Journal of Research in Personality 93 (2021) 104122

Contents lists available at ScienceDirect

Journal of Research in Personality

journal homepage: www.elsevier.com/locate/jrp

Using available signals on LinkedIn for personality assessment

Sébastien Fernandez *, Marie Stöcklin, Lohyd Terrier, Sowon Kim

Ecole hôtelière de Lausanne, HES-SO University of Applied Sciences and Arts Western Switzerland, Route de Cojonnex 18, 1000 Lausanne 25, Switzerland

ARTICLE INFO

Keywords:
LinkedIn
Social media
Personality
Big five
Signaling theory

ABSTRACT

LinkedIn is considered the most effective social network website for job seekers and recruiters. Although LinkedIn profiles are regularly accessed to evaluate candidates, we know very little about the type of information conveyed. The aim of this study is to determine if LinkedIn profiles convey accurate information about individuals' personality traits. Drawing from signaling theory, we expect that individuals portray themselves in a manner that will reflect their personality. To examine this assertion, 607 LinkedIn profiles were coded on 33 indicators. Regression analyses and classification statistics demonstrate that Linkedin profiles contain accurate signals of personality traits. Potential use and limitations of LinkedIn as a source of accurate information about personality are discussed.

1. Introduction

LinkedIn is the largest professional social network with over 690 million users across more than 200 countries and territories worldwide (LinkedIn, 2020). It allows job seekers and employed individuals to search for new job opportunities or receive job offers (Johnson & Leo, 2020; LinkedIn Press Center, 2016). Companies use LinkedIn to advertise job offers and communicate about their brand. It is predicted that LinkedIn might replace paper résumés in a near future (Schwabel, 2011) and some experts already claim that social media (including LinkedIn) might offer an alternative to traditional selection methods. Despite its popularity at work and its potential as a selection tool, little is known about the capacity of LinkedIn to offer useful information for workplace decisions.

In this study, we analyze personality using the big five model, which is the most widely used and accepted model of personality (McCrae & John, 1992). This model comprises the following personality traits: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism.

We believe that it is of the utmost importance to determine how LinkedIn might convey accurate information about personality given the current context of increased mistrust on personality assessment (Morgeson et al., 2007). One of the primary reasons LinkedIn users are active on this platform is to convey information about job experiences and skills, but LinkedIn might also offer clues about the candidate's personality. Personality is considered to be an important construct in employee selection. Human resource professionals assume personality tests to be valid (Furnham, 2008), place more emphasis on selected personality traits than intelligence during selection (Kausel et al., 2016; Lievens et al., 2005; Tews et al., 2011), and ask personality-related questions during selection interviews (Huffcutt et al., 2001). Moreover, personality predicts consequential outcomes for organizations, such as job performance (Barrick et al., 2001), counterproductive work behaviors (Berry et al., 2007) and turnover intentions (Spence, 1973; Zimmerman, 2008).

While extensive studies have examined the association between information on nonprofessional social media such as Facebook or Twitter and personality (see Azucar et al., 2018), surprisingly only two studies have shown that LinkedIn can convey accurate information about personality (Roulin & Levashina, 2019; Van de Ven et al., 2017). Both studies found that extraversion could be accurately observed from LinkedIn profiles. However, we still lack understanding on why individuals would not signal other personality traits through LinkedIn. In this study, we extend these prior studies by asserting that individuals do in fact provide much more information than meets the eye.

1.1. Signaling theory

Signaling theory has its origin in economics and biology (Spence, 1973; Zahavi, 1975) and explains why certain signals are reliable and others are not (Donath, 2008). Signaling theory offers a promising theoretical framework to understand individuals' behavior on LinkedIn. According to Spence (1973), any signaling system is composed of a sender, a receiver, and a signal transmitted by the sender to the receiver.

* Corresponding author.
E-mail address: sebastien.fernandez@ehl.ch (S. Fernandez).

https://doi.org/10.1016/j.jrp.2021.104122
Received 28 January 2021; Received in revised form 11 June 2021; Accepted 14 June 2021
Available online 18 June 2021
0092-6566/

Signals have the power to transmit information about an unobservable characteristic of the sender (e.g. intelligence or personality). Signaling theory is used to describe behavior in a context of cooperation between two parties with conflicting/competitive goals, such as personnel selection (Bangerter et al., 2012). For instance, in hiring, candidates and recruiters cooperate to see if there is a good match between the candidate and the organization. However, the candidate's goal is to be selected, whereas the recruiter's goal is to select the best candidate. According to signaling theory, both recruiters and applicants will share accurate information if this serves their interest. Signals will be accurate only if they are hard to fake or if they impose a cost on the sender such that only individuals who really possess the skill or the trait will be able to bear the cost (Bangerter et al., 2012).

Drawing from this theory in the context of self-presentation on LinkedIn, we expect individuals to portray themselves accurately only if it might attract potential recruiters or provide additional evidence of their capacity and willingness to take specific job responsibilities. The reason for this would be to impress recruiters and to distinguish themselves from other candidates. LinkedIn might then be a vehicle for accurate information. Recruiters might be looking for honest signals from individuals, which may be of two kinds: costly signals and hard-to-fake signals. Costly signals imply that applicants have invested a lot of time and/or resources to demonstrate them. They might, for instance, refer to the presence of specific extracurricular activities, professional activities, or degrees. Having graduated from a college with honors might constitute a costly signal of high conscientiousness, as it requires many hours per week over many years to graduate with high grades. As LinkedIn is a vehicle for transmitting information about education, professional experiences, precisely costly signals, individuals are likely to send accurate information about themselves. Hard-to-fake signals are not under conscious control. For instance, it is difficult to fake a cognitive ability test. However, it is easy to claim to be intelligent in a job interview because it is not a hard-to-fake signal. Signals are more likely to be accurate when the cheating cost is high or salient. Because LinkedIn profiles can be viewed by current and former colleagues, supervisors, or friends, it might be disadvantageous for individuals to provide false information. While candidates can customize their letter of motivation and CV to the organization where they are applying, it might be impractical to do so on LinkedIn. It might also be unwise to provide inaccurate information on LinkedIn because an individuals' reputation might suffer if their professional connections realize they are not telling the truth or stretching the truth.

In addition, signaling theory offers insight into the dynamic exchanges between individuals and organizations over time. When an honest signal is detected by organizations, applicants are likely to adapt over time and find ways to alter the honest signal. For instance, there is now accumulating evidence that applicants can fake good results in a personality test when administered in a selection context (Morgeson et al., 2007). Each time organizations identify signals that are not hard-to-fake, applicants will adapt over time by modifying the signals they send (Bangerter et al., 2012).

1.2. LinkedIn

Most recruiters use LinkedIn to recruit and select candidates (e.g. Guilfoyle et al., 2016; Hartwell & Campion, 2020) to gather relevant information about applicants, such as prior work experience, educational background, technical skills, professionalism, or writing skills (Hartwell & Campion, 2020). Other research shows that they investigate candidates' profiles to assess person-job fit and person-organization fit (Chiang & Suen, 2015), or more simply to determine how well-connected candidates are, and to gauge their level of professionalism through the way they are dressed (Zide et al., 2014).

Recruiters can form impressions about candidates based on a diversity of information available on LinkedIn. This includes information about job experience, education, extracurricular activities, skills, languages, recommendations, courses, or grades. In addition to these pieces of information that are also available in a candidate's résumé, specific information found exclusively on LinkedIn, (e.g. number of connections, posts, and pictures; a summary; recommendations from other individuals; influencers followed) can be accessed via this social network.

Despite the richness of information contained in LinkedIn profiles, there is a paucity of research examining whether information available on LinkedIn has convergent validity. Based on signaling theory, we expect that individuals use their LinkedIn profile to convey information about their personality. For instance, Roulin and Levashina (2019) have shown that LinkedIn offers accurate signals for skills, such as leadership, planning or communication. More specifically on personality, there is support so far that LinkedIn conveys accurate signals with regard to extraversion (Roulin & Levashina, 2019; Van de Ven et al., 2017). The number of connections, the number of endorsements, and the presence of a profile picture constituted valid signals of extraversion, whereas the number of words in a profile was a signal of conscientiousness, and the presence of a summary was a signal of openness. Overall, these two studies concur that LinkedIn offers many signals of individuals' extraversion but very few signals of other personality traits.

1.3. Signals of personality traits on LinkedIn

Drawing from signaling theory, we postulate that individuals have an interest in signaling their personality traits through the presence of a variety LinkedIn indicators[1]. Due to the public nature of information conveyed on LinkedIn, we posit that these signals provide accurate information on the personality of LinkedIn users.

1.3.1. Signals of openness to experience

Openness to experience refers to curiosity, intellectual complexity, unconventional thinking and proneness to fantasy. Individuals who score high on openness to experience are interested in artistic hobbies (Wolfradt & Pretz, 2001) and professions that require creativity (Larson et al., 2002). As such, we postulate that individuals scoring high on openness, are more likely to indicate extracurricular activities related to art. In addition, people scoring high on openness to experience tend to personalize their environment to make it distinctive (Gosling et al., 2002). They might therefore insert background photographs that reflect their creativity and artistic interests. Furthermore, driven by curiosity, individuals who score high on openness to experience are interested in developing new competences such as learning a second language (Ghonsooly et al., 2012). Consequently, we anticipate they report mastering more languages than people scoring low on the same trait. Individuals who score high on openness to experience tend to have more diverse interests, thus, we expect them to follow more influencers on LinkedIn. People who score high on the trait of openness to experience tend to care more about universalism values (Parks-Leduc et al., 2015). As such, they tend to be more environmentally engaged (Milfont & Sibley, 2012), and they might be more likely to report activities that demonstrate this interest. Finally, as LinkedIn users can list their skills, we hypothesize they are more likely to report skills such as curiosity and creativity, which are characteristics often associated with individuals scoring high on openness to experience.

H1: Individuals scoring high on openness to experience signal this trait by the presence of the following LinkedIn indicators: a) they are more likely to have an artistic background photograph; b) they list skills related to curiosity or creativity; c) they report mastering more languages; d) they are more likely to report artistic extracurricular

[1] As suggested by an anonymous reviewer, we would like to emphasize here that a high score only means the person is more likely to possess the characteristic implied by the label of the trait, and not that a high score is more valuable than a low score.

activities; e) they are more likely to report extracurricular activities related to social responsibility; f) they follow more influencers.

1.3.2. Signals of conscientiousness

Individuals who score high on conscientiousness tend to be organized, purposeful, achievement-striving and rule-oriented. The increased efforts and persistence of individuals who score high in conscientiousness often lead them to be successful in academic contexts (Poropat, 2009), job contexts (Barrick et al., 2001) and during job search (Kanfer et al., 2001). Conscientious individuals seem to be better prepared and anticipate the impression they make on others. For this reason, we expect that they present themselves as more formally dressed than less conscientious persons. As they are more thorough, they might put more effort into crafting complete and flawless profiles. Thus, conscientious individuals might be inclined to write more, which would result in them completing more sections on their LinkedIn profile (e.g. personal summary, descriptions for past work experiences, and list of courses attended in college). We also expect their LinkedIn profiles to contain fewer spelling mistakes, which undermine others' perception of a person's level of conscientiousness (e.g. Vignovic & Thompson, 2010). As a another consequence of putting more effort into the design of their LinkedIn profile, conscientious individuals might be more likely to regularly check that their profile is updated. They tend to be more persevering than their less conscientious counterparts and might ensure they periodically visit their profile to ensure they have not forgotten to add recent degrees obtained or recent professional experiences. As conscientiousness is associated with higher grades (Cole et al., 2009; Poropat, 2009), we hypothesize that individuals scoring high on conscientiousness will be more likely to provide information about their GPA (Grade Point Average) and/or academic awards. Furthermore, as they tend to set higher goals for themselves, we expect they try to obtain more certifications. In addition, conscientious individuals often participate in extracurricular activities during their studies (Rubin et al., 2002) or take on additional responsibilities at work (Chiaburu et al., 2011). For this reason, we expect that they mention more extracurricular activities, such as student ambassadors or class representatives. As conscientious individuals tend to manage their time more effectively (Van Eerde, 2003) and possess better organizational skills (Bartram, 2005), we assume time management and organization skills to be listed more often. Finally, as conscientious individuals tend to perform better across contexts than less conscientious individuals (Barrick et al., 2001), and as conscientiousness is considered by many recruiters and managers to be one of the most important criteria for performance (Scholarios & Lockyer, 1999; Ohme & Zacher, 2015), we anticipate a greater number of recommendations received for those who score higher on conscientiousness.

H2: Individuals scoring high on conscientiousness signal this trait by the presence of the following LinkedIn indicators: a) their portrait shows they are formally dressed; b) they completed the summary section; c) they describe their prior work experiences; d) they have an updated profile; e) they list the courses they attended in college; f) their profile contains fewer spelling mistakes; g) they are more likely to report their GPA, having obtained an academic award or an additional certification; h) their profile is more likely to contain recommendations from former supervisors; i) they are more likely to indicate extra-curricular activities; j) they are more likely to indicate organizational skills in the skills section of their profile.

1.3.3. Signals of extraversion

Extraversion is positively related to networking (Wolff & Kim, 2012) and past studies conducted on social media have shown that extraverts possess more connections than introverts (Gosling et al., 2011). Extraverts also interact more frequently with social media and post more pictures (Gosling et al., 2011). They tend to live more often in city centers than in the suburbs (Jokela et al., 2015), and tend to be less interested by environments that are quiet than those that promote social connections (Oishi et al., 2015). They might be then more inclined to signal their extraversion by adding a background picture which portrays their appreciation toward noisy, crowded, and vibrant environments that facilitate human interactions As such, we expect them to insert background pictures with cities or people. Prone to overconfidence (Schaefer et al., 2004), we expect extraverts to list more skills than introverts. Moreover, at ease in social interactions, they tend to be natural leaders (Judge et al., 2002), convey charisma (Bono and Judge, 2004) and be good at presenting information in front of others (Bartram, 2005). For these reasons, we hypothesize that extraverts are more likely to list leadership, social skills, and public speaking among their skills. Due to their proactivity and activity level, past research has shown that people who report experience in leadership and practicing sports might be more extraverted than those who do not report this kind of information (Cole et al., 2009). Due to their need to seek stronger sensory stimulation (Eysenck et al., 1982), it has been observed that extraverts might be more likely to participate in physical activities than introverts (Wilson & Dishman, 2015). Although sports may seem superfluous to a LinkedIn profile, it is likely that extraverted individuals would report sports activities as a way to differentiate themselves from other candidates (Roulin & Bangerter, 2013). Finally, we expect extraverts to be more likely to add pictures to illustrate past work experiences. It might then be another way for them to signal their level of engagement on LinkedIn, as they do so on other social network websites (Gosling et al., 2011).

H3: Individuals scoring high on extraversion signal this trait by the presence of the following indicators: a) they have more professional connections; b) they are more likely to include a background photograph representing human interactions; c) they list more skills; d) they are more likely to list specific skills, such as leadership, social skills, or public speaking; e) they are more likely to indicate they have participated in sports activities; f) they are more likely to indicate that they had taken a leadership role in an extra-curricular activity; g) they are more likely to insert pictures in their LinkedIn profile.

1.3.4. Signals of agreeableness

People who score high on the trait of agreeableness express prosocial values such as universalism and benevolence (Parks-Leduc et al., 2015). They tend to be selfless and believe that it is important to help others. Extensive studies have documented that agreeableness is the best predictor of prosocial behavior (e.g., Habashi et al., 2016). Therefore, people who score high on agreeableness might recommend others' competences on LinkedIn or list experiences such as volunteering activities. Due to their desire to help others (Graziano et al., 2007) and their ability to support and cooperate with others (Bartram, 2005), agreeable individuals contribute positively to team efforts (Bell, 2007). Finally, they are easily satisfied when they work as part of a team (Peeters et al., 2006), and hence could be more likely to list skills related to teamwork and collaboration. Due to their good-natured personality, it has also been shown that agreeable people are more likely to smile than less agreeable people (Cuperman & Ickes, 2009; Naumann et al., 2009). We also anticipate they do so on their LinkedIn portrait.

H4: Individuals scoring high on agreeableness tend to signal this trait by the following indicators: a) they smile more on their portrait; b) they are more likely to report skills related teamwork; c) they are more likely to recommend their peers; d) they are more likely to indicate volunteering activities and peer tutoring activities.

1.3.5. Signals of neuroticism

Neuroticism is a trait which is difficult to observe accurately at zero-acquaintance as it is a trait which is mainly affective and thus less visible (Vazire, 2010; Zillig, Hemenover & Dienstbier, 2002). As such, we have not identified specific indicators that could indicate neuroticism. In support of this assertion, studies conducted on other social media have shown that neuroticism is the second most difficult trait to observe (after agreeableness; Azucar et al., 2018). We assume however that some signals of extraversion (e.g. public speaking and leadership) might also be related to lower scores on neuroticism. Individuals scoring high on neuroticism could be less likely to report these skills in their LinkedIn profile.

1.4. Gender differences and signaling

Research has shown that women tend to score higher on neuroticism and agreeableness than men, whereas men tend to score higher on certain facets of extraversion such as assertiveness (for a review, see Hyde, 2014). In addition, some outcomes are not predicted by the same traits among men and women. For instance, neuroticism predicts academic achievement in men but not in women, whereas openness to experience only predicts academic achievement among female students (Nguyen et al., 2005). Other studies have shown that a firmer handshake indicated high openness to experience among women but not among men (Chaplin et al., 2000), or that conscientiousness was only related to a neat appearance among men (Naumann et al., 2009). Past studies have also demonstrated gender differences in the way individuals portray themselves on LinkedIn (Tifferet & Vilnai-Yavetz, 2018; Zide et al., 2014). For example, men are more likely than women to receive recommendations on LinkedIn (Zide et al., 2014) and they are less likely to smile in their portrait (Tifferet & Vilnai-Yavetz, 2018). Because gender differences have been reported in the past, we test if LinkedIn indicators signal personality to the same extent among men and women.

RQ1: Do men and women signal their personality in the same manner on LinkedIn?

1.5. Prediction of personality based on LinkedIn

If individuals signal certain personality traits through multiple LinkedIn indicators, observers might rate these traits accurately. Recent studies have shown, however, that only extraversion was rated accurately on LinkedIn profiles (Roulin & Levashina, 2019; Van de Ven et al., 2017). As a consequence, we want to determine if the systematic consideration of multiple LinkedIn signals offers a viable strategy for assessing accurately a person's personality.

In this study, we use classification statistics (Fleiss, 1981) in addition to regression and correlations analyses, which are more traditionally used in personality psychology. Whereas correlations and regression analyses might uncover a positive and significant relationship between the number of connections and the level of extraversion of an individual, classification statistics aim at answering a different set of questions. For example, classification statistics will determine the probability of accurately classifying a person scoring high or low on extraversion based on one or more signals.

RQ2: Is it possible to determine personality based on LinkedIn signals? If so, how accurately?

2. Method

2.1. Participants and procedure

The participants are graduates (N = 607) from a hospitality management school in Switzerland (60.5% of them are women; Age, M = 24.45; SD = 1.63 with the youngest participant being 22 years old and the oldest being 35 years old). This sample was chosen for two reasons. First, most of the people who have studied in this management school had LinkedIn profiles. Second, there are more than 120 different nationalities represented among the student body, which ensure cultural diversity. Having participants from different geographic regions ensures that our conclusions might be more generalizable than data collected with participants from the same cultural background. We collected data in two stages. The first stage of data collection ran from September 2013 until June 2015, in which these graduates were still students and completed a 300-item personality questionnaire as part of an Organizational Behavior course requirement. Participants gave their consent that the collected data could be used as part of a research project. Participants graduated between June 2016 and June 2017. The second stage of data collection took place during summer 2018. In spite of this time lag of three years and some results showing that the personality of young adults change over a three-year period, the rank-order consistency of personality remains satisfactory to high (with correlations ranging from $r = 0.64$ to $r = 0.74$) over this period of time (Specht et al., 2011). We think our approach was conservative as it might be more difficult to observe significant correlations between LinkedIn indicators and self-reported personality measured years before LinkedIn profiles were coded. The LinkedIn profiles of all the graduates were assessed separately by two co-authors of this study. These researchers coded all the LinkedIn profiles based on the indicators listed in Table 1.

Since our sample size (N = 607) was constrained by the number of individuals who had been administered the personality questionnaire, we conducted a post hoc power analysis. We examined a range of observed effect and sample sizes for a two-tailed test with alpha set at 0.01 using G*Power 3.1.9.7 (Faul, Erdfelder, Lang, & Buchner, 2007). Considering effect sizes observed ($\rho = 0.20$) by Roulin and Levashina (2019) between extraversion and LinkedIn indicators, the power of our study is 0.992 (for men, N = 239, power is 0.71; for women, N = 368, power is 0.90). However, past studies have shown that extraversion can be better detected than other personality traits on social media (Azucar et al., 2018). To detect correlations around $\rho = 0.10$, the power in our study is the following: 0.46 (below the traditional threshold set at 0.80). This value was derived from Cohen (1988) and Gignac and Szodorai (2016) who, for different reasons, advocate that correlations at 0.10 represent small effects but with potential practical consequences. We considered that aiming at detecting correlations below $r = 0.10$ would not be of any practical consequence. Finally, we would like to add that our study has enough power to detect effect sizes/correlations of $\rho = 0.14/r = 0.10$ on the full sample ($\rho = 0.21/r = 0.17$ on the subsample of men, $\rho = 0.18/r = 0.13$ on the subsample of women).

2.2. Measures

2.2.1. Personality traits

We used the International Personality Item Pool 300-item version of the NEO-PI facet scales (IPIP NEO-PI, International Personality Item Pool, n.d) to measure the big five traits and their facets. Participants used a 5-point scale ranging from 1 (very inaccurate) to 5 (very accurate) to respond to the items. Alpha coefficients for the five traits range from 0.87 to 0.95, which is in line with values reported in other studies (Goldberg, 1999; Goldberg et al., 2006). Descriptive statistics and intercorrelations between personality traits can be found in Appendix A.

2.2.2. LinkedIn indicators

Two types of indicators were used in this study (binary and continuous variables)[2]. Regarding binary variables, we checked whether indicators were present in the profile. For example, we checked if participants provided information about their academic results or if they held a leadership role in a college committee. To do this, two coders rated separately the profiles. When there was disagreement, the two coders checked simultaneously the profiles and agreed on a common rating. After discussion, the two coders reached perfect agreement for the binary variables. Regarding continuous variables, the inter-rater correlation between the two ratings was computed and was considered satisfactory in every case (smile, $r = 0.80$, $p < .01$; number of connections, $r = 0.99$, $p < .01$; number of skills, $r = 0.99 < p < .01$; number of languages, $r = 1.00$, $p < .01$; number of influencers, $r = 1.00$

[2] Two other variables have been coded and are available in the dataset. They are not mentioned in the paper because we found that the theoretical underpinning for including them was not as strong as for the other indicators.

Table 1
Measurement of all the LinkedIn indicators.

Indicators	Measurement
Openness to experience	
Artistic picture	1 = a background picture representing a landscape or of artistic nature is present; 0 = no background picture like this
Curiosity	1 = The skill "curiosity" (or "creativity, open-mindedness, innovation") is listed in the section "Skills and Endorsements"; 0 = this skill is not listed
Number of languages	Number of languages appearing in the section "Accomplishments" or "Skills and endorsements"
Social responsibility	1 = the person has belonged to a committee devoted to social responsibility in the school where he/she graduated; 0 = no indication of belonging to such student committee[3]
Artistic activity	1 = the person has belonged to a committee devoted to art in the school where he/she graduated; 0 = no indication of belonging to such student committee
Influencers	Number of influencers followed by the person
Conscientiousness	
Professional attire	1 = person wears a suit jacket; 0 = person does not wear a suit jacket[4]
Summary	1 = The individual has written more than two sentences in the summary section; 0 = No summary (or summary of less than two sentences)[5]
Experience described	1 = The individual has at least included one sentence related to the last professional experience to describe competences or tasks related to the position; 0 = no description[6]
Profile updated	1 = Information appearing in the job title, summary or job experiences have been updated in the last 6 months; 0 = information is outdated of more than 6 months.[7]
Inattentiveness (R)	1 = there is a spelling mistake appearing on a title, or a duplicate (e.g. the same experience appearing twice in the same section); 0 = no duplicate or spelling mistake[8]
Organization	1 = The skill "organization" (or "time management, conscientiousness") is listed in the section "Skills and Endorsements"; 0 = this skill is not listed
Grade Point Average	1 = the person indicates information about grades (numerical information, percentile, or graduated with honors); 0 = no mention of this kind of information
Award	1 = person mentions having received an academic award (e.g. best thesis award) or won an academic competition; 0 = no mention of this kind of information
Additional certification	1 = the person indicates having attended a summer school or done an additional certification during bachelor studies; 0 = no mention of this kind of information
List of courses	1 = the person lists at least six courses attended during studies; 0 = no mention of the courses (or less than six courses mentioned)
Ambassador	1 = the person has been an ambassador in the school where he/she graduated; 0 = no indication of being a student ambassador in the past
Class representative	1 = the person has occupied a representative role in in the school where he/she graduated; 0 = no mention of a representative role
Recommendation received	1 = the person has been recommended by at least one supervisor or teacher; 0 = the person has not been recommended yet
Curiosity	1 = The skill "curiosity" (or "creativity, open-mindedness, innovation") is listed in the section "Skills and Endorsements"; 0 = this skill is not listed
Extraversion	
Number of connections	Number of connection appearing below the name (0–500)[9]
Human interactions	1 = a background picture representing people or city is present; 0 = no background picture like this present
Number of skills	Number of skills that are listed in the section "Skills and Endorsements"
Social skills	1 = The skill "social skills" (or "communication, people skills, emotional intelligence") is listed in the section "Skills and Endorsements"; 0 = this skill is not listed
Leadership	1 = The skill "leadership" is listed in the section "Skills and Endorsements"; 0 = this skill is not listed
Public speaking	1 = The skill "public speaking" (or "presentation skills") is listed in the section "Skills and Endorsements"; 0 = this skill is not listed
Sport activity	1 = the person mentions having participated in a sport activity in college; 0 = no mention of a sport activity in college
Leadership role	1 = the person indicates being president, vice-president or head (marketing, HR, finance, etc) in a committee; 0 = no mention of a leadership role.
Additional pictures	1 = the person provides additional pictures in the summary, experience or education section; 0 = no additional picture
Agreeableness	
Smile	The extent to which individuals smile in their portrait was coded on a 7-point Likert scale (1 = not at all; 7 = a lot). This scale was inspired by Meier et al. (2010).
Teamwork	1 = The skill "teamwork" (or "groupwork") is listed in the section "Skills and Endorsements"; 0 = this skill is not listed
Volunteer activities	1 = there is a volunteer activity in the experience section or in the volunteer experience section, 0 = no indication of volunteer activity
Peer tutoring	1 = the person reports having helped other students in college by providing peer tutoring sessions 0 = no indication of having delivered peer tutoring sessions
Recommendation given	1 = the person has at least recommend once another person; 0 = the person has not yet recommended someone else

[3] We only considered the school in which they obtained their bachelor even if some of them reported participation in student committee in high school. This choice was motivated by our willingness to identify similar categories between participants of the study.

[4] We decided to rate professional attire in this manner as it would be less subjective than a Likert scale as used in other studies (e.g. Fernandez, Stosic & Terrier, 2017). Moreover, as both men and women wear suit jackets in professional settings, coding this element is appropriate for both genders.

[5] We chose two sentences because we observed some individuals listing three adjectives and we thought it would not represent as much effort as individuals who wrote a lengthier description.

[6] The last professional experience was preferred over the current professional experience. We considered it would be unlikely individuals describe their current professional experience if they were recently appointed to this position because they had not yet the time to familiarize themselves with it.

[7] The threshold of 6 months was chosen because all the profiles were coded in summer 2018. As months do not always appear, we could track if what appeared in the profile of the individuals described their current situation in 2018.

[8] We coded only spelling mistakes or duplicates in the titles, with the rationale that all the individuals divulgate this information on their profile. We thought that people who write much more information are more likely to make mistakes, but it would not be due to inattentiveness in that case.

[9] Because one cannot have access to the specific number of connections individuals have on LinkedIn if they have more than 500 connections, the maximum value was set at 500. When individuals have more than 500 connections, this information is presented as such "500+ connections". It is however possible to determine their number of followers if they have created, shared or commented posts on LinkedIn.

$< p < .01$). For these variables, the average rating was considered in the analyses. Intercorrelations between LinkedIn indicators can be found in Appendix B.

2.3. Analyses

We used SPSS 25 to perform correlations and regressions analyses. All significant tests reported in the article are two-tailed. Classification statistics such as sensibility, specificity, positive predictive value, negative predictive value, hit rate and likelihood ratio were computed separately for each LinkedIn indicator. Classification statistics aim to determine if indicators or test can classify accurately a person in the right group. In our study, we ran classification statistics to determine if

LinkedIn indicators might classify accurately individuals as scoring high or low on a specific personality trait. These two groups were identified by considering only the top and lowest tercile on each personality trait.

3. Results

3.1. LinkedIn indicators of openness to experience

Table 2 and presents descriptive statistics concerning the LinkedIn indicators (as well as intercorrelations with the big five traits). Despite the very low percentages observed for some indicators, there is no apparent range restrictions as these indicators correlate with the personality trait they are supposed to signal. Six LinkedIn indicators were hypothesized to reflect openness to experience. As shown in Table 2, all of them correlate with self-reported openness to experience. These results support *H1*. We should however mention that some of these indicators reflect other personality traits (see Table 3). For instance, individuals who are conscientious, extraverted and emotionally stable are also more likely to post an artistic picture. Individuals who report participating in social responsibility activities tend to score higher on agreeableness. Finally, the number of influencers is related as strongly (if not more) to extraversion compared to openness to experience.

3.2. LinkedIn indicators of conscientiousness

For conscientiousness, we identified 13 potential LinkedIn indicators. Eleven indicators were indeed related to conscientiousness, but two of them were not (professional attire, and inattentiveness). Overall, these results support *H2*. Professional attire was related negatively to neuroticism. It means that individuals who are calm and stable (scoring low on neuroticism) are more likely to be formally dressed than people scoring high on neuroticism. Some signals of conscientiousness are also related to traits other than conscientiousness. For instance, individuals who write a summary tend to score higher on extraversion and lower on neuroticism. Those who describe their experiences tend to be more agreeable and those who keep their profile updated tend to be more extraverted. It is also worth mentioning that individuals who report having held representative roles in college tend to be more extraverted.

3.3. LinkedIn indicators of extraversion

For extraversion (where nine indicators were hypothesized to be related to this trait), seven indicators were related significantly to this trait (number of connections, human interactions, sport activity, leadership role, additional pictures, number of skills, and leadership skill). Only two indicators were not related to extraversion: social skills and public speaking. Overall, these results support *H3*. It is interesting to note that four LinkedIn indicators of extraversion are negatively correlated to neuroticism. It seems then that emotionally stable individuals are more likely to report sports activities, to post additional pictures to their profile, report a higher number of skills and are more likely to report leadership as a skill than their neurotic counterparts.

3.4. LinkedIn indicators of agreeableness

We hypothesized five indicators to be related to agreeableness but only three of them (smile, teamwork and volunteer activity) were significantly related to agreeableness. We also observe that three indicators, which were supposed to measure agreeableness, also correlate with conscientiousness. These results only partially support *H4*.

3.5. Gender differences in signaling

First, we examine if men and women differ on the LinkedIn indicators. As shown in Table 4, men tend to follow a higher number of influencers ($t(605) = 2.34$, $p = .02$, $d = 0.19$), are more formally dressed

Table 2
Descriptive statistics for the LinkedIn indicators and correlations with the personality trait they are signaling.

	M(SD)	r_{Openness}	*p*	95% CI
Artistic picture	14.8%	0.16	< 0.001	[0.08, 0.24]
Curiosity	4%	0.10	0.02	[0.02, 0.18]
Number of languages	4.13 (1.00)	0.12	0.006	[0.04, 0.20]
Social responsibility	7%	0.08	0.045	[0.00, 0.16]
Artistic activity	6%	0.09	0.024	[0.01, 0.17]
Influencers	2.21 (5.59)	0.08	0.040	[0.08, 0.24]
	M(SD)	$r_{\text{Conscientiousness}}$	*p*	95% CI
Professional attire	81%	-0.01	0.80	[-0.09, 0.07]
Summary	28%	0.13	0.001	[0.05, 0.21]
Experience described	34%	0.14	0.001	[0.06, 0.22]
Profile updated	80%	0.11	0.006	[0.03, 0.19]
Inattentiveness (R)	12%	0.03	0.61	[-0.05, 0.11]
Organization	11%	0.18	< 0.001	[0.10, 0.26]
Grade Point Average	20%	0.19	< 0.001	[0.11, 0.27]
Award	10%	0.14	< 0.001	[0.06, 0.22]
Additional certification	22%	0.19	< 0.001	[0.11, 0.27]
List of courses	16%	0.13	0.002	[0.05, 0.21]
Ambassador	25%	0.15	< 0.001	[0.07, 0.23]
Class representative	6%	0.09	0.02	[0.01, 0.17]
Recommendation received	7%	0.09	0.02	[0.01, 0.17]
	M(SD)	$r_{\text{Extraversion}}$	*p*	95% CI
Number of connections	401 (133)	0.32	< 0.001	[0.24, 0.40]
Human interactions	5.1%	0.11	0.009	[0.03, 0.19]
Number of skills	15.8 (8.4)	0.16	< 0.001	[0.08, 0.24]
Social skills	14%	0.04	0.38	[-0.04, 0.12]
Leadership	29%	0.11	0.01	[0.03, 0.19]
Public speaking	19%	0.07	0.10	[-0.01, 0.15]
Sport activity	11%	0.17	< 0.001	[0.09, 0.25]
Leadership role	31%	0.15	< 0.001	[0.07, 0.23]
Additional pictures	24%	0.12	0.002	[0.04, 0.20]
	M(SD)	$r_{\text{Agreeableness}}$	*p*	95% CI
Smile	4.59 (1.85)	0.21	< 0.001	[0.13, 0.29]
Teamwork	73%	0.12	0.004	[0.04, 0.20]
Volunteer activities	35%	0.15	< 0.001	[0.17, 0.23]
Peer tutoring	8%	0.06	0.14	[-0.02, 0.14]
Recommendation given	9%	0.07	0.09	[-0.01, 0.15]

N = 607.

Table 3
Intercorrelations between the LinkedIn indicators and all the big five traits.

Indicators	O	C	E	A	N
Openness to experience					
Artistic picture	**0.16****	0.11**	0.14**	0.04	-0.12**
Curiosity	**0.10***	0.02	0.06	0.08	0.01
Number of languages	**0.12****	0.05	0.02	0.03	-0.07
Social responsibility	**0.08***	0.03	-0.02	0.10*	0.03
Artistic activity	**0.09***	0.02	0.04	0.08	-0.05
Influencers	**0.08***	0.07	0.09*	0.03	0.02
Conscientiousness					
Professional attire	-0.06	**-0.01**	-0.04	-0.03	-0.10*
Summary	0.05	**0.13****	0.09*	-0.04	-0.09*
Experience described	-0.01	**0.14****	0.06	0.09*	-0.02
Profile updated	0.03	**0.11****	0.09*	0.07	-0.01
Inattentiveness (R)	0.06	**0.03**	0.01	-0.02	0.01
Organization	-0.02	**0.18****	0.08*	0.10	-0.05
Grade Point Average	-0.09*	**0.19****	-0.10*	0.08	-0.02
Award	-0.05	**0.14****	-0.05	0.06	0.02
Additional certification	-0.04	**0.19****	0.00	-0.01	-0.05
List of courses	0.05	**0.13****	0.05	0.04	-0.06
Ambassador	0.04	**0.15****	0.01	0.05	-0.07
Class representative	0.00	**0.09***	0.09*	0.06	-0.03
Recommendation received	-0.01	**0.09***	0.07	-0.01	-0.06
Extraversion					
Number of connections	0.10*	0.08	**0.32****	0.01	-0.08
Human interactions	-0.03	-0.01	**0.11****	-0.04	0.02
Number of skills	0.05	0.08	**0.16****	-0.04	-0.13**
Social skills	0.08	0.06	**0.04**	0.05	-0.01
Leadership	0.07	0.03	**0.11****	-0.07	-0.11*
Public speaking	0.05	-0.02	**0.07**	-0.04	0.01
Sport activity	0.04	-0.01	**0.17****	-0.07	-0.16**
Leadership role	0.08	0.08	**0.15****	0.04	-0.09
Additional pictures	0.07	0.09*	**0.12****	0.01	-0.12**
Agreeableness					
Smile	0.03	0.03	0.04	**0.21****	0.10*
Teamwork	0.03	0.14**	0.07	**0.12****	-0.06
Volunteer activities	0.08	0.10*	0.09	**0.15****	0.03
Peer tutoring	-0.03	0.12**	-0.02	**0.06**	-0.02
Recommendation given	0.09*	0.06	0.09*	**0.07**	-0.03

N = 607. * p < .05; ** p < .01.
O = openness to experience; C = conscientiousness; E = extraversion; A = agreeableness; N = neuroticism.

(χ^2 (1, 515) = 11.18, p = .001, φ = 0.15), have more often a summary (χ^2 (1, 604) = 12.13, p < .001, φ = 0.14), receive more recommendations (χ^2 (1, 605) = 5.33, p = .02, φ = 0.09), are more likely to post a background photograph representing human interactions (χ^2 (1, 605) = 4.78, p = .03, φ = 0.09), report a higher number of skills (t(561) = 3.33, p = .001, d = 0.29), list leadership (χ^2 (1, 561) = 6.26, p = .01, φ = 0.11), and public speaking more often (χ^2 (1, 561) = 7.20, p = .007, φ = 0.11), describe more often a sports activity as part of their extracurricular activities (χ^2 (1, 605) = 13.11, p < .001, φ = 0.15), provide additional pictures (χ^2 (1, 605) = 18.22, p < .001, φ = 0.17), and are more likely to give recommendations (χ^2 (1, 605) = 3.87, p = .05, φ = 0.08) than women.

On the other hand, women are more likely to indicate they have participated in social responsibility activities (χ^2 (1, 604) = 7.69, p = .006, φ = 0.11), are more likely to have a profile updated (χ^2 (1, 605) = 5.03, p = .03, φ = 0.08), tend to smile more on their portrait (t(561) = -6.67, p < .001, d = 0.58), and are more likely to have participated in activities aimed at helping other students (χ^2 (1, 605) = 6.99, p = .008, φ = 0.11) than men.

We also test if the 33 indicators represent signals of the same personality traits among men and women. To test this, we converted the correlations using a Fisher's r to z transformation. The correlations between each signal and the personality traits appear for each gender in Table 4. Results show that 9 out of 33 indicators signal the same trait in men and women (openness: artistic picture; conscientiousness: experience described, organization, GPA, academic award, additional certification; extraversion: number of connections, sport activity, leadership role). These indicators are indeed related significantly to the personality trait they are supposed to signal in both groups, and the correlations do not differ significantly between men and women. It is noteworthy to emphasize that we identified different signals of agreeableness for men and women. On the one hand, the extent to which individuals smile only indicate agreeableness among men. On the other hand, teamwork and volunteer activities only signal agreeableness for women. Among other differences observed between the two groups, curiosity and social responsibility are only related to openness among women (and the number of languages is related to openness among men). The presence of a summary and having an updated profile are only related significantly to conscientiousness among men (and the presence of a list of courses is related to conscientiousness among women).

Table 4
Descriptive statistics and correlations between LinkedIn indicators and the big five traits among men and women.

Indicators	Men *M(SD)*	Women *M(SD)*	Men *r*	Women *r*	Fisher z_r
Openness					
Artistic picture	0.16	0.14	0.15*	0.18**	-0.37
Curiosity	0.04	0.05	-0.01	0.16**	−2.05*
Number of languages	4.09 (1.07)	4.16 (1.01)	0.22**	0.05	2.08*
Social responsibility	0.04	0.10**	-0.07	0.14**	−2.53**
Artistic activity	0.05	0.06	0.16*	0.05	1.33
Number of influencers	2.87 (5.90)**	1.79 (5.35)	0.07	0.11*	−0.48
Conscientiousness					
Professional attire	0.88***	0.76	-0.03	0.02	-0.60
Summary	0.36***	0.23	0.26**	0.06	2.47**
Experience described	0.60	0.55	0.20**	0.11**	1.11
Profile updated	0.76	0.83*	0.24**	0.01	2.81**
Inattentiveness	0.86	0.89	0.02	0.05	-0.36
Organization	0.10	0.11	0.21**	0.16**	0.62
GPA	0.29	0.20	0.22**	0.16**	0.75
Academic award	0.08	0.11	0.17**	0.12*	0.61
Additional certification	0.26	0.20	0.20**	0.20**	0
List of courses	0.16	0.16	0.04	0.19**	−1.82*
Ambassador	0.22	0.27	0.09	0.18**	−1.10
Class representative	0.07	0.06	0.13*	0.07	0.73
Recommendation received	0.10*	0.05	0.12	0.09	0.36
Extraversion					
Number of connections	410.87 (135.39)	393.23 (132.24)	0.28**	0.34**	-0.80
Human interactions	0.08*	0.04	0.13*	0.10	0.36
Number of skills	17.25 (9.17)**	14.86 (7.75)	0.08	0.21**	−1.59
Social skills	0.15	0.14	0.01	0.05	-0.48
Leadership	0.35*	0.25	0.09	0.12*	-0.36
Public speaking	0.25*	0.15	0.08	0.06	0.24
Sport activity	0.17**	0.08	0.18**	0.15**	0.37
Leadership role	0.33	0.29	0.14*	0.15**	-0.12
Additional pictures	0.33***	0.18	0.11	0.13*	-0.24
Agreeableness					
Smile	3.95 (2.03)	4.98 (1.60)***	0.08	0.20**	−1.47
Teamwork	0.71	0.74	0.23**	0.04	2.33*
Volunteer activity	0.30	0.38	0.24**	0.01	2.81*
Peer tutoring	0.04	0.10**	0.05	0.02	0.36
Recommendations given	0.12*	0.07	0.10	0.09	0.12

Men: N = 239; Women: N = 368. * p < .05; ** p < .01; O = openness to experience; C = conscientiousness; E = extraversion; A = agreeableness; N = neuroticism.

3.6. Unique LinkedIn indicators to predict self-reported personality

If recruiters use LinkedIn indicators to make inferences about a candidate's personality, the unique predictors for each personality trait must be identified. To answer this question, we ran four hierarchical regression analyses to predict respectively openness to experience, conscientiousness, extraversion, and agreeableness. In each regression analysis, we entered gender and age in the first step, and then all the LinkedIn indicators that were hypothesized to be related to the personality trait. Results appear in Table 5 and demonstrate that we identified two unique predictors of openness (artistic picture and curiosity), three unique predictors of conscientiousness (organization, additional certification, GPA), three unique predictors of extraversion (number of connections, sport activities, and human interactions), and three unique predictors of agreeableness (smile, teamwork, and volunteer activity). The percentage of variance explained for each trait observed shows that extraversion and conscientiousness are better signaled on LinkedIn than agreeableness and openness to experience.

Table 5
Results from hierarchical regression analyses to predict self-reported personality traits.

	B	ΔR^2	*p*
Openness to experience			
Gender	0.09^{+}		0.05
Age	0.11*		0.01
Control variable		0.02*	0.01
Artistic picture	0.13**		0.004
Curiosity	0.09*		0.03
Number of languages	0.08		0.06
Social responsibility	0.06		0.14
Artistic activity	0.08		0.06
Number of influencers	0.08		0.06
LinkedIn indicators		0.06**	< 0.001
Conscientiousness			
Gender	0.13**		0.004
Age	0.15**		0.001
Control variables		0.03**	< 0.001
Professional attire	0.03		0.46
Summary	0.08		0.10
Experience described	0.04		0.36
Profile updated	0.03		0.45
Inattentiveness	0.04		0.42
Organization	0.17**		< 0.001
GPA	0.11*		0.02
Award	0.01		0.76
Additional certification	0.11*		0.02
List of courses	0.02		0.72
Ambassador	0.09		0.07
Class representative	0.07		0.11
Recommendation received	0.01		0.84
LinkedIn indicators		0.12**	< 0.001
Extraversion			
Gender	-0.04		0.36
Age	0.01		0.76
Control variables		0.00	0.58
Number of connections	0.28**		< 0.001
Human interactions	0.10*		0.02
Number of skills	0.02		0.72
Social skills	-0.01		0.78
Leadership	0.07		0.14
Public speaking	0.00		0.93
Sport activity	0.10*		0.01
Leadership role	0.01		0.76
Additional picture	0.05		0.23
LinkedIn indicators		0.13**	< 0.001
Agreeableness			
Gender	0.29**		<0.001
Age	0.07		0.11
Control variables		0.08**	< 0.001
Smile	0.16**		< 0.001
Teamwork	0.12**		0.004
Volunteer activity	0.14**		0.001
Peer tutoring	0.00		0.99
Recommendation given	0.07		0.08
LinkedIn indicators		0.06**	< 0.001

N = 607. $^{+}$ $p = .05$; * $p < .05$; ** $p < .01$; Gender (1 = female; 0 = male).

3.7. Classification accuracy of LinkedIn indicators

Based on the 12 unique predictors identified through the hierarchical regression analyses, we determined the percentage of individuals scoring high (vs. low) on each trait that have one or more signal of this trait on their LinkedIn profile. For instance, even though we have identified that individuals with more signals of conscientiousness on LinkedIn are more likely to score higher on conscientiousness, we do not know the percentage of conscientious individuals that possess three signals of conscientiousness on LinkedIn. In order to do so, we only selected the highest tercile (33%) on the four traits (which corresponds respectively to the most open, the most conscientious, the most extraverted, and the most agreeable individuals) and the lowest tercile (which corresponds respectively to the least open, the least conscientious, the least extraverted, and the least agreeable individuals). We then computed classification statistics (Fleiss, 1981). These analyses were conducted on the full sample of participants (and not each gender group). As these analyses require only binary variables, we modified the continuous variables in the following manner: for the number of connections, we separated individuals who had 500 connections from those who had less than 500 connections; for the number of languages, for the smile, we separated those who were rated a score of 7 from the others[3]. These statistics are rarely used in personnel selection but they are often used in medicine and clinical psychology. One reason that accounts for this lack of use is that most predictors and variables in personnel selection are not categorical variables, but quantitative variables (e.g. intelligence, job performance, or personality traits). Classification statistics offer, however, information that is relevant to decision-makers. For instance, they offer information about the probability to hire a candidate who is conscientious if a specific LinkedIn indicator is used. Sensibility, specificity, positive predictive value, negative predictive value, hit rate and likelihood ratio are all presented in Table 5 (with values provided for specific LinkedIn indicator in Appendix C).

Sensibility represents the proportion of individuals who score high on the personality trait and who possess the number of characteristics indicated. For instance, recruiters will only identify 5% of the individuals scoring high on openness to experience if they consider individuals who have two LinkedIn indicators of openness such as the presence of an artistic picture and that curiosity is listed as a skill.

Specificity refers to the percentage of people who do not possess a characteristic and are correctly rejected by the indicator chosen. For instance, a specificity of 98% as shown in Table 6 means that 98% of the individuals who score low on openness to experience do not have two indicators reflecting high openness on their LinkedIn profile.

The positive predictive power refers to the probability that a positive result on a test comes from a person who possesses the characteristic of interest. As shown in Table 6, the more an individual possesses LinkedIn indicators reflecting a certain trait, the more likely this person evaluates oneself high on this trait. For instance, all the individuals who possess three indicators of high conscientiousness score high on this trait. This also holds true for people who possess three indicators of high extraversion and three indicators of high agreeableness.

The negative predictive power represents the probability that a negative result comes from a person who does not possess the characteristic we would like to assess. For instance, it might represent the percentage of individuals who do not present any signal of

[3] We chose the value of 500 for the number of connections because it is the maximum number of connections that can be visible in a person's LinkedIn profile if the person is not active on LinkedIn. We chose the value of 7 for the smile because this value indicated that both coders assessed the person as smiling a lot. We therefore considered this value to be the most meaningful and useful in applied settings (e.g. recruiters can easily identify a candidate smiling a lot, but it would be more difficult to identify a person smiling moderately for instance).

Table 6
Classification statistics of LinkedIn indicators.

	Sens	Spec	PPP	NPP	Hit rate	LR+
Openness						
2 indicators	0.05	0.99	0.83	0.49	0.50	4.63
1 indicator	0.30	0.94	0.85	0.55	0.61	5.18
Conscientiousness						
3 indicators	0.02	1.00	1.00	0.56	0.56	∞
2 indicators	0.22	0.96	0.82	0.60	0.63	5.56
1 indicator	0.60	0.76	0.67	0.70	0.69	2.52
Extraversion						
3 indicators	0.03	1.00	1.00	0.47	0.48	∞
2 indicators	0.21	0.95	0.81	0.51	0.55	3.85
1 indicator	0.75	0.76	0.78	0.73	0.75	3.10
Agreeableness						
3 indicators	0.03	1.00	1.00	0.49	0.50	∞
2 indicators	0.43	0.80	0.70	0.56	0.61	2.19
1 indicator	0.90	0.26	0.57	0.70	0.59	1.21

Sens = sensibility; spec = specificity; PPP = positive predictive power; negative predictive power; LR+ = likelihood ratio.

conscientiousness and score low on conscientiousness. All the negative predictive power values range from 0.47 to 0.73. For instance, 73% of the individuals who do not have any indicator of extraversion tend to rate themselves as low in extraversion.

The hit rates present the overall percentage of individuals accurately classified. Hit rates range from 0.48 to 0.75. Overall, even if it is possible to identify with high certainty people scoring high on the traits (very few false positives), using LinkedIn to evaluate personality traits leads to a large number of false negatives. There are indeed lots of individuals scoring high on conscientiousness, openness, extraversion and agreeableness who do not have LinkedIn indicators portraying them as scoring high on these traits.

Finally, the positive likelihood ratio (LR+) represents the number of true positive divided by the number of false positives. A visual inspection of Table 6 shows that individuals scoring high on openness to experience are 4.5 times more likely to have two indicators of openness on LinkedIn than those scoring low. All individuals who possess three indicators of conscientiousness tend to perceive themselves as conscientious individuals. The same holds true for extraversion and agreeableness. All the individuals who possess three indicators of extraversion/agreeableness perceive themselves as extraverted/agreeable persons. These results indicate that individuals who have many indicators signaling a specific trait are very likely to score high on this trait.

Overall, these results show that people who signal one of their personality traits through two or three indicators on their LinkedIn profile tend to score high on this trait. We find no individual scoring low on the trait who provides three or more indicators related to it. However, the classification statistics reveal also that there is a large proportion of individuals who score high on a certain trait and do not signal their personality through their LinkedIn profile. For instance, only 2% of conscientious individuals' profile contains three signals of conscientiousness.

4. Discussion

The aim of this study was to test to which extent LinkedIn offers accurate information about personality. We identified 33 LinkedIn indicators to serve as signals of personality traits. Our results demonstrated that most of these indicators provide signals of the expected personality traits. To summarize, openness to experience is signaled by the inclusion of an artistic background picture, by speaking more languages, by having participated in artistic extra-curricular activities, by manifesting interest in social responsibility activities, by listing skills related to curiosity and creativity, and by following many influencers. Conscientiousness is signaled by having a profile that has been recently updated, by having a summary and having written a description regarding past job experiences or provided a list of courses attended at college, by listing organizational skills, by reporting past grades, having received an academic award or having attended additional certifications, by being recommended by a teacher or a supervisor, and by holding specific roles such as class representatives or student ambassador. Extraversion is signaled by possessing a high number of connections, by having a background picture representing human interactions, by listing more skills, by listing leadership skills, by having more pictures accompanying job experiences, by reporting sports activities, and by occupying leadership roles. Finally, agreeableness is signaled by listing teamwork skills, by smiling, and by demonstrating volunteer activities. There are a few exceptions. For instance, our results show that professional attire and inattentiveness are not useful signals of conscientiousness. Public speaking and social skills are not useful signals of extraversion, and giving recommendations is not a relevant signal of agreeableness. A sole indicator does not necessarily signal only one single personality trait but can signal several traits. For instance, having held a class representative role indicates both high conscientiousness and high extraversion. Being skilled in teamwork denotes a high level of agreeableness and a high level of conscientiousness.

Our study extends previous accounts of the relationship between extraversion and the way individuals portray themselves on LinkedIn (Roulin & Levashina, 2019; Van de Ven et al., 2017) and shows that LinkedIn offers signals about personality traits other than extraversion. Different reasons might explain this discrepancy between past research and ours. First, we analyzed a larger array of LinkedIn indicators than past studies. Our analysis included 33 indicators and all of them were theoretically derived from the big five model of personality. In comparison, Van de Ven et al. (2017) analyzed 17 indicators, whereas Roulin and Levashina (2019) took 10 indicators into consideration. Our study included a wider range of LinkedIn indicators that were not analyzed in past studies. For instance, we analyzed the type of skills listed in the profile, if information about academic achievement, or the specific type of extracurricular activities, was presented. Second, we coded profiles of individuals who had already completed their studies, whereas Van de Ven et al. (2017; Study 1) and Roulin and Levashina (2019) considered students. It is possible that participants in our study had more complete profiles. In support of this argument, we observed, for instance, that participants have a much larger number of connections ($M = 401$; $SD = 133$) than in those two studies (Van de Ven et al. (2017): $M = 278$; $SD = 162$; Roulin & Levashina (2019): $M = 153$; $SD = 139$)[4]. However, the participants in our study were less likely to include a summary. We note also that some of our findings differ from those obtained by Roulin and Levashina (2019). For instance, LinkedIn indicators such as the presence of recommendations, the inclusion of a summary, or a description for professional experiences were not related to conscientiousness in Roulin and Levashina (2019). We see here two explanations. First, we used the IPIP NEO-PI facets scales whereas Roulin and Levashina (2019) have relied on the 20-item Mini-IPIP (Donnellan et al., 2006). While convenient and valid, this short measure of the big five traits might substantially increase both Type 1 and Type 2 errors (Credé et al., 2012). This might explain why Roulin and Levashina (2019) have not found relationships between these indicators and conscientiousness. The second explanation lies in the industry in which the participants work. As most of our participants work in the hospitality and service industries, they may put more emphasis on signals that portray extraversion than conscientiousness. It could then explain why they have more connections than participants in Roulin and Levashina (2019) and why they are less likely to include a summary.

[4] As pointed out by an anonymous reviewer, this difference might also occur because our data have been collected five years later than those obtained by Van de Ven (2017). As LinkedIn and its number of users have grown significantly, the higher number of connections might also result from this growth.

In contradiction to our hypotheses, we identified a few indicators that were not related to personality. Notably, inattentiveness (with the presence of spelling mistakes) was not a signal of low conscientiousness. This result is noteworthy because recruiters tend to be sensitive to spelling mistakes and consider they reflect low professionalism or low conscientiousness (Martin-Lacroux, 2017). Our results do not show that individuals whose LinkedIn profiles contain spelling mistakes are less conscientious than those who did not make spelling mistakes. A recent study has pointed out that recruiters tend to be sensitive to spelling mistakes on social media (Hartwell & Campion, 2020), but our results suggest that spelling mistakes might not convey relevant signals of a candidate's personality. The fact that 12% of the profiles contained spelling mistakes or duplicates (in a sample of university graduates) leads to the conclusion that these mistakes reflect some momentary inattentiveness (we observed many instances of "manager" spelled "manger"). As there is no proofreading system directly integrated into LinkedIn, mistakes are probably more frequent than in documents prepared on Microsoft Office, which contain proofreading tools like a spell and grammar check. There was a second indicator (professional attire) that failed to predict conscientiousness. This is at odds with past studies that have shown a correlation between conscientiousness and formal attire (e.g. Borkenau & Liebler, 1992). It should be noted that all participants studied in a hospitality management institution in which a formal dress code is imposed. It is therefore possible that professional attire is not a relevant indicator of conscientiousness in our study because participants are accustomed to dressing in a professional manner. To support this, descriptive statistics show that 81% of our participants wore a suit jacket (e.g., blazer, suit, etc.) in their portrait. In addition, public speaking was not a signal of extraversion, but additional analyses conducted at the facet-level have demonstrated that most of the indicators that failed to signal a personality trait could signal more specific facets (see Appendix D).

We would like to further discuss indicators that are related to conscientiousness, and more precisely the presence of information about academic achievement. While some recruiters may not consider GPA to be useful (Kwok et al., 2011; Ross & Young, 2005), our study points to another conclusion. Individuals who post information about their grades on their LinkedIn profiles tend to be more conscientious than those who do not post this kind of information. First, individuals who are conscientious tend to have better grades than those scoring lower on conscientiousness (Poropat, 2009). As a result, they might be more inclined to report this information. Second, conscientious individuals might be more likely to reveal their grades because they tend to value achievement more than individuals scoring lower on conscientiousness (Parks-Leduc et al., 2015). As grades reflect past achievements, conscientious individuals might be more willing to share this information than individuals scoring low in conscientiousness. These results, in combination with meta-analytic evidence that grades are predictive of future job performance (Roth et al., 1996), points to the conclusion that recruiters might benefit from considering GPA during the selection process, at least when conscientiousness is an important predictor of job success.

4.1. Theoretical implications

First, our study demonstrated that LinkedIn offers honest signals about an individual's personality and we would like to explain this in light of signaling theory (Bangerter et al., 2012). Signaling theory considers that accurate information can be sent by candidates through costly signals and hard-to-fake signals. On the one hand, costly signals are those who take a lot of time or effort to be emitted. For instance, all the LinkedIn indicators that refer to past experience can be considered as costly signals (one costly of openness to experience would be to having participated in an art committee, one costly signal of conscientiousness would be to have held a representative role, or being an ambassador, among the costly signals of extraversion we can find the participation in sport activities, or the occupation of leadership roles in college, finally, the presence of volunteer activities might represent a costly signal of agreeableness). On the other hand, hard-to-fake signals are signals which are not under conscious control (Bangerter et al., 2012). It is difficult to identify any LinkedIn indicator that could be clearly categorized as a hard-to-fake signal. We can assume most LinkedIn users prepare their profile meticulously and might even ask others to verify that their LinkedIn profile contains no mistake. Therefore, most of the signals that are available are under conscious control. However, the cheating cost of sending inaccurate information on LinkedIn is important as this information can be validated by others. We then assume that LinkedIn indicators such as the number of connections or the listed skills are accurate signals of personality, not because they are hard-to-fake but because the cheating cost is important. An alternative explanation might be brought by self-verification theory (Swann, 2012), which affirms that individuals want to be perceived by others in the same way they see themselves. Hence, individuals would not necessarily portray accurate information due to the risk of being caught by other, but because they want to communicate accurate information to others about their personality and skills.

Second, our results indicate that extraversion and conscientiousness are the traits that are the most consistently associated with the presence of signals on LinkedIn. First, we had identified more LinkedIn indicators for these two traits than for agreeableness and openness to experience. Second, LinkedIn indicators for extraversion and conscientiousness explained more variance in self-reported extraversion and conscientiousness respectively than LinkedIn indicators for agreeableness and openness to experience. Several explanations may be offered to explain that there exists more signals of extraversion and conscientiousness. First, extraversion might be a trait that individuals want to signal due its perceived importance in life (Latham & Von Stumm, 2017; Williams, Munick, Saiz, & FormyDuval, 1995, whereas conscientiousness could be signaled due to its perceived and actual importance at work (Barrick et al., 2001; Dunn et al., 1995). On the other hand, individuals might be less likely to signal agreeableness or openness to change because the value of these traits might be more context-dependent. For instance, a high score on agreeableness might be an asset for positions in team settings, but not necessarily when competition is required. In the same manner, being open to change would be an asset only when innovation and creativity are required for successful performance on the job (Judge & Zapata, 2015). Second, according to trait activation theory (Tett et al., 2013) and the realistic accuracy model (e.g. Funder, 2012), different contexts activate behaviors pertaining to different traits. As LinkedIn is aimed at facilitating connections with other professionals (something which is common to Facebook) and finding job opportunities, we think this social networking website is more likely to activate signals for personality traits that are relevant to these goals. By comparison, Facebook is aimed at connecting with family and friends, and share events in one's private life. As such, individuals will signal other aspects of their personality. A recent meta-analysis has shown that extraversion and openness to change were the traits that could be the most accurately inferred from Facebook (Azucar et al., 2018). It seems then that individuals are more likely to convey signals of openness to change on Facebook. For instance, individuals indicate when they went to an art gallery or the type of music they like, which refer mostly to openness to experience (Chapman & Goldberg, 2017; Rentfrow & Gosling, 2003).

Finally, we would like to relate our study to Brunswik's lens model (1956). According to Brunswik (1956), unacquainted individuals form accurate perceptions of a target person's level of extraversion for instance, if there exists valid cues (e.g. number of connections) and if they use these cues in their impression formation. Even though our study does not respond to the question about whether unacquainted people can form accurate impression of candidates based on LinkedIn profiles, it addresses the first part of the model about cue validity. As stated previously, many accurate LinkedIn indicators (valid cues) have been observed for agreeableness, conscientiousness, extraversion, and openness to experience. We can then assume that observers could in theory detect these traits by examining LinkedIn profiles. However, past studies have shown that observers were only capable to accurately infer extraversion, but not other personality traits (Roulin & Levashina, 2019; Van de Ven et al., 2017). As our study points to the identification of valid indicators of four of the big five traits, we think observers might struggle to use cues related to other traits. In other words, if past studies have shown that observers were inaccurate for judging other traits than extraversion, it was not due to a lack of valid cues, but rather to a poor use of cues. Past studies have however shown that cue utilization can be enhanced even with brief training interventions. For instance, Powell and Bourdage (2016) have demonstrated that observers could infer more accurately a person's personality in a job interview after a short training intervention in the use of valid cues in job interviews. In a similar manner, Cole et al. (2005) have observed that a short training intervention increased observer accuracy at detecting a candidate's personality from a résumé.

4.2. Practical implications

We would like to discuss why LinkedIn might constitute an interesting selection method in the future. Self-reported personality questionnaires are often criticized on the grounds that they can be easily faked in selection contexts (Morgeson et al., 2007). Due to additional verifiability by their connections, it seems less likely that individuals fake information on LinkedIn (Hartwell & Campion, 2020). In support of this assertion, we observed that the skills that individuals listed on their profile corresponded well with their self-reported personality. Individuals who listed teamwork were more agreeable and conscientious than those who did not list this skill. The ones who listed organization skills were more conscientious that those who did not. It means that the skills indicated on LinkedIn profiles can be trusted as an accurate source of information about a candidate's personality. Our conclusion is that LinkedIn profiles are saturated with personality information and that this information might be relevant when it comes to making hiring decisions. We hope future studies will be conducted to examine the predictive and incremental validity of LinkedIn indicators over self-reported personality traits.

As many features that characterize LinkedIn also appear on résumés, it would be interesting to investigate if LinkedIn offers a more accurate signal of a person's personality than the screening of a résumé. Past studies have shown that candidates signal their personality through the information that appear on their résumé (Burns, Christiansen, Morris, Periard, & Coaster, 2014; Cole et al., 2009). On the one hand, the standardized structure of LinkedIn profiles might prevent recruiters from accessing additional signals of personality. For instance, it is not possible to change the font in LinkedIn, but the use of unusual fonts on a résumé serves as a signal of openness to experience (Burns et al., 2014)(. On the other hand, the use of LinkedIn offers additional advantages in comparison to résumés. First, LinkedIn profiles offer valid personality signals that cannot be obtained through résumés. For instance, the number of connections a person has on LinkedIn offers useful information to judge this person's level of extraversion. The skills section also offers insights into the LinkedIn user's personality that cannot be obtained on a résumé. Second, according to signaling theory, we might expect signals emitted by candidates on LinkedIn to be more honest than those obtained in résumés. Due to the public nature of LinkedIn profiles, candidates have to be more honest because the cost of cheating might be higher than in a résumé. Third, LinkedIn allows companies to access the profiles of passive candidates who will never apply to a job but might be a good fit for a position. For all these reasons, we anticipate recruiters will continue to rely on LinkedIn as a source of information about candidates, and we think this social network website might prove a useful add-on to the hiring manager's selection toolkit. Although other social media such as Facebook offer accurate information about personality (Azucar et al., 2018), they have failed so far to demonstrate any value in work contexts (Van Iddekinge et al., 2016; Zhang et al., 2020). Recent research has also shown that job seekers perceive cybervetting on LinkedIn as more fair, more valid, and less invasive than cybervetting on Facebook, Twitter and Instagram (Cook et al., 2020)

Based on our results, practitioners might think that using LinkedIn information alone could suffice to gather insightful personality information. In the current state of our knowledge, we would caution recruiters and managers from doing so. There is greater evidence showing that self-reported personality predicts performance across contexts (Barrick et al., 2001). It thus seems preferable to use LinkedIn indicators in combination with personality questionnaire. Hence, if candidates score equally on conscientiousness but three of them also list organizational skills on their LinkedIn profiles and provide information about their GPA, recruiters might shortlist these three candidates, as they are more likely to be conscientious than candidates who have the same scores but who do not provide positive indicators of conscientiousness on LinkedIn. We would also advise against relying on a single indicator. Our analysis has shown that participants who had three indicators of conscientiousness score higher on conscientiousness than those who had only two signals of conscientiousness. Moreover, some specific LinkedIn indicators were related to more than one personality trait. Finally, some indicators were signals of the trait for one gender but not the other. Overall, our results show that it is a more conservative and more appropriate approach to rely on multiple signals of personality than on a single indicator. First, it might prove to be more valid. Second, it might be perceived as more appropriate by recruiters. Recruiters tend to be resistant to mechanical approaches in selection (e.g. Highhouse, 2008; Van der Zee et al., 2002). They like to have a say in how information is collected and used. Recruiters should have a list of the signals of the desired traits for a position and compare candidates in the number of signals that are available on their LinkedIn profile. This approach will ensure fairness because it prompts hiring professionals not to consider age, gender or sociodemographic group (even though this information is, of course, present). On a final note, it is important to mention here that classification statistics present the advantage of being more easily understood by a larger public than correlations and regressions. Indeed, managers often struggle to understand the meaning of correlations (Cucina, Berger, & Busciglio, 2017; Highhouse, Brooks, Nesnidol, & Sim, 2017). We hope therefore the results conveyed in this study can then be easily understood by managers and be applied in organizational settings.

4.3. Limitations and future research

First, personality was only measured through a self-report. There is now growing evidence that observer ratings of personality provide information that is not captured by self-ratings (Connelly & Ones, 2010; Oh et al., 2011). Hence, it is essential to confirm that LinkedIn indicators also signal personality as perceived by others and not only through self-reports.

Second, our study was conducted based on a homogenous sample. Even though participants had very diverse nationalities, they all were young, educated, and came from the same hospitality management school. As shown by other scholars (Brenner et al., 2020), there are some segments of the population that are more likely to have a LinkedIn account than others. More specifically, individuals who went to college are more likely to have a LinkedIn account that those who have never attended college. It means that personality inferences based on LinkedIn could mainly be done for more educated people. Another corollary of this is that some LinkedIn indicators analyzed in our study were tied to the specific environment in which the study was conducted, notably regarding the extracurricular activities.

Third, self-rated personality was assessed a few years before LinkedIn profiles were coded. As personality traits are not fixed and one's standing on a trait might change over time (Specht et al., 2011), we do not know if LinkedIn indicators identified in our study reflect the personality of the individuals after they have graduated. For instance, some indicators of conscientiousness (e.g. GPA) might indicate participants' level of conscientiousness during their studies, but might be less capable to predict their level of conscientiousness in work settings.

Future research could explore if signals of personality identified on LinkedIn in this study remain consistent signals of the same traits across different continents, age groups, and settings. More precisely, it would be interesting to see if LinkedIn indicators in samples of employees working in the same company (but coming from different educational backgrounds) predict the same personality traits. In addition, future research could build on our findings about gender and LinkedIn, as it seems that men and women signal their personality traits via different indicators. Finally, future studies might be conducted to train assessors to code LinkedIn profiles and determine if their ratings predict significant outcomes such as employee performance, turnover, leadership effectiveness, organizational citizenship behaviors, or counterproductive work behaviors. The final step would be then to examine the incremental validity of those LinkedIn ratings over self-reported personality and other selection methods.

5. Conclusion

Our study offers empirical evidence that LinkedIn can be used to accurately infer LinkedIn users' personality. In addition to past studies that have shown that the trait of extraversion could be reliably inferred from LinkedIn profiles (Roulin & Levashina, 2019; Van de Ven et al., 2017), this study shows that there are a wide variety of indicators that signal a person's level of conscientiousness. There are also valid indicators of agreeableness and openness albeit to a lesser extent than for extraversion and conscientiousness. Our work extends previous studies conducted on LinkedIn and personality by only targeting profiles of individuals who are already in the job market and by analyzing a broader array of indicators than previously examined. Our findings call for additional research to examine if LinkedIn indicators that have been identified as valid in our study are replicable in samples with older individuals and in more diverse samples. Future research will also examine if LinkedIn indicators contain trait-relevant information beyond the scope of self-reports, and offer incremental validity to predict consequential workplace outcomes such as job performance, turnover, or leadership effectiveness.

6. Author note and contributions of authors

This study was not preregistered. The data are available as supplementary material. Sébastien Fernandez contributed to the conceptualization, data collection, data analysis, and writing. Marie Stöcklin participated in the data collection, review and editing. Lohyd Terrier contributed to the conceptualization, review and editing. Sowon Kim contributed to the conceptualization, review and editing of the paper. We would like to thank Andrew Brenner for proofreading the manuscript.

CRediT authorship contribution statement

Sébastien Fernandez: Conceptualization. **Marie Stöcklin:** Writing - review & editing. **Lohyd Terrier:** Conceptualization, Writing - review & editing. **Sowon Kim:** Conceptualization, Writing - review & editing.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrp.2021.104122.

References

Azucar, D., Marengo, D., & Settanni, M. (2018). Predicting the big five personality traits from digital footprints on social media: A meta-analysis. *Personality and Individual Differences, 124*, 150–159. https://doi.org/10.1016/j.paid.2017.12.018

Bangerter, A., Roulin, N., & König, C. J. (2012). Personnel selection as a signaling game. *Journal of Applied Psychology, 97*(4), 719–738. https://doi.org/10.1037/a0026078

Barrick, M. R., Mount, M. K., & Judge, T. A. (2001). Personality and performance at the beginning of the new millennium: What do we know and where do we go next? *International Journal of Selection and Assessment, 9*(1&2), 9–30. https://doi.org/10.1111/ijsa:2001.9.issue-1&210.1111/1468-2389.00160

Bartram, D. (2005). The Great Eight competencies: A criterion-centric approach to validation. *Journal of Applied Psychology, 90*(6), 1185–1203. https://doi.org/10.1037/0021-9010.90.6.1185

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: A meta-analysis. *Journal of Applied Psychology, 92*(3), 595–615. https://doi.org/10.1037/0021-9010.92.3.595

Berry, C. M., Ones, D. S., & Sackett, P. R. (2007). Interpersonal deviance, organizational deviance, and their common correlates: A review and meta-analysis. *Journal of Applied Psychology, 92*(2), 410–424. https://doi.org/10.1037/0021-9010.92.2.410

Bono, J. E., & Judge, T. A. (2004). Personality and transformational and transactional leadership: A meta-analysis. *Journal of Applied Psychology, 89*, 901–910. https://doi.org/10.1037/0021-9010.89.5.901

Borkenau, P., & Liebler, A. (1992). Trait inferences: Sources of validity at zero acquaintance. *Journal of Personality and Social Psychology, 62*, 645–657. https://doi.org/10.1037/0022-3514.62.4.645

Brenner, S., Aksin Sivrikaya, S., & Schwalbach, J. (2020). Who is on LinkedIn? Self-selection into professional online networks. *Applied Economics, 52*(1), 52–67. https://doi.org/10.1080/00036846.2019.1638497

Brunswik, E. (1956). *Perception and the representative design of psycho-logical experiments*. Berkeley: University of California Press.

Burns, G. N., Christiansen, N. D., Morris, M. B., Periard, D. A., & Coaster, J. A. (2014). Effects of applicant personality on resume evaluations. *Journal of Business and Psychology, 29*(4), 573–591. https://doi.org/10.1007/s10869-014-9349-6

Chaplin, W. F., Phillips, J. B., Brown, J. D., Clanton, N. R., & Stein, J. L. (2000). Handshaking, gender, personality, and first impressions. *Journal of Personality and Social Psychology, 79*(1), 110–117. https://doi.org/10.1037/0022-3514.79.1.110

Chapman, B. P., & Goldberg, L. R. (2017). Act-frequency signatures of the Big Five. *Personality and Individual Differences, 116*, 201–205. https://doi.org/10.1016/j.paid.2017.04.049

Chiaburu, D. S., Oh, I. S., Berry, C. M., Li, N., & Gardner, R. G. (2011). The five-factor model of personality traits and organizational citizenship behaviors: A meta-analysis. *Journal of Applied Psychology, 96*(6), 1140–1166. https://doi.org/10.1037/a0024004

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum.

Chiang, J. K. H., & Suen, H. Y. (2015). Self-presentation and hiring recommendations in online communities: Lessons from LinkedIn. *Computers in Human Behavior, 48*, 516–524. https://doi.org/10.1016/j.chb.2015.02.017

Cole, M. S., Feild, H. S., Giles, W. F., & Harris, S. G. (2009). Recruiters' inferences of applicant personality based on resume screening: Do paper people have a personality? *Journal of Business and Psychology, 24*(1), 5–18. https://doi.org/10.1007/s10869-008-9086-9

Cole, M. S., Feild, H. S., & Stafford, J. O. (2005). Validity of resume reviewers' inferences concerning applicant personality based on resume evaluation. *International Journal of Selection and Assessment, 13*(4), 321–324. https://doi.org/10.1111/ijsa:2005.13.issue-410.1111/j.1468-2389.2005.00329.x

Connelly, B. S., & Ones, D. S. (2010). An other perspective on personality: Meta-analytic integration of observers' accuracy and predictive validity. *Psychological Bulletin, 136*(6), 1092–1122. https://doi.org/10.1037/a0021212

Cook, R., Jones-Chick, R., Roulin, N., & O'Rourke, K. (2020). Job seekers' attitudes toward cybervetting: Scale development, validation, and platform comparison. *International Journal of Selection and Assessment, 28*(4), 383–398. https://doi.org/10.1111/ijsa:v28.410.1111/ijsa:12300

Credé, M., Harms, P., Niehorster, S., & Gaye-Valentine, A. (2012). An evaluation of the consequences of using short measures of the Big Five personality traits. *Journal of Personality and Social Psychology, 102*(4), 874–888. https://doi.org/10.1037/a0027403

Cucina, J. M., Berger, J. L., & Busciglio, H. H. (2017). Communicating criterion-related validity using expectancy charts: a new approach. *Personnel Assessment and Decisions, 3*(1), 1–14. https://doi.org/10.25035/pad.2017.001

Cuperman, R., & Ickes, W. (2009). Big five predictors of behavior and perceptions in initial dyadic interactions: Personality similarity helps extraverts and introverts, but hurts "disagreeables". *Journal of Personality and Social Psychology, 97*(4), 667–684. https://doi.org/10.1037/a0015741

Donath, J. (2008). Signals in social supernets. *Journal of Computer Mediated Communication, 13*(1), 231–251. https://doi.org/10.1111/j.1083-6101.2007.00394.x

Donnellan, M. B., Oswald, F. L., Baird, B. M., & Lucas, R. E. (2006). The mini-IPIP scales: Tiny-yet-effective measures of the Big Five factors of personality. *Psychological Assessment, 18*, 192–203. https://doi.org/10.1037/1040-3590.18.2.192

Dunn, W. S., Mount, M. K., Barrick, M. R., & Ones, D. S. (1995). Relative importance of personality and general mental ability in managers' judgments of applicant qualifications. *Journal of Applied Psychology, 80*(4), 500–509. https://doi.org/10.1037/0021-9010.80.4.500

Eysenck, H. J., Nias, D. K. B., & Cox, D. N. (1982). Sport and personality. *Advances in Behaviour Research and Therapy, 4*(1), 1–56. https://doi.org/10.1016/0146-6402(82)90004-2

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research methods, 39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fernandez, S., Stosic, G., & Terrier, L. (2017). Does your résumé photograph tell who you are? *Personality and Individual Differences, 104*, 186–189. https://doi.org/10.1016/j.paid.2016.08.006

Fleiss, J. L. (1981). *Statistical methods for rates and proportions* (2nd ed.). New York: John Wiley.

Funder, D. C. (2012). Accurate personality judgment. *Current Directions in Psychological Science, 21*(3), 177–182. https://doi.org/10.1177/0963721412445309

Furnham, A. (2008). HR professionals' beliefs about, and knowledge of, assessment techniques and psychometric tests. *International Journal of Selection and Assessment, 16*(3), 300–305. https://doi.org/10.1111/j.1468-2389.2008.00436.x

Ghonsooly, B., Khajavy, G. H., & Asadpour, S. F. (2012). Willingness to communicate in English among Iranian non–English major university students. *Journal of Language and Social Psychology, 31*(2), 197–211. https://doi.org/10.1177/0261927X12438538

Gignac, G. E., & Szodorai, E. T. (2016). Effect size guidelines for individual differences researchers. *Personality and Individual Differences, 102*, 74–78. https://doi.org/10.1016/j.paid.2016.06.069

Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. In I. Mervielde, I. Deary, F. De Fruyt, & F. Ostendorf (Eds.), *Personality Psychology in Europe* (Vol. 7, pp. 7–28). Tilburg, the Netherlands: Tilburg University Press.

Goldberg, Lewis R., Johnson, John A., Eber, Herbert W., Hogan, Robert, Ashton, Michael C., Cloninger, C. Robert, et al. (2006). The international personality item pool and the future of public domain personality measures. *Journal of Research in Personality, 40*(1), 84–96. https://doi.org/10.1016/j.jrp.2005.08.007

Gosling, S. D., Augustine, A. A., Vazire, S., Holtzman, N., & Gaddis, S. (2011). Manifestations of personality in online social networks: Self-reported Facebook-related behaviors and observable profile information. *Cyberpsychology, Behavior, and Social Networking, 14*(9), 483–488. https://doi.org/10.1089/cyber.2010.0087

Gosling, S. D., Ko, S. J., Mannarelli, T., & Morris, M. E. (2002). A room with a cue: Personality judgments based on offices and bedrooms. *Journal of Personality and Social Psychology, 82*(3), 379–398. https://doi.org/10.1037/0022-3514.82.3.379

Graziano, W. G., Habashi, M. M., Sheese, B. E., & Tobin, R. M. (2007). Agreeableness, empathy, and helping: A person× situation perspective. *Journal of Personality and Social Psychology, 93*(4), 583–599. https://doi.org/10.1037/0022-3514.93.4.583

Guilfoyle, S., Bergman, S. M., Hartwell, C., & Powers, J. (2016). Social media, big data, and employment decisions: Mo' Data, Mo' Problems? In N. R. Landers, & B. G. Schmidt (Eds.), *Social media in employee selection and recruitment: Theory, practice, and current challenges* (pp. 127–155). Cham: Springer International Publishing.

Habashi, M. M., Graziano, W. G., & Hoover, A. E. (2016). Searching for the prosocial personality: A Big Five approach to linking personality and prosocial behavior. *Personality and Social Psychology Bulletin, 42*(9), 1177–1192. https://doi.org/10.1177/0146167216652859

Hartwell, Christopher J., & Campion, Michael A. (2020). Getting social in selection: How social networking website content is perceived and used in hiring. *International Journal of Selection and Assessment, 28*(1), 1–16. https://doi.org/10.1111/ijsa:v28.110.1111/ijsa:12273

Highhouse, S. (2008). Stubbon reliance on intuition and subjectivity in employee selection. *Industrial and Organizational Psychology: Perspectives on Science and Practice, 1*, 333–342. https://doi.org/10.1111/j.1754-9434.2008.00058.x

Highhouse, S., Brooks, M. E., Nesnidol, S., & Sim, S. (2017). Is a .51 validity coefficient good? Value sensitivity for interview validity.*International. Journal of Selection and Assessment, 25*(4), 383–389. https://doi.org/10.1111/ijsa.12192

Huffcutt, A. I., Conway, J. M., Roth, P. L., & Stone, N. J. (2001). Identification and meta-analytic assessment of psychological constructs measured in employment interviews. *Journal of Applied Psychology, 86*(5), 897–913. https://doi.org/10.1037/0021-9010.86.5.897

Hyde, Janet Shibley (2014). Gender similarities and differences. *Annual review of psychology, 65*(1), 373–398. https://doi.org/10.1146/annurev-psych-010213-115057

Johnson, Michael A., & Leo, Christopher (2020). The inefficacy of LinkedIn? A latent change model and experimental test of using LinkedIn for job search. *Journal of Applied Psychology. Advance online publication., 105*(11), 1262–1280. https://doi.org/10.1037/apl0000491

Jokela, M., Bleidorn, W., Lamb, M. E., Gosling, S. D., & Rentfrow, P. J. (2015). Geographically varying associations between personality and life satisfaction in the London metropolitan area. *Proceedings of the National Academy of Sciences, 112*(3), 725–730. https://doi.org/10.1073/pnas.1415800112

Judge, T. A., Bono, J. E., Ilies, R., & Gerhardt, M. W. (2002). Personality and leadership: A qualitative and quantitative review. *Journal of Applied Psychology, 87*(4), 765–780. https://doi.org/10.1037/0021-9010.87.4.765

Judge, T. A., & Zapata, C. P. (2015). The person–situation debate revisited: Effect of situation strength and trait activation on the validity of the Big Five personality traits in predicting job performance. *Academy of Management Journal, 58*(4), 1149–1179. https://doi.org/10.5465/amj.2010.0837

Kanfer, R., Wanberg, C. R., & Kantrowitz, T. M. (2001). Job search and employment: A personality motivational analysis and meta-analytic review. *Journal of Applied Psychology, 86*, 837–855. https://doi.org/10.1037/0021-9010.86.5.837

Kausel, E. E., Culbertson, S. S., & Madrid, H. P. (2016). Overconfidence in personnel selection: When and why unstructured interview information can hurt hiring decisions. *Organizational Behavior and Human Decision Processes, 137*, 27–44. https://doi.org/10.1016/j.obhdp.2016.07.005

Kwok, L., Adams, C. R., & Price, M. A. (2011). Factors influencing hospitality recruiters' hiring decisions in college recruiting. *Journal of Human Resources in Hospitality & Tourism, 10*(4), 372–399. https://doi.org/10.1080/15332845.2011.588571

Larson, L. M., Rottinghaus, P. J., & Borgen, F. H. (2002). Meta-analyses of Big Six interests and Big Five personality factors. *Journal of Vocational Behavior, 61*(2), 217–239. https://doi.org/10.1006/jvbe.2001.1854

Latham, R. M., & Von Stumm, S. (2017). Mothers want extraversion over conscientiousness or intelligence for their children. *Personality and Individual Differences, 119*, 262–265. https://doi.org/10.1016/j.paid.2017.07.037

Lievens, F., Highhouse, S., & De Corte, W. (2005). The importance of traits and abilities in supervisors' hirability decisions as a function of method of assessment. *Journal of Occupational and Organizational Psychology, 78*(3), 453–470. https://doi.org/10.1348/096317905X26093

LinkedIn (2020). LinkedIn business highlights from Microsoft's FY20 Q3 earnings. Retrieved from https://news.linkedin.com/2020/april/linkedin-business-highlights-from-microsoft-s-fy20-q3-earnings.

LinkedIn Press Center (2016). "2016 Global talent trends: Data on how candidates want to be recruited ", available at https://business.linkedin.com/talent-solutions/job-trends/2016-talent-trends-home#global (accessed February 13, 2018).

Martin-Lacroux, Christelle (2017). "Without the spelling errors I would have shortlisted her…": The impact of spelling errors on recruiters' choice during the personnel selection process. *International Journal of Selection and Assessment, 25*(3), 276–283. https://doi.org/10.1111/ijsa:2017.25.issue-310.1111/ijsa:12179

McCrae, Robert R., & John, Oliver P. (1992). An introduction to the five-factor model and its applications. *Journal of Personality, 60*(2), 175–215. https://doi.org/10.1111/jopy.1992.60.issue-210.1111/j.1467-6494.1992.tb00970.x

Meier, B. P., Robinson, M. D., Carter, M. S., & Hinsz, V. B. (2010). Are sociable people more beautiful? A zero-acquaintance analysis of agreeableness, extraversion, and attractiveness. *Journal of Research in Personality, 44*(2), 293–296. https://doi.org/10.1016/j.jrp.2010.02.002

Milfont, T. L., & Sibley, C. G. (2012). The big five personality traits and environmental engagement: Associations at the individual and societal level. *Journal of Environmental Psychology, 32*(2), 187–195. https://doi.org/10.1016/j.jenvp.2011.12.006

MORGESON, FREDERICK P., CAMPION, MICHAEL A., DIPBOYE, ROBERT L., HOLLENBECK, JOHN R., MURPHY, KEVIN, & SCHMITT, NEAL (2007). Reconsidering the use of personality tests in personnel selection contexts. *Personnel Psychology, 60*(3), 683–729. https://doi.org/10.1111/peps.2007.60.issue-310.1111/j.1744-6570.2007.00089.x

Naumann, L. P., Vazire, S., Rentfrow, P. J., & Gosling, S. D. (2009). Personality judgments based on physical appearance. *Personality and Social Psychology Bulletin, 35*(12), 1661–1671. https://doi.org/10.1177/0146167209346309

Nguyen, N. T., Allen, L. C., & Fraccastoro, K. (2005). Personality predicts academic performance: Exploring the moderating role of gender. *Journal of Higher Education Policy and Management, 27*(1), 105–117. https://doi.org/10.1080/13600800500046313

Oh, I., Wang, G., & Mount, M. K. (2011). Validity of observer ratings of the five-factor model of personality traits: A meta-analysis. *Journal of Applied Psychology, 96*, 762–773. https://doi.org/10.1037/a0021832

Ohme, M., & Zacher, H. (2015). Job performance ratings: The relative importance of mental ability, conscientiousness, and career adaptability. *Journal of Vocational Behavior, 87*, 161–170. https://doi.org/10.1016/j.jvb.2015.01.003

Oishi, S., Talhelm, T., & Lee, M. (2015). Personality and geography: Introverts prefer mountains. *Journal of Research in Personality, 58*, 55–68. https://doi.org/10.1016/j.jrp.2015.07.001

Parks-Leduc, L., Feldman, G., & Bardi, A. (2015). Personality traits and personal values: A meta-analysis. *Personality and Social Psychology Review, 19*(1), 3–29. https://doi.org/10.1177/1088868314538548

Peeters, M. A., Rutte, C. G., van Tuijl, H. F., & Reymen, I. M. (2006). The big five personality traits and individual satisfaction with the team. *Small Group Research, 37*(2), 187–211. https://doi.org/10.1177/1046496405285458

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin, 135*(2), 322–338. https://doi.org/10.1037/a0014996

Powell, D. M., & Bourdage, J. S. (2016). The detection of personality traits in employment interviews: Can "good judges" be trained? *Personality and Individual Differences, 94*, 194–199. https://doi.org/10.1016/j.paid.2016.01.009

Rentfrow, P. J., & Gosling, S. D. (2003). The do re mi's of everyday life: The structure and personality correlates of music preferences. *Journal of Personality and Social Psychology, 84*(6), 1236–1256. https://doi.org/10.1037/0022-3514.84.6.1236

Ross, C. M., & Young, S. J. (2005). Resume preferences: Is it really "business as usual"? *Journal of Career Development, 32*(2), 153–164. https://doi.org/10.1177/0894845305279162

Roth, P. L., BeVier, C. A., Switzer, F. S., III, & Schippmann, J. S. (1996). Meta-analyzing the relationship between grades and job performance. *Journal of Applied Psychology, 81*(5), 548–556. https://doi.org/10.1037/0021-9010.81.5.548

Roulin, N., & Bangerter, A. (2013). Students' use of extra-curricular activities for positional advantage in competitive job markets. *Journal of Education and Work, 26*(1), 21–47. https://doi.org/10.1080/13639080.2011.623122

Roulin, Nicolas, & Levashina, Julia (2019). LinkedIn as a new selection method: Psychometric properties and assessment approach. *Personnel Psychology, 72*(2), 187–211. https://doi.org/10.1111/peps.2019.72.issue-210.1111/peps.12296

Rubin, Robert S., Bommer, William H., & Baldwin, Timothy T. (2002). Using extracurricular activity as an indicator of interpersonal skill: Prudent evaluation or recruiting malpractice? *Human Resource Management, 41*(4), 441–454. https://doi.org/10.1002/(ISSN)1099-050X10.1002/hrm.v41:410.1002/hrm.10053

Schaefer, P. S., Williams, C. C., Goodie, A. S., & Campbell, W. K. (2004). Overconfidence and the big five. *Journal of Research in Personality, 38*(5), 473–480. https://doi.org/10.1016/j.jrp.2003.09.010

Scholarios, Dora, & Lockyer, Cliff (1999). Recruiting and selecting professionals: Context, qualities and methods. *International Journal of Selection and Assessment, 7*(3), 142–156. https://doi.org/10.1111/ijsa:1999.7.issue-310.1111/1468-2389.00114

Schwabel, D. (2011). "5 reasons why your online presence will replace your resume in 10 years", Forbes Magazine, February 21, p. Retrieved from www.forbes.com/sites/danschawbel/2011/02/21/5-reasons-why-your-online-presence-will-replace-your-resume-in-10-years/ 1.

Specht, J., Egloff, B., & Schmukle, S. C. (2011). Stability and change of personality across the life course: The impact of age and major life events on mean-level and rank-order stability of the Big Five. *Journal of Personality and Social Psychology, 101*(4), 862–882. https://doi.org/10.1037/a0024950

Spence, M. (1973). Job market signaling. *Quarterly Journal of Economics, 87*, 355–373. https://doi.org/10.2307/1882010

Swann, W. B., Jr. (2012). Self-verification theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (pp. 23–42). Sage Publications.

Tett, R. P., Simonet, D. V., Walser, B., & Brown, C. (2013). Trait activation theory. In N. Christiansen, & R. Tett (Eds.), *Handbook of psychology at work* (pp. 71–100). Routledge.

Tews, M. J., Stafford, K., & Tracey, J. B. (2011). What matters most? The perceived importance of ability and personality for hiring decisions. *Cornell Hospitality Quarterly, 52*(2), 94–101. https://doi.org/10.1177/1938965510363377

Tifferet, S., & Vilnai-Yavetz, I. (2018). Self-presentation in LinkedIn portraits: Common features, gender, and occupational differences. *Computers in Human Behavior, 80*, 33–48. https://doi.org/10.1016/j.chb.2017.10.013

van de Ven, N., Bogaert, A., Serlie, A., Brandt, M. J., & Denissen, J. J. (2017). Personality perception based on LinkedIn profiles. *Journal of Managerial Psychology, 32*(6), 418–429. https://doi.org/10.1108/JMP-07-2016-0220

Van der Zee, K. I., Bakker, A. B., & Bakker, P. (2002). Why are structured interviews so rarely used in personnel selection? *Journal of Applied Psychology, 87*(1), 176–184. https://doi.org/10.1037/0021-9010.87.1.176.

Van Eerde, W. (2003). A meta-analytically derived nomological network of procrastination. *Personality and Individual Differences, 35*(6), 1401–1418. https://doi.org/10.1016/S0191-8869(02)00358-6

Van Iddekinge, C. H., Lanivich, S. E., Roth, P. L., & Junco, E. (2016). Social media for selection? Validity and adverse impact potential of a Facebook-based assessment. *Journal of Management, 42*(7), 1811–1835. https://doi.org/10.1177/0149206313515524

Vazire, S. (2010). Who knows what about a person? The self–other knowledge asymmetry (SOKA) model. *Journal of Personality and Social Psychology, 98*(2), 281–300. https://doi.org/10.1037/a0017908

Vignovic, J. A., & Thompson, L. F. (2010). Computer-mediated cross-cultural collaboration: Attributing communication errors to the person versus the situation. *Journal of Applied Psychology, 95*(2), 265–276. https://doi.org/10.1037/a0018628

Williams, J. E., Munick, M. L., Saiz, J. L., & FormyDuval, D. L. (1995). Psychological importance of the" Big Five": Impression formation and context effects. *Personality and Social Psychology Bulletin, 21*(8), 818–826. https://doi.org/10.1177/0146167295218004

Wilson, K. E., & Dishman, R. K. (2015). Personality and physical activity: A systematic review and meta-analysis. *Personality and Individual Differences, 72*, 230–242. https://doi.org/10.1016/j.paid.2014.08.023

Wolff, H.-G., & Kim, S. (2012). The relationship between networking behaviors and the Big Five personality dimensions. *Career Development International, 17*(1), 43–66. https://doi.org/10.1108/13620431211201328

Wolfradt, U., & Pretz, J. E. (2001). Individual differences in creativity: Personality, story writing, and hobbies. *European Journal of Personality, 15*(4), 297–310. https://doi.org/10.1002/per.409

Zahavi, A. (1975). Mate selection: A selection for a handicap. *Journal of Theoretical Biology, 53*, 205–214. https://doi.org/10.1016/0022-5193(75)90111-3

Zhang, Liwen, Van Iddekinge, Chad H., Arnold, John D., Roth, Philip L., Lievens, Filip, Lanivich, Stephen E., et al. (2020). What's on job seekers' social media sites? A content analysis and effects of structure on recruiter judgments and predictive validity. *Journal of Applied Psychology, 105*(12), 1530–1546. https://doi.org/10.1037/apl0000490

Zide, J., Elman, B., & Shahani-Denning, C. (2014). LinkedIn and recruitment: How profiles differ across occupations. *Employee Relations, 36*(5), 583–604. https://doi.org/10.1108/ER-07-2013-0086

Zillig, L. M. P., Hemenover, S. H., & Dienstbier, R. A. (2002). What do we assess when we assess a Big Five trait? A content analysis of the affective, behavioral, and cognitive processes represented in the Big Five personality inventories. *Personality and Social Psychology Bulletin, 28*, 847–858. https://doi.org/10.1177/0146167202289013

Zimmerman, R. D. (2008). Understanding the impact of personality traits on individuals' turnover decisions: A meta-analytic path model. *Personnel Psychology, 61*(2), 309–348. https://doi.org/10.1111/j.1744-6570.2008.00115.x