LinkedIn as a New Selection Method: Psychometric Properties and Assessment Approach

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Abstract

Various surveys suggest LinkedIn is used as a screening and selection tool by many hiring managers. Despite this widespread use, fairly little is known about whether LinkedIn meets established selection criteria, such as reliability, validity, and legality (i.e., no adverse impact). We examine the properties of LinkedIn-based assessments in two studies. Study 1 shows that raters reach acceptable levels of consistency in their assessments of applicant skills, personality, and cognitive ability. Initial ratings also correlate with subsequent ratings done one-year later (i.e., demonstrating temporal stability), with slightly higher correlations when profile updates are taken into account. Initial LinkedIn-based ratings correlate with self-reports for more visible skills (leadership, communication, and planning) and personality traits (Extraversion), and for cognitive ability. LinkedIn-based hiring recommendations are positively associated with indicators of career success. Potential adverse impact is also limited. Profiles that are longer, include a picture, and have more connections are rated more positively. Some of those features are valid cues to applicants' characteristics (e.g., applicants high on Conscientiousness have longer profiles). In Study 2, we show that an itemized LinkedIn assessment is more effective than a global assessment. Implications of these findings for selection and future research are discussed.

Keywords: LinkedIn; cyber-vetting; psychometric properties.

LinkedIn as a New Selection Method: Psychometric Properties and Assessment Approach

One of the most pervasive innovations in employment selection and recruiting over last several years has been the use of social media, including LinkedIn and Facebook. Companies review job applicants' social media profiles to make initial screening decisions (Bohnert & Ross, 2010; Brandenburg, 2008; Roth, Bobko, Van Iddekinge, & Thatcher, 2016). It is assumed, that social media profiles allow companies to gather information about applicants' personality, skills, experiences, and values, and examine the degree to which applicants' qualifications are aligned with the job requirements or fit with the organizational culture (Bangerter, Roulin, & König, 2012; Roulin & Bangerter, 2013b).

The purpose of this study is to provide a systematic assessment of LinkedIn as a new selection measure. We focus on LinkedIn and not on Facebook for several reasons. First, LinkedIn is a professional social media created to facilitate the job search and career development (Weidner, O'Brien, & Wynne, 2016), whereas Facebook is a personal social media created to facilitate the interaction between friends and family members (Karl, Peluchette, & Schlaegel, 2010; Roulin, 2014). As such, LinkedIn should provide more job-related information regarding applicants than Facebook. Second, the use of Facebook in selection might increase legal liabilities for companies. Protected information, including applicants' age, ethnicity, and disability, may be more visible and readily available on Facebook than LinkedIn (e.g., Levashina, Peck, & Ficht, 2017). The use of such information in selection may be illegal (Brandenburg, 2008; V. Brown & Vaughn, 2011; Davison, Maraist, Hamilton, & Bing, 2012; Slovensky & Ross, 2012) and resulting in biased decisions and discrimination (Van Iddekinge, Lanivich, Roth, & Junco, 2016). Moreover, company use of applicant information posted on Facebook has been associated with negative reactions from applicants, who perceive it as an invasion of their privacy (Stoughton, Thompson, & Meade, 2015). In contrast, the use of information posted on LinkedIn should be associated with positive reactions from applicants (Stoughton, 2016).

Selection research has identified a number of different criteria to assess and examine the potential value of selection methods, with authors listing 5 to 10 different criteria (Gatewood & Field, 2001; Heneman, Judge, & Heneman, 2000; Noe, Hollenbeck, Gerhart, & Wright, 2008). The most frequently mentioned criteria, include *reliability, validity, legality (i.e., potential adverse impact), and standardization*. Yet, social media (LinkedIn more particularly) have been used to make selection decisions with little consideration of whether such an approach meets established selection standards or criteria (Davison, Bing, Kluemper, & Roth, 2016). We propose that it is time to look back, provide a systematic assessment of LinkedIn as a new selection measure, and evaluate if it meets such criteria or represents a fad or a false start.

We build on the realistic accuracy model (RAM; Funder, 1995), which highlights how information characteristics (e.g., quality, richness, visibility) influences the accuracy of raters' judgments, to examine the psychometric properties of LinkedIn-based assessments in two studies. In Study 1, we examine the interrater reliability and temporal stability of LinkedIn assessments. We also examine convergent validity (or the relationship between raters' inferences from LinkedIn profiles and applicants' cognitive ability test scores and self-reports of skills and Big Five personality traits) and criterion-related validity. Raters' use of LinkedIn information to make hiring recommendations is also explored. In Study 2, we explore how standardizing assessments by using an itemized approach to rate LinkedIn profiles influences interrater reliability and adverse impact.

LinkedIn as a Selection Tool

LinkedIn is the largest and fastest-growing professional social media, with more than 530 million users in over 200 countries in 2017 (linkedin.com). LinkedIn usage is not associated with age, gender, or education, but is slightly more popular for high-income individuals (Blank & Lutz, 2017), thus making it a potentially relevant platform for recruiting or assessing a variety of applicants. Indeed, according to various surveys, LinkedIn is extensively used in recruitment and selection. It has been suggested that over 40% of job seekers use LinkedIn to find jobs (Collmus, Armstrong, & Landers, 2016), 94% of hiring managers use it for recruitment (Guilfoyle, Bergman, Hartwell, & Powers, 2016), and 85% for selection purposes (Kluemper, Mitra, & Wang, 2016). In addition to its free version, LinkedIn offers organizations various fee-based recruitment solutions enabling managers to easily find, interact, screen, and select job applicants (Black, Washington, & Schmidt, 2016; Nikolaou, 2014).

LinkedIn profiles contain an abundance of job-related information about job applicants. Users include information about their education, professional experiences, projects, volunteering or associative activities, the skills they possess, and/or the computer programs they master (Shields & Levashina, 2016). LinkedIn profiles thus work as extended online résumés (Kluemper, 2013; Zide, Elman, & Shahani-Denning, 2014). LinkedIn also affords users features traditional résumés cannot offer: connect with other users, join interest groups, publish news/posts or comment on others' posts, and follow organizations. Users' listed skills can also be endorsed by members of their network, and such endorsements become visible on the user's profile. Connections can even generate additional skills that users have not listed themselves (Carr, 2016). Moreover, users can request detailed written recommendations from their connections. In summary, LinkedIn profiles include features of traditional résumés, rolodexes, reference checks, and recommendation letters (Collmus et al., 2016).

As part of a preliminary study, we surveyed 70 North American hiring managers about their perceptions of LinkedIn vs. established selection methods (see the online supplement for more details). We found that this sample of hiring managers considered LinkedIn to be equivalent to résumés in terms of construct validity for assessing personality and in terms of predictive validity, and only slightly less valid than résumés for assessing skills and cognitive ability. Yet, LinkedIn-based ratings of skills, personality, and cognitive ability were perceived as being less valid than interview-based ratings of the same applicant characteristics. There is also initial evidence that hiring managers rely on applicants' profiles to assess person-job or person-organization fit (Chiang & Suen, 2015).

The Realistic Accuracy Model and LinkedIn Assessments

In the present research, we propose to examine LinkedIn-based assessments, building on RAM (Funder, 1995, 1999, 2012). RAM describes the process by which a judge attempts to accurately assess individual characteristics of a target person. RAM has been used to examine judgments about a variety of characteristics, including skills, abilities (e.g., Warr & Bourne, 1999), and personality (e.g., Blackman & Funder, 2002; Letzring, Wells, & Funder, 2006). Although it was initially used for judgments based on face-to face interactions (e.g., Blackman & Funder, 2002; Letzring et al., 2006), it has been recently applied to social media based judgments (Collmus et al., 2016; Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011; Kluemper, Rosen, & Mossholder, 2012), and is thus relevant for LinkedIn-based judgments.

The accuracy of judges' assessments depends on four characteristics (Funder, 1995, 1999). First, the environment used to make assessments should include information *relevant* to the trait. That is, the target's displayed behaviors should usually be associated with a specific personality trait or a characteristic. Second, this information should be *available* to the judge. Availability is facilitated when the behavior is frequently displayed and a large quantity of information is accessible to the judge. Third, the judge must *detect* the information made available. It depends on the judge's willingness, attention, and abilities to detect the information. Finally, the judge must *utilize* the information: interpret it and classify it correctly to assess the trait of interest.

The *relevance*, *availability*, *detection*, and *utilization* can either facilitate or impede accurate judgments. The *relevance* and *availability* are particularly pertinent for examining LinkedIn-based assessments of applicants' characteristics, because they depend on the traits being assessed and the selection method being used. The *detection* and *utilization* depend primarily on individual characteristics of the rater and the use of collected information during selection. When relevance is high, traits are more visible and the behaviors relevant to the trait are more frequently displayed by the target, resulting in more accurate trait assessment (Funder, 1999). In addition, when availability is high, more quantity and better quality of information about the trait become available, resulting in more accurate trait assessment (Letzring et al., 2006).

Reliability of LinkedIn Assessments

For LinkedIn to be considered a valuable selection measure, one must demonstrate that profile-based assessments are reliable and not contaminated with errors (Kluemper et al., 2016; Roth et al., 2016). Interrater reliability assesses the degree to which ratings of the same LinkedIn profile are consistent across assessors. Yet, interrater reliability has been examined only in the context of Facebook. Using 63 assessors to rate 6 profiles, Kluemper and Rosen (2009) found high levels of reliability of Facebook-based personality ratings, with intra-class correlation coefficients (ICCs) ranging from .93 for Extraversion to .99 for Conscientiousness. In a subsequent study with only three raters providing personality ratings for 274 profiles, Kluemper et al. (2012) obtained interrater reliability (i.e., ICCs) ranging from .43 for Emotional Stability to .72 for Extraversion. Van Iddekinge et al. (2016) found lower levels of reliability between two raters evaluating 416 profiles for applicants' knowledge, skills, abilities, and other characteristics (KSAOs; average ICC = .14) and suitability ratings (ICC = .23). These findings suggest that applicants' personality can be reliably measured on Facebook, but that the reliability of skills (i.e., KSAOs) or suitability is lower.

The content of LinkedIn largely differs from Facebook. Thus, the reliability coefficients may not generalize from Facebook to LinkedIn assessments (Davison et al., 2016). According to RAM (Funder, 1995, 1999), assessments of traits that are more visible (i.e., when behaviors relevant to the trait are displayed more frequently) and associated with more information (i.e., more quantity of information about the trait is made available) should be more accurate and lead to high interrater reliability. On social media, relevant information about personality traits are likely to be found in sections about personal preferences or out-of-work activities. Although users of professional platforms like LinkedIn can provide personal information on their profile, this information is usually less visible and less frequent than on personal social media like Facebook. As such, LinkedIn provides less opportunities to reliably assess applicants' personality than Facebook profiles and, although raters should demonstrate reliability, we expect somewhat lower levels of interrater reliability to be reached (e.g., as compared to Kluemper & Rosen, 2009). However, LinkedIn profiles include a large quantity of job-related information about education, skills, professional experiences, projects, volunteering or associative activities, and professional groups (Shields & Levashina, 2016). As such, information about applicants' skills and abilities should be more readily available to raters on LinkedIn profiles. Thus, we expect to observe larger interrater reliability about the LinkedIn-based skills and abilities assessments than the reliability about the Facebook-based skills and abilities assessments reported in Van Iddekinge et al. (2016). Similarly, we expect to observe higher levels of reliability for hiring recommendations, which should be based on an overall assessment of the LinkedIn profile, than overall Facebook-based ratings (e.g., the suittability ratings in Van Iddekinge et al., 2016).

Hypothesis 1. Raters demonstrate consistency in their LinkedIn-based ratings of (a) skills, (b) personality traits, (c) cognitive ability, and (d) hiring recommendations.

Temporal Stability of LinkedIn Assessments

Social media profiles are dynamic in nature and can be regularly updated by users. As such, it is important to assess the temporal stability of LinkedIn assessments. Unfortunately, existing research is limited to language-based assessments of Facebook profile, and there is no empirical examination using human ratings or focused on LinkedIn (Davison et al., 2016). According to RAM (Funder, 1995, 1999, 2012), judges' ratings are more accurate for *good targets*. A key feature of such targets is that their behaviors are consistent over time or across situations. Relevant traits of targets demonstrating consistent patterns of behaviors can be accurately assessed even by unfamiliar judges. This RAM principle thus suggests that social media assessments should demonstrate higher temporal stability when profiles include content that is stable over time and/or demonstrates consistent patterns of behaviors.

Most social media platforms (e.g., Facebook) encourage users to regularly update their profile to highlight both important changes in their lives and daily experiences or activities (Slovensky & Ross, 2012). Raters assessing the profile of a Facebook user at different points in times would likely be facing largely different information, thus leading to inconsistent ratings. In contrast, LinkedIn profiles are generally more static (Guilfoyle et al., 2016). Indeed, LinkedIn differentiates itself from other social media in that it focuses primarily on the static profile content related to employment, whereas "posting" or dynamic content is less central (Shields & Levashina, 2016). Therefore, because the content is likely to be fairly consistent over time, we expect to find temporal stability of ratings based on LinkedIn profiles.

However, temporal stability might still be impacted by naturally occurring profile edits and updates: when users change employment, obtain a promotion, acquire additional education, and/or accumulate work experience. Such updates are infrequent for experienced workers, but more common for workers in earlier career stages. For instance, college students initially have limited information to populate their LinkedIn profiles. As they accumulate work experience, they likely update their profile to highlight new responsibilities and newly developed skills, or accumulate endorsements for their skills. Similarly, as they progress through their education or enter the job market, they likely update their profile with information (e.g., degree, GPA, awards) that is often used by hiring managers to assess cognitive abilities (Cole, Rubin, Feild, & Giles, 2007). In sum, college students likely update their profile to reflect changes in their qualifications or provide more information, which might help raters achieving more accurate assessments. The temporal stability of ratings of skills and cognitive ability and, indirectly, overall hiring recommendations is likely attenuated. And, we expect that controlling for profile updates (i.e., how much profiles have been edited) increases the temporal stability for these characteristics. However, the temporal stability of personality ratings should not increase, because updates likely do not provide more relevant information to assess such traits.

Hypothesis 2. LinkedIn ratings of (a) skills, (b) personality traits, (c) cognitive ability, and (d) hiring recommendations demonstrate temporal stability.

Convergent Validity of LinkedIn Assessments

To be considered as a valid selection method, hiring managers' LinkedIn-based assessments of applicants' qualifications should converge (i.e., correlate) with test scores or self-report of the same qualifications (Roth et al., 2016). The limited empirical evidence suggests that ratings of personality traits (Kluemper et al., 2012) and cognitive ability (Kluemper & Rosen, 2009) based on Facebook profiles demonstrate convergence with self-reports, but ratings of skills do not (Van Iddekinge et al., 2016). However, research on convergent validity for LinkedIn ratings is lacking. The RAM principle of availability proposes that raters can more accurately assess traits that are more visible and include richer and more representative information (Funder, 1995, 1999). Broadly speaking, LinkedIn profiles include more information about job-related skills and cognitive abilities, but less information about applicants' personality, compared to Facebook profiles (Davison et al., 2016; Roth et al., 2016; Roulin & Bangerter, 2013b). Indeed, LinkedIn encourages users to describe their education background, skills they possess, or past work experiences (Shields & Levashina, 2016), which is not the case in typical Facebook profiles. In contrast, Facebook profiles offer rich and representative information allowing raters to accurately judge users' personality (Kluemper et al., 2012), whereas LinkedIn does not invite applicants to provide extensive personal information on profiles.

Following the same availability principle from RAM (Funder, 1995, 1999), LinkedIn might allow raters to better judge specific skills or personality traits that are particularly visible and provide raters with more frequent cues regarding the target's (i.e., applicant's) standing on the skill or trait. This should result in improved convergent validity for the assessment of visible skills and personality traits. We focus on a set of eight skills that are identified as the top employability skills or essential skills for managers across jobs: leadership, planning, communication, teamwork, information seeking, problem solving, conflict management, and adaptability (e.g., Woo, Sims, Rupp, & Gibbons, 2008). We argue that LinkedIn profiles generally offers more information about four of those skills (i.e., leadership, planning, communication, and teamwork skills; Davison et al., 2012; Kluemper et al., 2016; Roth et al., 2016), thus making them more visible and likely helping achieve higher convergence. The extent to which applicants possess leadership skills is likely to be reflected in the types and numbers of leadership activities (e.g., association president, team captain, supervisor job) that are key in resume screening (B. K. Brown & Campion, 1994) and also visible on LinkedIn profiles, but also through recommendations and endorsements by LinkedIn connections. The extent to which applicants possess planning or organization skills is likely to be reflected in the structure and completeness of the LinkedIn profile, or the ability to manage multiple activities concurrently (e.g., school and work or volunteering; Roulin & Bangerter, 2013a). Applicants' communication skills are likely to be reflected in the clarity of description, and the amount of details provided, regarding work experiences and accomplishments. Teamwork skills could be visible through group activities, such as students' clubs, fraternities/sororities, and college team sports. Thus, applicants' leadership, planning, communication, and teamwork skills might be easier to infer from LinkedIn profiles. In contrast, applicants' level of information seeking, problem solving, conflict management, and adaptability might be more difficult to infer because these skills are generally less visible on a LinkedIn profile.

Similarly, some personality traits might be more visible than others. For instance, judgement accuracy is higher for more visible traits, such as Extraversion, than for less visible traits, that is, Emotional Stability, Conscientiousness, Agreeableness, and Neuroticism (e.g., Connelly & Ones, 2010). The limited research on résumé screening also demonstrates that recruiters are more effective at assessing applicant Extraversion than other personality traits

(Cole, Feild, Giles, & Harris, 2009). Extraverts tend to be more active and provide more information on social media (Gosling et al., 2011). Social media offer specific opportunity to demonstrate sociable, assertive, or active behaviors, and thus Extraversion (Collmus et al., 2016). For instance, LinkedIn orientation towards creating professional connections and highlighting career accomplishments may allow recruiters to accurately assess Extraversion. Extraverts are likely to have more connections, better highlight career accomplishments, report more volunteering activities, and have more interest groups, therefore making this trait more visible.

Finally, résumé-based assessments of education credentials, academic achievements, and work experience are associated with applicants' cognitive abilities (Cole, Feild, & Giles, 2003). Most LinkedIn profiles include this information, sometimes with even more detail than traditional résumés (Shields & Levashina, 2016). We thus expect LinkedIn to be a pertinent platform to assess applicants' cognitive abilities.

Hypothesis 3. LinkedIn-based assessments are correlated with (a) applicants' self-reports of visible skills (i.e., leadership, planning, teamwork, and communication skills) but not less-visible skills (i.e., information seeking, problem solving, conflict management, and adaptability), (b) applicants' self-reports of visible personality traits (i.e., Extraversion) but not less-visible traits (i.e., the other four traits), and (c) applicant's cognitive ability test scores.

Predictive Validity of LinkedIn Assessments

In addition to convergent validity, decisions based on social media should demonstrate predictive (or criterion-related) validity. Recent research suggests that Facebook-based suitability ratings are not associated with job performance or turnover (Van Iddekinge et al., 2016). However, LinkedIn might be a more promising platform. Indeed, LinkedIn profiles usually include job-related information similar to biodata inventories (Roth et al., 2016), recommendations or skill endorsements from colleagues or employers (Weidner et al., 2016), and overall more authentic information (Shields & Levashina, 2016). This is aligned with the RAM principles of providing richer, more representative, and more ingenuous information regarding traits of interest (Funder, 1995). Moreover, there is initial evidence that LinkedIn content can be used to predict work outcomes. In a study of over 200 employees, Robinson, Sinar, and Winter (2014) coded past turnover, the number of companies employees worked for, and the number of positions previously held based on LinkedIn profiles. All three indicators were associated with employees' self-reported intentions to stay. Similarly, LinkedIn ratings may be positively associated with job-related outcomes, such as job performance or career success. In the present study, we propose that raters' hiring recommendations based on their assessments of the LinkedIn profiles would predict career success measured 1-2 years later. Thus, we propose:

Hypothesis 4. The LinkedIn-based hiring recommendation are positively associated with indicators of career success (i.e., demonstrate predictive validity).

Adverse Impact Potential of LinkedIn Assessments

Another important standard for any selection method is its legality. It is important to demonstrate that scores or ratings are consistent across different groups, and that a measure does not unfairly discriminate against applicants based on sex, race, or against other features of protected groups. Facebook profiles generally include written content and pictures allowing raters to easily obtain information about applicant age, ethnicity, religion, sex, and disabilities (Schmidt & O'Connor, 2016). Extant research on Facebook-based assessments has highlighted potential adverse impact of such assessments, with more positive ratings reported for female and White applicants (Van Iddekinge et al., 2016). However, Van Iddekinge and colleagues explained these effects by differences in posted content, such as women posting more pictures with friends or minorities engaging more in social or political causes. Such content is specific to Facebook and not included in most LinkedIn profiles. LinkedIn users are not expected to post non-work-related pictures or mention their political preferences. But, one can still identify gender and ethnicity based on profile pictures or age based on graduation date. As a result, in the present study, we empirically examine if LinkedIn-based ratings are prone to gender or ethnicity biases. Given the limited theoretical foundations (e.g., adverse impact is not directly associated with RAM principles), the dearth of empirical research on adverse impact on LinkedIn, and the differences with Facebook content, we propose to explore this issue with a research question:

Research Question 1. Are LinkedIn-based assessments potentially prone to adverse impact leading to lower ratings for women or minority applicants?

Profile Features Associated with Higher LinkedIn Ratings

Although there is evidence that managers do use LinkedIn to make initial screening decisions (Kluemper et al., 2016), there is little research on how they do it. Zide et al. (2014) asked managers to describe information they use to assess LinkedIn profiles and identified 14 components of LinkedIn profiles, including achievements, education, number of connections, profile completeness, profile photograph, recommendations, or skills and expertise. Granted, this was only a pilot study based on interviews with five managers. Chiang and Suen (2015) asked five managers to assess 20 LinkedIn profiles each. Managers judged whether applicants provided information that was persuasive and credible across 14 components (e.g., profile photograph, profile summary, experience, volunteer experience, education, recommendations, or endorsed skills). Applicants were evaluated more positively when managers perceived applicant information as persuasive and credible. However, they did not directly examine the impact of the fourteen components on ratings. Although this is an area that remains under-researched, it is reasonable to start with examining the impact of components that are unique to LinkedIn profiles. Indeed, LinkedIn profiles are considered as digital résumés (Kluemper, 2013; Zide et al., 2014), but they also offer users the opportunity to provide information that is not available on traditional résumés. And, the RAM principle of availability (Funder, 1995, 1999) suggests that raters should value profiles that make more (and high-quality) information available.

First, research suggests that pictures have more impact than verbal content on ratings of social media profiles (Van Der Heide, D'Angelo, & Schumaker, 2012). A photo is a rather undesirable feature of résumés (at least in North America), but is an expected component of LinkedIn profiles. In addition to this normative expectation, RAM suggests that raters can better assess targets that are perceived to be ingenuous (Funder, 1995). Applicants who do not include a photo in their profile might be perceived as hiding something (Davison et al., 2016), and thus rated more negatively.

Second, the number of connections is an important component of LinkedIn profiles and is absent in the résumés. Zide et al. (2014) argued that the number of connections is an indicator of applicant networking skills and might be relevant for many jobs, including recruiting, marketing, sales, or public relations. According to RAM (Funder, 1995), the number of connections thus represents information that is particularly relevant to assess valuable job qualifications, leading to more positive evaluations.

Third, profile length (or the degree of completeness) is also a unique component of LinkedIn profiles. There are normative expectations for the length of résumés. Typically, applicants with limited work experience are advised to have one-page résumés, whereas experienced applicants are advised to have two-page résumés. LinkedIn profiles do not have such length expectations, allowing applicants to include as much information as they want. Long profiles are likely to be more comprehensive and include detailed information about skills and work experiences. Roth et al. (2016) proposed that assessments would be more valid when based on larger amounts of information. This is consistent with RAM because making more information available to judges allows for a more accurate assessment of targets (Funder, 1995, 1999). As such, raters should value profiles that are more comprehensive, thus resulting in higher evaluations.

Finally, skill endorsements are important unique features of LinkedIn profiles. Collmus et al. (2016) argue the total number of skill endorsements received by applicants can be used as a valuable indicator of experience level with stated skills, resulting in higher ratings. Carr (2016) suggests that applicants are more likely to possess skills they state on LinkedIn than on traditional résumés because of higher "warranting values." Coworkers and current or previous employers have the opportunity to confirm stated skills by endorsing them or to refute them by posting comments. This feedback mechanism creates an incentive for LinkedIn users to only list skills connections can confirm. Further, endorsements limit applicants abilities to engage in online impression management or deception by listing skills they do not actually possess (Roulin & Levashina, 2016; Shields & Levashina, 2016). This is also in line with RAM, which suggests that *good targets* provide more ingenuous and non-distorted information (Funder, 1995, 1999). There is some preliminary empirical evidence supporting the existence of such a mechanism. For instance, individuals instructed to create a LinkedIn profile tend to engage in less deception in profile sections including verifiably objective information (Guillory & Hancock, 2012). Thus, skill endorsements should be associated with increased ratings.

Hypothesis 5. Having (a) a longer LinkedIn profile, (b) a profile photo, (c) more connections, and (d) more skill endorsements is positively related to hiring recommendations.

Profile Features as Signals of Applicants' Qualifications

From the perspective of the organization, what matters most is the quality of LinkedIn-based hiring recommendations. More precisely, if raters positively evaluate longer profiles including pictures, more connections and more skill endorsements, their assessments would be valid to the extent to which those features are associated with applicants' true qualifications (i.e., signals of their skills, personality traits, or cognitive ability; Roulin & Bangerter, 2013b). In contrast, if those features are not related to applicants' qualifications, then raters should be instructed to ignore them. As such, in order to better understand the potential value of those profile features, we propose to explore their relationships with applicant cognitive ability scores, and self-reports of skills and personality. Again, given the limited theoretical foundations or empirical research on social media profile features associated with applicant qualifications, we propose to explore this issue with a research question:

Research Question 2. What is the relationship between profile length, profile photo, number of connections, and skill endorsements and applicants' cognitive ability and self-reported skills and personality?

Global vs. Itemized LinkedIn Assessments

According to RAM, judgments are more accurate (i.e., reliable and valid) if made by *good judges* (Funder, 1995, 1999). One core feature of *good judges* is that they are more knowledgeable regarding traits to be assessed and which behaviors are relevant to assess them. Although such knowledge can be a function of personal experiences, Funder (1995) argues that a *good judge* can be fostered by explicit teaching. Similarly, a key contribution of personnel selection research in the last decades has been the development of tools and methods helping hiring managers improve the quality of assessments and hiring decisions. For instance, there is ample evidence that structuring employment interviews improves reliability and validity, while reducing biases and adverse impact (Campion, Palmer, & Campion, 1997; Levashina, Hartwell, Morgeson, & Campion, 2014). One key feature of structured interviews is scoring standardization. Instead of relying on a global evaluation of applicants, interviewers can rely on a more itemized evaluation of applicants along multiple established criteria (Lievens & De Paepe, 2004). Decomposing holistic judgments into multiple ratings provides interviewers a frame of reference (Melchers, Lienhardt, von Aarburg, & Kleinmann, 2011), and leads to improvements in validity and interrater reliability (Campion et al., 1997). Similarly, Roth et al. (2016) argue that standardizing social media assessments is difficult but could increase validity. We thus propose to explore global and itemized assessments of LinkedIn profiles.

Because using social media screening is an emerging practice and most organizations have no internet search policies (Roth et al., 2016), it is likely that hiring managers rely on holistic judgments when assessing applicants' profiles. Such assessments would involve the rater browsing applicants' LinkedIn profiles and making an overall global (or clinical) judgment about their level of suitability. Yet, like with interviews, we argue that it is possible to decompose the LinkedIn assessment process. This would involve asking raters to focus on a series of job-relevant qualifications (e.g., skills, personality traits, and cognitive ability), and then to assess each of them on a rating scale before evaluating an applicant's suitability. Previous research across a range of fields has consistently demonstrated better psychometric properties for decomposed methods over holistic ones (Grove & Meehl, 1996; Kuncel, Klieger, Connelly, & Ones, 2013). Altogether, like decomposing ratings in interviews, we expect itemizing LinkedIn assessments will have the same benefits on psychometric properties, such as improving interrater reliability and diminishing potential adverse impact.

Hypothesis 6: Itemized LinkedIn assessments are associated with (a) higher interrater reliability and (b) lower risk of adverse impact than global assessments.

Study 1 – Psychometric Properties of LinkedIn Assessments

Method

Sample

Our sample of applicants was composed of 133 senior business students from two universities, one in Canada (60%) and one in the U.S. (40%). Canadian students were recruited with the help of the school's career center and were looking for an internship (i.e., a three-month full-time placement in a local organization) at the time of the study. U.S. students were recruited through a career-oriented course and were looking for a job at the time of the study. Mean age was 21.48 (*SD* = 2.67). The sample was gender-balanced (49% female). It included a majority of White students (64.5%), but also 22.3% Asian, 5% Black, 2.5% Middle Eastern, and 1.7% Hispanic students (and 4.1% self-categorized as "other"). Although most LinkedIn users are experienced workers, our sample of senior business students is representative and practically relevant for several reasons. First, students and recent college graduates account for over 40 million of the platform users, Millennials are joining this social media faster than any other demographic group, and LinkedIn has identified college students as its key target for future growth (linkedin.com). Second, assessment of applicants' qualifications based on social media has been described as mostly relevant for entry-level jobs (Carr, 2016), which are the jobs university students and graduates largely apply for. Finally, we recruited only students who were real job applicants, that is, they were active job seekers, and we assessed their real LinkedIn profile (i.e., available online for actual organizations or managers to see).

Procedure

Our data collection and coding took place over three years. Between 2014 and early 2015, participants were initially asked to use their existing LinkedIn profile (or create one if they did not have one, using their real name) and connect with a profile created for the study. They were also asked to complete an online questionnaire, including self-reported measures of personality and skills, and a cognitive ability test. In 2015 and 2016, participants' profiles were assessed by two groups of raters, and the content of their profiles was recorded and coded. Initial assessments of profiles were performed six months to a year after the connection This allowed participants time to familiarize themselves with LinkedIn, complete and/or update their profiles, connect with colleagues, etc. The second assessment was performed a year later, allowing us to assess temporal stability. Appropriately determining a time interval for social media assessments is critical to assess stability. Having longer intervals between assessments creates more opportunities for users to edit and/or update the content of their profile, which might distort assessments of temporal stability (Davison et al., 2016). Yet, because LinkedIn profiles are updated less frequently than Facebook profiles (Guilfoyle et al., 2016), we chose a one-year interval between the two assessments of profiles by raters. Finally, the criterion coding was done in 2017 (i.e., two years after the initial assessment and one year after the last one) to ensure enough time passed between the profile assessments and our measure of career success. Our study procedures for Study 1 (and Study 2) were approved by the University of Manitoba Faculty Ethics Board (Protocol #J2013-180).

Measures

Self-reported Personality. Personality was measured with the 20-item Mini-IPIP (Donnellan, Oswald, Baird, & Lucas, 2006): a short scale with four items measuring each of the Big-Five personality factors ensuring similar coverage of facets as broader measures. Responses were made on five-point Likert scales. Reliability coefficients were similar to those obtained by Donnellan et al.: Extraversion (α = .80), Agreeableness (α = .70), Conscientiousness (α = .68), Emotional stability (α = .56), and Openness/Imagination (α = .73).

Self-reported Skills. Participants reported the degree to which they believed possessing eight skills/competencies, and each skill was measured with three items adapted from Woo et al. (2008). These skills are also partly overlapping with the KSAOs used by Van Iddekinge et al. (2016). All measures were on five-point Likert scales. Reliability coefficients were acceptable to good, considering the use of only three items: leadership (α = .73), planning (α = .66), communication (α = .80), teamwork (α = .77), information seeking (α = .72), problem solving (α = .67), conflict management (α = .73), and adaptability (α = .67). Research on self–other rating agreement suggests that self-ratings can sometimes be under- or overestimated, but self-enhancement is more likely in evaluative (vs. research) settings (Fleenor, Smither, Atwater, Braddy, & Sturm, 2010). Moreover, meta-analytical evidence suggests that although self–other (i.e., supervisor) performance ratings correlate only .22 (or .34 when corrected for measurement error), leniency in self-ratings is quite low overall (i.e., d = .32 between self and supervisory ratings; Heidemeier & Moser, 2009). In addition, extensive literature from cognitive and educational psychology demonstrates that individuals are capable of providing reasonably accurate estimates of their own abilities, with r_s between self-reports and objective test performance ranging from .29 to .52 (e.g., Ackerman & Wolman, 2007; DeNisi & Shaw, 1977; Mabe & West, 1982). Based on the existing literature, and because we measured skills in a non-evaluative (or non-high-stake) context, we argue that participant self-reports of skills should not largely be biased by over-estimation or leniency.

Cognitive Ability Test Scores. Participants' cognitive ability was measured with the Wonderlic Test (WPT-Q), an 8-minute timed assessment which includes a series of 30 verbal, numeric and logic problems. The Wonderlic has been established as a reliable and valid measure of cognitive abilities (Hunter, 1989).

Profile Ratings. The profiles were assessed six months to one year after the participants connected with us (Time 1) by a group of nine MBA raters (5 males, 4 females) and about 18 to 24 months after the connection (Time 2) by another group of eight MBA raters (5 males, 3 females). Each profile was assessed by two independent raters at both T_1 and T_2. To increase the external validity of our findings (i.e., simulate how hiring managers would assess profiles), we recruited Canadian MBA students with extensive professional experience who were enrolled in an advanced Human Resources Management course. They were asked to imagine that they were judging the LinkedIn profiles of potential applicants for an entry-level general management position. Raters were asked to spend as much time as they deemed necessary on each profile, and they rated profiles for one hour in total to avoid fatigue. They assessed the applicants' skills and personality with one-item measures. Ratings were made on five-point Likert scales, which is likely the approach used (consciously or unconsciously) in practice by hiring managers. In addition, this approach is similar to ratings of KSAOs in Van Iddekinge et al. (2016), and has been successfully used to assess personality (e.g., Gosling, Rentfrow, & Swann, 2003). Raters also assessed cognitive ability using the one-item approach from Kluemper and Rosen (2009) (i.e., "Estimate the user's IQ. Remember that the average IQ is 100, and one-sixth of the population has IQs less than 85, with one-sixth scoring over 115"). Finally, they made hiring recommendations with a 5-item measure (e.g., "I would recommend this applicant for the position," α_{T1} =.95 and α_{T2} = .96) adapted from Kluemper et al. (2012).

Profile Content Coding. In parallel to profile assessment by our MBA raters, a trained research assistant and the first author coded objective features of LinkedIn profiles. First, in order to capture the length/comprehensiveness of the profile, we saved each profile as a PDF (using the LinkedIn "save to PDF" option). We then counted the number of words in the profile. Next, we coded the presence (i.e., yes/no) of the following features: a main profile picture, the picture being a professional shot (i.e., high quality headshot with professional dress), a summary section, written recommendations (from colleagues or employers), school major, GPA, awards received, involvement in extracurricular activities. We then coded the number of connections the user had, the total number of skills listed, the number of skill endorsements, and the number of interest groups the user was a member of. Finally, we coded the level of details provided for work experiences, with 0 = no work experience listed in the profile, 1 = the user only provides the job title/role and the organization for each experience listed, and 2 = the description contains information about the job profile, key responsibilities, and/or accomplishments.

Career Success. About two years after the Time-1 ratings and one year after the Time-2 ratings, another trained research assistant and the first author coded the profiles to obtain criterion data. Because our participants were senior business students with majors across the discipline, we decided to code for four broad indicators of career success. First, we coded if they obtained a job in line with degree and major (e.g., business analyst, financial advisor – coded 1) vs. no job or a job that did not require a college education (e.g., restaurant waiter, sales' associate in retail – coded 0). Second, we coded if participants had a management role (yes = 1 vs. no = 0). Third, we coded if they had received a promotion in either the same organization or by moving to another organization (e.g., from assistant manager to manager – coded 1 vs. 0). Finally, we counted the number of jobs in line with participants' degrees since graduation. Importantly, we checked if the LinkedIn profiles had been regularly or recently updated by the user. Profiles that had not been updated (and thus did not provide accurate criterion data) were not coded and were excluded from the analyses.

Results

Interrater reliability. We examined the interrater reliability of LinkedIn-based assessments (Hypothesis 1) by calculating the intra-class correlation coefficient (ICC) for the two raters assessing the profile (Table 1). We used the ICC (1, k) model (i.e., one-way random with mean ratings) because the two raters for each profile were drawn from a total of nine or eight raters (Shrout & Fleiss, 1979)[1]. We found that raters tend to rate skills consistently, with average ICCs across all skills = .45 for T_1 and .40 for T_2, although we note that the ICC for T_2 was particularly low for two skills, namely conflict management (.03) and leadership (.04). Raters' assessments of personality (average ICC = .37 for T_1 and .54 for T_2), cognitive ability (ICC = .63 for T_1 and .57 for T_2), and hiring recommendations (ICC = .58 for T_1 and .75 for T_2) also demonstrated interrater reliability, consistent with Hypotheses 11a, b, c, and d.

Temporal stability. We examined the temporal stability of LinkedIn-based assessments over time (Hypothesis 2) with correlations between the average ratings of the same skill/trait at the two time points (Table 1). We note that because ratings were made by different groups of raters at T_1 and T_2, our results should be interpreted as relative (and not absolute) coefficients of stability. Ratings demonstrated stability for skills (ranging from r = .39, p < .01 for conflict management to r = .57, p < .01 for planning, with an average r = .51 across all skills), personality (ranging from r = .43, p < .01 for Conscientiousness to r = .65, p < .01 for

[1] We note that our ICCs (1, k - i.e., one-way random) are different from, and thus not directly comparable to, those reported by Kluemper et al. (2012), who used ICC (2, 3 - i.e., two-way random) because the same three evaluators rated all the profiles, or by Van Iddekinge et al. (2016), who used ICC (2) because they relied on 86 raters examining 5 profiles and then obtained ratings from a second evaluator for only a subsample of the profiles.

Extraversion, with an average $r = .52$ across all skills), and cognitive ability ($r = .58$, $p < .01$). Temporal stability was also demonstrated for hiring recommendations ($r = .52$, $p < .01$). Altogether, these findings provide support to Hypotheses 2a, b, c, and d. Yet, they also suggest that ratings of some specific skills (e.g., planning, communication) and personality traits (e.g., Extraversion) are more stable over time than others.

Additionally, we computed partial correlations between the average ratings of the same skill/trait/recommendation at T_1 and T_2, controlling for updates made in the profile (measured as the change in profile length – i.e., number of words in the profile) between the two ratings. On average, participants increased their profile length by 98.07 words ($SD = 174.36$). As expected, stability coefficients increased (slightly) for skills (average partial $r = .53$), cognitive ability (partial $r = .62$), and hiring recommendations (partial $r = .58$). Stability did not improve for personality (average partial $r = .52$).

Convergent validity. We examined the convergent validity of LinkedIn-based assessments (Hypothesis 3) using the correlations between self-reported measures or test scores and LinkedIn ratings of skills, personality, and cognitive ability at the two time points, as well as the average across both times (Table 1). We report both observed correlations (*r*) and correlations corrected for unreliability (ρ)[2]. As anticipated, we observed positive and significant correlations between self-reports and ratings of visible skills (i.e., average $r = .26$, $p < .01$ for leadership, .23, $p < .05$ for planning, and .22, $p < .05$ for communication, and ρ above .30 for all three). Yet, the convergent validity of teamwork was lower than expected (average $r = .11$, *ns* and $\rho = .20$). In line with our expectations, we did not find convergent validity for the less-visible skills (e.g., information seeking, problem solving, with average *r*s ranging from .04

[2] We also include a more comprehensive table, which contains correlations between all self-reports, LinkedIn-based ratings (averaged across times 1-2), and criterion data, in the online supplement.

to .14, all *ns*). Overall, these findings provide partial support for H3a. For personality, and in line with H3b, Extraversion was the only trait with clear positive and significant correlations between self-reports and ratings (average $r = .20$, $p < .05$ and $\rho = .30$), whereas the correlations for the other traits were non-significant (average *r*s ranging from -.02 to .10, all *ns*). In support for H3c, cognitive ability ratings were positively associated with the test scores and significant (average $r = .30$, $p < .01$, and $\rho = .37$), although this effect was mostly driven by a strong correlation for T_2 ($r = .38$). Notably, we found generally stronger correlations for skills and cognitive ability at T_2 (i.e., when ratings were done 18 to 24 months after the profile creation or connection) than at T_1.

Predictive validity. We examined the criterion-related validity of LinkedIn-based judgments (Hypothesis 4) using the observed correlations between raters' hiring recommendations at Times 1-2, as well as correlations corrected for unreliability, and the four indicators of career success (Table 2). We note that the sample sizes were somewhat smaller ($N = 112$ for T1, $N = 88$ for T2) given that (a) some participants' profiles were not available anymore or (b) were never updated by the user (making criterion coding impossible). Hiring recommendations were positively and significantly associated with obtaining a job in line with one's degree (average $r = .20$, $p < .05$, and $\rho = .24$), with the number of jobs aligned with the degree (average $r = .25$, $p < .01$, and $\rho = .27$), and with being promoted (average $r = .20$, $p < .05$, and $\rho = .21$). However, recommendations were not associated with having a management role (average $r = .09$, *ns* and $\rho = .08$). Altogether, our results provide partial support for H4. We also observed similar patterns when examining the correlations between ratings of individual skills/traits and the career success outcomes[3].

[3] See the correlations between the average ratings (across T_1 and T_2) of skills, personality, and cognitive ability, and the four career success indicators in Supplemental Table B (in the online supplement). In addition, following the suggestion made by one anonymous reviewer, we also conducted relative weight analyses (Tonidandel & LeBreton, 2015) to explore whether ratings of specific skills and traits were more strongly associated with career success

Adverse impact. The potential adverse impact of LinkedIn ratings (RQ1) was tested first with ANOVAs, and then with regressions, using the T_2 ratings. We examined potential differences associated with gender and ethnicity. We also explored potential country of residence differences because our sample includes a mix of Canadian and U.S. profiles. However, because our LinkedIn users were all students with limited variance in age (SD = 2.67), we did not examine adverse impact associated with age. Comparisons between the profiles of male and female users showed no difference in hiring recommendations: d = .07, p = .68. Comparisons between the profiles of White and non-White users showed slightly higher scores for White (M = 3.69, SD = .79) than non-White (M = 3.38, SD = 1.02) users, F(1, 124) = 3.68, d = .34, p = .06. Canadian profiles also received slightly higher hiring recommendations (M = 3.68, SD = .81) than U.S. profiles (M = 3.36, SD = 1.03) users, F(1, 128) = 3.85, d = .34, p = .05. A significant effect for country (but not ethnicity) was also observed in Model 1 of the regression analyses (Table 4). However, this effect disappeared once other profile features were included in the regressions (i.e., in Models 2 and 3 – see below). Overall, our findings suggest that LinkedIn assessments are not prone to adverse impact when examining gender, and only small-to-moderate adverse impact when examining ethnicity or country of residence.

Profile features and ratings. Descriptive statistics and correlations for LinkedIn profiles features are presented in Table 3. We examined the profile features associated with higher ratings (Hypothesis 5) with regressions using the rating at T_2 (Table 4). In addition to users' gender, ethnicity, and country, profile length (i.e., the number of words in the profile) was included in Step 2. This step allowed us to test if more comprehensive profiles are rated more positively, but also to control for profile length when examining the impact of other features.

criteria. Results are present in Supplemental Table C.

Results highlighted a strong effect of profile length in Model 2, $B = .62$, $p < .01$, explaining 37% of variance over and above users' demographic characteristics, and supporting H5a. In Model 3, we added the other profile features (including profile picture, number of connections, and endorsement). Adding all the other profile features mentioned in past research explained an additional 21% of variance in total. As anticipated, hiring recommendations were positively related to the presence of a picture ($B = .26$, $p < .01$ – supporting H5b) and the number of connections ($B = .26$, $p < .01$– supporting H5c). Yet, contrary to H5d, accumulating more skill endorsements was not associated with higher ratings. Moreover, having a professional picture, listing more skills, or being member of more groups were not associated with ratings.

Profile features and self-reports. Finally, in order to better understand the potential value of profile lengths, profile photo, number of connections, and skill endorsements as valid cues of applicants' qualities (RQ2), we examined how those features correlated with users' self-reports of skills, personality, and cognitive ability (Table 5). Of note, results highlighted that more conscientious users possessed longer profiles ($r = .22$, $p < .05$). Users higher in cognitive ability ($r = .40$, $p < .01$), Extraversion ($r = .18$, $p < .05$), and self-reported communication ($r = .21$, $p < .05$) were more likely to include a profile picture. Those higher in Extraversion ($r = .24$, $p < .01$), as well as self-reported leadership ($r = .26$, $p < .01$), planning ($r = .25$, $p < .01$), communication ($r = .22$, $p < .05$), and information-seeking ($r = .20$, $p < .05$) had more connections. Those higher in Extraversion ($r = .25$, $p < .01$), as well as self-reported leadership ($r = .20$, $p < .05$) and information-seeking ($r = .19$, $p < .05$) received more skill endorsements.

Study 2 – Global vs. Itemized Assessments

In order to examine the impact of itemizing on the psychometric properties of LinkedIn assessments (Hypothesis 6), we conducted a second study. The study asked another group of

MBA raters to assess a series of business students' profiles (from Study 1) using a global and (later on) itemized approach.

Method

Sample

A group of 24 MBA students from a U.S. university participated as raters in the study as part of a class assignment. The sample was gender-balanced (46% female), with a majority of White students (79%).

Procedure & Measures

Each MBA rater was asked to assess two groups of ten LinkedIn profiles (i.e., a total of 20 different profiles): the first 10 using a global or holistic approach and the next 10 using an itemized approach. Raters received a package with instructions to access profiles and how to assess them (see below), the list of profiles to code, and were given the ratings to do as "homework" (and thus could take as much time as needed to rate ten profiles). Both ratings were performed in 2017, with about a week between the two types of assessments. Raters received a different list of 10 profiles for each assessment, and a total of 118 profiles (out of the original 133 still connected with our research profile) were scored by at least two raters.

Global assessments. Rater were asked to imagine that they were hiring managers for a large North American company and were involved in the initial screening of job applicants for an entry-level general management position. They were asked to spend a few minutes reviewing the content of each of the ten applicants' LinkedIn profile and make hiring recommendations for the position on a 1-5 scale (1 = Very low to 5 = Very high).

Itemized assessments. Raters were provided with similar instructions as above. However, this time, they were asked to assess the applicants on eight skills (the same as in Study 1 – e.g., leadership, communication), the Big-5 personality traits, and cognitive ability, and then make hiring recommendations. Each qualification was assessed with one item (similar to the skills and personality ratings from Study 1). All ratings were made on a 1-5 scale (1 = Very low to 5 = Very high).

Results

To examine if itemizing LinkedIn assessments improves interrater reliability, we computed ICCs for global vs. itemized ratings following the same approach used in Study 1 (Table 6). For the global assessments, raters only provided a general hiring recommendation based on applicants' LinkedIn profiles. The interrater reliability for this overall assessment was relatively low (ICC = .38). For itemized assessments, we found higher levels of interrater reliability for skills (ICCs ranging from .43 to .60), personality traits (.49 to .62, except for Emotional Stability = .24), and cognitive ability (.47). Importantly, the ICC for itemized hiring recommendations was .60: substantially higher than the for unstructured ratings. Overall, our results thus provide support for H6a.

We also report the uncorrected convergent validities (with respect to self-report ratings obtained in Study 1) for the itemized assessments, as well as the convergent validities corrected for unreliability (ρ). Of note, we observed the same pattern of correlations as in Study 1, with higher validities for visible skills like communication (r = .22, ρ = .34), leadership (r = .21, ρ = .33), and planning (r = .18, ρ = .29), but also for Extraversion (r = .31, ρ = .47) and cognitive ability (r = .27, ρ = .39).

To test if itemizing LinkedIn assessments helps reduce the risk of adverse impact, we compared hiring recommendations for sub-groups (i.e., for gender, ethnicity, and country of residence) for different levels of structure with ANOVAs. For gender, we found no difference between female and male profiles for global assessments (*M* = 2.96, *SD* = .95 vs. *M* = 3.00, *SD* = 1.05, $F(1,113) = 0.04$, $d = .04$, $p = .84$), but observed higher ratings for women with itemized assessments (*M* = 3.54, *SD* = .87 vs. *M* = 3.01, *SD* = 1.01, $F(1,113) = 9.13$, $d = .57$, $p < .01$). For ethnicity, we found higher ratings for the profiles of White than non-White participants for global assessments (*M* = 3.16, *SD* = .90 vs. *M* = 2.65, *SD* = 1.10, $F(1,113) = 7.08$, $d = .50$, $p < .01$) and no significant difference was found for the itemized assessment (*M* = 3.37, *SD* = .90 vs. *M* = 3.07, *SD* = 1.09, $F(1,113) = 2.63$, $d = .31$, $p = .11$). For country of residence, we found no significant difference for any of the two assessment approaches (i.e., $d = .03$ and .16). Overall, itemizing LinkedIn assessments tends to reduce potential adverse impact associated with ethnicity, but it also leads to slightly more favorable ratings for women than men, thus providing only partial support for H6b.

Discussion

Theoretical and Practical Implications

A key contribution of personnel selection research has been the examination and improvement of the psychometric properties of selection methods. The structured employment interview, and the dissemination of best practices to interviewers, is a prime example (Levashina et al., 2014). In sharp contrast, the use of social media as a selection tool is an example of research lagging far behind practice, and thus represents a critical challenge for selection researchers (Roth et al., 2016). Indeed, many hiring managers use social media to screen, assess, and select job applicants (Kluemper et al., 2016). They use social media information to infer applicants' characteristics, and rely on these inferences to make hiring recommendations (Chiang & Suen, 2015). Whether inferred correctly or incorrectly, such inferences matter because they influence organizations' hiring decisions. Yet, existing empirical evidence about the reliability and validity of such inferences is scarce and largely limited to ratings based on personal social media like Facebook (e.g., Kluemper et al., 2012; Van Iddekinge et al., 2016). Despite offering potentially more job-relevant information (Davison et al., 2016) and being extensively used for recruitment and selection (Kluemper et al., 2016; Nikolaou, 2014), professional platforms like LinkedIn have essentially been ignored by researchers. The present research contributes to filling these theoretically- and practically-important gaps in several ways, as we describe below. More generally, it confirms that the core principles of RAM, such as how judgment accuracy depends on the relevance and availability of information about a trait of interest (Funder, 1995, 1999), are also applicable to assessments of professional social media.

We first examined the psychometric properties (i.e., reliability, validity, and legality) of LinkedIn-based assessments of applicant skills, personality, cognitive ability, and hiring recommendations. All attributes demonstrate similar levels of interrater reliability (ICC_{skills} = .19-.61; $ICC_{personality}$ = .26-.57, $ICC_{cognitive\ ability}$ = .60, $ICC_{recommendation}$ = .67). Overall, interrater reliability levels are similar to (or slightly smaller than) those obtained with Facebook for personality (ICCs .43 to .72, Kluemper et al., 2012), but they are higher than those obtained for skills and hiring recommendations (ICC = .14 for KSAOs and .23 for suitability ratings; Van Iddekinge et al., 2016). This is in line with the RAM principles of relevance and availability (Funder, 1995, 1999) because Facebook profiles provide more visible and relevant information about personality; whereas, LinkedIn provides more information about skills and abilities. Moreover, LinkedIn-based reliability levels generally meet the established criterion for ICC of .50 as suggested by Kluemper and Rosen (2009). Correlations between ratings done with a one-year interval also suggested that LinkedIn ratings demonstrate temporal stability (r_{skills} = .39-.58; $r_{personality}$ = .43-.65, $r_{cognitive\ ability}$ = .58, $r_{recommendation}$ = .52). Ratings were also more stable for skills, cognitive ability, and recommendations when controlling for profile updates. Although lower stability results for skills might appear to be a limitation of using LinkedIn as a selection tool, they might also reflect true changes in skills over time (e.g., through education and work experience). However, future research could specifically examine how applicants update their profile to reflect newly acquired skills, and how this translates into more accurate assessments by raters.

We then examined convergent validity and found significant correlations between LinkedIn ratings and self-reports only for more visible skills, such as leadership (r_{avg} = .26), planning (r_{avg} = .23), and communication (r_{avg} = .22) but not for less visible skills, such as conflict management or information seeking. Only the correlations for teamwork were smaller than expected. These findings suggest that the validity of ratings depends on the visibility of the attribute being inferred and the relevance of the information provided, which is also consistent with RAM (Funder, 1995). LinkedIn may allow applicants to display representative information about specific skills. For instance, applicants may describe their leadership roles in multiple settings (e.g., work, school, and volunteering). They may also be able to demonstrate planning skills through the structure and completeness of the LinkedIn profile and by highlighting their ability to handle multiple activities (e.g., school or work and volunteering). Finally, they may demonstrate their communication skills through clear and elaborate descriptions of professional and social experiences.

Convergent validity was also demonstrated only for Extraversion ratings (r_{avg} = .20 in Study 1 and r = .31 in Study 2) but not for the other (less visible) personality traits, again consistent with RAM (Funder, 1995, 1999). Although the validity coefficients for LinkedIn-based ratings of Extraversion are somewhat smaller than those of Facebook-based ratings (r

= .28, r = .44; Kluemper et al., 2012), or meta-analytical estimations of observer ratings' validity (r = .45; Connolly, Kavanagh, & Viswesvaran, 2007), they are sensibly higher than the validity of résumé ratings of Extraversion (r = .13, Cole et al., 2009). The weaker validity coefficients for the other Big-Five personality traits were also similar to those obtained with résumés (Cole et al., 2009) but smaller than those found with Facebook (Kluemper et al., 2012) or observer ratings (Connolly et al., 2007). This is not surprising given that Facebook offers more opportunities to users to highlight their personality through information regarding interests, posts, or pictures, as compared to LinkedIn. For instance, on Facebook, users may indicate their passion for arts in their main profile or post pictures of their visit to a museum, thus emphasizing being high on Openness. The same user would not have many opportunities to emphasize this on their LinkedIn profile, unless job-related. As such, LinkedIn may not represent the best social media platform for hiring managers to assess applicants' personality, except for Extraversion.

We also found evidence of convergent validity for LinkedIn-based assessments of cognitive ability (r_{avg} = .30 in Study 1, r = .27 in Study 2). This is comparable to (or slightly higher than) the r = .23 obtained by Van Iddekinge et al. (2016) with Facebook. Interestingly, in Study 1, convergent validity was stronger at T_2 than T_1, which could be due to LinkedIn profiles being updated and incorporating more relevant information (i.e., about 98 more words on average from T_1 to T_2), thus allowing raters to provide a better judgement of the applicants' cognitive ability. Altogether, our convergent validity correlations can be considered "moderate" in magnitude, when compared to recent benchmarks for applied psychology research proposed by Bosco, Aguinis, Singh, Field, and Pierce (2015). Indeed, they reported r = .09 and .26 as the boundaries for a "moderate" effect (i.e., 33rd and 67th percentile) based on a meta-analysis of 147,328 correlational effects sizes. And most of our significant findings fall within those boundaries.

LinkedIn-based hiring recommendations were positively associated with several career success indicators (i.e., obtaining a job aligned with one's education, number of jobs, and promotions), although it was not associated with having management responsibilities. Our results highlight the potential of LinkedIn to predict relevant career outcomes and are thus more encouraging than the reported lack of predictive validity for Facebook-based suitability ratings (Van Iddekinge et al., 2016). Moreover, our results, coupled with the findings for turnover from Robinson et al. (2014), suggest that LinkedIn has the potential to predict a variety of relevant job-related outcomes.

The findings that LinkedIn-based hiring recommendations were not associated with adverse impact for gender, and only small-to-moderate effects for ethnicity (with the non-White group composed mostly of Asian students, with some Black, Middle-Eastern, and Hispanic students) and country of residence are encouraging. These effect sizes are lower for gender and equivalent for ethnicity to ones obtained by Van Iddekinge et al. (2016) for Facebook suitability ratings. The Canadian vs. American differences in ratings observed could be because the raters in Study 1 were from a Canadian university and may thus have favored local profiles. Importantly, the (small) effect of ethnicity and country of residence disappeared when other profile features were included in the analyses. It could thus be that the profile content of White vs. non-White and Canadian vs. American students objectively differed in our study. For instance, White students were more likely to have a profile picture than non-White students (96% vs. 80%), and Canadians had on average more connections than Americans (169 vs. 128). As we discuss below, including a picture and having more connections were key features of profiles receiving higher ratings.

We found three key characteristics of successful profiles: profile length, profile picture, and number of connections. However, listing more skills, collecting endorsements, joining groups, or describing volunteering involvements all had a negligible impact on recommendations. These findings are consistent with past research. Indeed, a more comprehensive profile may signal that applicants have more experience to display, invested more effort building a complete profile, or are simply more conscientious (Roth et al., 2016). And, studies similarly showed that Facebook users are judged largely based on pictures they post, how many "friends" they have, and who those friends are (Utz, 2010; Van Der Heide et al., 2012).

Moreover, our findings suggest that at least some of those features could be valid cues of applicants' qualifications. Profile length was positively related to Conscientiousness. Including a picture was positively related to self-reported communication, Extraversion, and cognitive ability. The number of connections was positively related to self-reported leadership, planning, communication, information-seeking, and Extraversion.

Finally, our second study highlighted that itemizing LinkedIn assessments were more reliable than global assessments. With the itemized approach, we asked raters to assess a wide range of constructs (i.e., skills, personality traits, and cognitive ability) with one-item measures. With the global assessment, we asked raters to assess only one construct (i.e., hiring recommendations) with one-item measure. Our findings confirm the positive impact of standardization observed with other selection methods, like interviews (Levashina et al., 2014) or assessment centers (Melchers et al., 2011), also applies to social media assessments. The results also suggest that an itemized approach can mitigate risks associated with adverse impact for non-White applicants, but might favor female over male applicants. Although our study was not oriented towards a specific job, organizations could use a similar approach, but instruct hiring managers to focus only on job-relevant qualifications.

Practical Implications

From a practical perspective, and although our findings and the existing literature highlight several limitations associated with cyber-vetting, our results suggest that organizations that do (or want to do) cyber-vetting might be encouraged to screen applicants based on LinkedIn instead of Facebook. Our research further illustrates which (and to what extent) applicant characteristics can be reliably and validly assessed based on LinkedIn profiles. For instance, hiring managers can reliably assess and make valid inferences about Extraversion, planning or communication skills, and cognitive abilities using LinkedIn. However, they should refrain from attempting to assess conflict management, adaptability, or personality traits other than Extraversion. Our findings also illustrate the practical importance of providing managers with a frame of reference (with a structured process and decomposed ratings) when assessing online profiles of applicants.

Our results regarding profile features associated with higher hiring recommendations have direct practical implications for job applicants, whereas those about valid cues of applicants' qualifications have implications for organizations and hiring managers. Applicants could be encouraged to include a profile picture and complete all sections of their profile to make it as comprehensive as possible, and thus increase chances of receiving more positive ratings. Organizations should encourage managers to focus on those particular profile features that are valid cues about applicants' qualifications or personality traits required to perform the job (e.g., profile comprehensiveness as a valid signal of Conscientiousness) and ignore other cues unrelated to applicants' true qualifications.

Limitations and Future Research Directions

This study represents an initial attempt to assess the value of LinkedIn as a selection tool. However, it has a number of limitations that could be dealt with by additional research. Our sample of profiles was limited in size, as such our findings should be replicated with a larger group of LinkedIn users. Our sample was only composed of business students (i.e., with limited professional experiences, and thus limited profile content). On the one hand, because profiles of this population are shorter and more similar to one another, it may be easier for raters to reach similar conclusions about applicants' qualifications. On the other hand, the limited information available may force raters to make assumptions about the likelihood that an applicant possesses a particular skill or personality trait, thus potentially reducing reliability or validity. More experienced workers may have more comprehensive LinkedIn profiles (e.g., with more work experience, more skills listed, more recommendations, etc.), which may lead to more reliable and valid assessments according to the RAM principles (Funder, 1995). Overall, whether applicants' level of experience (and indirectly the quantity of information available to raters) facilitates or impedes interrater reliability of LinkedIn profiles remains to be examined. To bolster the external validity of our findings, all ratings were obtained from senior MBA students (with work experience and enrolled in HR courses). In Study 1 and the itemized part of Study 2, they were asked to assess traits using one-item measures (likely more similar to hiring managers' cyber-vetting practices, but suboptimal in terms of measurement). Yet, to further increase external validity, field studies with HR managers assessing the profiles of applicants for specific jobs could be conducted. Furthermore, skills were assessed via self-reports, which could lead to inflated scores. And, some of our skills and personality measures demonstrated relatively low internal consistency (e.g., problem solving, adaptability, conscientiousness, and emotional stability). Although this is typical for short measures like the mini IPIP (Donnellan et al., 2006), further studies could attempt to replicate our findings with longer measures.

Our criterion data for Study 1 was based on coding career success from LinkedIn profiles. Although imperfect, this approach was warranted, given the wide range of majors of our participants and the difficulty of obtaining job performance data from a multitude of supervisors and organizations. However, future research could obtain job performance data, and more directly evaluate if LinkedIn-based assessments can achieve higher predictive validity than Facebook-based assessments (Van Iddekinge et al., 2016). We also did not examine criterion-related validity in Study 2 given the temporal proximity between profile assessments and career success ratings. Yet, future studies could examine if itemizing assessments helps increase predictive validity. Moreover, our evaluation of itemized vs. global LinkedIn assessments was based on a generic (i.e., non-job-specific) approach. Future studies could explore if standardizing assessments is more effective when focused on job-relevant qualifications only, for instance by designing rating scales to assess skills or personality traits identified through a job analysis. The design of Study 2 was also not counterbalanced (i.e., all raters started with the global and then used the itemized approach). However, having raters start with an itemized approach would likely have impacted their subsequent global assessments. Finally, our research was focused on LinkedIn, and we compared our results to those obtained in previous studies using Facebook. Yet, future research could also directly compare the psychometric properties of various social media, for instance by having raters assess the qualifications of the same applicants using their LinkedIn vs. their Facebook profiles.

Conclusion

Cyber-vetting, or hiring managers' attempts to assess applicants' qualifications based on social media profiles, has become an inevitable reality of personnel selection. However, research suggests that assessments based on personal social media, such as Facebook, raises legal and ethical issues and offers limited predictive power. Our research examined the key psychometric properties of assessing applicants using LinkedIn, the most prevalent professional social media platform. Although our study identifies the risk and limitations associated with LinkedIn-based assessments, we believe that it represents a superior alternative to Facebook.

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Table 1. Psychometric Properties of LinkedIn Assessments (Study 1)

	Interrater Reliability			Temporal stability (T1-T2)		Observed Convergent Validity (r)			Corrected Convergent Validity (ρ)		
	T_1	T_2	Average	r	Partial r	T_1	T_2	Average	T_1	T_2	Average
Skills											
Leadership	.40	.04	.22	.48**	.51**	.22**	.23*	.26**	.41	1.00	.70
Planning	.52	.40	.46	.57**	.60**	.16†	.27**	.23*	.27	.43	.35
Communication	.59	.63	.61	.58**	.60**	.19*	.23*	.22*	.28	.32	.30
Teamwork	.40	.57	.49	.50**	.51**	.11	.13	.11	.20	.20	.20
Information seeking	.41	.61	.51	.47**	.51**	.01	.17	.10	.02	.26	.14
Problem solving	.47	.40	.44	.56**	.59**	.12	.19	.14	.21	.37	.29
Conflict management	.34	.03	.19	.39**	.41**	.09	.04	.08	.18	.27	.23
Adaptability	.46	.53	.49	.49**	.53**	.00	.11	.04	.00	.19	.09
Personality											
Extraversion	.41	.63	.52	.65**	.66**	.22**	.15	.20*	.39	.21	.30
Agreeableness	.50	.61	.55	.49**	.47**	.08	.10	.10	.13	.15	.14
Conscientiousness	.14	.38	.26	.43**	.43**	.01	.13	.08	.03	.26	.14
Emotional stability	.31	.57	.44	.44**	.43**	.01	-.05	-.02	.02	-.09	-.03
Openness	.47	.51	.49	.60**	.61**	.10	.04	.06	.17	.07	.12
Cognitive ability	.63	.57	.60	.58**	.62**	.18	.38**	.30**	.23	.50	.37
Hiring recommendation	.58	.75	.67	.52**	.58**	-	-	-	-	-	-

Note: N=128 for T_1 and 103 for T_2 for reliability, with Intra-class Correlations coefficients with ICC (1, k). N=119 for T_1 and the average, and 96 for T_2 (but 92 and 72 for cognitive ability) for validity, with values being correlations between self-reports/test scores and LinkedIn assessments. Partial correlation controlling for change in profile content. Corrected validities (ρ) computed with $r_{xy}/\text{sqrt}(r_{xx}*r_{yy})$. ** $p< .01$, * $p< .05$.

Table 2. Predictive Validity of LinkedIn Assessments (Study 1)

			Observed Predictive Validity (r)			Corrected Predictive Validity (ρ)		
	M	*SD*	T_1	T_2	Average	T_1	T_2	Average
Obtained job in line with degree	.55	.50	.16	.24*	.20*	.21	.28	.24
Has a management role	.13	.34	.07	.06	.09	.09	.07	.08
Has been promoted	.12	.32	.24*	.09	.20*	.32	.10	.21
Number of jobs in line with degree	.82	.98	.22*	.22*	.25**	.29	.25	.27

Note: *N*=112 for T1 and the average across both times, *N*=88 for T2; validity based on hiring recommendations (with alphas = .58 and .75); Corrected validities computed with $r_{xy}/\mathrm{sqrt}(r_{xx} * r_{yy})$. ** $p < .01$, * $p < .05$.

Table 3. Descriptive Statistics and Correlation for Demographics, Profile Features, and Hiring Recommendations (Study 1)

		M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Gender	0.48	0.50													
2	White	0.65	0.48	-.08												
3	Canada	0.58	0.49	.15	-.06											
4	Word count	3.97	3.38	-.06	.08	.14										
5	Profile picture	0.89	0.31	.09	.28**	.12	.25*									
6	Prof. picture	0.20	0.40	.00	-.01	.11	.25*	.17*								
7	Summary	0.53	0.50	.02	.08	.10	.45**	.29**	-.09							
8	Nb. connections	1.53	1.39	-.04	.04	.14	.39**	.31**	.31**	.01						
9	Nb. groups	2.32	5.13	-.08	-.16	.00	.32**	.15	.02	.09	.46**					
10	Descr. experiences	1.60	0.55	.11	.18*	.01	.49**	.34**	.02	.40**	.16	.11				
11	Nb. skills	13.18	8.37	.03	-.05	-.09	.38**	.36**	.15	.19*	.52**	.56**	.34**			
12	Nb. endorsements	36.94	60.42	.14	.09	-.14	.24*	.20*	.18*	-.12	.64**	.38**	.17	.54**		
13	Recommendations	0.06	0.24	.07	-.02	.01	.14	.08	.03	.05	.30**	.30**	.07	.31**	.27**	
14	Hiring rec.	3.62	0.86	-.03	.19	.19	.65**	.50**	.30**	.30**	.61**	.29**	.45**	.44**	.40**	.38**

Note: N=103-133. Gender: 1 = Female, 0 = Male; Ethnicity: 1 = White, 0 = Non-white; Country: 1= Canada, 0 = U.S.; Picture: 1 = Yes; 0 = No. Word count and number of connections in 100s. $^{**}p < .01$, $^{*}p < .05$.

Table 4. Regression Predicting Hiring Recommendations based on LinkedIn (Study 1)

	Model 1		Model 2		Model 3	
	b (SE)	*Beta*	*b* (SE)	*Beta*	*b* (SE)	*Beta*
(Constant)	3.17 (.20)		2.69 (.16)		1.91 (.20)	
Gender	-.04 (.17)	-.02	.04 (.13)	.02	-.04 (.12)	-.02
Ethnicity	.31 (.17)	.18	.25 (.13)	.15	.09 (.12)	.05
Country	.40 (.19)	.21*	.22 (.15)	.11	.21 (.14)	.11
Profile length (word count)			.15 (.02)	.62**	.10 (.02)	.38**
Profile picture					.78 (.22)	.26**
Professional picture					.15 (.14)	.07
Presence of a summary					.03 (.13)	.02
Number of connections					.16 (.06)	.26**
Number of groups					.00 (.01)	.03
Description of experiences					.06 (.08)	.06
Number of skills					-.00 (.01)	-.03
Number of endorsements					.00 (.00)	.13
Recommendations					-.35 (.27)	-.09
F-value		2.74		19.58		13.24
R^2		.08		.45		.66
ΔR^2				.37**		.21**

Note: N=100. Gender: 1 = Female, 0 = Male; Ethnicity: 1 = White, 0 = Non-white; Country: 1= Canada, 0 = U.S.; Picture: 1 = Yes; 0 = No. Word count and number of connections in 100s. $^{**}p < .01$, $^{*}p < .05$, $^{\dagger}p < .10$.

Table 5. Descriptive Statistics and Correlations between Profile Features and Self-reports (Study 1)

			Correlations									
	M	SD	Word count	Profile picture	Profess. picture	Summary	Nb. connect.	Nb. groups	Descr. exper.	Nb. skills	Nb. endors.	Recom-mendation
Leadership	4.20	0.63	.09	.15	.06	.23**	.26**	.06	.07	.14	.20*	-.01
Planning	4.35	0.58	.07	.09	-.06	.10	.25**	.18*	.08	.08	.17	.08
Communication	4.16	0.71	.09	.21*	.04	.24**	.22*	.10	.10	.09	.05	.03
Teamwork	4.54	0.53	.13	.08	-.04	.14	.07	.04	.04	.08	.11	-.04
Info seeking	4.25	0.61	.05	.09	-.13	.08	.20*	.14	.01	.11	.19*	.02
Problem solving	4.33	0.54	.04	.06	-.09	.11	.17	.03	.04	.07	.06	-.05
Conflict management	4.13	0.63	-.05	.12	-.05	.24**	.16	.06	.05	.04	.02	-.03
Adaptability	4.45	0.55	.04	.16	-.20*	.17	.15	.09	.15	.12	.15	-.13
Extraversion	3.33	0.86	.00	.18*	.01	.13	.24**	.05	.13	.15	.25**	-.05
Agreeableness	3.86	0.67	.03	.10	.10	.06	-.02	-.08	.14	.00	.15	-.07
Conscientiousness	3.90	0.71	.22*	-.04	-.04	.10	-.07	-.06	.05	.12	.14	.08
Emotional stability	3.45	0.70	.03	.11	-.10	.04	-.13	-.11	.02	-.02	-.07	-.16
Openness	3.73	0.71	-.04	.16	-.12	.21*	-.13	-.12	.07	.00	-.04	-.05
Cognitive ability	23.00	5.25	.18	.40**	.16	.30**	.15	.01	.33**	.01	-.01	-.05

Note: N=103-133 (except N=94 for cognitive ability). ** $p < .01$, * $p < .05$.

Table 6. Interrater Reliability & Convergent Validity for Global vs. Itemized LinkedIn Assessments (Study 2)

	Interrater Reliability (*ICCs*)		Convergent Validity Itemized	
	Global	Itemized	Observed (*r*)	Corrected (*ρ*)
Skills				
Leadership	-	.56	.21*	.33
Planning	-	.58	.18	.29
Communication	-	.53	.22*	.34
Teamwork	-	.60	.14	.21
Information seeking	-	.50	.04	.07
Problem solving	-	.50	.12	.21
Conflict management	-	.43	.14	.25
Adaptability	-	.46	.17†	.31
Personality				
Extraversion	-	.54	.31**	.47
Agreeableness	-	.58	.09	.14
Conscientiousness	-	.49	.14	.24
Emotional stability	-	.24	.07	.19
Openness	-	.62	.04	.06
Cognitive ability	-	.47	.27*	.39
Hiring recommendation	.38	.60	-	-

Note: N=118. Intra-class correlation coefficients with ICC (1, k). Corrected validities computed with $r_{xy}/\text{sqrt}(r_{xx}*r_{yy})$. ** $p < .01$, * $p < .05$.

Online Supplement: Hiring Managers' Perceptions Survey

In order to examine how hiring managers viewed ratings of applicants based on LinkedIn as compared to more established selection measures, we conducted a preliminary survey online. We recruited 70 hiring managers (mostly Canada- or U.S.-based, 73% female, 72% university-educated, involved in hiring for 6.7 years on average, and assessing on average 59.9 applicants per month) with the help of a local HR association, a business school alumni group, and through personal connections on social media. Our study procedures for this supplementary study were approved by the University of Manitoba Faculty Ethics Board (Protocol #P2014:128).

Hiring Managers' perceived convergent validity of LinkedIn ratings

We asked managers how accurately they perceived they could assess applicants' skills, personality, and cognitive ability, based on a LinkedIn profile, as well as two popular and established selection instruments: résumés and job interviews. Managers rated the same eight skills as in our main studies, the Big-Five personality traits, and cognitive ability. All items were introduced with "how well do you think you can assess the following traits or characteristics of job applicants based on [their LinkedIn profile/their resume/a job interview with them]" and presented with a short definition of the skill/trait/ability. For instance, the planning skill was worded as "their ability to plan and organize their work", the personality trait of conscientiousness as "if they are precise and conscientious vs. sloppy and distracted", and cognitive ability as "their intelligence or level of cognitive abilities". Responses were made on 1-5 rating scales (with 1 = Impossible for me to assess, and 5 = I can assess this perfectly).

We examined hiring managers' perceived convergent validity for assessments based on LinkedIn profiles, résumés, and job interviews with three separate repeated-measure ANOVAs. Descriptive statistics can be found in the Supplementary Table A below.

For the perceived convergent validity to assess skills, the ANOVA examined the method effect (i.e., LinkedIn vs. resume vs. interview), the skill effect (i.e., the 8 skills), and the method x skill interaction. We found a significant method effect, F (2, 68) = 138.42, $p < .01$, $\eta_p^2 = .80$ a significant skill effect, F (7, 63) = 17.18, $p < .01$, $\eta_p^2 = .66$, and a significant method x skill interaction, F (14, 56) = 6.42, $p < .01$, $\eta_p^2 = .62$. Of particular interest, the method effect showed that LinkedIn (M = 2.26, SE = .09) was perceived as slightly less valid than résumés (M = 2.52, SE = .08, $p < .01$) and as largely less valid than interviews (M = 3.84, SE = .06, $p < .01$). This pattern was similar across all eight skills, although managers perceived LinkedIn to be more valid to assess some skills (e.g., communication - M = 3.00, SE = .14) than others (e.g., conflict management - M = 1.57, SE = .08).

For the perceived convergent validity to assess personality, the ANOVA examined the method effect (i.e., LinkedIn vs. resume vs. interview), the personality trait effect (i.e., the 5 traits), and the method x skill interaction. Again, we found a significant method effect, F (2, 68) = 237.72, $p < .01$, $\eta_p^2 = .88$, a significant trait effect, F (4, 66) = 27.79, $p < .01$, $\eta_p^2 = .63$, and a significant method x trait interaction, F (8, 62) = 19.35, $p < .01$, $\eta_p^2 = .71$. The method effect showed that LinkedIn (M = 2.13, SE = .10) was perceived as valid as résumés (M = 2.11, SE = .09. p = 77), but significantly less valid than interviews (M = 3.84, SE = .07, $p < .01$). The pattern was similar across personality traits, although managers perceived LinkedIn to be more valid to assess some traits (e.g., Conscientiousness - M = 2.90, SE = .14) than others (e.g., Emotional stability - M = 1.61, SE = .11).

For the perceived convergent validity to assess cognitive ability, we also found a significant effect of the type of method, F (2, 68) = 87.97, $p < .01$, $\eta_p^2 = .72$. LinkedIn (M = 2.49, SE = .11) was perceived as slightly less valid than résumés (M = 2.63, SE = .10, p = .04) but significantly less valid than interviews (*M* = 3.87, *SE* = .07, $p < .01$).

Hiring Managers' perceived predictive validity of LinkedIn ratings

We also asked managers about their perception of the predictive validity of LinkedIn, résumés, and interviews with the item "how well can you predict how well applicants will perform on the job based on [their LinkedIn profile/their resume/a job interview with them]" (with the same 1-5 scale as above).

We examined hiring managers' perceived predictive validity for assessments based on LinkedIn profiles, résumés, and job interviews with one repeated-measure ANOVA. We found a significant effect of the type of method, F (2, 68) = 53.02, $p < .01$, $\eta_p^2 = .61$. LinkedIn (*M* = 1.86, *SE* = .11) was perceived as valid as résumés (*M* = 1.90, *SE* = .12, $p = .52$), but significantly less valid than interviews (*M* = 3.17, *SE* = .12, $p < .01$).

Supplemental Table A: Hiring Managers' Validity Perceptions for LinkedIn, Resumes, and Job Interviews

	LinkedIn				Resume				Job Interview			
	M	*SE/SD*	95% C.I.		*M*	*SE/SD*	95% C.I.		*M*	*SE/SD*	95% C.I.	
Convergent validity												
Skills												
Overall	2.26	0.09	2.09	2.44	2.52	0.08	2.35	2.69	3.84	0.06	3.72	3.96
Leadership	2.40	1.00	2.16	2.64	2.47	0.94	2.25	2.70	3.80	0.69	3.63	3.97
Planning	2.24	0.95	2.02	2.47	2.66	0.98	2.42	2.89	3.70	0.69	3.54	3.86
Communication	3.00	1.13	2.73	3.27	3.16	1.00	2.92	3.40	4.40	0.69	4.24	4.56
Teamwork	2.14	0.97	1.91	2.37	2.39	1.00	2.15	2.62	3.67	0.85	3.47	3.87
Information seeking	2.31	0.94	2.09	2.54	2.66	0.99	2.42	2.89	3.79	0.59	3.65	3.93
Problem solving	1.89	0.79	1.70	2.07	2.23	0.85	2.02	2.43	3.86	0.57	3.72	3.99
Conflict management	1.57	0.65	1.42	1.73	1.93	0.82	1.73	2.12	3.84	0.63	3.69	3.99
Adaptability	2.56	1.06	2.30	2.81	2.67	0.96	2.44	2.90	3.67	0.77	3.49	3.86
Personality												
Overall	2.13	0.10	1.93	2.34	2.11	0.09	1.94	2.28	3.84	0.07	3.71	3.98
Extraversion	1.96	1.11	1.69	2.22	1.86	0.92	1.64	2.08	4.31	0.60	4.17	4.46
Agreeableness	1.74	0.91	1.53	1.96	1.74	0.74	1.57	1.92	3.71	0.80	3.52	3.91
Conscientiousness	2.90	1.17	2.62	3.18	2.96	1.12	2.69	3.22	3.76	0.75	3.58	3.94
Openness	2.46	1.09	2.20	2.72	2.39	0.94	2.16	2.61	3.83	0.72	3.66	4.00
Emotional stability	1.61	0.89	1.40	1.83	1.61	0.82	1.42	1.81	3.60	0.87	3.39	3.81
Cognitive ability	2.49	0.94	2.26	2.71	2.63	0.82	2.43	2.82	3.87	0.56	3.74	4.01
Predictive validity	1.86	0.92	1.64	2.08	1.90	0.97	1.67	2.13	3.17	0.96	2.94	3.40

Note: N=70. SEs are presented for the "overall" skills and personality scores, SDs are presented for all other scores.

Supplemental Table B: Correlations Between Self-reports/test Scores, Average Ratings (i.e., average of T_1 and T_2 ratings) of Skills, Personality, and Cognitive Ability, and Criterion Data for Study 1

	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Self-reported/test scores																
1. Leadership	4.20	0.63														
2. Planning	4.35	0.58	.56													
3. Communication	4.16	0.71	.62	.46												
4. Teamwork	4.54	0.54	.55	.49	.35											
5. Information seeking	4.25	0.60	.45	.48	.39	.33										
6. Problem solving	4.33	0.54	.49	.56	.54	.40	.62									
7. Conflict management	4.13	0.64	.61	.45	.68	.46	.45	.60								
8. Adaptability	4.45	0.55	.56	.50	.41	.65	.46	.52	.45							
9. Agreeableness	3.33	0.86	.24	.08	.27	.04	.05	.02	.20	.20						
10. Conscientiousness	3.86	0.67	.34	.28	.26	.34	.19	.19	.19	.32	.23					
11. Openness	3.90	0.71	.29	.26	.26	.35	.33	.27	.28	.24	-.07	.23				
12. Emotional stability	3.73	0.71	.18	.18	.23	.18	.32	.34	.36	.26	.14	.15	.10			
13. Cognitive ability	3.45	0.70	.16	.13	.16	.25	.09	.25	.25	.28	.05	.15	.32	.22		
14. Hiring recommend.	23.00	5.25	.25	.29	.24	.19	.18	.22	.30	.30	.02	.27	.06	.27	.22	
LinkedIn-based ratings																
15. Leadership	2.92	0.86	.26	.20	.22	.15	.10	.20	.11	.08	.17	-.02	.10	-.02	-.03	.28
16. Planning	3.14	0.89	.23	.23	.19	.13	.01	.15	.11	.09	.15	.03	.05	.04	-.01	.28
17. Communication	3.11	0.76	.30	.21	.22	.17	.10	.18	.15	.09	.15	.08	.16	.05	.06	.39
18. Teamwork	3.41	0.86	.25	.13	.19	.11	.04	.09	.10	.04	.15	.01	.06	.01	-.08	.29
19. Information seeking	3.11	0.76	.23	.23	.23	.14	.10	.16	.12	.12	.17	.03	.07	.01	.02	.33
20. Problem solving	3.07	0.80	.26	.23	.23	.08	.10	.14	.16	.08	.10	-.04	-.01	-.01	.00	.33

(table continues on the next page)

	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14
LinkedIn-based ratings																
21. Conflict management	2.82	0.75	.15	.13	.17	.07	.00	.09	.08	-.01	.18	.02	.03	-.01	-.08	.22
22. Adaptability	3.35	0.81	.27	.18	.18	.11	.03	.10	.12	.04	.17	.05	.08	.05	.00	.32
23. Agreeableness	3.02	0.78	.29	.21	.26	.12	.05	.16	.13	.10	.20	.04	.01	.09	-.05	.39
24. Conscientiousness	3.25	0.91	.27	.16	.25	.11	.12	.14	.15	.06	.16	.10	.14	.08	.02	.30
25. Openness	3.18	0.77	.31	.24	.29	.12	.17	.22	.16	.08	.11	.04	.08	.07	.01	.38
26. Emotional stability	3.02	0.71	.26	.19	.28	.11	.08	.15	.15	.14	.20	.04	.08	.06	.00	.35
27. Cognitive ability	3.22	0.87	.24	.10	.16	.06	.05	.11	.08	.02	.12	.03	.13	-.04	-.02	.32
28. Hiring recommend.	3.22	0.70	.21	.19	.17	.06	.00	.08	.03	.00	.08	-.01	-.04	-.04	-.12	.30
29. Conflict management	3.34	0.61	.27	.22	.24	.14	.10	.15	.11	.04	.11	.05	.11	-.01	.03	.32
Criterion data																
30. Job in line degree	0.55	0.50	.07	.21	.09	.16	.16	.18	.14	.18	.10	-.12	.16	.03	.05	-.08
31. Management role	0.13	0.34	.10	.11	.15	.12	.13	.11	.11	.15	.23	-.11	.07	.06	.14	-.10
32. Been promoted	0.12	0.32	.03	.12	.19	.09	.03	.10	.04	.12	.13	.07	.22	.03	.05	.02
33. Number of jobs	0.82	0.98	.11	.24	.13	.14	.19	.17	.10	.23	.17	-.10	.18	-.05	.10	-.13

(table continues on the next page)

	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
LinkedIn-based ratings																		
15. Leadership																		
16. Planning	.86																	
17. Communication	.89	.87																
18. Teamwork	.89	.86	.89															
19. Information seeking	.85	.88	.86	.83														
20. Problem solving	.83	.90	.83	.82	.90													
21. Conflict management	.88	.88	.84	.85	.84	.85												
22. Adaptability	.84	.90	.89	.87	.86	.86	.85											
23. Agreeableness	.86	.85	.88	.87	.83	.82	.84	.87										
24. Conscientiousness	.83	.84	.89	.87	.82	.82	.83	.87	.88									
25. Openness	.81	.81	.85	.84	.81	.81	.79	.82	.88	.87								
26. Emotional stability	.84	.88	.85	.83	.84	.83	.85	.87	.89	.88	.86							
27. Cognitive ability	.78	.79	.84	.82	.76	.77	.79	.83	.84	.89	.85	.85						
28. Hiring recommend.	.81	.84	.82	.81	.82	.80	.78	.83	.81	.79	.77	.81	.79					
29. Leadership	.83	.86	.90	.85	.89	.87	.82	.86	.87	.88	.84	.84	.84	.84				
Criterion data																		
30. Job in line degree	.14	.16	.11	.13	.18	.20	.10	.14	.14	.16	.13	.15	.10	.06	.20			
31. Management role	.06	.06	.02	.06	.05	.00	.05	.03	.05	.03	-.04	-.04	-.05	-.02	.09	.30		
32. Been promoted	.19	.23	.16	.15	.21	.19	.15	.17	.16	.13	.10	.16	.11	.16	.20	.27	.35	
33. Number of jobs	.19	.24	.13	.17	.26	.24	.12	.18	.20	.19	.16	.19	.12	.12	.25	.73	.44	.46

Note: N=126 for correlations among self-reports (except N=97 for cognitive ability), N=119 for LinkedIn ratings, and N=102 for criterion data. Correlations among self-reports above .18 are significant at $p < .05$, and those above .23 are significant at $p < .01$. We note that inter-correlations among LinkedIn-based ratings are high (i.e., ranging from .77 to .90). This can be explained by the limited information available about these characteristics in some profiles, making them difficult to assess and likely leading to contamination in the ratings (i.e., halo effects). This represents a potential limitation associated with Linked-based assessments.

Supplemental Table C: Relative Weight Analyses for LinkedIn Ratings of Skills, Personality, and Cognitive Ability Predicting Career Success (Study 1)

	Obtained job in line with degree (Logistic Regression RWA)			*Has a management role (Logistic Regression RWA)*			*Has been promoted (Logistic Regression RWA)*			*Number of jobs in line with degree (Multiple Regression RWA)*		
	RRW	*RSRW*	*95% C.I.*	*RRW*	*RSRW*	*95% C.I.*	*RRW*	*RSRW*	*95% C.I.*	*RRW*	*RSRW*	*95% C.I.*
Ratings of…												
Leadership	.008	.062	.003-.009	.009	.053	.002-.009	.007	.068	.003-.006	.021	7.280	.008-.031
Planning	.011	.083	.003-.015	.018	.104	.004-.026	.020	.203	.006-.026	.018	6.186	.008-.021
Communication	.007	.053	.002-.007	.010	.056	.003-.010	.005	.055	.002-.004	.014	4.979	.007-.016
Teamwork	.006	.048	.003-.006	.010	.057	.003-.010	.005	.047	.003-.003	.016	5.571	.007-.020
Information seeking	.013	.105	.002-.023	.015	.084	.004-.020	.013	.130	.003-.017	.016	5.756	.006-.020
Problem solving	.020	.152	004-.040	.011	.064	.003-.014	.007	.075	.003-.007	.033	11.631	.013-.065
Conflict management	.009	.075	.003-.013	.010	.056	.003-.010	.006	.059	.003-.005	.034	12.012	.014-.064
Adaptability	.007	.055	.003-.007	.009	.052	.003-.009	.006	.065	.003-.005	.024	8.308	.010-.037
Extraversion	.006	.048	.002-.006	.014	.079	.003-.016	.006	.058	.003-.005	.027	9.444	.010-.048
Agreeableness	.011	.081	.002-.016	.010	.056	.003-.010	.004	.041	.002-.003	.014	5.028	.008-.016
Conscientiousness	.006	.044	.002-.005	.017	.100	.002-.027	.006	.061	.002-.006	.015	5.438	.006-.020
Emotional stability	.006	.044	.002-.006	.009	.052	.002-.010	.003	.029	.001-.002	.015	5.159	.005-.020
Openness	.008	.063	.003-.010	.022	.130	.004-.036	.005	.055	.002-.004	.026	9.094	.010-0.42
Cognitive ability	.011	.087	.002-.020	.011	.061	.003-.013	.005	.056	.002-.004	.012	4.113	.005-.013
R^2			.132			.173			.096			.284

Note: N=102 (ratings averaged across all raters). Based on Tonidandel and LeBreton's (2015) RWA-Web tool; RRW = Raw Relative Weight; RSRW = Rescaled Relative Weight; 95% confidence intervals for RRW based on 10,000 bootstraps.