various sub-groups, we can confidently assert that the findings would persist even if evaluators were on average more or less educated, more or less active on social media, younger or older and so on. Particularly noteworthy is the substantial support provided by the Recruiters sample. The successful replication of results in a different evaluator pool, one year after the initial wave, significantly strengthens the validity of our findings. Furthermore, the inclusion of evaluators with managerial and hiring experience in the second pool further enhances the overall validity of the results. The results also remain strong and significant when we weigh the General Public regression according to the United States population.[14] It is also worth noting that the participant pool challenges other experimental methods as well. Lab experiments are rarely conducted using a representative sample, and correspondence studies are restricted to the population of employers who seek for employees at a specific time and specific jobs. Acquisti and Fong (2020), for example, indicate their sample has a small representation of Republican employers in a way that could blur or hide the treatment effects.

Validity compared to other methods We position our method between two strands of the recruitment literature - correspondence studies and lab or online experiments using human-resource workers as evaluators. The General Public sample resembles correspondence studies in that our evaluators are paid to make choices without being informed that this is an experiment. Both samples resemble lab experiments in that we collect a rich data set of evaluator characteristics, ratings, and behaviour. Naturally, this method has its disadvantages as well.

As in correspondence studies, our evaluators are not informed that the candidates are fictitious and the General Public evaluators are also not informed they are participating in an experiment (the evaluators in the Recruiters sample are also not informed, however, since Prolific is primarily used for research, we did not explicitly write this is an actual recruitment task). In this sense, our setting is closer to real life than lab experiments or online surveys. A disadvantage of our setting is that evaluating candidates online as an outsourcing task is not the most common practice.[15]

The incentives in our experiment differ from the incentives recruiters face in a correspondence study. However, while our evaluators are not directly incentivised to make the correct decision, Mechanical Turk workers and Prolific participants can receive negative customer feedback that affects their future employment opportunities. In a sense, this indirect incentive scheme is similar to most firms. Human resource employees are usually not incentivised "per recruitment". If they do a good job, they keep their position. Section 4.3 provides evidence that our evaluators are well motivated to do a good job.

5 Conclusion

Using a large-scale online experiment conducted in two waves (February-April 2022 and October-December 2023), we show that information revealed on social media significantly affects job candidate evaluation. An unappealing profile showing interest in gaming and jokes about work has a detrimental effect on the candidate's rating, equivalent to the value of nine years of on-the-job experience, according to our findings. Furthermore, our findings indicate that in the United States, in the third decade of the second millennium, the absence of a social media account has a more pronounced effect than experiencing mental health problems or having a two-year employment gap in the recent past. The

[14] See Table B.3 and Figure A.4 in the appendix for a comparison of the baseline and balanced results. Figure 3 shows that the treatment effects and order of effect size remain for sub-groups based on observable characteristics.

[15] Although some media reports indicate that it is a common practice, for example, the following quote from Harvard Business Review: "Many U.S. companies - about 40%, according to research by Korn Ferry - have outsourced much if not all of the hiring process to 'recruitment process outsourcers,' which in turn often use subcontractors, typically in India and the Philippines" (Cappelli 2019).

experimental findings are robust to variation in candidate and evaluator characteristics and replicate well in a second wave of evaluation conducted by evaluators with managerial and hiring experience.

Our results bear important implications for stakeholders in the recruitment process - workers, employers, researchers, and policymakers. While current recommendations for job seekers include avoiding hate, racism, alcohol, and drugs, we show that job seekers should be much more cautious than that about the content they reveal on social media. We further show that when well managed, social media presence is crucial for a good rating in the evaluation process.

Employers should consider how to guide their HR team when using social media for screening. This is also a concern from a general welfare perspective. Our experimental recruiters harshly judge people with unappealing social media content. As far as we have found, this kind of content does not indicate an equivalent decrease in productivity to these types of social media users in their workplace. Likewise, no evidence indicates that individuals without social media profiles are less competent or productive in their work. Consequently, our findings imply that recruitment based on these assessments may not be optimal, resulting in sub-optimal matches at the organizational level and reduced efficiency in the labour market, which can ultimately detrimentally affect overall welfare.

From the perspective of policymakers, the strong impact of information revealed on social media raises the concern that social media reinforces existing patterns of labour market discrimination. Further, the strong effect of not having a profile indicates that not revealing any information on social media is also penalised. A policy aimed at reducing labour market discrimination should consider these changes in recruitment patterns and adjust the regulations accordingly.

For researchers, this paper highlights the importance of social media in future correspondence studies. Of more than 100 correspondence studies published since 2015, only 3 included social media profiles for the candidates.[16] With 90 percent of employers looking for content on social media and with social media content having such a strong effect, studies that refrain from including social media might be studying only a partial effect.

[16] Our analysis based on the studies documented in the register of correspondence experiments on the website of Stijn Baert, https://users.ugent.be/~sbaert/research_register.htm, accessed on 15.5.2022.

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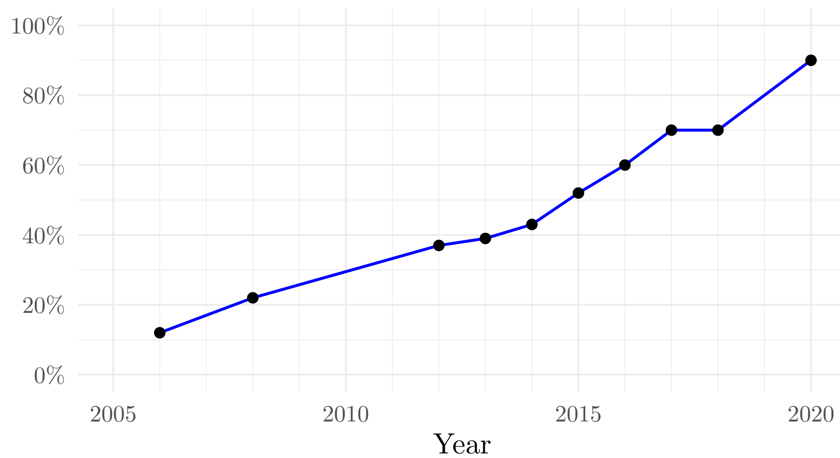
Appendices

A Figures

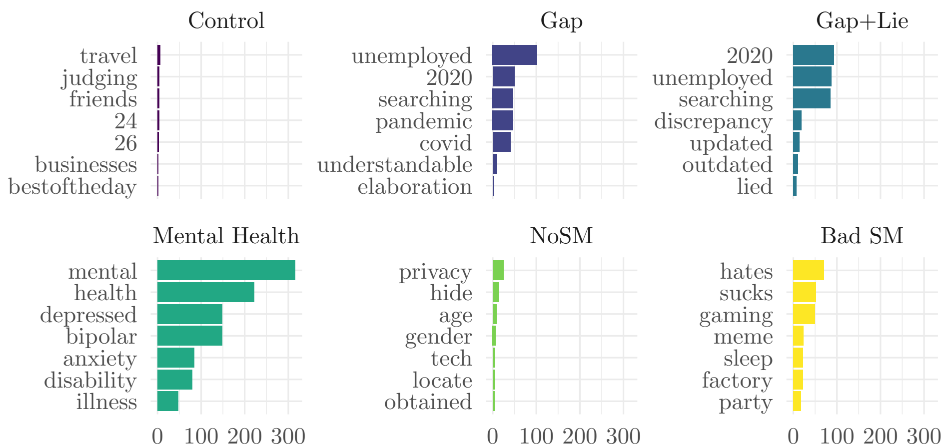
Figure A.1: Share of Employers using social media in the screening process



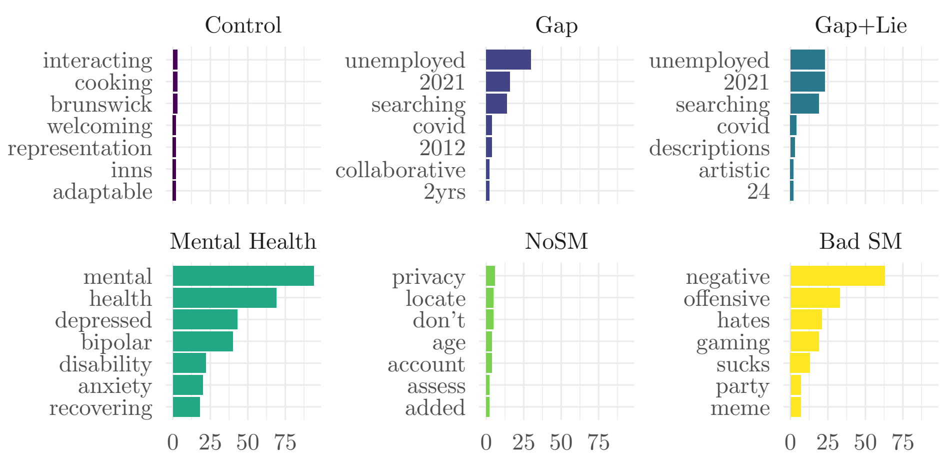
Notes: According to the Careerbuilder surveys from 2006 to 2018, the number of hiring managers who "used social networking sites to research job candidates during the hiring process", went from 12% to 70% (Careerbuilder 2018), and according to 'the Manifest 2020 recruitment survey' 90% of employers say "social media is important when evaluating a job candidate" (Mckeon 2020).

Figure A.2: Term frequency in notes by treatment

(a) General Public

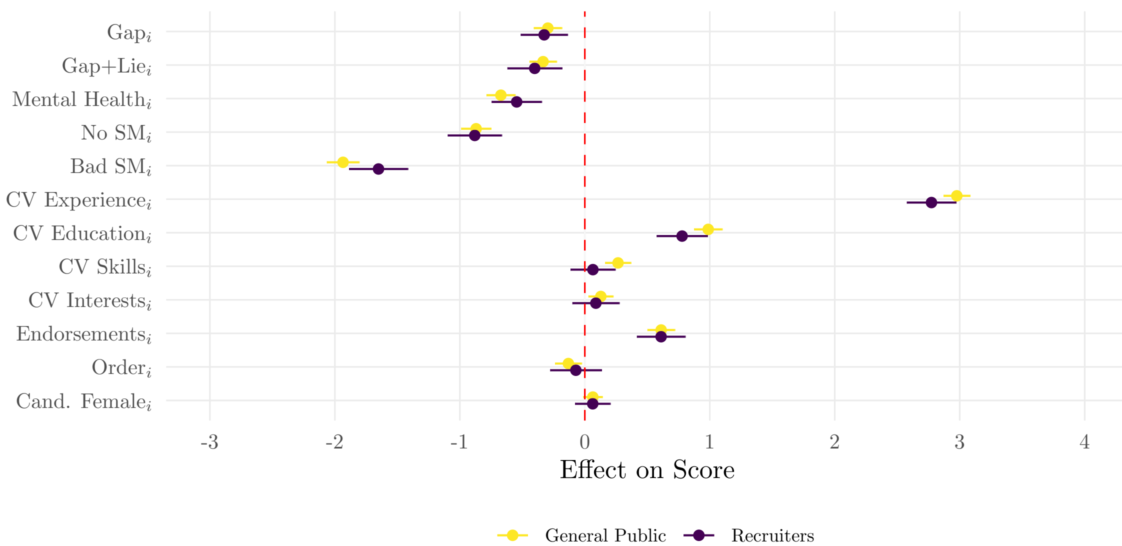


(b) Recruiters



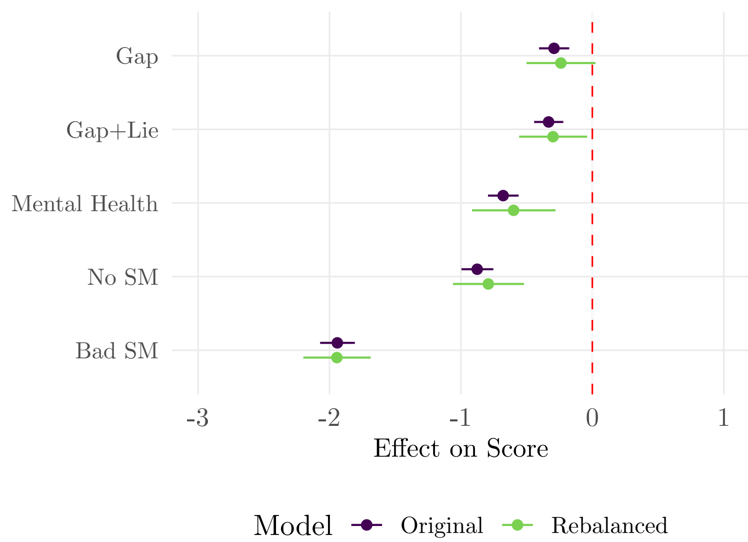
Notes: The graphs show the top seven terms that were commonly used by participants in the notes section for each treatment but not in the other treatments. This is calculated by 'Term Frequency times Inverse Document Frequency' ($TF\text{-}IDF$) (Salton and Buckley 1988). The bars show the simple term frequency of that term in the notes of that treatment.

Figure A.3: Coefficient plot - OLS regression for determinants of candidate score



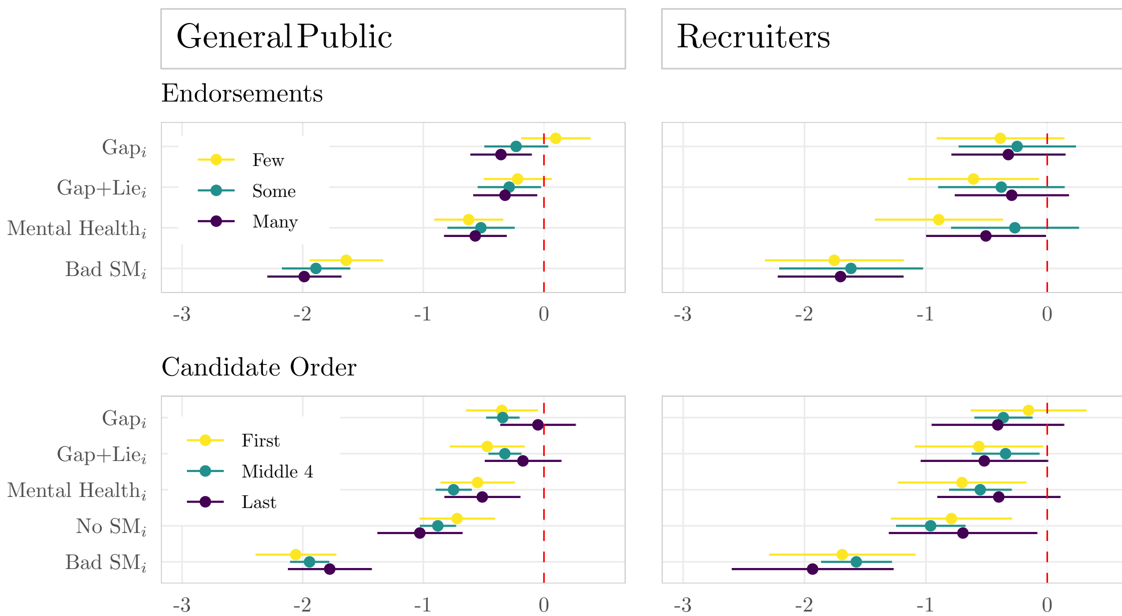
Notes: Coefficients from an OLS regression (error bars indicate 95% confidence intervals). Dependent variable is candidate score from 0 to 10. Explanatory variables include candidate characteristics - experience, education, LinkedIn endorsements, gender, and order in which the candidate was shown, and treatment dummies. All variables apart from dummy variables are demeaned and scaled by the range so that all elements of the vector lie between -0.5 and 0.5. Gap - two year employment gap indicated in the employment section of the CV and the social media. Lie + Gap - two year employment gap indicated in the employment section of the social media and not on the CV, creating contradiction. Mental Health - hashtags and groups in the social media content, indicate mental health problems. No SM - social media table indicates - no social media account found. Bad SM - hashtags include - #gaming, #fuckmylife; groups include - "I Hate Monday Mornings" and automatic screening report indicates - "grammar is bad, language is generally neutral but sometimes negative or rude". For more information on covariates see appendix Table B.2.

Figure A.4: Treatment Effects - General Public



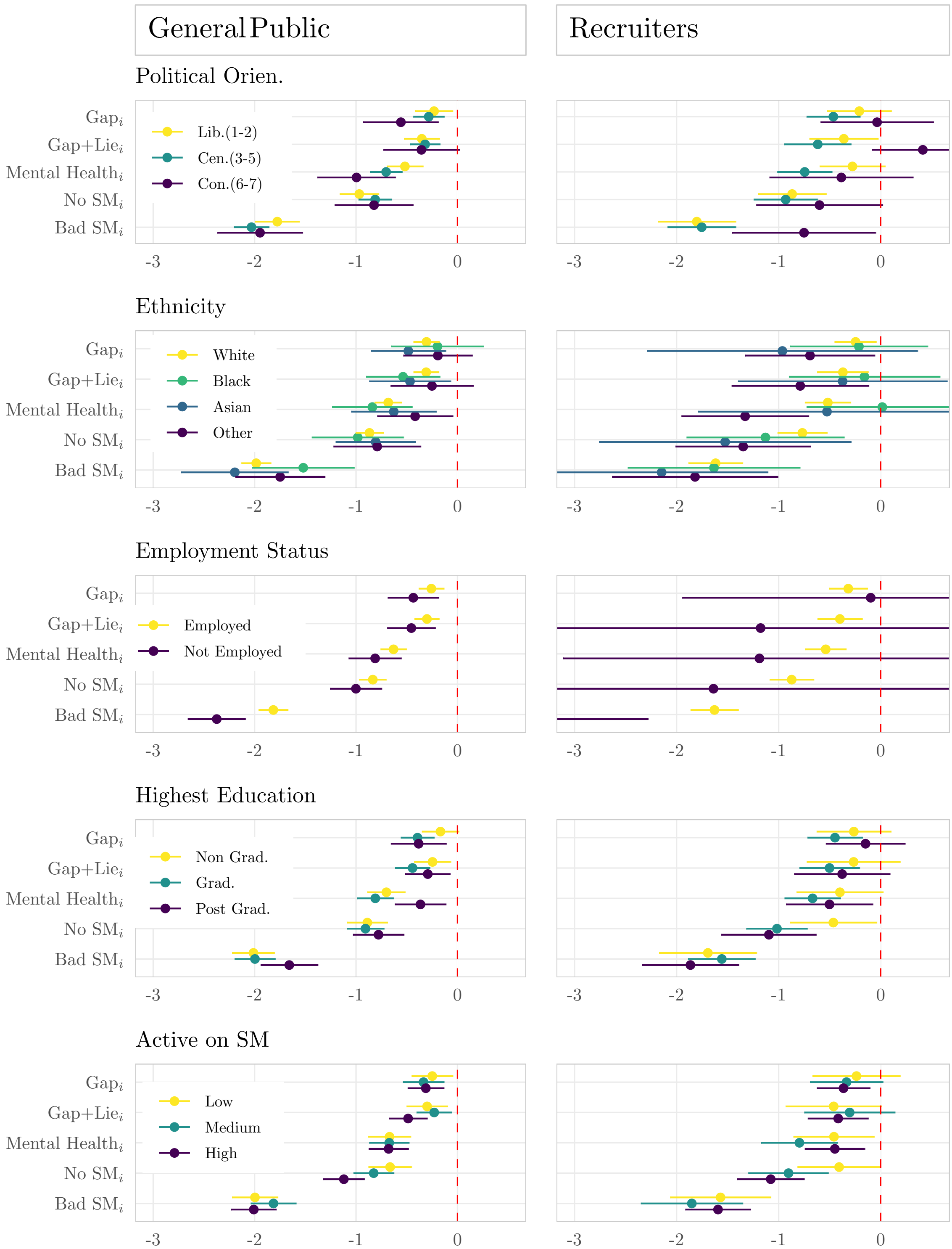
Notes: Treatment effects relative to the control treatment. Treatment effect coefficients from an OLS regression (error bars indicate 95% confidence intervals). The dependent variable is the candidate score from 0 to 10. With evaluator fixed-effects and standard errors clustered on the evaluator level. The plot shows both the original coefficients and the coefficients following multivariate reweighting using Entropy balancing (Hainmueller 2012, implemented using ebalance R function). Control variables include candidate characteristics - experience, education, skills, interests, LinkedIn endorsements, gender, and candidate order on the screen. Variables used for rebalancing to the US population are age, gender, ethnicity, education, marital status, employment status, level of conservatism, social media usage - Twitter, Instagram, Facebook, and Snapchat. Treatments are Gap - two-year employment gap indicated in the employment section of the CV and the social media; Gap+Lie - two-year employment gap indicated in the employment section of the social media and not on the CV, creating contradiction; Mental Health - hashtags and groups in the social media content, indicate mental health problems; No SM - social media table indicates - no social media account found; Bad SM - hashtags include - #gaming, #fuckmylife; groups include - “I Hate Monday Mornings” and automatic screening report indicates - “grammar is bad, language is generally neutral but sometimes negative or rude”.

Figure A.5: Treatment effects are robust to different types of candidate.



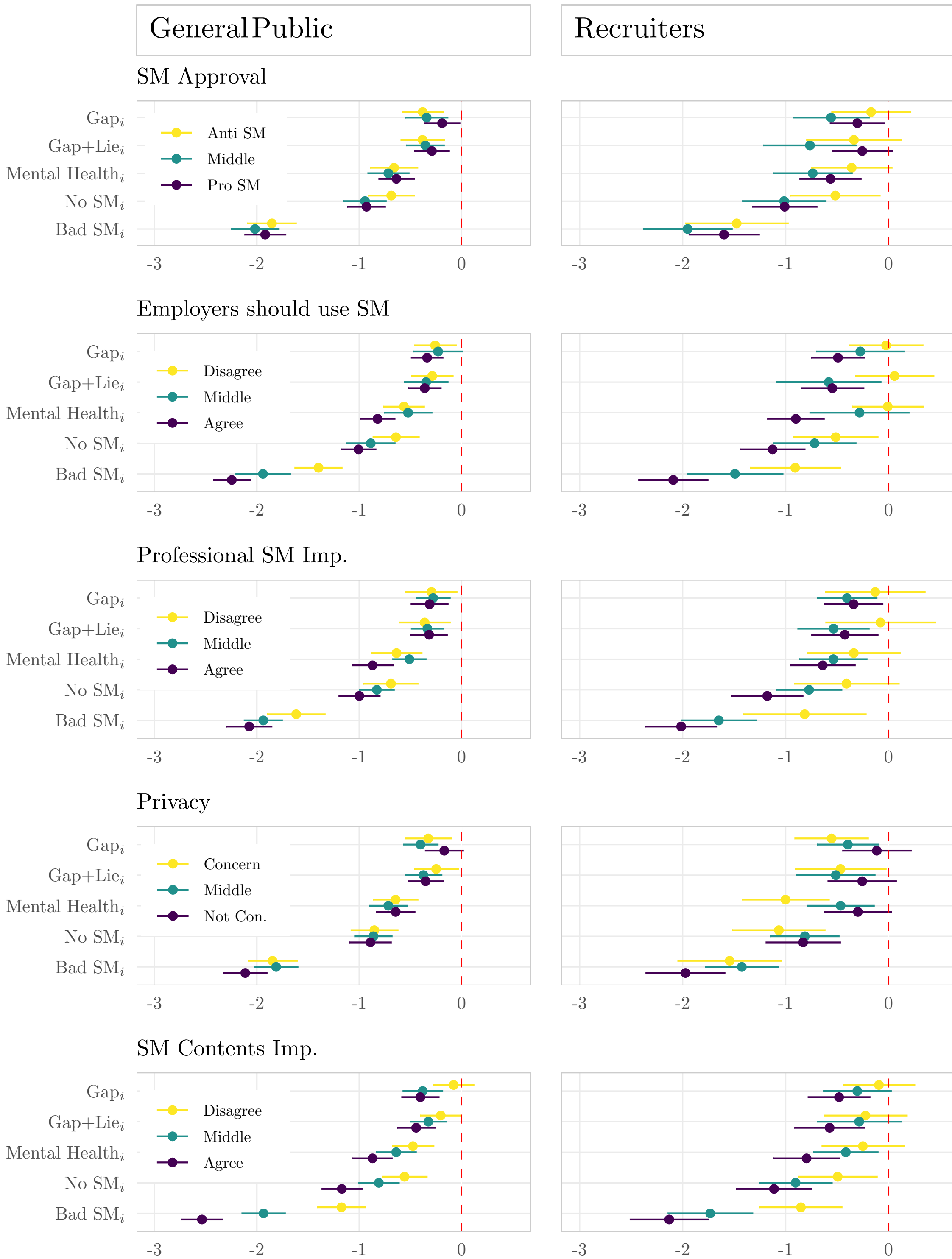
Notes: Treatment effect coefficients (with 95% confidence intervals) from regressing candidate scores onto treatment variables and candidate characteristics for various subgroups of candidates. The graphs show data partitioned by candidate characteristics: the number of endorsements of skills in the social media data and the order in which the CVs were shown.

Figure A.6: Treatment effects are robust to different types of evaluator.



Notes: Treatment effect coefficients (with 95% confidence intervals) from regressing candidate scores onto treatment variables and candidate characteristics for various subgroups of evaluators. The graphs show self-reported evaluator characteristics: political orientation on a scale of one to seven, ethnicity, employment status, highest education and a joint index for how active they are on six social media platforms.

Figure A.7: Treatment effects are robust to different types of evaluators opinions.



Notes: Treatment effect coefficients (with 95% confidence intervals) from regressing candidate score onto treatment variables and candidate characteristics for various subgroups. The graphs show data partitioned by evaluator opinions: general approval of social media; how much the evaluator thinks employers should use SM in recruitment, how important the evaluator thinks it is to have a professional SM presence, how unconcerned the evaluator is with privacy in relation to SM, how important the evaluator thinks SM contents are in the context of recruitment.

B Tables

Table B.1: Summary Statistics Comparing our Sample with the U.S. Population

	Original (N=1500)	Recruiters (N=500)	U.S Population
Age			
- Mean (SD)	39.833 (12.029)	43.132 (10.733)	38.2
- Range	18.000 - 78.000	24.000 - 70.000	
Eval. Gender			
- Female	932 (62.1%)	210 (42.0%)	50.8%
- Male	551 (36.7%)	284 (56.8%)	49.2%
- Other	17 (1.1%)	6 (1.2%)	
Eval. Ethnicity			
- Asian	95 (6.3%)	23 (4.6%)	5.9%
- Black or African American	126 (8.4%)	43 (8.6%)	13.4%
- White	1156 (77.1%)	385 (77.0%)	60.1%
- Other	123 (8.2%)	49 (9.8%)	20.6%
Education			
- Not Graduate	912 (39.2%)	134 (26.8%)	62.2%
- Graduate	588 (60.8%)	366 (73.2%)	37.8%
Eval. Marit. Stat.			
- Married or Domestic Partnership	741 (49.4%)	307 (61.4%)	47.8%
- Not Married	759 (50.6%)	193 (38.6%)	52.2%
Eval. Employ. Stat.			
- Employed for wages	918 (61.2%)	461 (92.2%)	41.57%
- Out of work	97 (6.5%)	1 (0.2%)	5.9%
- Retired	72 (4.8%)	2 (0.4%)	29.4%
- Self-employed	257 (17.1%)	31 (6.2%)	8.75%
- A homemaker	70 (4.7%)	0 (0.0%)	4.28%
- Other	86 (5.7%)	5 (1.0%)	10.1%
Eval. 'Conservative'			
- Mean (SD)	3.411 (1.628)	3.368 (1.697)	3.366
- Range	1.000 - 7.000	1.000 - 7.000	0.000 - 7.000
Twitter			
- Mean (SD)	3.348 (2.132)	3.880 (2.094)	1.864
- Range	1.000 - 7.000	1.000 - 7.000	1.000 - 7.000
Instagram			
- Mean (SD)	3.819 (2.087)	4.226 (2.000)	2.612
- Range	1.000 - 7.000	1.000 - 7.000	1.000 - 7.000
Facebook			
- Mean (SD)	4.555 (2.029)	4.744 (1.955)	4.105
- Range	1.000 - 7.000	1.000 - 7.000	1.000 - 7.000
Snapchat			
- Mean (SD)	2.141 (1.827)	2.408 (1.956)	2.0375
- Range	1.000 - 7.000	1.000 - 7.000	1.000 - 7.000

Notes: The U.S. population values for variables Age, Eval. Gender, Eval. Ethnicity, Education, Eval. Marit. Stat. are from the US census. Eval. Employ. Status is from the BRFSS survey. Eval. Conservative is from the GSS survey. Twitter, Instagram, Facebook and Snapchat are from Pew Research.

Table B.2: Variable names and their descriptions.

Name	Description	Source
Treatment Variables		
Gap_i	Candidate had a work experience gap for the last two years as indicated in CV and SM.	
Lie+Gap_i	Candidate had a work experience gap for the last two years but claimed to be employed on the CV.	
Mental Health_i	Candidate SM indicated the applicant was suffering from mental health issues.	
No SM_i	Stated that the candidate's SM could not be found.	
Bad SM_i	Candidate had relatively unappealing SM data.	
Candidate Characteristics		
Experience_i	Years of job experience on application.	
Education_i	Years of education on CV.	
Skills_i	Categorical variable of skills on CV.	
Interests_i	Categorical variable of hobbies and interests on CV.	
Cand. Female_i	Candidate is female.	
Order_i	Order that the candidate was shown to the evaluator.	
Teamwork_i	The number of LinkedIn endorsements for the skill of Teamwork	
Time Management_i	The number of LinkedIn endorsements for the skill of Time Management.	
$\text{Microsoft Office}_i$	The number of LinkedIn endorsements for the skill of Microsoft Office.	
Administration_i	The number of LinkedIn endorsements for the skill of Administration.	
$\text{Customer Service}_i$	The number of LinkedIn endorsements for the skill of Customer Service.	
Endorsements_i	The mean of the five above LinkedIn endorsements of skills.	
Evaluator Characterristics		
Age_j	Age of the evaluator.	Census
Eval. Female_j	Evaluator is female.	Census
Eval. Ethnicity_j	Ethnicity of the Evaluator.	Census
Eval. Education_j	Highest education level of the evaluator.	Census
Graduate_j	Evaluator is a graduate.	Based on Eval. Education
$\text{Eval. Marit. Stat.}_j$	Marital status of the evaluator.	Census

Eval. Employ. Stat.$_j$	Employment status of the evaluator.	BRFSS, variable :'EMPLOY1' Madden 2014
Eval. 'Conservative'$_j$	Self declared political orientation of the evaluator from liberal to conservative.	NORC GSS, variable: 'polviewy' Smith 2018
Twitter$_j$	How active the evaluator is on Twitter.	Pew Research, Social Media Use in 2021 Auxier and Anderson 2021
Instagram$_j$	How active the evaluator is on Instagram.	Pew Research, Social Media Use in 2021 Auxier and Anderson 2021
Facebook$_j$	How active the evaluator is on Facebook.	Pew Research, Social Media Use in 2021 Auxier and Anderson 2021
Snapchat$_j$	How active the evaluator is on Snapchat.	Pew Research, Social Media Use in 2021 Auxier and Anderson 2021
LinkedIn$_j$	How active the evaluator is on LinkedIn.	Pew Research, Social Media Use in 2021 Auxier and Anderson 2021
TikTok$_j$	How active the evaluator is on TikTok.	Pew Research, Social Media Use in 2021 Auxier and Anderson 2021
Evaluator Opinions		
Stay in touch.$_j$	Evaluator agreement with: 'Social networks are a great way for people to stay in touch with one another'.	Social Media Affinity Scale Gerlich, Browning, Westermann, et al. 2010
Too much time.$_j$	Evaluator agreement with: 'It consumes too much time to maintain and/or read social networking pages.' (Reversed such that higher means disagreement)	Social Media Affinity Scale Gerlich, Browning, Westermann, et al. 2010
Employers should use SM.$_j$	Evaluator agreement with: 'Potential and/or existing employers should use information found on social networking pages to make decisions about prospective and/or existing employees.'	Social Media Affinity Scale Gerlich, Browning, Westermann, et al. 2010
Professional SM Imp.$_j$	Evaluator agreement with: 'I think it is important to have a professional social media presence.'	Social Media Affinity Scale Gerlich, Browning, Westermann, et al. 2010
Lost control of data.$_j$	Evaluator agreement with: 'People have lost control over how personal information is collected and used by all kinds of entities.' (Reversed such that higher means disagreement)	Pew Research center's internet project/GFK privacy panel Madden 2014
Data concern (advertisers)$_j$	Evaluator agreement with: 'I am concerned about advertisers and businesses accessing the data I share on social media platforms.' (Reversed such that higher means not concerned)	Pew Research center's internet project/GFK privacy panel Madden 2014
Data concern (employers)$_j$	Evaluator agreement with: 'I am concerned about future and current employers accessing the data I share on social media platforms.' (Reversed such that higher means not concerned)	Pew Research center's internet project/GFK privacy panel Madden 2014
Notic. Exper. Inc.$_j$	Evaluator saw evidence of work experience inconsistencies in the application.	

Notic. Educ. Inc.$_j$	Evaluator saw evidence of education and qualification inconsistencies in the application.
Notic. Health Prob.$_j$	Evaluator saw evidence of health problems in the application.
Notic. Crime$_j$	Evaluator saw evidence of criminal activity in the application.
Notic. Discrim.$_j$	Evaluator saw evidence of discriminatory behaviour in the application.
Notic. Anything Else$_j$	Evaluator saw evidence of anything else we should be aware of in the application.
Teamwork Imp.$_j$	Importance the evaluator places on teamwork.
Communi. Imp.$_j$	According to the evaluator, how important is it that an applicant has communication skills.
Admin. Imp.$_j$	According to the evaluator, how important is it that an applicant has administration skills.
Cust. Serv. Imp.$_j$	According to the evaluator, how important is it that an applicant has customer service skills.
IT Skills Imp.$_j$	According to the evaluator, how important is it that an applicant has IT skills.
Exper. Imp.$_j$	According to the evaluator, how important is it that an applicant has good previous working experience.
Educ. Imp.$_j$	According to the evaluator, how important is it that an applicant has a good education.
Hobbies Imp.$_j$	According to the evaluator, how important is it that an applicant has interests and hobbies outside of work.
CV Contents Imp.$_j$	According to the evaluator, how important are the contents of the applicant's resume for the recruitment process.
SM Contents Imp.$_j$	According to the evaluator, how important are the contents of the applicant's social media accounts for the recruitment process.
Active on SM$_j$	Mean of variables Twitter, Instagram, Facebook, Snapchat, LinkedIn and TikTok.
SM Approval$_j$	Mean of variables 'Stay in touch.', 'Too much time.', 'Employers should use SM.', and 'Professional SM Imp.'

Privacy_j	Mean of variables 'Lost control of data.', 'Data concern (advertisers)', and 'Data concern (employers)'

Table B.3: Models

	General Public			Recruiters	
	OLS	Ordered Logit	Rebalanced	OLS	Ordered Logit
	(1)	(2)	(3)	(4)	(5)
Gap_i	-0.292^{***}	-0.346^{***}	-0.239^{*}	-0.320^{***}	-0.482^{***}
	(0.057)	(0.066)	(0.133)	(0.095)	(0.113)
Gap+Lie_i	-0.333^{***}	-0.376^{***}	-0.299^{**}	-0.399^{***}	-0.460^{***}
	(0.056)	(0.066)	(0.131)	(0.111)	(0.114)
Mental Health_i	-0.679^{***}	-0.795^{***}	-0.599^{***}	-0.543^{***}	-0.709^{***}
	(0.059)	(0.066)	(0.161)	(0.102)	(0.113)
No SM_i	-0.876^{***}	-0.891^{***}	-0.792^{***}	-0.880^{***}	-0.912^{***}
	(0.061)	(0.066)	(0.137)	(0.110)	(0.114)
Bad SM_i	-1.940^{***}	-2.266^{***}	-1.944^{***}	-1.651^{***}	-1.804^{***}
	(0.066)	(0.072)	(0.130)	(0.120)	(0.119)
Observations	9,000	9,000	9,000	3,000	3,000
Adjusted R^2	0.450		0.494	0.395	

Notes: Robust standard errors clustered on evaluator. Dependent variable is candidate score from 0 to 10. Original is an unweighted regression. 'Rebalanced' is a weighted regression with weights calculated using Entropy balancing (Hainmueller 2012, implemented using ebalance R function) to match the US population. Control variables comprise candidate characteristics - experience, education, skills, interests, LinkedIn endorsements, gender, and the order in which the candidate is shown. Variables used for rebalancing to the US population are age, gender, ethnicity, education, marital status, employment status, level of conservatism, social media usage (Twitter, Instagram, Facebook, and Snapchat). Treatments are Gap - two year employment gap indicated in the employment section of the resume and the social media; Lie + Gap - two year employment gap indicated in the employment section of the social media and not on the resume, creating contradiction; Mental Health - hashtags and groups in the social media content, indicate mental health problems; No SM - social media table indicates - no social media account found; Bad SM - hashtags include - #gaming, #fuckmylife; groups include - 'I Hate Monday Mornings' and automatic screening report indicates - 'grammar is bad, language is generally neutral but sometimes negative or rude'. *p<0.1; **p<0.05; ***p<0.01

Table B.4: Non-Parametric Pairwise Comparisons with Bonferroni Adjustment

(a) General Public

Treatment	Gap	Gap+Lie	Mental Health	No SM	Bad
Control	***	***	***	***	***
Gap		ns	***	***	***
Gap+Lie			***	***	***
Mental Health				**	***
No Data					***

(b) Recruiters

Treatment	Gap	Gap+Lie	Mental Health	No SM	Bad
Control	***	***	***	***	***
Gap		ns	ns	***	***
Gap+Lie			ns	***	***
Mental Health				ns	***
No Data					***

Notes: Pairwise comparisons conducted using Wilcoxon signed-rank test. Shows Bonferroni adjusted p-values. *p<0.10; **p<0.05; ***p<0.01

Table B.5: Examples of Evaluator Notes on Job Candidates with No Social Media Data

Note	Increased Uncertainty	Red Flag	Low Skills	Ask for Info
Great bachelors at a great university. Good experience at hotels. No social media, so lack of other information. I feel like a manager in the tourism industry must be good at social media.	1		1	
No social media data is a concern but this could be cleaned up in an interview	1			1
This applicant has a stable employment history and plenty of experience, but I wish they had social media so I could gather a better idea of what they're really like (people always present the best versions of themselves on their resumes).	1			
good work experience in the field of hotel and guest relations. No social media to back up resume.	1			
Lots of experience, better education than other resumes, lack of social platform doesnt allow enough info to rank above applicant 5	1			
Limited education and experience. No digital footprint whatsoever. Potentially paranoid and non tech savvy.		1	1	
Very good experience. No educational qualifications. Ask about lack of social media.		1		1
Sparse resume. May be too young and inexperienced for this position. What kind of young person has no social media. Alternate name?		1		
Based on the applicant's resume, they certainly seem qualified. However, the complete lack of any social media data is just flat out strange considering the times we live in. Too hard to tell, I would probably avoid this candidate.		1		
Resume looks great, but there is no social media and while that may not be something required, I still think for this particular job that it is important to have experience and knowledge of some kind of using and utilizing social media.			1	
I quite like they have no social media. Neither do I. I like to keep my private life private and separate from work.				

Notes: The table includes a few examples of evaluator notes attached to the candidates without social media and categorized to the different causes suggested to reduce candidates' ratings. Increased Uncertainty: Notes in this category express concerns about less available information due to the lack of social media data. Red Flag: Notes that consider the absence of a social media profile as a red flag, odd, or indicative of the candidate hiding something. Low Skills: Notes that suggest that not having a profile could imply lower relevant skills. Ask for Info: Notes that suggest asking for additional information.

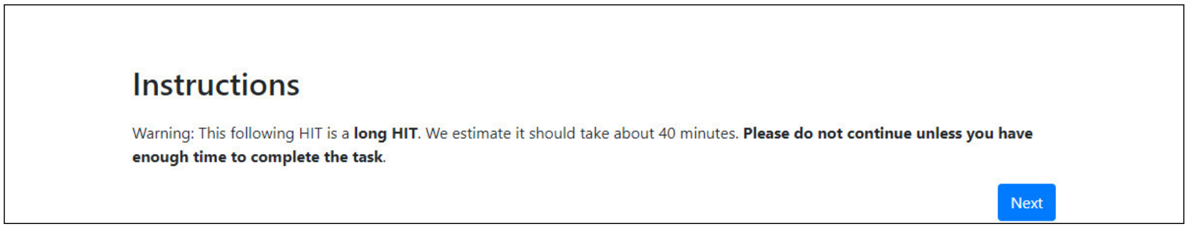
Table B.6: Interactions between candidate characteristics and treatment

	Gap	Lie+Gap	Mental Health	No SM	Bad SM
General Public					
CV Experience	0.07	0	-0.27	**0.42****	**-0.44****
CV Education	0.03	0.02	-0.08	0.24	-0.08
CV Skills	-0.16	-0.02	-0.11	0.02	0.09
CV Interests	-0.1	**-0.44****	0.05	-0.15	0.12
Endorsements	-0.22	0.07	-0.02		-0.02
Order	0.18	0.14	-0.01	-0.28	0.08
Applic. Female	0.03	-0.08	-0.07		0.21
Recruiters					
CV Experience	0.12	0.1	-0.26	0.41	-0.01
CV Education	-0.06	0.24	-0.18	0.42	0.34
CV Skills	-0.02	-0.32	0.07	0	-0.37
CV Interests	0.29	0.51	0.12	0.26	0.36
Endorsements	0.03	-0.17	0.18		0.06
Order	-0.3	0	0.29	-0.12	-0.31
Applic. Female	-0.18	-0.27	-0.34		0.25

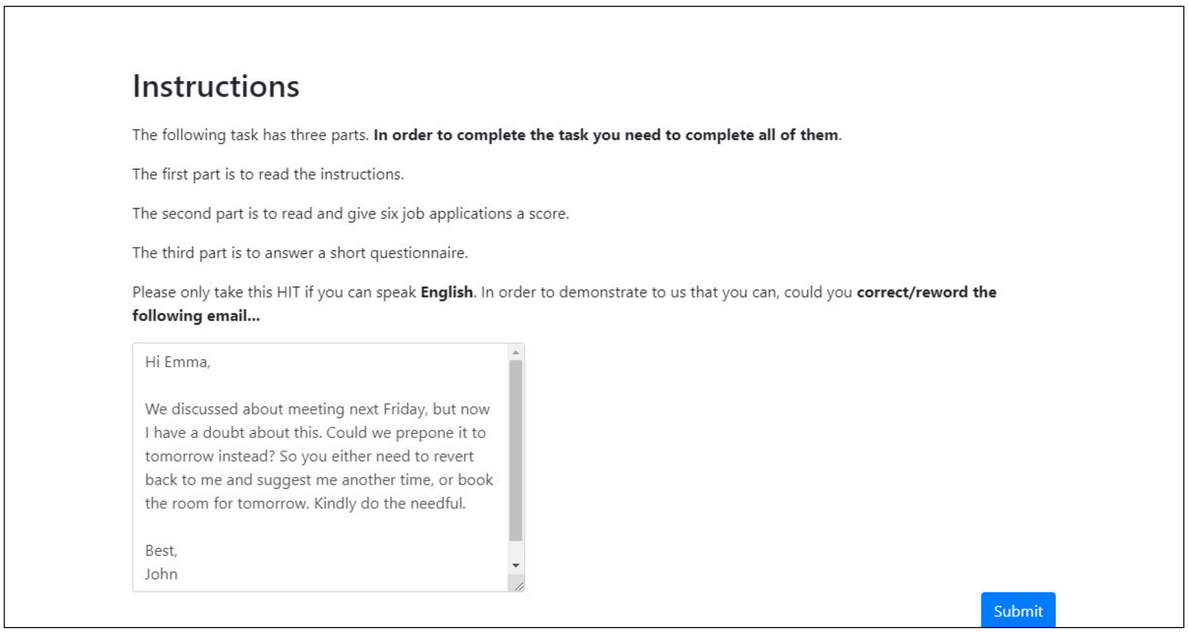
Notes: Table of coefficients of application characteristics interaction terms. Obtained by regressing application score on application characteristics, treatment variables, and the covariate in question interacted with each of the treatment variables. Explanatory variables are demeaned and standardized such that the coefficient value represents the effect of moving from the fifth to the ninety-fifth percentile apart from dummy variables (Eval. Female and Cand. Female). See detailed description of the variables in appendix Table B.2. *p<0.1; **p<0.05; ***p<0.01.

C Design

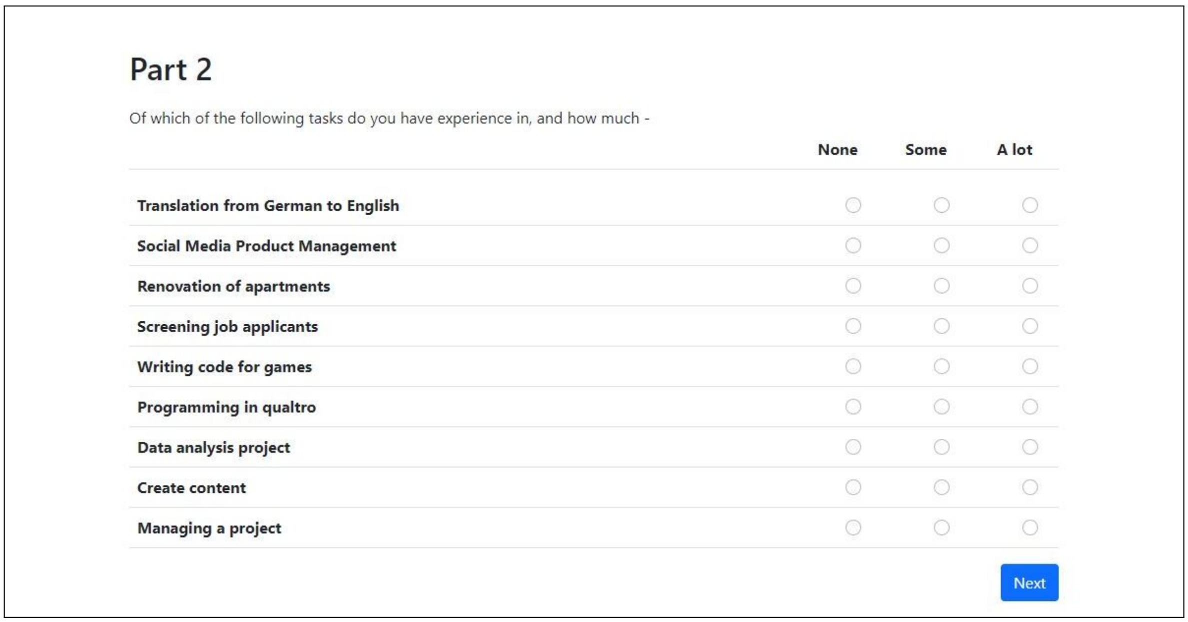
Figure C.1: The evaluation platform



(a) Screen 1 - continue only if you have the time



(b) Screen 2 - English proficiency and concentration test



Part 2

Of which of the following tasks do you have experience in, and how much -

	None	Some	A lot
Translation from German to English	○	○	○
Social Media Product Management	○	○	○
Renovation of apartments	○	○	○
Screening job applicants	○	○	○
Writing code for games	○	○	○
Programming in qualtro	○	○	○
Data analysis project	○	○	○
Create content	○	○	○
Managing a project	○	○	○

Next

(c) Screen 2A - Hiring experience verification (only on Prolific)

Instructions

We help companies fill job vacancies. There are many candidates so we outsource part of the evaluation. We have assigned you six candidates. Your task is to read their résumés as well as some further information and pre-screen them.

See Place of Work and Job Description

(d) Screen 3 - General instructions

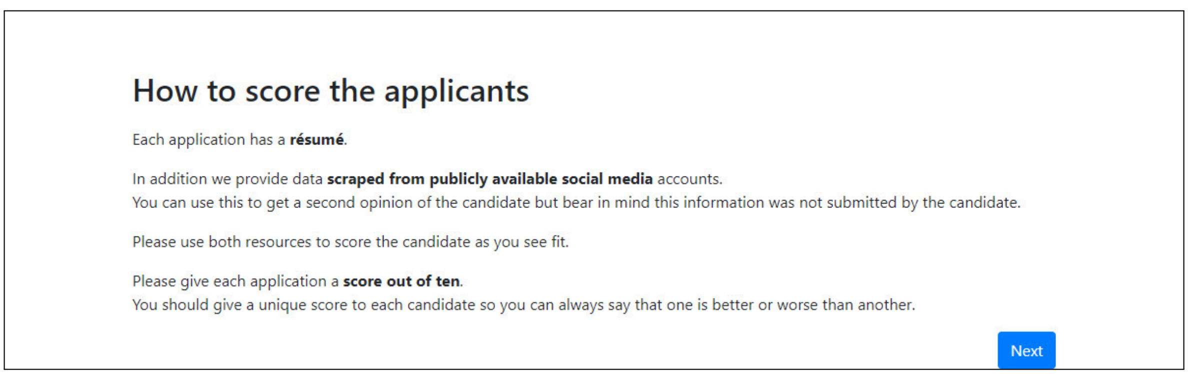
Place of Work: Luxury Retreat and Wellness Resort

Our beach-side resort offers 100 luxury rooms nestled in tranquil surroundings allowing our guests to unwind and get away from it all and enjoy the area. We offer a spa, a wellness center, yoga classes and our restaurant offers a wide range of local and seasonal cuisine. Nearby beaches, trails, wine tastings, and golf opportunities are all on our doorstep.

See Job Description

(e) Screen 4 - Place of work

(f) Screen 5 - Job description



(g) Screen 6 - rating instructions

Applicant Screening

Please give each application a unique score between zero and ten.

Instructions	Applicant 1	Applicant 2	Applicant 3	Applicant 4	Applicant 5	Applicant 6
	Score	Score	Score	Score	Score	Score

You can view the application by clicking on the links above in the tabbed menu. When you are finished rating all six résumés, click the submit button.

You should give each a unique score so you can always say that one application is better or worse than another.

Below we remind you of the working environment and job description.

Place of Work: Luxury Retreat and Wellness Resort

Our beach-side resort offers 100 luxury rooms nestled in tranquil surroundings allowing our guests to unwind and get away from it all and enjoy the area. We offer a spa, a wellness center, yoga classes and our restaurant offers a wide range of local and seasonal cuisine. Nearby beaches, trails, wine tastings, and golf opportunities are all on our doorstep.

Job Description: Office Manager

The Office Manager will be responsible for the daily management of all administrative and office support operations. We are looking for an experienced manager with excellent customer service skills who will fit well into our team. Candidates should be hard-working, organized and reliable.

Duties Include:

- Overseeing office activities
- Dealing with guests in courteous and timely manner
- On-boarding of new employees
- Coordinating and creating agenda for monthly staff meetings
- Promoting a friendly and welcoming environment for guests

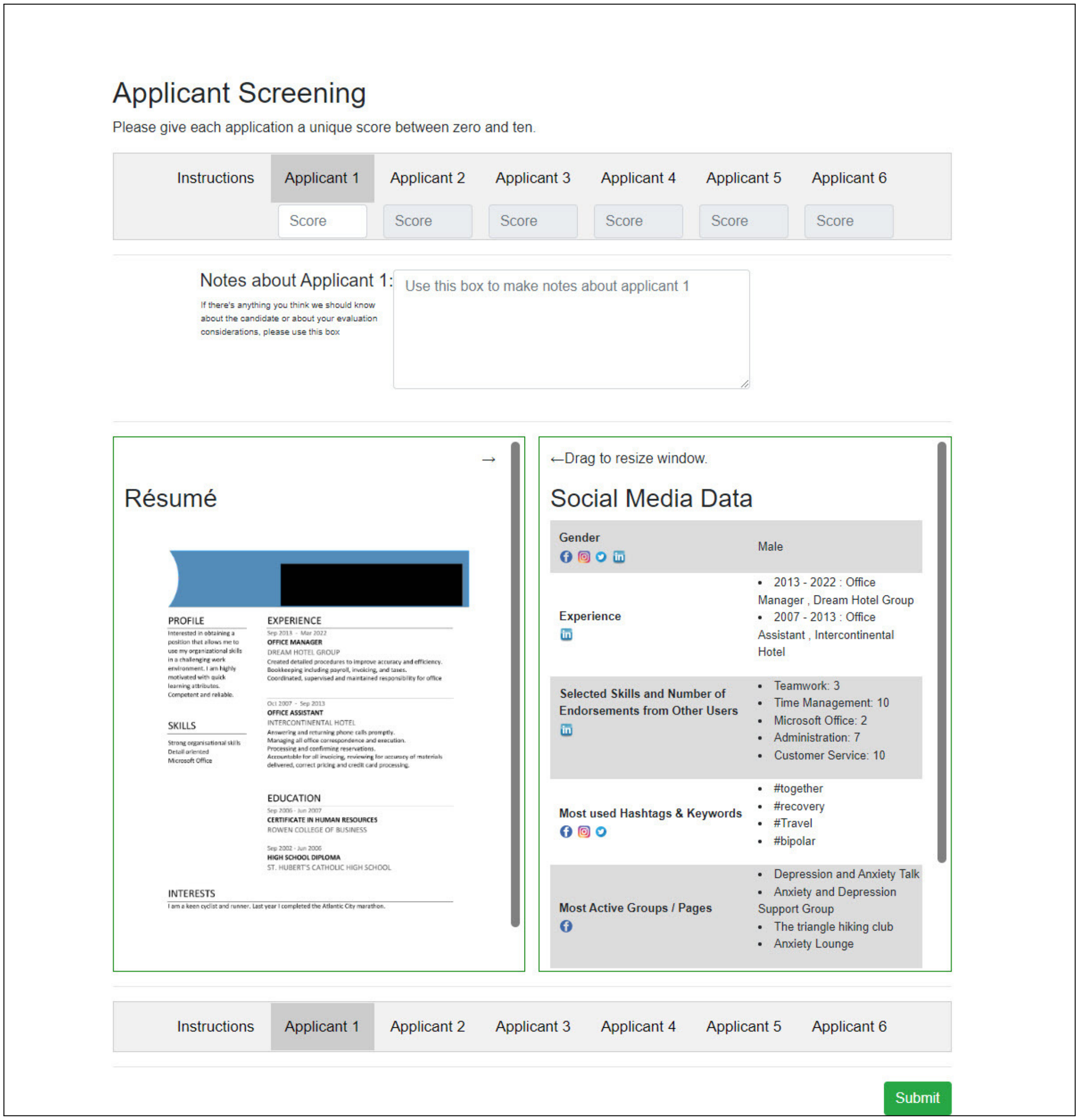
Each application has a **résumé**.

In addition we provide data **scraped from publicly available social media** accounts.
You can use this to get a second opinion of the candidate but bear in mind this information was not submitted by the candidate.

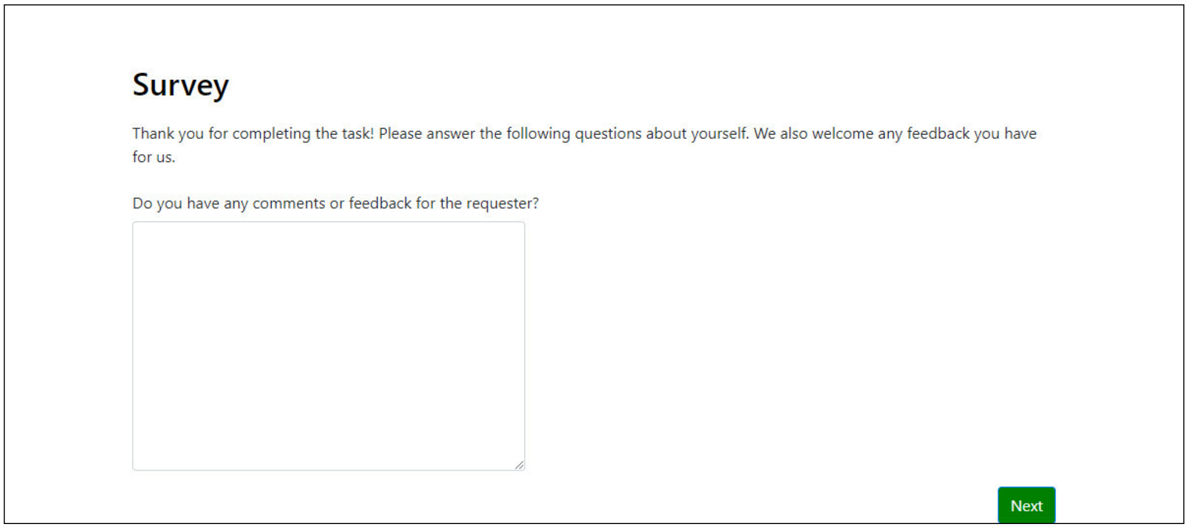
Please use both resources to score the candidate as you see fit.

Submit

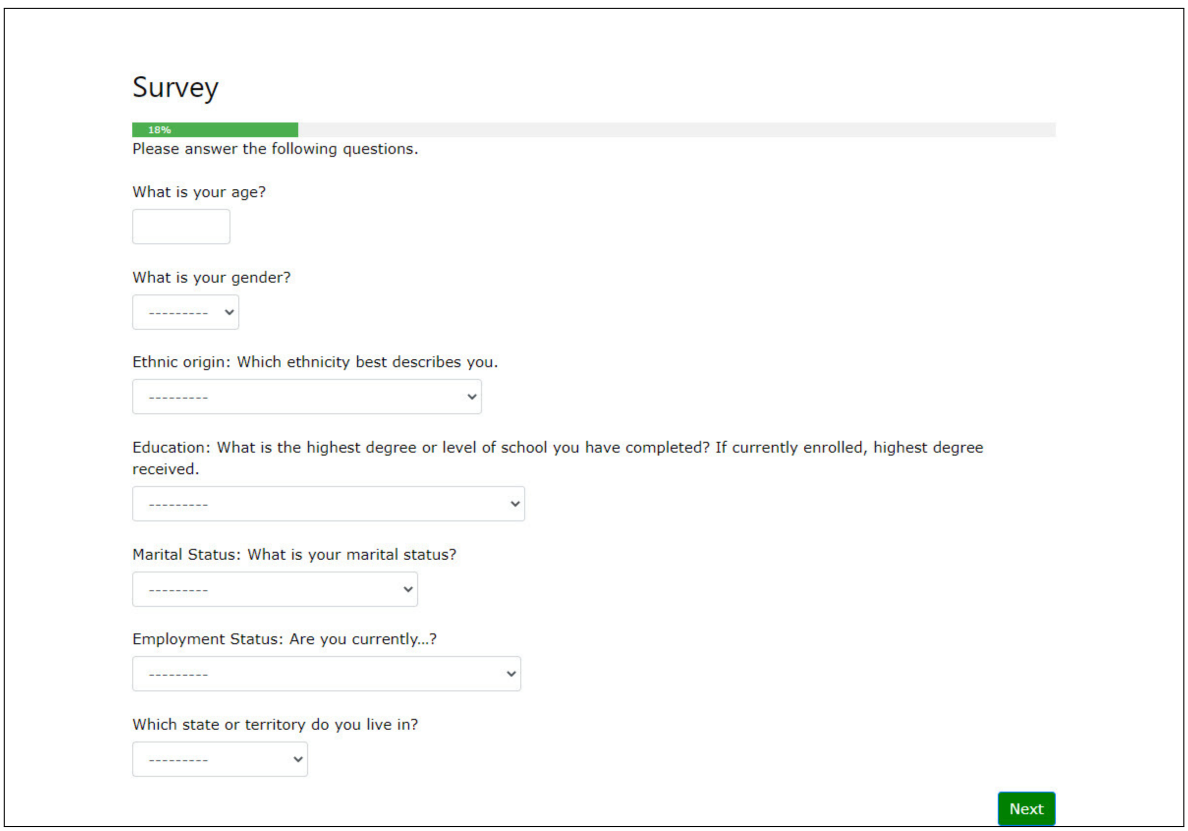
(h) Screen 7 - Main task screen, instructions



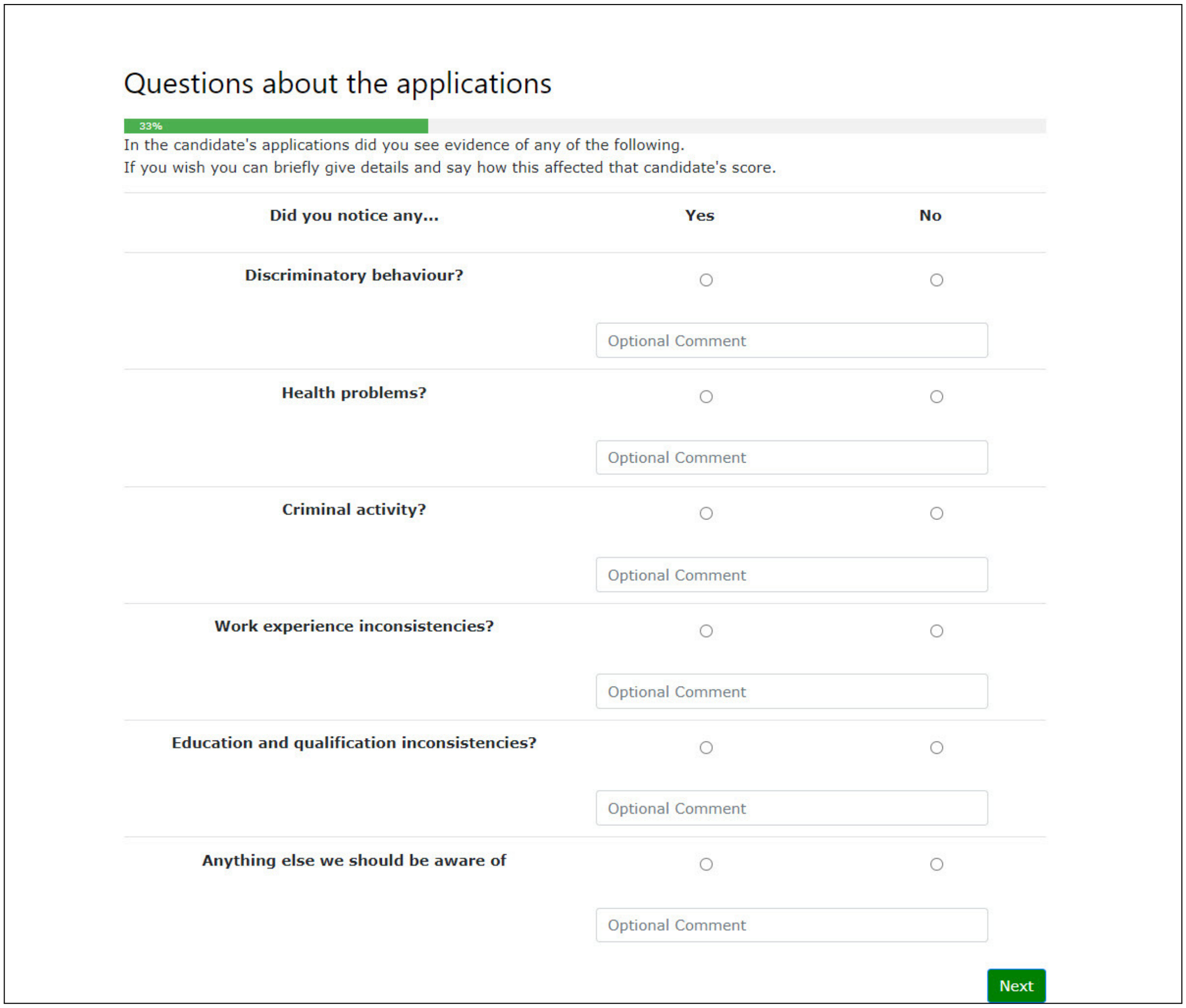
(i) Screen 8 - Main task screen, candidate example



(j) Screen 9 - General feedback



(k) Screen 10 - survey, Personal information



Questions about the applications

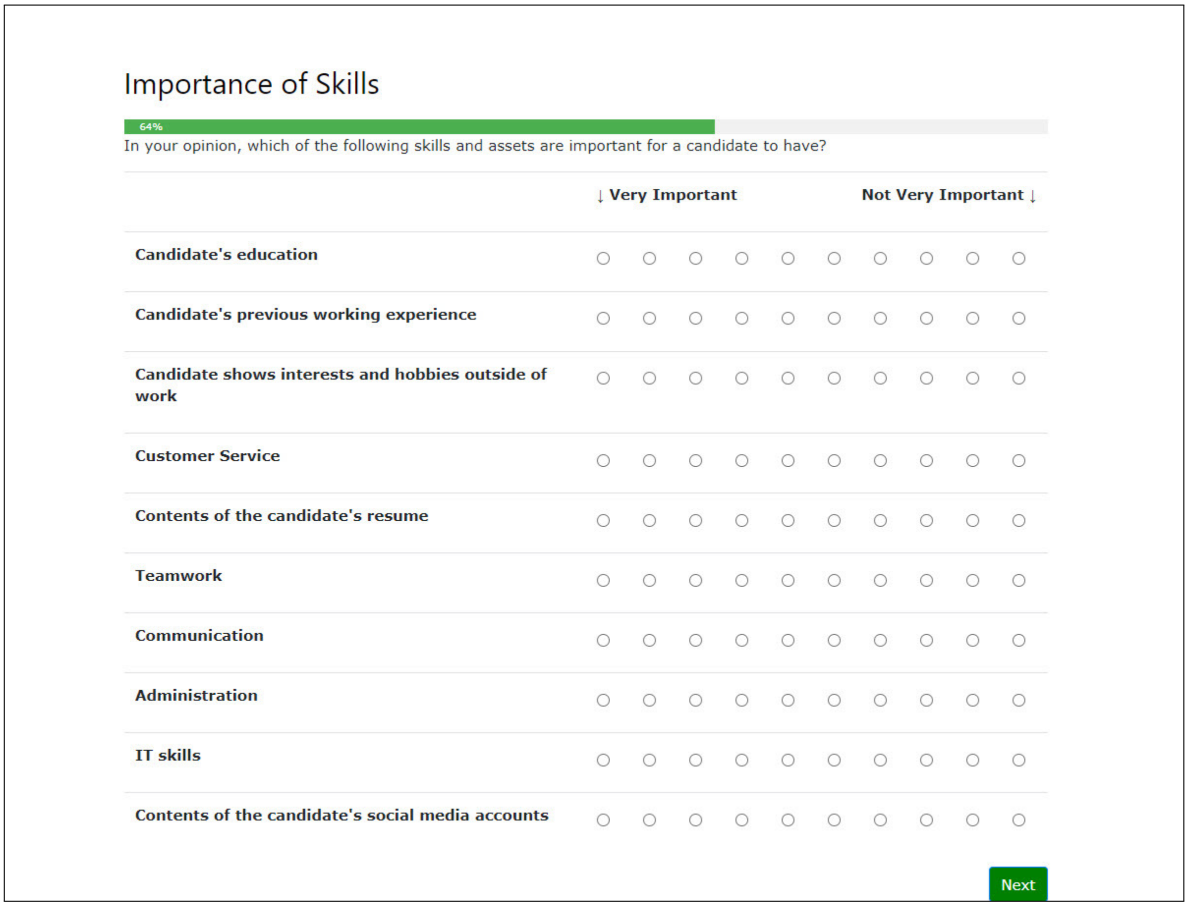
33%

In the candidate's applications did you see evidence of any of the following.
If you wish you can briefly give details and say how this affected that candidate's score.

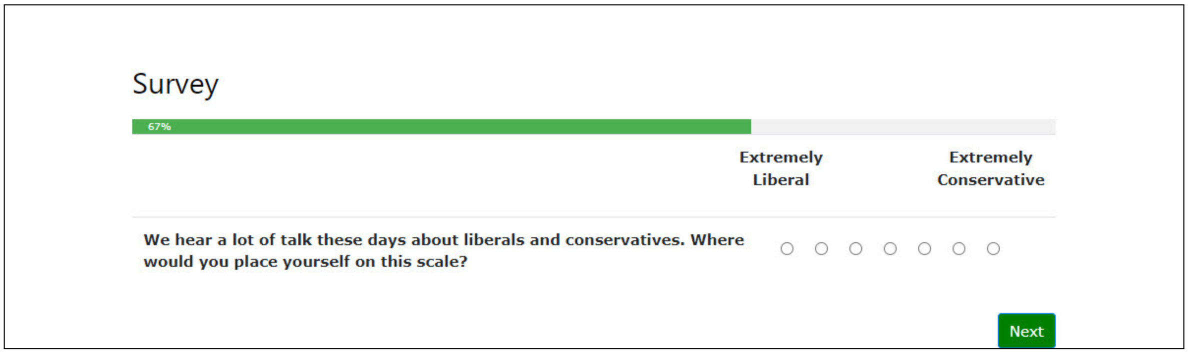
Did you notice any...	Yes	No
Discriminatory behaviour?	○	○
	Optional Comment	
Health problems?	○	○
	Optional Comment	
Criminal activity?	○	○
	Optional Comment	
Work experience inconsistencies?	○	○
	Optional Comment	
Education and qualification inconsistencies?	○	○
	Optional Comment	
Anything else we should be aware of	○	○
	Optional Comment	

Next

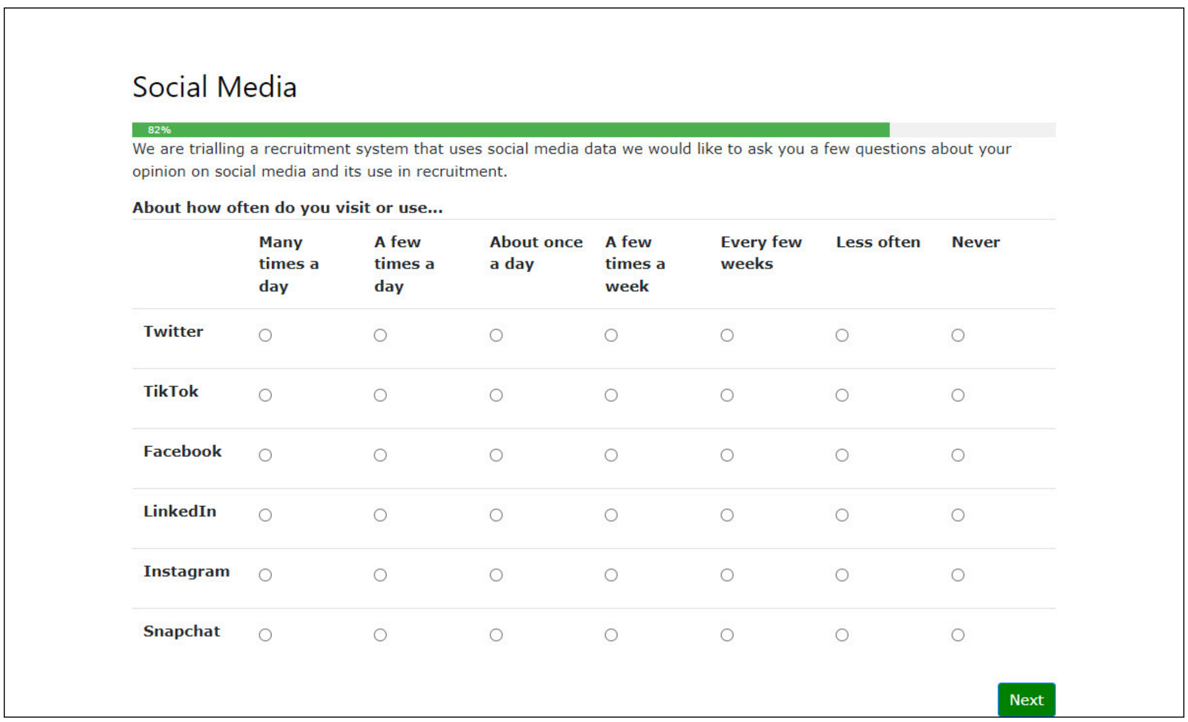
(l) Screen 11 - survey, Did you notice anything worth mentioning?



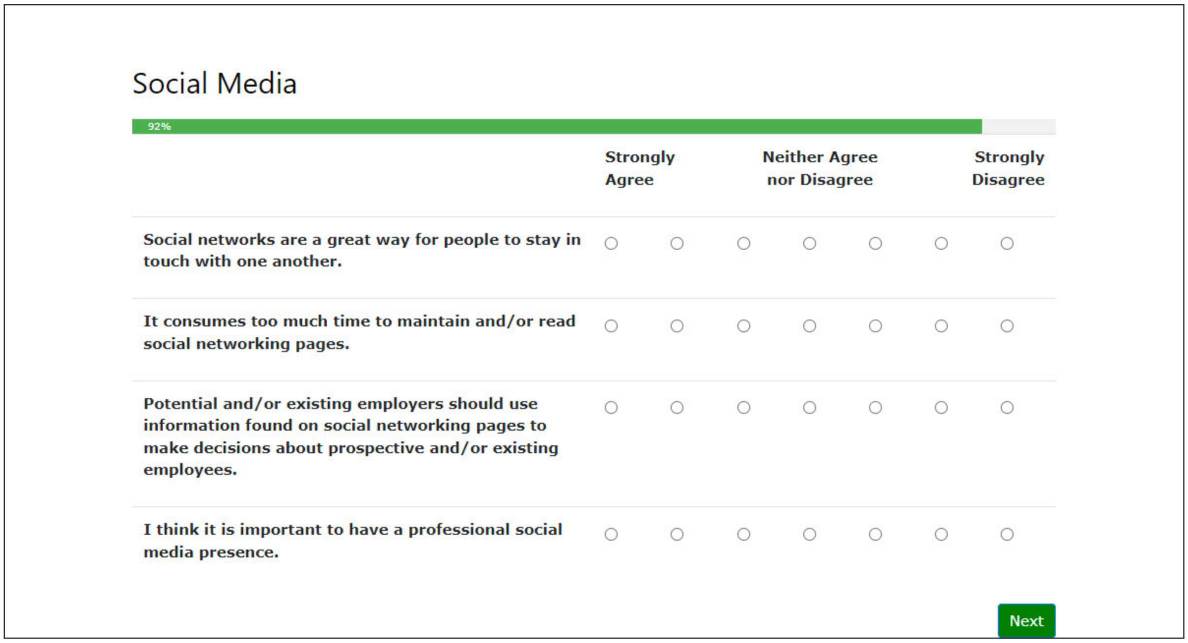
(m) Screen 12 - survey, How important is ... in your opinion?



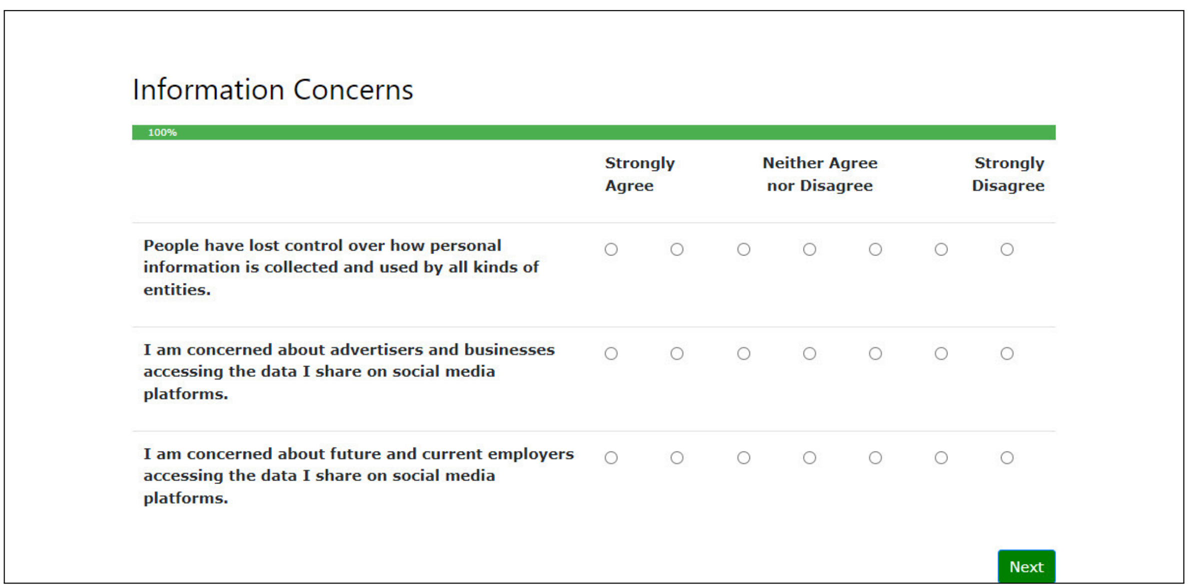
(n) Screen 13 - Survey, conservative - liberal scale



(o) Screen 14 - Survey, social media usage



(p) Screen 15 - Survey, opinions about social media



(q) Screen 16 - Survey, privacy concerns

Table C.1: Candidate Resume Possibilities

Experience

Years	18.50	17.50	12.75	12.25	6.00	4.00
Profile	Enthusiastic and reliable hotel manager with nearly twenty years experience in hospitality. Excellent organisational and social skills as both a team leader and provider of dedicated customer service. Motivated to provide memorable experiences for guests.	Hard worker with many years experience of front office and general management. Exceptional team player with excellent communication skills. Seeking a position that requires me to utilize my abilities to provide excellent customer service.	Organized and dedicated individual with a positive attitude. Able to meet challenges, handle multiple assignments under pressure and tight deadlines. Good team player and excellent time management skills.	Interested in obtaining a position that allows me to use my organizational skills in a challenging work environment. I am highly motivated with quick learning attributes. Competent and reliable.	I am goal oriented, able to work in a fast paced environment and meet deadlines. I am reliable and experienced. I am currently in search of a full-time work opportunity in an environment where I can use my management skills.	Seeking rewarding employment in the hospitality sector. Have worked in hospitality with a wide range of responsibilities including serving and office work.
Job 1 Title	Manager	Front Office Manager	Office Manager	Office Manager	Housekeeping Supervisor	Supervisor
Firm 1	Ocean Place Resort and Spa	Hampton Inn by Hilton North Brunswick	Grand Beach Hotel	Dream Hotel Group	Holiday Inn	Redd’s Restaurant, Bar and Catering
Text 1	• Oversaw day-to-day operations in the front office • Conducted onboarding and training for front office staff • Improved staff morale with a positive work environment • Provided exceptional customer service • Cultivated a welcoming environment for guests	• Responsible for oversight of front office operations. • Tasked with the creation of weekly financial status reports. • Extensive experience in on-boarding procedures. • Provided support and direction for staff. • Responsible for maximizing guest satisfaction.	• Performed all Office Manager duties • Created office procedures for administrative office personnel • Created and monitored staff schedules • Monitored budgets and reviewed financial transactions	Created detailed procedures to improve accuracy and efficiency. Bookkeeping including payroll, invoicing, and taxes. Coordinated, supervised and maintained responsibility for office	Keep area presentable for guests and clients. Inspect rooms and correct mistakes. Assignment and project coordination. Ensure all issues resolved	• Prioritizes various responsibilities quickly • Meets deadlines • Learns new information quickly
Job 2 Title	Assistant Front Office Manager	Front Office	Office Clerk	Office Assistant	Housekeeping	-
Firm 2	Homewood Suites by Hilton	Four Points by Sheraton	The Watson Hotel	Intercontinental Hotel	Americas Best Value Inn	-

Text 2	• Front desk responsibilities and scheduling • Prioritised good customer service • Assisted in onboarding of new employees • Responsible for sale and distribution of appropriate literature. • Attended Leadership Development classes	• Managed front-end operations • Processed and confirmed reservations • Introduced new key performance indicators • Improved front office operations	• Worked closely with management to maintain office standards • Correspondence with guests and employees • Responsible for all office supply procurement • Staffing when office manager was unavailable	• Answering and returning phone calls promptly. • Managing all office correspondence and execution. • Processing and confirming reservations. • Accountable for all invoicing, reviewing for accuracy of materials delivered, correct pricing and credit card processing.	• Daily housekeeping duties. • Restock rooms. • Make sure the surroundings of the property are presentable	-

Notes: This table shows the possible values for the work experience on the resume. The first row shows the total number of years of work experience. The social media content only showed the corresponding job title and the years worked there.

Education

Years	16	15	14	13	12	9
Qualific. 1	Certificate of Hospitality Management	Certificate in Hospitality Services	Associates Degree in Human Resources	Certificate in Human Resources	High School Diploma	GED
School 1	Central Penn. Community College	The Chubb Institute Springfield, PA	Stonybrook University NY	Rowen College of Business	Boca Raton Community High School	Bucks County Comm. College Newtown, PA
Qualific. 2	Bachelor of Science in Business Administration	Associate Degree in Business Management	High School Diploma	High School Diploma	-	-
School 2	University of Pennsylvania	Thomas Jefferson University	Cardinal O'Hara High School	St. Hubert's Catholic High School	-	-
Qualific. 3	High School Diploma	General HS Diploma in Art/Computers	-	-	-	-
School 3	St. Hubert's Catholic High School	Harry S Truman High School Levittown, PA	-	-	-	-

Notes: This table shows the possible values for the education section on the resume. The first row shows the total number of years in education. 'Qualific. 1' shows the name of the acquired qualification and 'School 1' the school from which it was acquired.

Skills

	A	B	C	D	E	F
Skill 1	Management Skills	Administration	Good Team Player	Strong organisational skills	Good Time Management	Word
Skill 2	Customer Care Skills	Interpersonal Skills	Motivated	Detail oriented	MS Office	Punctuality
Skill 3	Excellent Communication Skills	Customer Service	Professional	Microsoft Office	-	-
Skill 4	Fluent in Spanish	Problem Solving	-	-	-	-

Notes: This table shows the possible values for the skills section on the resume.

Interests

	a	b	c	d	e	f
Interests	In my spare time I enjoy yoga and producing nature videos and I volunteer for a local charity “The food trust” helping them create media content for their website.	I am a keen cyclist and runner. Last year I completed the Atlantic City marathon.	I am an avid portrait photographer and recently reached the final in the ‘Shoot the Frame’ photography competition.	In my spare time I enjoy swimming and playing volleyball, I play for a team which competes in local competitions.	Outside of work I enjoy painting and regularly attend a life drawing class.	In my freetime I enjoy reading and watching tv.
Hashtags & Key-words	#Nature, #fitness, #blessed	#Travel, #life, #music	#Happy, #photooftheday, #photography	#selfie, #funny, #bestoftheday	#summer, #art, #style	#beautiful, #food, #sunset

Notes: This table shows the possible values for the Interests section on the resume. The top row shows the text from the resume. The bottom row shows the corresponding hashtags from the social media content in the baseline.

Table C.2: Treatment Social Media Content

	Baseline		Bad			Mental Health Issues	
Most used Hashtags & Keywords	*one from:* #teamwork, #together, #collaborationiskey, #community, #thankyou, #teammate	*plus one set:* a: #Nature, #fitness, #blessed, b: #Travel, #life, #music, c: #Happy, #photooftheday, #photography, d: #selfie, #funny, #bestoftheday, e: #summer, #art, #style, f: #beautiful, #food, #sunset	*two from:* #tgif, #weekendvibes, #itsonlytuesday, #tired, #fuckmylife	*one from:* #nosleep, #party, #happyhour	*one from:* #xbox, #gaming, #fortnite	#recovery	*plus one from:* #therapy, #bipolar, #bipolardisorder
Most Active Groups / Pages	*one from:* Walking and talking, The triangle hiking club, Philadelphia networking group, Being neighbourly: philadelphia, Philly Social Adventures, Philadelphia roommates	*plus three from:* NowThis, Adele, Rate My Plate, Group, The Simpsons, It's Gone Viral, Will Smith, STREET FOOD LOVE, House, Chefclub, vin Diesel, Food & Wine, The Big Bang Theory Tasty, Taylor Swift, Fine Cooking, Game of Thrones, Viral TRND, Katy Perry, Food52, FRIENDS (TV Show), Bored Panda, Bruno Mars, Cooking Light, Greys Anatomy	*two from:* Work Sucks Meme Factory, I Love/Hate My Job, I Hate Monday Mornings	*plus two from:* grand theft auto V, Call of Duty, Super Smash Bros, Pokemon Sword, Monster Hunter World, Diablo, Borderlands		*three from:* Defeat Depression, Anxiety and Depression Support Group, Depression and Anxiety Talk, Anxiety Lounge, Schizophrenia Support Group, Bipolar disorder and Manic depression SUPPORT GROUP, Positive Depression/Bipolar Happy Place	
Automatic Screening Report on SM Activity	Social media language: generally positive Interactions: generally positive Spelling and grammar: very good		Social media language: generally neutral Interactions: sometimes negative, sometimes offensive language Spelling and grammar: bad			Same as baseline.	

Notes: Table shows social media content we used to implement the treatments. Treatments Gap and Gap+Lie had the same content as the Baseline. The No SM treatment had no content. Treatments Bad and Mental Health displayed content selected randomly from their respective columns. The Mental Health treatment hashtag section displayed '#recovery' plus one from the right hand column plus two from the baseline, and the groups section displayed three groups from the list displayed here one from the baseline column.