Human Judgments In Hiring Decisions Based On Online Social Network Profiles

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***Abstract*—Online social networks have changed the ways in which people communicate and interact, and have also impacted the business landscape. One recent trend is firms using online social networks as a part of the job hiring process. Firms scrutinize potential employees using their social network profiles, sometimes even seeking access to restricted parts of the profile, for example by demanding applicants to hand over their passwords.**

We explore the key criteria and profile components that affect perceptions about a user. Our results are based on datasets consisting of reports of participants who actually took part in a task of evaluating candidates. Participants volunteered their Facebook profiles and CVs, to be examined by other participants who provided a detailed report about their job-suitability.

We find that in screening based on social network profiles, a profile owner's education and demographic traits correlate with their job-suitability rating. Many profile components, including textual posts, pictures, likes, and even the friend list, relate to an applicant's perceived job-suitability.

Further, diverse criteria play a role in forming job-suitability perceptions, including education and skills, personality, offensive content, physical appearance, interests and age, gender, family status or other demographic traits.

Thus screening based on social networking websites is very different from CV based screening, where we find that the dominant criterion is education and skills, with personality being a remote second.

I. Introduction

Online social networks have gained enormous popularity in recent years, and capture huge amounts of data regarding social interactions [1], [2], [3], [4], [5]. Such networks had a significant influence both on peoples' personal lives, as well as the business world [6], [7], [8], [9], [10].

Analyzing social network data allows locating influencers in the network, predicting links and physical locations of users, and finding potential customers [11], [12], [13], [14]. Further, mining data from social networks allows making relatively accurate judgments regarding properties of a profile owner, including personality [15], [16], [17], [18], [19], [20], demographic traits [21], and even sexual orientation, religion and political opinions [22].

Many hiring managers use information from candidate profiles while screening job applicants [23], [24], with some managers even asking applicants to provide them with account passwords so they can access restricted parts of the profile [25], [26], [27].

A recent survey found that 45% of employers use social networking sites while researching job candidates [28], highlighting the need to study how such information is used.

One possible hypothesis stipulates that employers who browse **resumes (CVs)** focus on *skills, previous experience and education* [29], [30], so this should also be the focus in social network based screening. In contrast, **face-to-face job interviews** cover not only skills but also *interests, attitude and personality* [31], [32], [33]. Social network profiles have far richer content than resumes, including thoughts, opinions and sentiments about a wide range of topics. Thus, an opposite hypothesis posits that social network screening covers a wider set of issues, similarly to face-to-face job interviews.

We analyze factors affecting how people perform job applicant screening using social network profiles, using reports provided by participants who we actually let perform such a screening task in practice.

We examine two datasets. To generate our **social network screening dataset**, each of 236 participants volunteered their own **Facebook profile** to be evaluated. Then, 517 other participants each examined several of these volunteered profiles and provided a detailed report regarding the job-suitability of the profile owners. This process yielded 869 job-suitability reports.

Our **CV screening dataset** was constructed in a similar manner, except the reports were based on volunteered **CVs**. It relates to 294 CVs and 980 participants who examined several such CVs, yielding 4595 reports.

We asked participants questions designed to measure the *relative importance* of various profile components and of specific criteria in assessing job suitability. The **profile components** include parts of the social network profile, and are listed in Table I.

The **job-suitability criteria** (simply **criteria** for short) include aspects, factors and concerns that can affect perceptions regarding an applicant's job suitability, and are listed in Table II. [1]

[1] As discussed at length in the results section, we chose these specific criteria following an initial topic model (LDA) based analysis of the reports regarding candidates. In this sense, rather than us choosing the criteria to focus on a priori, we let our data speak for iteslf — the criteria used are the result of applying data mining methods to analyze the reports and identify the main criteria driving peoples' judgements.

We examine which components and criteria people *expect* to affect ratings and which of them are *actually* important in practice.

II. Methodology

Our methodology relies on applying data mining techniques to our two datasets relating to peoples' judgements regarding job candidates: the social network screening dataset, ralating to to judgements based on candidates' Facebook profiles, and the CV screening dataset, ralting to judgements based on standard CVs.

We first applied an LDA [34] topic model analysis to identify the high level issues that people examine when evaluating candidates. We then examined the numerical ratings and trained a machine learning model to predict the overall rating given to a candidate, based on the evaluation of specific aspects of the candidate. Finally, we used the trained predictive model and applied statistical factor importance measures in order to rank issues by their relative ability to predict the overall rating.

The social network screening dataset includes $n_s^{soc} = 869$ reports. These were sourced by having $n_p^{soc} = 236$ participants contribute their **Facebook profiles** to be judged by other people, and having each of $n_r^{soc} = 517$ other participants examine several such contributed profiles and compose a report about them.

Similarly, the CV screening dataset includes $n_s^{CV} = 4595$ reports, using $n_p^{CV} = 294$ participants who contribute their **CV** to be judged, and $n_r^{CV} = 980$ participants rating the CVs. Participants who volunteered their profile lowered their privacy settings, granting raters access to restricted content.

Participants: The participants in both datasets were sourced through Amazon Mechanical Turk, a crowdsourcing marketplace, that allows requesters to post tasks and workers to perform these tasks for a fee. [2]

Our candidates were 48% male and 52% female, with an average age of 30.56. Our interviewers were 37% male and 63% female, with an average age of 29.6 (STD=8.7). 76% of the interviewers identified their ethnicity as white, 9.3% as African-American / Black, and 3.8% as Hispanic (the reminder identifying as other ethnicities).

45.8% identified their religion as Christian and 41.2% identified themselves as not religious or unaffiliated (the reminder either identified themselves as having another religion or preferred not to answer the question).

In terms of educational background, 31.9% of the interviewers said they have completed secondary school education, 46% of the interviewers said they have started or completed a first degree, and 12% indicated they have started or completed a master's degree.

The Rating Task: We asked each rater to provide a report for several randomly allocated profiles or CVs. Each report included an overall candidate rating, between 0 and 100 (0 being the worst), and a few paragraphs of free text providing reasons for the given rating.

Each participant could provide a report for at most five profiles, receiving a payment of \$1 per each report. We expected raters to spend roughly 10 minutes examining a profile and writing a report, but most raters took a bit less time than that.

We first examine *correlations* between demographic traits of the profile owner and their job-suitability rating in the social network screening dataset.

We then use data mining methods to analyze **specific factors** affecting human judgments in job applicant screening based on social network profiles, trying to determine which profile components and which job-suitability criteria have more impact on the ratings given to candidates.

To identify the factors most predicative of the overall candidate rating, we asked raters to give a rating based only on *specific* profile components or criteria in addition to the overall candidate rating. For example, we asked raters to rate a candidate's job suitability based only on their profile picture (ignoring other profile components), or to rate a candidate's attitude and personality (ignoring other criteria). We call these **focused ratings**, as raters focused their attention on only one domain at a time.

We then train a *predictive model* whose goal is to regress the overall rating a candidate receives based on the focused ratings of the profile components and criteria. Once the model is trained, we employ various statistical factor importance measures with the goal of identifying the relative influence of various inputs on the output of the machine learning model.

To determine the *actual* importance of components or criteria in determining overall rating in the screening task, we used a multiple linear regression model. The target variable was the overall rating, and as predictor variables we used two sets of focused ratings: the set of criteria ratings and the set of profile component ratings.

We then apply measures of relative factor importance, based on multiple linear regression, to determine which criteria or components are most predictive of the overall rating. [3]

We then investigate whether the criteria people focus on when screening candidates using CVs differ from the criteria people focus on when screening candidates using their social network profiles. We do this by examining the CV screening dataset and using the same methodology to measure the relative importance of the job-suitability criteria in CV based screening (contrasting these with the measures obtained for social network based screening).

III. Results

The social network screening dataset consists of $n_s^{soc} = 869$ reports, provided by $n_r^{soc} = 517$ raters who each evaluated

[2]We note that crowdsourced evaluators may have different opinions than those of professional HR staff, who are trained to screen job candidates. Thus our results relate more to common impressions of job candidates by the general population. We discuss this in depth in the conclusions.

[3]We note that raters were not given information regarding a specific job opening, but were rather asked to assume the candidate is interviewing for a position similar to their current job.

Clearly the specific job affects the relative importance of various factors. For example, physical appearance is likely to be more important for a movie actor than for a position in accounting. We did not provide details for a specific position so as to obtain the relative importance of factors for an "average" job.

Profile component	Details
Profile picture	The main profile photo chosen by the profile owner
Photos	The remaining photos stored in the profile
Liked items and groups	Items liked and groups the owner is a member of
Friends	The list of the owner's friends in the social network
Posts	The textual posts of the owner (e.g. wall posts)

TABLE I: Social network profile components examined in this study.

Job-suitability criterion	Comments
Skills, experience and intelligence	
Attitude and personality	
Physical appearance	(e.g. their attractiveness or dress)
Offensive content and content relating to vices	(e.g. offensive language, drug or alcohol abuse)
Interests, activities and hobbies	
Age, family status, religious or political beliefs, or other demographic traits	

TABLE II: Criteria examined in this study.

several of the $n_p^{soc} = 236$ volunteered profiles.

Each report includes an *overall job-suitability rating*, additional *focused job-suitability ratings*, based only on a specific profile component or criteria, and a *textual report* - an explanation consisting of a few paragraphs of free text that support the given rating. The average rating was 64.69, with a standard deviation of 26.22, indicating a high dispersion of opinions regarding candidates.

To determine the **key criteria discussed in the textual reports**, we used the Latent Dirichlet Allocation (LDA) [34] topic model. This is a text data mining technique, which scans a set of documents to find key issues discussed in them. It allows automatically discovering topics based on data consisting of many such documents, where each topic is characterized by the most probable words appearing in documents dealing with that topic.

We consider each textual report given by a rater to a profile to be an individual document. We used an LDA analysis to describe each of the main topics discussed in the textual reports by its characteristic words.

Table III shows the clusters of words for each of the topics found in the LDA analysis, and a possible title for each word cluster, capturing our interpretation of the cluster.

The criteria and profile components shown in Table III emerge as topics discussed in the textual reports given by raters to support their ratings, and are thus likely to affect opinions formed by raters.

The clusters relate to various issues, including: experience education and skills; interests; personality; appearance; language and communication style; friends and family. The factors chosen for our analysis in the section on perceived and actual importance of profile components and job suitability criteria (listed in Table I and Table II) were selected after collecting a smaller sample of textual reports and applying the LDA based analysis.

Several correlations were found in the screening task data between self-reported demographic features of the profile owner, including educational background, gender and race and the overall job-suitability rating they received. The overall ratings of profiles of different education levels differed significantly: profiles with an education level of at least a first degree $\bar{x} = 70.95$ had higher ratings than candidates with an education level of less than a first degree $\bar{x} = 59.42$ ($p < 2.015 \times 10^{-11}$) The overall rating of women $\bar{x} = 68.77$ was higher than that of men $\bar{x} = 60.46$ ($p < 0.001$). [4] Also, ratings of profiles identifying as "White/Caucassian" $\bar{x} = 66.15$ were higher than of those identifying as "Black/African-American" $\bar{x} = 59.05$ ($p < 0.01$).

Such demographic factors are known to be correlated with judgments in hiring decisions [37], [38], [39], [40], [41], so it is not surprising to see such effects in job-suitability ratings based on social network profiles.

A. Factor Importance Measures

We now examine the relative importance of profile components and criteria in influencing and predicting applicant ratings. We quantify the relative importance of these factors in two ways.

One measure is *perceived importance*, relating to the relative influence people *think* a factor would have on ratings. Another measure is *actual importance*, relating to how predictive these factors are of actual job-suitability judgments made in practice.

To gauge **perceived importance**, *prior* to rating any actual candidates, we asked participants to think about how important each of the different profile components and each criterion would be in affecting their overall job-suitability rating of candidates. We asked them to allocate 100 points among the profile components and among the criteria accordingly.

Our measure of the perceived importance of a profile component is the average number of points allocated to that

[4]The stated p-values here and later in the paper hold under both a two-sided Student t-test and a Mann-Whitney U test. We note that the gender and job-suitability rating correlation we found stands in contrast to previous results indicating a bias towards men rather than women in hiring and promotion decisions in other contexts [35], [36].

Topic characteristic words	Possible interpretation (title)
experience education skills college school degree work engineering company employment student university	Experience, education, skills
interests likes video music games individual humor passionate political intelligence rounded views posts	Interests
creative smart intelligent people care outgoing immature picture employer need	Personality
young appearance pretty looks average normal intelligent kind nice happy real kids	Appearance, personality
posts language grammar offensive comments impression inappropriate English content spelling	Communication, language
friends family life pictures photos open age love oriented child updates	Friends, family
responsible potential job able level fact position fit employability time children married character cares	Personality, jobs, family
team fun sports active people relationship vulgar profanity writes shares educated ability	Interaction style
dedicated responsibility professional motivated history environment others clean work positive	Attitude

TABLE III: LDA analysis.

component across all participants. We obtained a perceived importance measure for each criterion using the same method.

The focused ratings in the screening task data reflect a rater's opinion regarding a profile *based only on one particular aspect*. As such, they are a rater's *subjective* opinion regarding a single aspect of the profile. A basic question regarding the importance of profile components or criteria is which aspects are predictive of the overall profile rating in a statistically significant way.

Further, given such a factor set, we wish to determine the *relative impact* of each factor. A common technique to do this is regressing a target variable using a set of predictor variables and applying a measure of "relative importance". Many such measures use linear models, including effect size measures (such as $\eta 2$ or ω^2 for ANOVA), and partial correlations, normalized regression coefficients or change in the coefficient of multiple determination (for multiple linear regression). [5]

To gauge **actual importance**, we applied multiple linear regression to the screening task data. Our target variable was the *overall* profile rating. We used two sets of predictors: the focused ratings of the profile components and the focused ratings of the criteria.

After fitting the model, we tested for statistical significance of the entire regression and for the significance of each individual factor's coefficient. Finally, we computed several factor importance measures based on the multiple regression.

The perceived importance of the profile components (average number of points allocated) is given in Table IV. 81% of the raters indicated that they have never hired people for a job in the past. We have included the results for the 19% who indicated they *were* in charge of hiring a person for a real-life job in the past in a separate column.

Table IV shows that survey participants expected textual posts to be the most important component. They expected the photos, the profile picture and the liked items to be of similar importance, and finally expected the friend list to have the least influence on the overall job-suitability rating.

[5] See [42], [43] for a discussion of importance measures. based on linear models.

Profile component	Average points (all raters)	Average points (past hirers only)
Posts	27.17	28.74
Photos	20.67	22.14
Profile picture	20.23	21.44
Liked items and groups	19.19	17.04
Friends	12.73	10.65

TABLE IV: Perceived importance of profile components.

Turning to the actual importance of the profile components, the regression of the overall rating from the profile component ratings had an overall fit of $R^2 = 0.456$, and was statistically significant ($F = 145$, $p < 2.51 \times 10^{-111}$). The coefficients of the profile component ratings were all significant at the $p < 0.001$ level.

Table V shows the significance levels and measures of the relative importance of each factor: partial correlations (PC), normalized regression coefficients (β) and change in the coefficient of multiple determination (CCMD). By partial correlations we refer to the correlation of one predictor variable and the target variable controlling for all the remaining predictor variables. By the change in the coefficient of multiple determination for a predictor variable x_i we refer to the change in R^2 value between the regression containing all predictors (including x_i) and the regression containing all predictions except x_i. The numbers in parentheses are the values renormalized to 100%.

These results indicate that the profile picture was the component that was most predictive of the overall rating. The posts, likes and photos were of similar importance, all less im-

Profile component	Significance	PC	β	CCMD
Posts	$p < 0.0001$	0.2386 (23%)	5.4817 (22.3%)	0.0328 (24.5%)
Photos	$p < 0.0001$	0.1641 (15.9%)	4.1446 (16.9%)	0.0150 (11.3%)
Profile picture	$p < 0.0001$	0.2967 (28.7%)	7.3743 (30.1%)	0.0525 (39.3%)
Liked items and groups	$p < 0.0001$	0.2040 (19.7%)	4.7306 (19.3%)	0.0236 (17.7%)
Friends	$p < 0.0002$	0.1319 (12.7%)	2.7860 (11.4%)	0.0096 (7.2%)

TABLE V: Actual importance of profile components in the screening task data (several relative importance measures based on the multiple regression).

portant than the profile picture. Finally, the component of least actual importance was the friend list. Figure 1 summarizes our results for profile components: perceived importance (values in Table IV) and actual importance (the partial correlations, PC, of Table V).

We now examine the job-suitability criteria. The perceived importance of the criteria is given in Table VI, showing that the participants expected all of the criteria to have considerable influence on the rating.

They expected the skills and intelligence of the applicant to be the most influential; they expected attitude and personality, as well as offensive content or content related to vices, to be slightly less influential (and of similar influence); they then expected the physical appearance and interests and activities of the applicant to be slightly less influential (and of similar influence); finally, they expected other demographic traits to be the least influential factor, though still of considerable influence (over 10% of the points).

The regression of the overall rating from the criterion ratings had an overall fit of $R^2 = 0.456$, and was statistically significant ($F = 120$, $p < 3.15 \times 10^{-110}$). The coefficients of all criterion ratings were significant at the $p < 0.001$ level. Table VII shows the significance levels and measures of relative importance of these factors.

Similarly to the perceived importance, all criteria had substantial actual importance. The *relative order* of these factors is similar to that of their perceived importance, except for offensive content or content relating to vices. This criterion was the second highest in perceived importance but only fourth in actual importance, indicating that participants may have overrated its influence on judgments. Though it is last in both perceived and actual importance, the criterion of age, family status, religious or political beliefs and other demographic traits, is still of considerable importance (roughly 10%).

We relied on people volunteering their social network profiles to be evaluated, so our results may be affected by a self-selection bias. In particular, people are less likely to volunteer their profile to be evaluated when they know the profile contains offensive content, which may lead to an under-weighting of the importance of the factor relating to offensive content or content relating to vices. [6]

Figure 2 summarizes the results regarding the criteria: perceived importance (average points of Table VI) and actual importance (partial correlations of Table VII).

[6]It may be possible to sample profiles uniformly at random, but it is impossible to gain access to restricted parts of these profiles without receiving the consent of the users, so we could not avoid such self selection biases while still using these "deep" parts of profiles.

B. CV Based Screening Versus Social Network Based Screening

We now turn to examine the differences between social network based screening and CV based screening. Clearly, CVs contain very different information than that present in social network profiles. Some criteria can clearly be evaluated by examining CVs. CVs certainly contain many details regarding the skills and education of applicants, and earlier work even indicates that people are capable of inferring some information about the attitude and personality of job candidates from their CVs [29], [30].

However, the remaining criteria are much more difficult to evaluate using CVs. Some participants may include their picture in their CV, allowing those examining it to get some information regarding their physical appearance, but most CVs do not contain such pictures. Similarly, most CVs do not contain information regarding an applicant's interests or hobbies (and in the few cases where such information is present, it is given in a very succinct manner).

Finally, the vast majority of CVs contains no demographic details regarding applicants, and candidates are extremely unlikely to put offensive content on their CVs or give hints of their vices.

Our results in the previous section indicate that the above factors are predictive of candidate ratings when evaluating them by their social network profiles. It is thus evident that CV based screening would focus on different factors than social network based screening.

Nonetheless, aiming to show these differences through a data-driven analysis, we applied the methodology described for the social network screening dataset on the CV screening dataset. This dataset consists of $n_s^{CV} = 4595$ reports, provided by $n_r^{soc} = 980$ raters who each evaluated several of the $n_p^{soc} = 294$ volunteered CVs.

Similarly to the social network screening dataset, each report included an overall job-suitability rating and additional focused job-suitability ratings, based only on a specific criterion. In the instructions to raters we explained to participants that many CVs may not contain information allowing them to judge candidates on all criteria. In cases where they were not confident, we asked the raters to provide their best estimate, and indicate this in their comments. Indeed, for criteria other than skills, education and intelligence and attitude and personality, most raters indicated they were not confident in providing a rating given the information in the evaluated CVs.

We computed the actual importance of the criteria in the CV screening dataset similarly to our analysis of the social

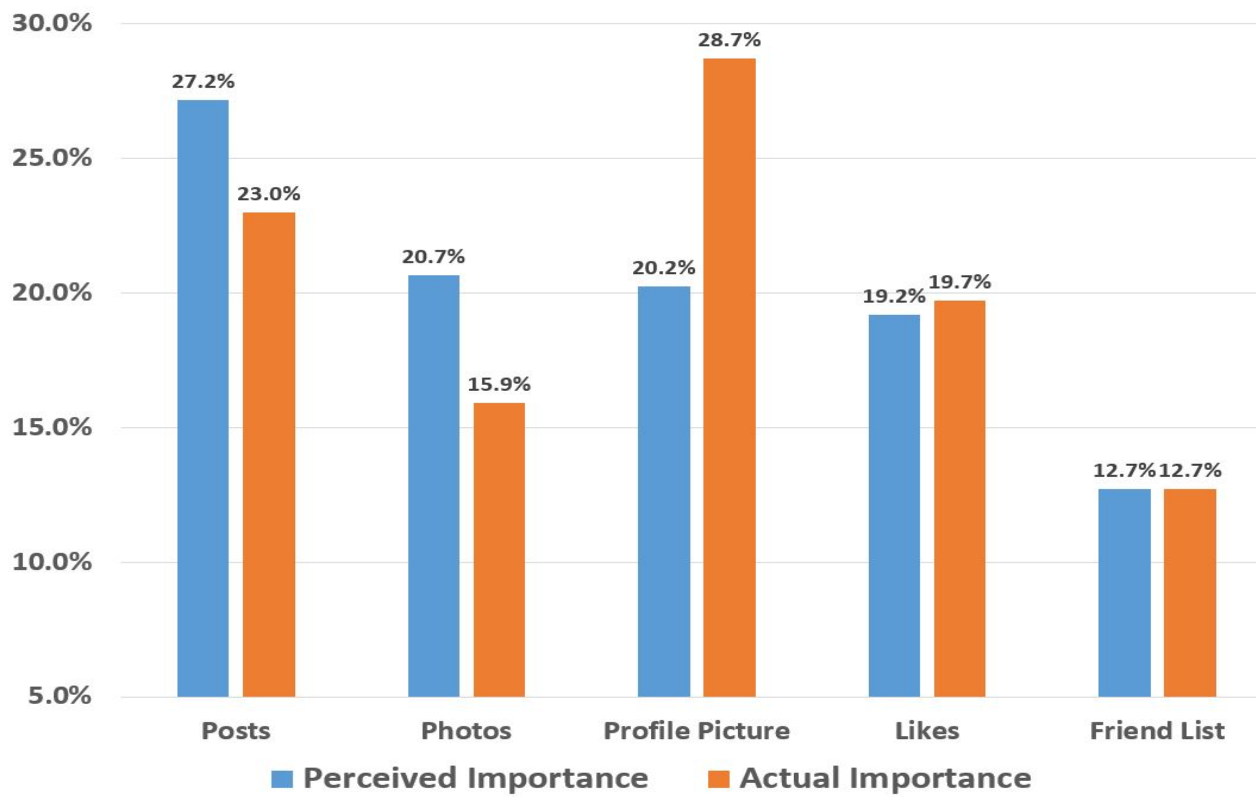

Fig. 1: Perceived and actual importance of profile components.

Job-suitability criterion	Average points (overall population)	Average points (past hirers only)
Skills, education and intelligence	21.72	21.75
Offensive content or content relating to vices	19.09	20.63
Attitude and personality	18.59	19.52
Physical appearance	15.15	15.21
Interests, activities and hobbies	14.66	13.84
Age, family status, religious or political beliefs, or other demographic traits	10.79	9.06

TABLE VI: Perceived importance of criteria.

network screening dataset. The regression of the overall rating from the criterion ratings in the CV screening dataset had an overall fit of $R^2 = 0.595$, and was statistically significant ($F = 1120$, $p < 1 \times 10^{-100}$). The coefficients of two criteria were significant at the $p < 0.01$ level: skills, experience and intelligence ($p < 1 \times 10^{-100}$), and attitude and personality ($p < 1 \times 10^{-23}$).

We computed various measures of actual importance of criteria, using the same process as for the social network screening task dataset. These are shown in Table VIII (corresponding to Table VII, but describing the importance of criteria in the *CV based screening data*).

Table VIII indicates that people who screen candidates based on CVs focus on their skills, education and intelligence. Judgments regarding attitude and personality are also slightly correlated with ratings in CV based hiring, but to a much smaller extent.

As expected, in contrast to our results regarding social network based screening, in CV based screening the remaining criteria examined *cannot* be shown to correlate with the overall ratings in a statistically significant manner.

Our results show that people who screen candidates based on social network profiles consider a wider set of criteria than those they consider when screening CVs. In CV based screening, people focus on skills, education and intelligence, and to a much lower extent on attitude and personality (consistently with the results of previous work [29], [30]); In social network based screening, these are still important, but the overall ratings also correlate with criteria such as physical appearance, offensive content or vices, interests and hobbies and age, family status, religious or political beliefs or other demographic traits.

Job-suitability criterion	Significance	PC	β	CCMD
Skills, education and intelligence	$p < 0.0001$	0.3220 (24.6%)	7.0956 (24.8%)	0.0629 (34.7%)
Attitude and personality	$p < 0.0001$	0.2722 (20.7%)	6.2401 (21.8%)	0.0435 (24%)
Physical appearance	$p < 0.0001$	0.2250 (17.1%)	4.8938 (17.1%)	0.0290 (16%)
Offensive content or content relating to vices	$p < 0.0001$	0.1911 (14.6%)	4.0664 (14.2%)	0.0206 (11.4%)
Interests, activities and hobbies	$p < 0.0001$	0.1533 (11.7%)	3.2575 (11.4%)	0.0131 (7.2%)
Age, family status, religious or political beliefs, or other demographic traits	$p < 0.0001$	0.1480 (11.3%)	3.0572 (10.7%)	0.0122 (6.7%)

TABLE VII: Actual importance of criteria in the **social network screening task** data (several relative importance measures based on the multiple regression).

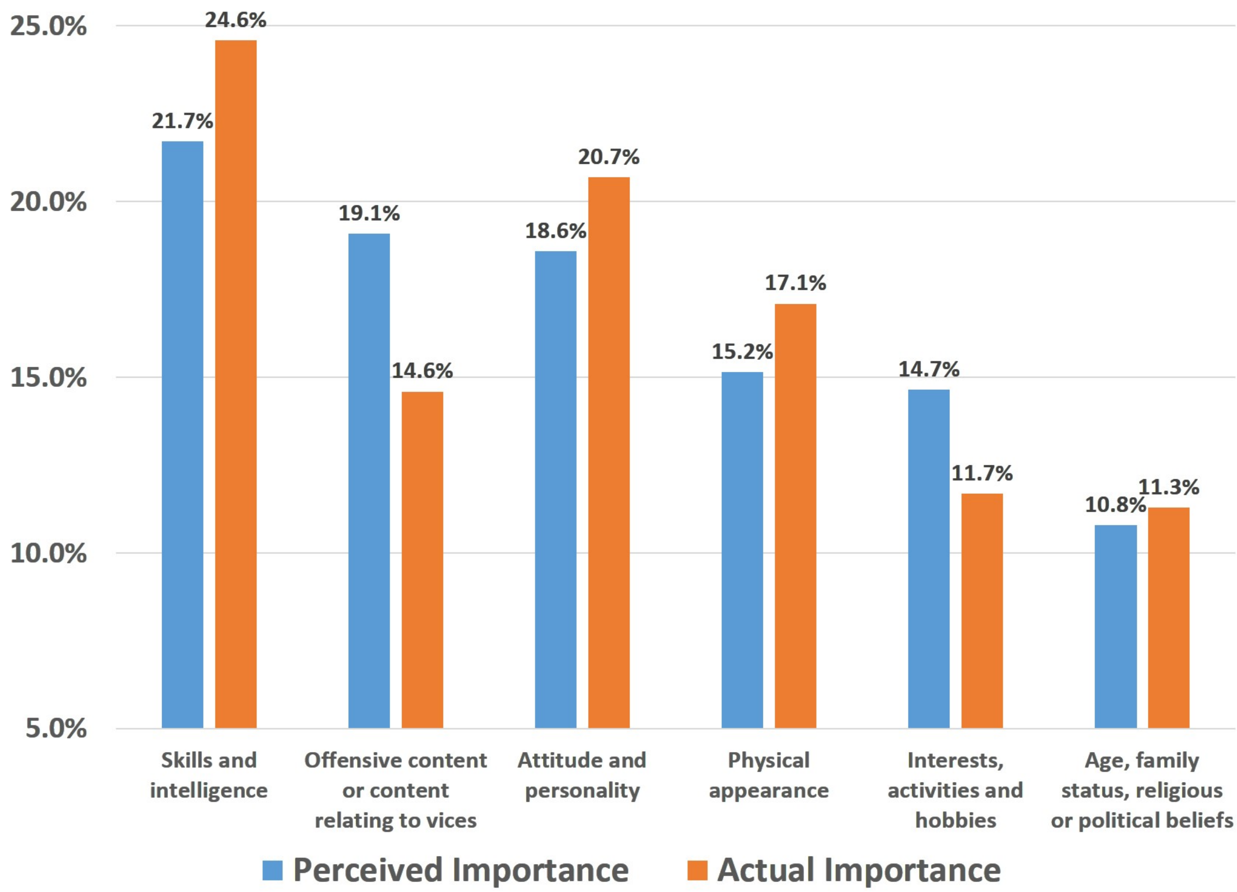

Fig. 2: Perceived and actual importance of criteria.

IV. Discussions and Conclusions

Our results indicate that job candidate screening using social network profiles goes far beyond the dry information about education and skills that is the focus of resumes. Raters consider criteria such as attitude, personality, physical appearance, interests and language and communication style.

Further, we found statistically significant correlations between a candidate's demographic traits such as educational background, ethnicity and gender, and their job-suitability rating. Such factors also affect hiring decisions in face-to-face interviews [37], [38], [39], [40], [41].

Hiring managers trying to fill a job opening sometimes receive many applications, and the screening process can take up their valuable time. Information from online social networks can be very effective in ruling out candidates, or in highlighting important issues to examine in depth during a face-to-face job interview. Further, analyzing an applicant's social network profile covers a wide breadth of issues, especially when given access to restricted parts of the profile. This may explain why some hiring managers continue to seek access to restricted profile data [25], [26], [27] even though this is likely to be perceived as *invading user privacy* [44], [45].

A few states in the USA have banned employers from demanding social network passwords during job-interviews [46], [47], but legislation regarding this issue is far from complete.

Job-suitability criterion	Significance	PC	β	CCMD
Skills, education and intelligence	$p < 0.0001$	0.7025 (73.38%)	17.02 (77.60%)	0.3947 (97.5%)
Attitude and personality	$p < 0.0001$	0.1457 (15.22%)	2.90 (13.20%)	0.0088 (2.17%)
Physical appearance	$p > 0.1$	0.0187 (1.95%)	0.35 (1.59%)	0.0001 (0.03%)
Offensive content or vices	$p > 0.1$	0.0360 (3.76%)	0.60 (2.73%)	0.0005 (0.13%)
Interests, activities and hobbies	$p > 0.1$	0.0376 (3.93%)	0.74 (3.39%)	0.0006 (0.14%)
Age, family status, religious or political beliefs, or other demographic traits	$p > 0.1$	0.0169 (1.76%)	0.33 (1.49%)	0.0001 (0.03%)

TABLE VIII: Actual importance of criteria in the **CV screening task data** (several relative importance measures based on the multiple regression).

Social network based screening seems to be similar to face-to-face interviews in that it allows a "deeper" analysis of candidates than CV based screening. However, social network based screening grants employers access to information they would find hard to obtain during a face-to-face meeting. Some questions are difficult, inappropriate or even illegal to ask during job interviews, such as questions relating to family status, alcohol or drug abuse, and religious or political beliefs. This information is present in social network profiles, and our results provide some evidence that it correlates with the raters' opinions.

A key appeal of online social networks is a user's ability to freely share information, thoughts or opinions with friends [48]. Some users may not be aware of the fact that hiring managers may use social network data for screening candidates, and others may share information as they are not aware of how harmful it can be to their job prospects, or as they are under the illusion that privacy settings give them complete control over how others can access pieces of content they share [49], [24].

However, privacy settings only help users who use them to restrict access to some content, and a password only protects users if they do not hand it over to hiring managers. [7]

Applicants may modify their profile to make themselves more appealing to employers [51], [52], [53]. This can take the form of removing information they believe potential employers may not like, or even generate content designed to form a certain impression. However, such modifications of the online social network profile comes at the cost of users self-censuring themselves, making social networks less useful and engaging [54], [55], [56].

Currently there is only limited legal regulation regarding using social networks for hiring decisions, so it seems likely that users would become more prudent and calculated in their online activity.

Job screening using social media also has *ethical and legal implications* [49], [56], [24]. We showed that people make many judgments regarding an applicant from their social network profile, and earlier work has already uncovered various data mining tools that allow inferring many job-relevant properties of people automatically and at low costs [22], [57], [58], [59]. [8]

Personal communication through online social networks is stored permanently, and could have negative job market consequences for a user years later. Using such data for job screening dissolves important boundaries between one's work and personal life.

Further, an employer's unauthorized use of information regarding a user from their social networke profile may constitute an invasion of privacy if the user had a reasonable expectation of privacy.

Finally, in cases where ratings and impressions from social network profiles correlate with certain demographic traits of the profile owner, hiring companies may be perceived to violate employment anti-discrimination laws if they examine a candidate's social network profile during the hiring process to seek information regarding some of the candidate's demographic traits relating to protected status groups (i.e. examining profiles could lead to discrimination based on age, family status, race or political beliefs, prohibited by anti-discrimination laws). [9]

Currently, there is a considerable *lack of clarity* regarding the legal standing of social network based job candidate screening.

Our study has *several important limitations*. Our methodology relied on an observational study rather than a controlled experiment. We noted some correlations between demographic traits and perceptions of job-suitability, but these do not indicate a directed causal relation between demographic traits and job-suitability ratings. It would be interesting to see whether a controlled experiment would show biases for or against certain populations when screening candidates using social network profiles.

Further, we used factor importance measures to estimate the relative importance of job suitability criteria, but relied on the opinions of crowdsourced raters, rather than trained human resources personnel. Clearly, trained human resources professionals may focus on different issues than our evaluators. In particular, they may be trained to disregard various demographic traits of the profile owner. Thus our results should be taken with a grain of salt, as they are more representative

[7] Companies may alternatively ask applicants to add the company's human resource manager as a friend, or to log into their account from the company's computer during an onsite interview. Hiring managers may even form judgments on candidates solely based on the properties of their social network friends [50].

[8] Although many such tools rely on social network profiles, similar inference can be made from other resources, such as website preferences and internet browsing history [60], [61].

[9] Several crowdsourced raters in our screening task have indeed commented that such demographic information should never be used for hiring decisions, asking to refrain from using it.

of positive or negative impressions of job candidates by a general non-expert population. Further work could examine the differences in the relative importance of criteria between human resources professionals, hiring managers of various industries and crowdsourced workers. [10]

Several questions remain open for further study. First, our data is based on Facebook profiles. Are there differences in job-suitability impressions based on different social networking websites? Do such other online social networks differ in the relative importance of the job-suitability factors examined in this work? Do employers use other online information stores such as personal websites or blogs to screen candidate for jobs?

Finally, could one develop technological solutions that would protect user privacy while still allowing employers to validate certain properties of their social networking profiles?

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