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Social Media, Personality, and Leadership as Predictors of Job Performance

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Timothy C. Lisk as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Psychology with a concentration in Organizational Behavior.

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Abstract

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A thorough assessment of privacy concerns, reviewer bias, and applicant computer familiarity informs this longitudinal study incorporating features derived from social media, personality, leadership, traditional selection methodology, and objective measures of employee performance to build an empirical foundation for future research. To date, limited research has embarked upon an in-depth examination of the organizational implications of using social media data to assess job applicants. This dissertation addresses the question of whether social media data matters in the practical context of talent selection. I begin with a review of pertinent online communication theories, including media richness, cues filtered out, and social information processing theories before applying their concepts to social media. I review accumulated evidence that signals from social media use can predict personality and explore less-studied links between social media and full leadership behavior, with a focus on transformational leadership. The review also integrates privacy behavior.

A survey covering personality, leadership, and privacy behavior, was completed by 107 call center agents who were subsequently invited to share their public Facebook profile. Of those, 48 volunteered to share quantitative and qualitative data from their public profile. A group of trained raters further coded profiles. The participants' employer also provided performance and retention data.

This study found mixed support for previously reported links between social media use and personality. An interaction of conscientiousness and computer skills predicted privacy skills and profile completeness, such that participants either high in both or low in both were more likely to have higher self-rated privacy skills and completed social media profiles. Raters were easily able to deduce demographic information from social media profiles, including gender, age, and ethnicity. Worryingly, evidence of bias in pass rates was detected based on raters' hire vs no-hire recommendations, though the degree of bias varied by pass rate threshold.

Finally, the various predictors were combined alongside scores from participants' original pre-hire selection assessments to determine whether there was incremental value in including them as part of a holistic selection process. Some support was found for the incremental utility of the entire battery, as personality, social media activity, human ratings of social media profiles, and self-reported transformational leadership behavior uniquely contributed to a Cox regression model predicting retention. Support for the battery approach was much weaker when predicting efficiency (average handle time) as only transformational leadership provided statistically significant predictiveness beyond the pre-hire assessment.

Altogether, this dissertation underscores the importance of relying on defensible selection methods to predict retention and performance outcomes. If social media is used in screening, it is best done in the context of other selection methods and should be based on computer-based automated screening rather than individual human ratings to reduce bias. This dissertation demonstrates that social media and leadership can add incremental prediction to selection decisions for entry-level jobs and makes recommendations for further research.

Keywords: social media, social networking, privacy, bias, disparate impact, selection, assessment, hiring, personality, leadership, retention, attrition, performance, average handle time (AHT), call center, contact center

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Contents

Introduction

The scope of data humankind creates and shares is exploding. Domo (2018) estimates that by 2020, humans will generate over 100 MB of data for every person on the planet, every minute. All this information can be collected, synthesized, analyzed, and mined, with the ultimate goal of greater understanding of who we are and why we do the things we do. However, humanity's natural curiosity often outpaces both our scientific understanding of how best to bring meaning to such data as well as our awareness of what information might be better off untouched. In few areas has this been more apparent than in social media.

According to the Pew Research Center (2018), 69% of American adults use social media. Social media includes Facebook, YouTube, Instagram, LinkedIn, SnapChat, Twitter, Reddit, TikTok, and many others. Facebook alone claimed more than 845 million users at the time of their Initial Public Offering (Facebook, 2012, p 1), or more than 12% of the global population. That number had grown to over 2 billion daily active users across Facebook, Instagram, and Whatsapp by 2019 (Facebook, 2019). Over 120 professionals join LinkedIn every minute (Domo, 2018). Sometimes referred to more narrowly as social networking sites (SNS), social media impact the daily lives of billions around the globe.

In a short time, social media have also had a significant impact on organizations. Potential abuses of social media information during the selection process have attracted much attention, but social media also have the potential of making the job search faster for applicants and more accurate for employers by quickly assessing an applicant's personality and leadership potential (Kluemper, Rosen, & Mossholder, 2012). Some research exists examining links between social media and personality, but only a handful of studies have extended social media predictors to job performance. Unfortunately they have relied upon complete social media profiles consisting of both public and private data. Although this is interesting insofar as it establishes links and increases our understanding of online behavior, private information generally cannot be used in a workplace context. An individual's decision or ability to change or take full advantage of their privacy settings remains unexamined in the context of employment screening. Further, some information in a typical social media profile may identify a user's protected class status. The impact of this data on recruiters or hiring managers who may be viewing social media profiles as part of their applicant screening criteria has not been examined. This study examined the use of social media privacy settings, demographic identifiers, and the efficacy of public profile information in predicting personality, leadership, and performance with greater accuracy than a standalone screening system in order to address these research gaps.

This study approaches the problem in a uniquely applied manner. A longitudinal study using actual entry-level workers took public social media profile data into account as a predictor, used objective measures of job performance, and compared them to an established, validated selection assessment. Concurrent data collection also helped control for changes to the social media software itself as well as changes in social media user behavior. Social media software is continuously updated and enhanced which can introduce unexpected confounds in any research study. For instance, Facebook engineers make thousands of changes to the application daily (Facebook, 2017). At the same time, user behavior also evolves. New cohorts of users join a platform and existing users become more experienced and sophisticated in their behavior. By collecting participant data regarding usage and privacy behavior as well as observing behavior over time, this study was able to control for such changes partially.

The use of social media in employment screening is likely more complex than has been reported in the popular press. When handled incorrectly, selection screening using social media profiles may result in poor quality and legally indefensible hiring decisions. Without knowing which variables in a public profile are predictive of performance or when it may make sense to supplement traditional selection procedures with social media information, screeners may make idiosyncratic judgments that lack job-relatedness. But through responsible screening, organizational researchers may be able to combine the array of information available in computer-mediated settings with organizational theory to structure supervised machine learning (ML) in such a way as to support predictions of future work performance in legally defensible ways. Legally defensible methods require frequent and varied data collection (afforded by social media), machine supervision from researchers and practitioners (Kattan, Adams, & Parks, 1993), as well as cooperation with the information technology (IT) professionals and engineers who will implement such systems. Automated screening has the potential to supplement existing processes to make better employee-employer matches at a reduced cost to both organizations and job applicants.

This study addresses unanswered questions and clarifies the existing research. Despite the ubiquity of social media, the incredible volume of information, and popular media concerns, to date, no longitudinal research exists linking social media profile information to job performance of actual employees while evaluating the incremental validity over established selection tools. Furthermore, research investigating links between social media and personality has failed to distinguish between public and private profile information (e.g., Amichai-Hamburger & Vinitzky, 2010). Users are becoming increasingly aware of both the mechanisms necessary to better self-monitor their online information and the potential abuses of their data. This study focuses on publicly available data, the same information that is accessible by potential employers, to determine whether it is sufficient to make job-related predictions and whether it may lead to discrimination in the selection process. Finally, although much advice is given to leaders as to how they should use social media in their organizations, the extent to which social media use can predict leadership behavior is rarely examined. As the accumulation of behavior defining our online selves inevitably grows, organizations will increasingly seek guidance regarding the appropriate use of social media information. By comparing social media predictions to traditional selection methods, this applied research provides a foundation for better understanding the holistic criterion, privacy, and legal implications of using social media to inform workforce selection decisions. In doing so, it provides social media guidance that organizations can apply in practice.

Online Communication

It is important to review electronically-mediated communication and theories such as media richness, cue-filtered out theory, and social information processing to understand behavior and communication in social media. Even though social media are relatively new, people have communicated online for decades, and social media interactions often derive from more fundamental research. Understanding how people communicate online and in a work context lays the foundation for linking online leisure activity in social media to subsequent work behavior.

IT and computer-mediated communication (CMC), in general, are becoming more integrated into the overlapping personal and professional lives of people around the world. A 2008 Pew study underscored the commonplace nature of CMC in organizations, reporting that 86% of working Americans used the Internet or email personally or professionally. By 2018, Internet use was nearly ubiquitous (Pew, 2018). Conducting business in an always-on global marketplace necessitates the use of technological alternatives to working in the same physical space. When properly harnessed, IT can increase efficiency, improve decision-making and access to information, restructure an industry to an organization's advantage, and allow organizations to pursue new business models (Alavi & Palmer, 2004).

CMC has several significant impacts on organizations. Before electronic communication, communication costs were high and individuals and organizations had comparatively limited access to information. Thanks to CMC and the supporting infrastructure, communication costs dropped and continue to decline while information has never been easier to access. CMC facilitates joint document preparation, knowledge management, the formation of communities of practice, telework or telecommuting, virtual or distributed teams, distance learning, and the shift to flat and lean organizations. CMC helps do this in part by serving as a substitute for some of the leadership behaviors previously under the domain of leaders and managers (Kerr & Jermier, 1978; Yukl, 2006). By placing information and the means to self-monitor and self-regulate in the hands of individuals and teams, some supervisory positions become unnecessary. Hierarchical, integrated organizations continue to see their internalized coordination weaken as flexibility and responsiveness become the new competitive advantage (Pickering & King, 1995). However, new technology and CMC should not be haphazardly implemented in a "me too" fashion. Effective implementation requires strategic thinking and alignment with both the organization and its constituents.

CMC is also subject to misuse, like any other tool. Poor implementation and training in work settings can result in miscommunication. At the extreme, it can sink individual careers or threaten entire organizations. Realizing their emails, instant messages (IM), and other electronic records can result in public relations disasters (Conlin & MacMillan, 2009) or be subject to subpoena; organizations increasingly monitor employee communication on and off the clock. A quarter of surveyed organizations have fired an employee for violating email policy (ePolicy Institute, 2004). IBM expects employees to follow detailed “Social Computing” guidelines (IBM Inc., 2008). CMC’s impact is felt at all levels: individuals, groups, and the organization as a whole, and the ability to engage in appropriate online behavior is now applicable to any job.

Computer-Mediated Communication

For this research, it is important to place boundaries on the definition of CMC. When it is narrowly defined, CMC refers to electronic, text-based communication (Bordia, 1997). This definition includes email, IM, and text messaging (also known as short message service or SMS). It is worth noting that the devices used to communicate do not have to be traditional access terminals – they can be mobile devices, video game consoles, tablets, or some other piece of technology yet to be conceived. A broader definition considers CMC not as a thing but as a process “by which people create, exchange, and perceive information using networked telecommunications systems (or non-networked computers) that facilitate encoding, transmitting, and decoding messages” (December 2008, p. 1).

The broad definition may more appropriately be called electronically-mediated communication. Electronically-mediated communication (EMC) can also be defined as much by what it is (communication mediated by an electronic device of some sort) as by what it is not. EMC effectively refers to any form of communication that is not face-to-face (FTF) or written down on paper (letters or books), though advances such as telepresence and e-book readers render even this distinction imperfect. With an open acknowledgment of the difficulties in pinning down a solid definition of CMC or EMC in the face of rapid technological change, this research employs EMC as a more appropriate definition as EMC more appropriately captures the breadth of communication media through which social media participants can interact.

Electronically-Mediated Communication

Electronically-mediate communication, whether in teams or in social media, is divided into two loose categories: synchronous and asynchronous (Bell & Kozlowski, 2002). Synchronous communication occurs when two parties interact in a real-time conversation. It includes IM or chat, shared whiteboards, mobile phones, telephones, and video/audio chat or conferencing. A non-EMC analog would be FTF communication, where two or more people in the same physical location engage in traditional conversation. Meanwhile, the presence of a pause or gap between each transmitted message is characteristic of asynchronous communication. Although an immediate response may be preferred, it is not *required* for the conversation to continue in asynchronous communication. Synchronous communication differs in that a clear break or a pause of sufficient length effectively ends the conversation. Participants determine this break or pause, which is subject to cultural and contextual variation. Any communication medium in which an “awkward pause” is impossible or very unlikely is therefore, arguably, asynchronous. Asynchronous EMC technologies include email, message boards and forums, wikis, blogs, voicemail, and short message service or text messaging (Johnson, 2006).

Confusion occurs when synchronous and asynchronous EMC overlap. Mobile phones are often synchronous, except when the caller leaves an asynchronous voicemail message. SMS is also asynchronous – except that experienced SMS users can engage in a conversation as quickly as any IM user. The distinction may lie in the sender’s expectations. When a sender communicates with an IM user who is currently online, the sender expects to receive a nearly instantaneous reply and engage in a conversation. When a sender communicates via SMS, they send their message knowing full well that the recipient may not be available or may not respond immediately. Flexible technology makes a solid definition difficult: even IM can be asynchronous. When a recipient is idle or unavailable, incoming messages are still displayed. If the recipient returns and responds to those messages when the original sender is now idle, an asynchronous exchange is taking place even though the software was designed to support synchronous communication. As the dichotomy between synchronous and asynchronous communication becomes less applicable, other important features of the different communication media may become more relevant. Media richness and participant adaptability, covered in the next section, help in understanding the breadth of behavior and contextual information available in social media and how it can be robust enough to predict behavior in organizations.

Media Richness and Cues Filtered Out (CFO) Theories

According to the social presence theory (Short, Williams, & Christie, 1976), the fewer cues or channels that exist in a medium, the more impersonal the communication becomes and the less "rich" the interactions. Anyone who has attempted to multitask while talking on the phone has experimented with social presence theory by artificially reducing the attention given to the few cues present in phone conversation. Cues include anything that helps senders convey their message to receivers, such as tone of voice, eye contact, body language, or facial expression. Kiesler, Siegel, and McGuire (1984) further explored this reasoning by proposing that EMC differs from FTF communication due to the lack of contextual, social cues in EMC. Media richness theory (Daft & Lengel, 1984; 1986) predicts an increasing need for FTF as messages become more complex or ambiguous. The grouping of theories that propose FTF as the superior communication medium due to its rich, multi-channel nature constitutes the CFO theory (Culnan & Markus, 1987; Walther, 1992). CFO theories of EMC were the first to gain widespread academic acceptance (Smolensky, Carmody, & Halcomb, 1990) and continue to receive empirical support (Bertacco & Deponte, 2005). Most social media platforms support moderately rich communication. They lack the full interpersonal cues of FTF communication but allow participants to embed significant contextual cues in their messages. Social media users can often include images, video, and audio alongside their text-based communication, or can signal non-verbal agreement or endorsement of an idea by clicking a “Like” button on Facebook or by re-tweeting it on Twitter (Kosinski, Stillwell & Graepel, 2013).

Social Information Processing (SIP)

Creative use and repurposing of social media software features to increase the clarity and emotional richness of social media communication is better explained by the social information processing perspective of EMC. Thus, understanding the potential for adaptive behavior across all EMC informs investigations of EMC use in the workplace and personal social media. Social information processing (SIP) was proposed as an extension of CFO and built upon it by attempting to explain how EMC can start as impersonal and adapt to become hyperpersonal (Walther, 1992; 1996). According to SIP, EMC users may have relational motivators that prompt them to decode text-based cues and derive psychological-level knowledge about other users, resulting in the management of relational changes and further encoding of relational messages. Holding the group of people communicating and the specific technology relatively constant, individuals will adapt to the medium and begin decoding more cues from others and encoding more of their cues.

Although not the first theory to recognize the potential for EMC users to adapt to their medium and encode communication cues (see Rice & Love, 1987), SIP continues to draw support. Research has found salient cues in the form of email greetings and closings (Waldvogel, 2007), email signatures (Rains & Young, 2006), usernames (Heisler & Crabill, 2006), and emoticons (Derks, Fischer, & Bos, 2008). Email messages were perceived as more polite than voicemail messages (Duthler, 2006). When they were not time-limited, EMC teams were just as intimate as FTF teams (Derks, Fischer, & Bos, 2008), and their task quality equaled that of FTF teams (Reid, Malinek, Stott, & Evans, 1996). EMC does not necessarily mean impersonal. As Carter (2003, p. 30) summarized, “effective and reliable nonverbal communication can actually exist in a technological mode.”

SIP and CFO have an uneasy coexistence. CFO seems to apply to strangers in new teams who may not work together again (discrete teams). SIP tends to be a better predictor of continuous teams whose members have met FTF and who have experience with the particular technology. Reality often falls somewhere between these two extreme examples. Liu, Ginther, and Zelhart (2002) found only partial support for SIP, though the presence of lurkers (participants who read but do not respond to messages in a group conversation) may mask stronger support for SIP in some organizations.

Research still needs to integrate the theories better or determine where one stops and the other begins. Kahai and Cooper (1999) reported that both task-oriented and socioemotional communication dropped in EMC teams, versus FTF teams, when team rewards limited deliberation time. Walther (1995) also reported findings highlighting the lack of clarity between the theories. Formality and task-orientation declined over time in EMC groups even as interpersonal ratings continued to exceed those of the comparison FTF groups. This relationship does not seem to support CFO because the EMC teams should have had poorer socioemotional ratings, but it also does not fit with SIP predictions, as task-orientation declined. Despite their inconsistencies, taken together and applied to the appropriate stages of team formation, CFO and SIP combined serve as a useful conceptual model for modern EMC in organizations.

Electronically-Mediated Communication in Social Media

Electronically-mediated communication is not a wholly recent concept. Throughout history, communication has either been FTF or mediated in some way. A letter written in haste, or the flourish with which John Hancock may have signed it, are both sources of subtle contextual cues. Telegraph operators could identify one another from the specific tapping patterns unique to each operator (Bryan & Harter, 1899), a discovery that eventually led to a rich stream of research around the keystroke dynamics of typists and computer users. Similar examples exist across other communication media. The avatar names people select in EMC (Heisler & Crabill, 2006) or the recipients they include in a message (Skovholt & Svennevig, 2006) are just the modern cues associated with mediated communication. Any employee who has fielded an urgent email copied to their boss – or even more stressful, their boss's boss – has experienced these cues firsthand.

Social networking sites such as MySpace, Facebook, Twitter, and Google+ further expanded the contextual cues available in EMC. What may have once been a private email chain can now be an open, persistent, searchable communication stream. Contextual cues include photographs, audio clips, videos, and even the commentary from third-party network members (friends-of-friends) only implicitly included in the conversation. The number of friends someone has, the content of their profile photos, and their writing style are all small indicators of the person behind the avatar. "Liking" a comment on Facebook not only adds context to a conversation within a discussion thread, but it can also provide insight into the user's personality even to others who were not participants in the original discussion (Kosinski et al. 2013). This rich interactivity has attracted hundreds of millions of people to these services. As many a user has discovered upon receiving a friend request from their mother, social media is no longer just for college students.

Using Electronically-Mediated Communication Cues for Prediction

Facebook users spend an average of 35 minutes per day using the app (Osman, 2018), interacting with friends, businesses, and others while surrounded by a breadth and depth of interpersonal contextual cues unrivaled by most communication media. The time spent using social media is more than sufficient to adapt to the medium and begin to use these cues to make judgments about others. However, making unconscious judgments about an individual's behavior online to guide one's communication is one thing. Using that information to predict their offline behavior, personality, leadership style, and workplace performance is another issue entirely.

Personality

Organizations regularly deploy assessments to predict outcomes like job performance based on personality traits such as conscientiousness (Barrick & Mount, 1991; Barrick & Mount, 2004). Foreknowledge of employees' personality dimensions may help organizations make better staffing and IT decisions without significant additional expenditures. Employers are able to make reliable predictions because an individual's personality dimensions are considered *traits*. Traits are recognizable (McAdams, 1995) patterns of behavior that are relatively stable over time (Allport & Odbert, 1936). In contrast, *states* are situation and context-dependent.

The most popular model of personality is the five-factor model (FFM) or Big Five model (Costa & McCrae, 1992; John & Srivastava, 1999; McCrae & Costa, 2003). The personality traits under the FFM are: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (often reversed and referred to as emotional stability). Openness to experience refers to the willingness to try new things. Conscientious individuals are considered reliable, organized, and efficient. Extraversion refers to outgoing, energetic individuals who tend to enjoy the stimulation of others or activity. Agreeable individuals tend to be friendly, exhibiting concern for others. Lastly, emotional stability refers to one's susceptibility to emotional reactions (particularly under stress). The link between FFM personality and job performance is well established (Tett, Jackson, & Rothstein, 1991). For example, conscientiousness and emotional stability positively predict job performance across a wide range of job types (Barrick & Mount, 1991; Barrick & Mount, 2004). For specific, relevant jobs, agreeableness, extraversion, and openness are also significant predictors of performance (Barrick, Mount & Judge, 2001). Kluemper et al. (2012) have linked social media personality to job performance, but the research in this area is anemic at best and will be covered more thoroughly later in this paper.

Leadership

Personality based on online behavior may help predict near-term workplace behavior in entry-level positions, but organizations are often interested in retaining employees and preparing them for future roles within the organization as well. Leadership is defined as influencing others to achieve a shared outcome, though there are likely at least as many definitions of leadership as researchers who study it (Yukl, 2006). However, transformational leadership is particularly suited toward studies of social media use among entry-level workers because it encompasses and encourages the development of leadership at all levels of an organization. Transformational leaders seek to empower, challenge, and inspire their followers to achieve goals benefitting the group (Bass & Riggio, 2006). Though leadership in organizations is most commonly associated with managerial or supervisory positions, Bass and Riggio (2006) state that "leadership can occur at all levels and by any individual. In fact, we see that it is important for leaders to develop leadership in those below them. This notion is at the heart of the paradigm of transformational leadership" (p. 2). An entry-level employee may not need to exhibit many leadership behaviors when first hired, but underlying interpersonal competencies that contribute to success in both entry-level and leadership positions may be desirable. Personality can be systematically assessed by scanning profile information. Can the same be said for leadership? Although some studies have examined the links between social media and personality, links between social media and leadership are unclear. Leadership through EMC has been studied most frequently under the mantle of virtual leadership, leadership distance, and distributed leadership (for a history of leader-follower distance, see Lewandowski & Lisk, 2012). Though not a perfect analog, research into distributed team leadership serves as a proxy for social media leadership research. Distributed and online leadership will be explored in more detail later in this paper.

Online Behavioral Monitoring

There has always been an interest in how communication and behavior in EMC might relate to personality and behavior in more traditional FTF settings. Only recently, however, has persistent monitoring of social media behavior enabled deep, longitudinal investigations of such communication. Software advances and ubiquitous computing are making it easier to track and analyze online activity. The buzz word "big data" has become increasingly popular over the past few years. Big data is defined here as the large-scale collection and analysis of data to feed ML algorithms. In reality, big data has been around for quite some time. Credit card monitoring and store loyalty programs are two examples. However, databases were often difficult to access and analyze, and the hardware and software requirements were steep barriers to widespread use.

The rapid increase in the depth and breadth of information that can be collected, along with the rise in cheap computing resources and widely available desktop analytics software, have only recently unshackled statistics and analytics. Now anyone with a reasonably powerful laptop and standard statistics program can generate basic insights from large datasets. In addition, declining computing and data storage costs have allowed organizations to collect and track users against a vast array of possible metrics.

Many commercial examples of the application of big data now exist (Table 1). Google tracks individual user preferences and Internet browsing habits to target online advertisements better. Netflix combines prior ratings, the ratings of similar users, and external information (e.g., movie critic ratings) to come up with customized viewing suggestions for each user. Amazon and other retailers track shoppers to predict shopping habits better, timing and value of promotions and manage their inventory. Online dating sites collect information from their users to better match partners.

These big data analytic practices have moved to the study of organizational behavior as well. In organizations, limited big data use has existed for decades. In larger organizations, annual satisfaction, multi-rater feedback, and other surveys are not new. Nor is the use of

Table 1

Commercial Uses of Big Data & Longitudinal User Tracking

Organization	Predictive Use
Google	Website usefulness & relevance; targeted advertisements
Netflix	Entertainment suggestions; new programming development
Amazon, Groupon, retailers, supermarkets	Targeted promotions; inventory control
eHarmony	Dating and personality-based matchmaking
Adaptive learning (e.g., Knewton)	Individually-tailored educational curriculums
Recruiters & Human Resources	Employee organizational citizenship behavior; career & employee well-being
Workforce analytics	Employee attrition and performance

frequently monitored performance data to aid decision-making, such as in manufacturing jobs and other individually accountable and quantifiable positions. What is new is the systematic aggregation and analysis of such information over time and across organizations. For example, Evolv (acquired by Cornerstone) tracked employees over their lifecycle to make selection recommendations and identify early warning signs of attrition and performance issues. Data from pre-hire selection assessments and skills tests, on-the-job satisfaction and exit surveys, post-hire attrition and performance metrics, and macro- and micro-economic indicators are pulled together, across tens of thousands of workers, to build vast datasets. In conjunction with established organizational theory, such data can be used to build more predictive selection instruments based on robust, transportable job profiles, as well as to detect and predict the impacts of changes in applicant pools, training programs, or management initiatives (Evolv, 2013). Yet for all the advances in this area, the use of big data in organizations has only started to scratch the surface.

The next major opportunity for understanding and predicting employee behavior comes from social networking. User tracking and prediction (to target advertisements to interested consumers) are already common in social media. Social media are also prime candidates for personality tracking and profiling. Through their communication and interaction with other members, users provide a rich tapestry of online behavior. Social science and IT are combining to specify the EMC communication cues in social media to answer key questions about online and offline behavior, namely: (a) how is online behavior different from offline behavior?; and (b) can online behavior be systematically measured and categorized?

Though the results are at times scattered or limited, online behavior does correlate with real, physical world behavior, and it can explain additional variance in dependent variables after accounting for traditional measurement methods. A broad range of social media behavior is predictive of FFM personality (Tables 2 and 3). The most frequently reported social media metric is not surprisingly also the easiest to study: number of friends. Number of social media connections is consistently and significantly related to extraversion, such that extraverts tend to have more friends than non-extraverts (Amichai-Hamburger & Vinitzky, 2010; Golbeck, Robles, & Turner, 2011; Garcia & Sikström, 2014; Gosling, Augustine, Vazire, Holtzman, & Gaddis, 2011; Kleanthous et al, 2016; Kosinski et al, 2014; Moore & McElroy, 2012). The number of friends has also been tied to conscientiousness (Amichai-Hamburger & Vinitzky, 2010). Extraverts, on the other hand, tend to have less density in their networks – that is, they are more

Table 2

Matrix of Personality and Social Media Correlates (Friends, Density, and Groups) by Study

	Personality Dimension (Openness, Conscientiousness, Extraversion, Agreeableness, Emotional Stability)				
Social Media Metric	O	C	E	A	ES
# of friends		1	1,2,3,5,7,8,9	5	9
Network density	(2)		(2)		
# of group memberships	8	6,(8)	8		
Use of personal information sections (e.g., date of birth, location)			(1)		
# features used in the personal information section	1			(1)	
Indicated a favorite website/URL	2				

(Parentheses indicate negative correlation); 1. Amichai-Hamburger & Vinitzky (2010); 2. Golbeck, Robles, & Turner (2011); 3. Gosling, Augustine, Vazire, Holtzman, & Gaddis (2011); 5. Moore & McElroy (2012); 6. Ross, Orr, Sisic, Arseneault, Simmering, & Orr (2009); 7. Garcia & Sikström (2014); 8. Kosinski et al (2014); 9. Kleanthous et al (2016).

Table 3

Matrix of Personality and Social Media Correlates (Frequency of Use) by Study

	Personality Dimension (Openness, Conscientiousness, Extraversion, Agreeableness, Emotional Stability)				
Social Media Metric	O	C	E	A	ES
# of posted photos			5	(1)††,5	
# of other photos posted (self absent)	3		3		
# of other photos posted (self present)			3		
# self photos posted to profile					(1)
# other photos posted to profile					1
Frequency of profile photo replacement	3		3		
More likely to have an uncommon profile photo (Black & White, artistic filter, etc.)			6		
# of posts					
# posts on own profile				5	
# posts on other profiles			7	5,7	(7)
# swear words posted		(2)			
# of incriminating posts		(4)		(4)	(4)
More likely to post to own wall					(6)
More likely to post photos (vs. text)					6
# of words referencing things seen or heard		(2)			
# of words referencing feelings				2	
# of words expressing anxiety					(2)
Hours spent on Facebook per week		(3)	3, 5		
# Facebook visits per week		(3)	3, (5)	3, (5)	5
# of self profile visits per week		(3)	3	3	
# of other profile visits per week			3	3	

(Parentheses indicate negative correlation); † = Male only; †† = Female only; 1. Amichai-Hamburger & Vinitzky (2010); 2. Golbeck, Robles, & Turner (2011); 3. Gosling, Augustine, Vazire, Holtzman, & Gaddis (2011); 4. Karl, Peluchette, & Schlaegel (2010); 5. Moore & McElroy (2012); 6. Ross, Orr, Sisic, Arseneault, Simmering, & Orr (2009); 7. Seidman (2013).

likely to have large, broad networks. This makes intuitive sense because there is only a limited amount of time that can be spent on each friend in a very large network.

Many social media metrics are more difficult to measure. Studies linking social media metrics to FFM personality most commonly approach the problem by asking study participants to grant the researcher full access to the participant's social media profile. The participants can do this in one of two ways. They can either "friend" the researcher (accept them into their private circle) or grant access by way of a plug-in. In studies where the participant "friends" the researcher, researchers then take a snapshot of the participant's profile information. A profile snapshot can be as simple as a literal screenshot of the front page, or a compilation of a few different sections of the participant's social media profile. Participants can also grant profile access to researchers via software plug-in. Once a researcher's plug-in has access to a participant's profile, they can use the plug-in to download information about that profile. Depending on the sophistication of the plug-in and the willingness of the participant to grant it access to their profile, the plug-in approach can typically gather greater depth and breadth of information.

Using more advanced data gathering techniques, researchers can quantify or code almost any behavior. The volume of content a user posts, whether text or photographs, generally correlates positively with openness to experience and extraversion. Agreeableness is also positively related to the volume of posts, though agreeable people are less likely to make incriminating posts (Karl, Peluchette, & Schlaegel, 2010). The relationship with emotional stability is more complex and depends on the type of content posted. Emotionally stable users are less likely to post text rather than photographs (Ross et al. 2009), and their messages are less likely to contain words expressing anxiety (Golbeck, Robles, & Turner, 2011). When emotionally stable users do post photographs to their profile, they are less likely to post photographs of themselves than of others (Amichai-Hamburger & Vinitzky, 2010). Finally, frequency of social media use has generally been linked to lower conscientiousness, higher extraversion, and higher agreeableness (Gosling et al., 2011). That said, Moore and McElroy (2012) reported conflicting results for hours spent and number of visits per week (social media use was linked to lower extraversion, agreeableness, and conscientiousness), so this is an area in need of further investigation.

Equally as important as the findings that various social media metrics can predict personality is the evidence that personality can be systematically measured and categorized online. Early research has demonstrated the feasibility of gathering social media information to assess the personality of users (Golbeck et al, 2011). However, researchers have focused on entire profiles and asked participants for total access to both their public and private information without distinction.

Privacy and Legal Issues using Social Media to Predict Personality

The fact is that not all online behavior is measurable. When using the Internet, people often have a choice to volunteer their identifying information or to remain anonymous. Even when identifiable, users allow and expect their behavior to be shared with third parties, including employers, to varying degrees (Brandenburg, 2008; Caers & Castelyns, 2011). Who shares, and how much, may provide additional insight into personality above and beyond the actual content they are sharing. To investigate public and private behavior online, one must look to the motivations behind anonymous online behavior and the legal considerations when using social media data for selection employment screening. Existing literature rarely distinguishes between public and private social media data. Even if publicly available social media data can by itself predict personality, that information may contribute to biased hiring decisions.

An obvious follow-up question in the context of organizational research is, “can we use social media profiles to predict personality and job outcomes *in a fair, just, and legal manner*?” Government officials, privacy advocates, and the popular press have recently highlighted cases of employers demanding applicants provide social media login details (full usernames and passwords) as part of the application process (e.g., Stern, 2012). To most casual observers, this is a clear violation of an applicant’s privacy. Except for some jobs that have historically required detailed background investigations before employment or the granting of a security clearance, the generally accepted argument is that an employer ought to have no more of an expectation of access to one’s private Internet logins than they should an applicant’s home.

Laws are already being passed to address these privacy concerns, often making it illegal for employers to require social media login details or access to privately posted content as a condition of employment (e.g., Illinois General Assembly Public Act 097-0875, 2012; Washington State Legislature Substitute State Senate Bill 5211, 2013). Although local regulations vary, there have been some attempts to consolidate laws consistently. In 2016, the Uniform Law Commission endorsed a set a standard employee and student privacy protections that have subsequently been introduced by New York and Hawaii state lawmakers (Uniform Law Commission, 2019). These are reasonable and welcome steps in support of personal privacy. However, not all information posted on social media profiles is private, sometimes unintentionally. In a study of privacy settings, Madejski, Johnson, and Bellovin (2012) found that not a single study participant established privacy controls with perfect accuracy. In other words, every participant in the study was either sharing some information with groups that had not intended to, or vice versa. The complexity of privacy configurations means that even those users with relatively secure, restricted profiles are still sharing some information. This unmonitored social media use, both private and public, may even be a better predictor of unmonitored job performance than monitored application data (Cascio & Aguinis, 2008). Cascio and Aguinis argue that low-stakes, unobtrusive behavior (as in social media) is more analogous to workplace conditions than high-stress screening during a job application. In a survey of social media users, 78% of respondents indicated they believed their social media profile reflected what they are really like (TIME, 2013). Seidman (2013) found authentic self-presentation behavior was higher among more extroverted social media users, with participants reporting a higher likelihood of sharing general information to a broad online audience relative to emotional or attention-seeking updates. Though the amount of available information is reduced when only examining public information, the findings of Madejski et al. suggest there is likely still enough public behavior in the average profile to be able to make some assumptions about a user's personality.

If social media profiles can be scraped for indicators of personality and a wealth of public profile indicators are accessible to both academics and practitioners, it follows that public indicators alone may be sufficient for making inferences about a user's personality.

- Hypothesis 1a: Publicly available profile information can be used to predict FFM personality consistent with findings from private profile information.
- Hypothesis 1b: Number of social media connections correlates with higher extraversion and agreeableness when publicly available.
- Hypothesis 1c: Number of group memberships correlates with conscientiousness when publicly available.

- Hypothesis 1d: Increased personal information completion correlates with higher openness and lower agreeableness when publicly available.

Personality and Privacy Behavior

An individual's ability and desire to share publicly versus privately in social media may also tell us more about their personality. To better understand sharing behavior online, one must examine the underlying tension between individual anonymity and the potential for increased surveillance. Since the creation of the Internet, there has been a struggle between the anonymous self and the opposing verified or nonymous self (also referred to as the authenticated self; Zhao, Grasmuck, & Martin, 2008). The anonymous self manifests as the behaviors that go untraced, behind a pseudonym, and often occur at the expense of verified users. Examples include spammed product reviews to promote goods falsely, anonymous "trolling" in forums (antagonistic comments posted to annoy and instigate devolving conversation), and computer cracking and infiltration. These all leverage the freedom of the anonymous self at the expense of other, validated users. But anonymity can also be a force for good. It can facilitate individual freedom, government transparency, social reform, as well as improvements in computer security. During the Arab Spring protests, organizers often relied on anonymity to communicate with one another (Storck, 2011). In the world of computer security, "white hat" hackers find system vulnerabilities and voluntarily report them to the broader security community and are among the many presenters at DEFCON, the world's largest annual security conference (Bratus, 2007). Most social media providers disallow or strongly discourage anonymous profiles (Reddit being a relatively mainstream exception), but do not place significant restrictions on the accuracy of individual posts.

The verified self, an online identity often using a real name and tied to a single person in the real world, is also a tool to be wielded for good or ill. In general, verified users tend to engage in more prosocial behavior than anonymous users (Zhao, Grasmuck, & Martin, 2008). Voluntarily verifying oneself online often unlocks a host of "free" services that come at the expense of privacy rather than money. These services are made possible by tracking individual behavior online that is subsequently used to improve advertising, marketing, and consumer behavior predictions. Verified users also provide weight to online communication that anonymous users typically cannot match. To combat spammed product reviews, Amazon now notes whether a reviewer is using his or her real name, whether they purchased the product in question, and whether or not they are an Amazon-certified expert in that product category.

As the verified self becomes more pervasive, it is becoming more difficult to maintain a truly anonymous identity online. Indeed, even though the average Internet user likely has one or more verified online profiles with different providers, they generally do not employ tools such as traffic encryption and virtual private networks (VPNs) that would allow them to have a more secure, anonymous online presence. Those with the luxury of online anonymity tend to be computer enthusiasts, IT professionals, or someone following their instructions for basic identity masking. As a result, most Internet users leave a behavioral trail that can be tracked and identified relatively accurately based on their verified profile information and online behavior. This behavioral trail can provide detailed insight into a user's interpersonal communication style and personality.

Many social media users are aware of this, and some take steps to restrict the visibility of their profiles to strangers. Job applicants who actively manage the privacy settings of their social media profiles and pay attention to the visibility of content they post to social media sites are likely to be the applicants who have the inclination, drive, and ability to do so. Indeed, Quercia et al. (2012) found modest correlations between both openness and extraversion and information disclosure among Facebook users, though extraversion was no longer predictive in a regression model. In a self-report study of personality and Facebook use, Seidman (2013) reported a negative association between emotional stability and general self-disclosure, and a correlation between extraversion and the frequency of authentic posts representing a participant's nonymous self. Conscientiousness was negatively related to disclosure of more anonymous content, for example "aspects of myself that I don't feel comfortable expressing online" (Seidman, 2013, p. 404). Given that active management of social media privacy settings requires an investment of time and energy on the part of the social media user (Madejski et al., 2012) and can include manipulating complex user account settings or self-monitoring to delete individual posts, those users who are more conscientious may be more likely to have taken the time to put privacy restrictions in place on their social media accounts.

- Hypothesis 2: Participants higher in conscientiousness will have more privacy restrictions on their social media profiles.

Although emotionally stable users may be less likely to share information on social media overall (e.g., Amichai-Hamburger & Vinitzky, 2010; Karl, Peluchette, & Schlaegel, 2010; Seidman, 2013), emotional stability is also positively related to social desirability (e.g., Ones, Visewesvaran, & Reiss, 1996). Although emotionally stable users may post less social media content, they may also be less likely to self-monitor their posts, delete content, or more carefully adjust their privacy settings.

- Hypothesis 3: Participants lower in emotional stability will have more privacy restrictions on their social media profiles.

In addition, sites like Facebook frequently add or change features of their software, and privacy settings may require updating (Nadon, Feilberg, Johansen, & Shklovski, 2018). Due to the complexity and continuous learning cycle, computer familiarity, the knowledge and ability to find the privacy settings and set them to desired levels, should moderate the degree to which personality predicts privacy settings

- Hypothesis 4: Computer familiarity moderates the relationship between personality (conscientiousness and emotional stability) and the degree to which privacy restrictions are enabled on a social media profile.

Social Media and Adverse Impact

Just because additional information about applicants is available online and may be legally accessible, that does not necessarily mean it is appropriate to use it for screening. Recruiters and hiring managers may easily misuse the information present in social media profiles intentionally or subconsciously to exclude applicants with particular characteristics from consideration. Recruiters may make implicit judgments based on information present in profile photos, including gender (Marlowe, Schneider, & Nelson, 1996), disability (Stone & Sawatzki, 1980), and weight (Pingitore, Dugoni, Tindale, & Spring, 1994). A photo of an applicant wearing professional attire is commonly assumed to be more likely to enhance an applicant's chances of receiving an employment offer than a photo in which the applicant is clearly intoxicated or acting irresponsibly. The profile photo is typically the most salient facet of a social media profile, but it is not the only metric subject to misuse. Age, gender, and ethnicity are often readily apparent in social media profiles through self-identification or inference (Kosinski et al. 2013). Users can explicitly note their demographic details using categories or free-text fields supplied by the social media platform. If the fields are not available or the user chooses not to complete them, age, gender, and ethnicity can still be inferred by viewing profile photos.

However, research on how this social media information is used or misused is limited – theory lags far behind practice (Ployhart, 2006). Few have researched the impacts, and organizations may not be willing to report the results of their internal investigations for fear of litigation. However, since subtle differences in applicant resumes (Thoms, McMasters, Roberts, & Dombkowski, 1999), verbal and nonverbal behavior (Rasmussen, 1984), and even attire (Francis & Evans, 1988) can impact screeners' decisions during the selection process, it stands to reason social media profile information can similarly influence screeners and lead to hiring decisions that cause adverse impact. In a study of LinkedIn profiles, Salter and Poeppelman (2013) found that profiles with a photo were rated more favorably, as were profiles with attractive photos.

At a minimum, screening processes are expected to meet or exceed the four-fifths (4/5ths) or 80% rule of thumb (Equal Employment Opportunity Commission, 1978). The 80% rule specifies that protected classes should have a pass rate (in the case of job selection, hire rate) no less than 80% of the pass rate of the highest-scoring subgroups. The use of procedures or screening tools that violate the 80% rule of thumb places an employer at risk of legal action. Even though there are exceptions for clearly demonstrated job relevancy, it would be difficult to argue the job relevancy of social media profile photos for the majority of jobs. In fact, the Equal Employment Opportunity Commission (EEOC) explicitly states employers "should not ask for a photograph of an applicant" (Equal Employment Opportunity Commission, 2012) during the selection process. However, photos and more are visible on most social media profiles. The rich combination of images, affiliations, and self-identification should make it relatively easy for a reviewer to determine various protected class affiliations from a Facebook profile.

- Hypothesis 5: Reviewers will be able to identify the age, gender, and ethnicity of applicants via their Facebook profile information with greater than 80% accuracy.

When reviewers have identified protected class information, it may lead to biased hiring decisions based on criteria that are not job-related (Salter et al., 2013).

- Hypothesis 6: Reviewers will violate the 80% rule for age, gender, and ethnicity when making hiring decisions using holistic social media profile information (i.e., overall hiring decision based on the content available on the main profile page).

Social Media Profile Personality as a Predictor of Job Performance

In the context of organizations, additional research is needed to determine whether a personality profile calculated from social media data can be used to predict individual or team performance and organizational satisfaction. Although a robust body of literature supports the link between personality and performance, there is scant research into the viability of using social media data to predict performance.

Only Kluemper et al. (2012) have taken a serious look at whether Facebook can predict job performance by tying personality, derived holistically by raters examining entire social media profiles, to job performance. This research is a good first step – it not only highlights the personality to job performance relationship, but it also demonstrates that other ratings of personality explained unique variance in job performance beyond self-ratings of personality. Job performance correlated with higher openness to experience, conscientiousness, agreeableness, and emotional stability.

However, this study does have shortcomings. Like most other research about social media profiles and personality, the sample was limited to predominately white college students (Kluemper et al., 2012). The job types reported by the limited subset of employed participants did include various entry-level positions (e.g., clerical, customer service, and sales), but participants only reported working an average of 26 hours per week (Kluemper et al.). It is reasonable to conclude the employed participants in this study may not represent full-time hourly workers. Rather, they were college students in part-time jobs that they are unlikely to pursue upon completion of their degrees. Finally, because raters scored participants' entire social media profiles holistically to determine their personality ratings, there is no way to know which of the dozens of available profile metrics were more or less influential in driving the overall personality score or prediction of job performance. Additional research is necessary to address these concerns.

Kluemper et al. (2012) were also restricted in their measurement of performance. Six months after collecting social media profile information, participants' supervisors were asked to complete an evaluation of in-role behavior and organizational citizenship behavior, but did not provide direct performance information. Though quantitative performance metrics are rarely easy to obtain for skilled professionals, many aspects of performance are often quantifiable among entry-level, hourly workers. For instance, in call centers, commonly quantified performance metrics include average handle time, customer satisfaction, and sales conversion rate.

Another post-hire outcome with cross-industry impact is attrition. Employee attrition can be a significant expense for any organization, but it is particularly painful in organizations with large hourly workforces such as call centers (Gans, Koole, & Mandelbaum, 2003). Academic researchers calculate attrition as the rate at which employees are statistically likely to leave the organization at a particular point in their tenure. However in practice, crude approximations are often measured instead (Fournier, 2000). Turnover analyses, calculations based on the number of people who left the organization divided by the number of total employees, are sensitive to sample sizes and seasonality and are difficult to analyze longitudinally. Whichever approach is used; however, the literature has not yet examined the possible links between social media personality and employee attrition.

To date, only Kluemper et al. (2012) have examined social media personality and workplace performance, and their findings did indicate social media can account for performance above and beyond self-reported personality. But they did not compare social media predictions to a validated selection system to determine whether social media information provides any additive value nor did they study job applicants. The question of whether social media provides incremental validity – whether it has any applied value for organizations – still has yet to be answered.

- Hypothesis 7: Social media activity adds significant incremental validity to predictions of performance and retention, beyond self-rated personality and pre-hire selection instruments.

Online Leadership Behavior and Prediction

It is important to look to analogous research from the distributed team's literature to understand the potential for monitoring and measuring leadership behavior online. The challenges leaders and followers face in distributed teams, and the behaviors they exhibit to overcome them may inform the behaviors in social media that are predictive of future performance.

Distributed Teams

Greenberg (2005) defined a team as “a group whose members have complementary skills and are committed to a common purpose or set of performance goals for which they hold themselves mutually accountable” (p. 300). In the strictest sense, a virtual team is a team that uses no FTF communication. Technology assists all of the team members' interactions with each other. Video conferencing, email, instant and text messaging, online forums, electronic whiteboards, telephone, and even standard mail are all examples of ways teams can communicate without sharing the same physical space and communicating FTF. But unlike virtual reality, which serves as an approximation of the real world, a virtual team is not an approximation of a team. Virtual teams exist on one end of a continuum, the other end of which is occupied by co-located, FTF teams that *exclusively* use FTF communication and do *all* of their work in the same physical location at the same time. Neither one of these opposites is an accurate description of the majority of modern teams. Today's teams are often somewhere in between, sometimes meeting FTF while maintaining relatively continuous communication with the help of IT.

Originally proposed as an additional subcategory of teams, the definition of "virtual team" does not always match its application. The all-encompassing definition of a virtual team, sometimes referred to as a network team (Scott & Einstein, 2001), includes two fundamental concepts: member dispersion and the use of technology to communicate (Townsend, DeMarie, & Hendrickson, 1998). Though dispersion is typically considered to be geographic, with team members being physically distant from one another, it also consists of boundaries that are more practical or temporal than physical. For example, team members living in the same city may not be very distant geographically, but they can still be separated by interdepartmental bureaucracy or snarled traffic. The closer team members are to each other physically, the more important the second qualification becomes the use of technology to communicate. Although use of technology and team member dispersion are certainly related, the correlation is not perfect. Office workers regularly email or instant message the person next to them instead of simply standing up and walking next door. Virtual teams often form to tackle assignments entirely within an organization's sprawling headquarters without ever meeting in person.

Over the past few years, there has been a gradual shift away from the categorical classification of virtual teams as geographically dispersed and a movement toward treating both dispersion and communication medium as a continuum present in all teams (Martins, Gilson, & Maynard, 2004). Moving away from the "either-or" comparisons implied by the term virtual teams and simultaneously specifying the pillars of distribution that affect all teams are steps in the right direction. In the context of this study, a virtual team is considered a team that communicates exclusively via electronic mediums, regardless of individual member distribution. When considering teams communication or dispersion, we refer to distributed teams (Adams, Toomey, & Churchill, 1999; Connaughton & Shuffler, 2007; Kirkman, Rosen, Tesluk, & Gibson, 2006; Mortensen & Hinds, 2001; Newell, David, & Chand, 2008). Team distribution allows us to focus on the aspects of distribution under examination and allows for more accurate comparisons of findings. The term virtual team is used too generically, while simultaneously being too specific, to meet this criterion. Dispersed teams (Connaughton & Daly, 2004; Hart & McLeod, 2003; Polzer, Crisp, Jarvenpaa, & Kim, 2006; Sole & Edmondson, 2002) is another name sometimes given to this concept, but its usage is less appropriate than distributed teams. Merriam-Webster defines distributed as "given out or delivered especially to members of a group," a more purposeful term than the most applicable definition of dispersed, "spread or distributed from a fixed or constant source" (Disperse, 2008; Distribute, 2008). Team members and their assignments are typically considered to be intentionally distributed rather than randomly dispersed.

Dimensions of Distribution in Teams

A focus on distributed teams (DTs) leads to the logical question: "Distributed how?" Under the umbrella of distributed teams, Bell and Kozlowski (2002) identified four main dimensions: temporal distribution, boundary spanning, lifecycle, and member roles. These dimensions act independently as sliding scales rather than dichotomies, and as such can fall anywhere on each spectrum.

Temporal distribution. Temporal distribution is the extent to which a distributed team acts in real-time (synchronous) or in distributed time (asynchronous). Although primarily relevant to teams spanning time zones, temporal distribution is an issue for any team whose members are not available to each other at the same time (Bell & Kozlowski, 2002). These could be telecommuters, shift workers, or even workers on flexible schedules at the same physical location who are active different times of the day. Most social media support both synchronous and asynchronous communication to facilitate communication between users.

Boundary spanning. Boundary spanning involves the permeability or flexibility of the boundaries DTs cross. These boundaries are often cultural or societal and include regional, organizational, and sub-unit cultural differences, language, and legal systems. Task complexity is expected to decrease the permeability of such boundaries – DTs need more structure when faced with complex tasks (Bell & Kozlowski, 2002). On social media, socio-technical boundaries range from language barriers to browser and operating system incompatibility.

Lifecycle. DT lifecycles range from discrete to continuous. DTs with discrete lifecycles are those that form to accomplish a more simplistic task and then disband. Teams with continuous lifecycles may still complete simple tasks, but they do so within a larger context (Bell & Kozlowski, 2002). Continuous teams persist much longer, and the simple tasks step towards a greater, more complex goal. The standard conceptualization of a DT is of a team that forms to accomplish a single, discrete task. Even though there are examples of DT persisting for years, such as a two-year research project at Whirlpool (Geber, 1995), these cases have traditionally been the exception. But now that the capacity for DTs has existed for some time, there exist continuous DTs that have worked together for years and organizations where they have become the norm. In social media, the notion of a lifecycle becomes even more muddied. User profiles and communication are often persistent, so many users must approach their communication as though there is no lifecycle. Although the specifics of a conversation are quickly forgotten, the content is archived and searchable. Even in the case of exceptions such as SnapChat, which make the ephemerality of communications a differentiating feature of their product, there typically exist methods to archive and retrieve "private" communication. Even if it were possible to control for all of the product features, the users themselves alter their behavior as they gain familiarity with a communication medium. Research suggests tenured members tend to use a social medium with decreasing frequency over time (Moore & McElroy, 2012).

Member roles. The fourth dimension is fairly straightforward. It refers to the number of different roles individual team members are expected to fill, starting with a singular role and extending to the jack-of-all-trades team member (Bell & Kozlowski, 2002). The extent to which the task at hand demands specific or fluid roles is also influenced largely by its complexity. Another name for member roles is role clarity. Traditionally, teams can be expected to do well when members know what they are supposed to be doing. Clear explanations from the leader regarding team member responsibilities and tasks can improve team performance, especially with complex tasks (Marks, Zaccaro, & Mathieu, 2000). Articulating member roles is an important part of effective distributed team leadership (Kayworth & Leidner, 2002). Efforts to clarify roles and tasks, the ability to communicate across boundaries, and the extent to which one can build and sustain an online following of inspired followers may all have identifiable and measurable behavioral markers in social media.

Online Leadership

Teams offer many potential benefits, including increased employee satisfaction and productivity, but these do not happen overnight or without guidance (Greenberg, 2005; Yukl, 2006). Leaders are still needed to facilitate tasks and maintain the group. Because leadership has been under the microscope for decades, there are widely supported theories we can apply to distributed teams. One such theory is transformational and transactional leadership (Bass, 1985; Bass & Avolio, 1997; Burns, 1978).

Successful transformational behavior simultaneously encourages employees to focus on the organization's goals and satisfies individual higher-order needs, whereas transactional leadership is more of a request and comply exchange between the leader and follower (Yukl, 2006). Transactional leadership is more concerned with detecting and correcting mistakes and rewarding compliance.

Although effective leaders exhibit both transformational and transactional leadership behavior, there is evidence to suggest transformational leadership is the preferred style when given a choice (Bass & Riggio, 2006). Entry-level workers who lack the authority to grant or deny resources and rewards are also more likely to be able to employ transformational leadership behavior than transactional. Although both transformational and transactional leadership have theoretical components, literature does not always support them (Yukl, 2006). Even at the broader level, traditionally useful leadership behaviors, especially transformational leadership, face particularly thorny challenges in EMC. The zeroes and ones that define the digital world often obscure the subtle nuances of personal communication (Bell & Kozlowski, 2002).

In cross-functional teams, teams that consist of members from different backgrounds and occasionally different organizations, research suggests leaders need technical expertise and cognitive, interpersonal, project management, and political skills (Ford & Randolph, 1992; Mumford, Scott, Gaddis, & Strange, 2002; Yukl, 2006). Technical expertise is the ability to communicate with team members on the technical aspects of the project, while cognitive skills help leaders solve complex problems. Interpersonal and political skills help the leader influence others and relate to team members. Planning and organizing requires project management skills. Leading online is not as simple as applying the same techniques one would use when leading a traditional team (Balthazard, Potter, & Warren, 2004; Hertel, Geister, & Konradt, 2005; Hoyt & Blascovich, 2003; Zigurs, 2003). Leaders often have a harder time in distributed settings because communication, task monitoring, and group and goal identification are more difficult to establish (Yukl, 2006). At the same time, some transactional tasks can be handed over to IT to assist with goal setting and performance monitoring. As technology evolves, so too will leaders and the behaviors necessary for their success (Avolio, Kahai, & Surinder, 2001).

Online leadership and relationships. Among social media, a lens of relationship building and basic influence shapes how we examine leadership. Spontaneous influence is connected to the message, rather than the communicator, and is often the type of influence behind quickly spreading “viral” online communications. The content of viral messages is often unexpected and easily shared with a user’s network, both in terms of software permitting simple sharing as well as social norms permitting the user to share the content in question. Viral content can come in the form of successes and missteps of popular figures in sports, entertainment, politics, and business, to music videos like Depacito, at the time of writing the most-viewed

YouTube video with over 6 billion views. Content that contains elements of an unfolding story or a topic with a novel, social component, such as an ongoing newsworthy or shared cultural event, can remain viral for an extended period and build or reinforce in-groups and tribes. Even after original viral context has lost its popularity, it can live on and reverberate across the Internet in the form of memes, remixed and repurposed in ways such that the derivative work surpasses the original in popularity. A topic as innocuous as the color of a wedding dress can still elicit passionate, good-spirited debate years after the original viral event, even when the dress is blue and black (Martin-Moro et al. 2015). Social media, therefore, make a fantastic medium for spontaneous online influence – the software facilitates the rapid spread of content across the network of users. However, the influence is tied more to the content of the message itself rather than the person delivering the message. In this sense, anonymous and validated users are both capable of wielding spontaneous influence, since the messenger is typically less important than the message. Finally, because it does not tend to build a relationship between the sender and receiver, spontaneous influence is more likely to be unidirectional from sender to receiver.

Sustained relationship building occurs when a social media user generates (or passes along) useful information regularly. Sustained online influence is often limited to domains of knowledge. For instance, Martha Stewart’s posts referencing arts and crafts projects likely influence her followers more than an in-depth analysis of global weather patterns. In that sense, sustained online influence is more similar to traditional leadership. It is this sustained communication that should be of interest to leaders online, particular on social media. Compared to the organization-to-consumer dialogue that largely prevailed over the past few hundred years, social media employ a persistent, complex, and higher risk form of communication than modern corporations are familiar with (Aula, 2010). Traditionally, corporations presented their communications in a largely unidirectional exchange with consumers, in essence attempting to send the most spontaneous, viral marketing message to potential customers. Despite being electronically mediated, social media and Internet communication often take the form of more natural, bi-directional conversations. As Sarah O'Farrell, a strategic planner at Ogilvy, put it, "We were used to broadcast media, the one-way message … now it's fast feedback, interactive, the message chopped up, challenged … we're back, if you like, to how we've been communicating for hundreds of years" (Heller, 2012, p. 87). To influence the online conversation, public relations practitioners have had to adapt to become regular users of social media (Sweetser & Kelleher, 2011). Sustained relationship building requires bidirectional communication that values the receiver.

In the broader social media environment, multiple individuals often comprise a single entity. For example, several support agents jointly manage the Samsung technical support profile on Twitter. At different times and with different consumers, agents essentially take turns acting as the representative of the channel. While doing so, they must appear unified – "on brand" – and adhere to established corporate communication policies. Yet even while representing the organization, the agents strive to include a personal element to their communication by including unique signatures on their posts. The agents also proactively manage the Samsung technical support profile by reciprocating follower requests (a community norm on Twitter) and by sending out links to helpful troubleshooting information and "How To" guides. These actions, however subtle, all help to proactively build rapport between Samsung and the customers interacting with the corporate Twitter profile.

If leadership behaviors are something that each team needs to some extent, the perfect leader will exhibit all of the needed behaviors. To the extent that a single leader does not encompass all of the needed behaviors, there are opportunities for other people and technology to substitute or fill the gaps. Leaders may not emerge and the team may be poorly led. But the potential exists for an additional leader or leaders to emerge and share leadership responsibility. This concept is similar to leadership substitutes theory (Kerr & Jermier, 1978). However, leadership substitutes theory typically focuses on the replacement of a single formal leader's behavior rather than team-wide shared leadership. It is important to note that leaders may emerge only briefly before reverting to follower roles, particularly in loosely structured, organic teams.

To build an influential relationship with online followers, leaders need to communicate frequently (Wittman, 2012), engage and interact with followers, and exhibit interpersonal sensitivity since online communication can reduce relational performance (Vickery, Droge, Stank, Goldsby, & Markland, 2004) and may be perceived more negatively than intended (Byron, 2008). These behaviors, more personal, align well with transformational leadership. Furthermore, interpersonal behavior falling under the transformational leadership umbrella should be identifiable through social media use as one of the primary goals of social media is to facilitate connection building and communication. Transactional leadership is important too, though it may be less important in social media, as software can be designed to substitute for a leader's facilitative behaviors (e.g., automatic scheduling and reminders) and detect and correct mistakes automatically (e.g., work output validation and real-time performance indicators).

- Hypothesis 8a: Social media profile metrics correlate with transformational leadership self-ratings.
- Hypothesis 8b: Number of social media friends correlates with transformational leadership self-ratings.
- Hypothesis 8c: Social media activity correlates with transformational leadership self-ratings.

Assuming transformational leadership can be measured using social media information, does it help predict performance? Links between transformational leadership and multi-level organizational outcomes are well established (Lowe, Kroeck, & Sivasubramaniam, 1996). In their meta-analysis, Judge and Piccolo (2004) also reported modest correlations between transformational leadership and leader performance. Personality facets such as extraversion, identified in childhood, can also predict future leader emergence (Reichard, Riggio, Guerin, Oliver, Gottfried, & Gottfried, 2011). Assuming social media can be used to identify leadership behavior early in an employee's career, in the longer term, it may help predict future leadership emergence. In the shorter term, it may also serve as an incremental predictor of performance, beyond personality and pre-hire selection tools, for entry-level customer service or sales positions that require empathy and rapid rapport building.

- Hypothesis 9: Social media-derived transformational leadership will predict job performance and retention, beyond personality and pre-hire selection instruments.

Methodology

Participants

The sample for this study included currently employed call center agents in mixed customer service and sales support positions. Common calls included helping customers create, update, or close accounts, assisting with billing inquiries, completing inbound purchasing requests, and light upselling. Participants were located in the United States and ranged in age from 19 to 58 (M = 30.6, n = 107). The sample was 52.3% female (n = 56) and most self-identified as Asian/Pacific Islander (43.6%), Caucasian (33.6%), or Hispanic (18.2%).

Procedure

Participant invitations were sent to approximately 800 call center agents who had been hired through the Evolv selection system and were currently employed. The Evolv application included a realistic job preview specific to the position (i.e., hours, pay, samples of “average” and “challenging” calls, and job requirements), an assessment validated for call center employees (including personality, work style preference, simulation, situational judgment, problem-solving, and technical knowledge questions), a typing test, an interactive voice response “voice audition”, and a job-specific behavioral interview guide for hiring managers. The assessment generated overall scores as well as sub-scores linked to specific post-hire outcomes.

Employees received an invitation to participate in the study via their employer’s internal corporate messaging system. Of the employees who received in invitation, 121 opened the survey. Employees who opted in first completed a questionnaire including personality and transformational self-report items as well as optional demographic information. At the end of the questionnaire, participants were asked to provide their email address if they wished to participate in the second half of the study. Those who volunteered were asked, via email, to then grant access to their main profile page for the collection of public profile information. This approach was taken because participants completing the questionnaire while at work may not have been able to access social media sites from behind employer firewalls. A narrowed sample of 48 participants opted in and shared their profile. Participants who shared profiles ranged in age from 20 to 49 (M = 30.2). The sample was 53.3% female and most self-identified as Asian/Pacific Islander (43.5%), Caucasian (39.1%), or Hispanic (13.0%). To summarize participation and drop-out, approximately 800 participants received the study invite on their corporate messaging system, 121 participants followed the initial invitation link, at least 113 completed a portion of the survey, the majority completed the optional demographic items in the survey (ethnicity n = 110, gender n = 107, age n = 107), and 48 survey participants also opted to share their public social media data. Sample sizes for the scales and analyses are reported based on complete data. This study used pairwise analyses and did not impute missing data.

The personality inventory was based on Goldberg's (1992) 50 item, 5-point Likert-style, short-form inventory of IPIP items, which was designed to measure Big Five personality constructs. Goldberg's short-form questionnaire was administered to 201 Amazon Mechanical Turk workers to shorten the scales. The scales were reduced with the goal of decreasing participant fatigue while maintaining minimum scale alphas of at least .80. Reliability analysis brought the 50 item inventory down to a 30-item scale (six items per scale) with Cronbach's alphas greater than .81 (openness alpha = .82, conscientiousness alpha = .81, extraversion alpha = .90, agreeableness alpha = .88, emotional stability alpha = .90, see also Appendix A for the complete study questionnaire). Ninety-three participants completed the personality items in the study and scale alphas ranged from .73 to .88, falling within DeVellis' (2016) range of respectable to very good scale alphas. To measure transformational leadership, a 40 item measure of transformational leadership designed specifically for self-report was used (Reichard, Riggio, & Smith, 2009). The transformational leadership self-report measure was developed to overcome deficiencies in the self-report version of the Multifactor Leadership Questionnaire, version MLQ-5X (Avolio & Bass, 1993), and uses a 7-point Likert-style scale ranging from "very strongly disagree" to "very strongly agree." Reichard et al. reported average reliabilities ranging from 0.78 to 0.92 for the transformational leadership scales. In this study, 79 participants completed the transformational leadership items and alphas ranged from .70 to .92. Similarly, computer skills (two items, range 2 – 14) and privacy skills (five items, range 5 – 35) were calculated from self-report, 7-point Likert scales created for this study and had alphas of .73 and .76, respectively, across the 78 participants who completed these items.

Publicly available Facebook information was scanned using custom software that captured a static snapshot of the participant's profile. The scanning tool collected information from the participant's main public Facebook page (profile photo, # of friends, # of followers, # of group memberships, # of likes, and basic demographic info if provided) as well as information on the "About Me" page (basic demographics and general interests) and "Photos" page (# of posted photos, # of profile photos, # of albums). This study captured number of followers to explore its practical utility. Number of friends is commonly analyzed in social media research because it is prevalent across Facebook and other social media platforms. Whereas friends are defined as bidirectional relationships (both users must agree to be friends), followers are unidirectional. Users can like or follow a profile without requiring the profile to like or follow them in return. Follower relationships are common on social media platforms like Twitter and Instagram but are available on Facebook as well. *Personal information completion* was calculated as a percentage across the birthday, gender, religion, and relationship status fields on the participant's social media profile. The captured information was intended to be representative of what a recruiter or hiring manager would look at when scanning an applicant's public Facebook profile. Information that participants had only shared privately or with friends was not collected by the plugin. Any quotes or descriptions of profiles presented in this study have also been obfuscated to protect privacy and confidentiality. This approach was taken to avoid sharing too many pieces of information, which could be used in a reverse search to triangulate the personally identifiable information of participants and identify them individually (Ohm, 2010).

Employee retention and performance data were provided by the employer. Both were analyzed 7 months after participants completed the online questionnaires and opted to share their social media profile information. Performance data were made available in the form of daily average handle time (AHT) metrics per employee, measured in seconds. Daily AHT data were averaged across a month to control for daily fluctuations in calls. Only basic participant demographic data and self-report questions regarding social media use and computer familiarity were collected in the research questionnaire because most standard information had already been recorded by either Evolv or the employer as part of the initial application process. Job application and assessment percentile scores from the Evolv assessment suite were also provided by Evolv.

Profile Coding

Qualitative review of the overall social media profiles was conducted by multiple raters (n = 7, 42.9% female), ranging in age from 30 to 64. All raters had experience interviewing and hiring candidates. Raters were tasked with determining protected class information (age, gender, and ethnicity) based on available profile information and asked to make yes or no hiring decisions based on the holistic page information (see Appendix B for rating instructions). Raters were provided with a screenshot of participants' main social media profile page, if it was publicly viewable, and then asked to rate the overall professionalism of the page (ICC = 0.647, p < .001, n = 40, two-way mixed) and whether or not they would move the candidate forward in the selection process based on their social media profile screenshot (82.5% agreement, n = 40). Raters were also asked to guess the age (ICC = 0.831, p < 0.001, n = 39, two-way mixed), gender (96.8% agreement, n = 40), and ethnicity of the candidate based solely on the social media profile screenshot. Demographic guesses were compared against the participant's reported demographic information to determine accuracy.

Analyses

Approximately seven months after participating in the study, employed participants' performance metrics and post-hire data were collected and analyzed. The general analysis strategy in this study was to move towards increasingly complex final models representative of what one might find in an applied selection context. This meant starting with simpler correlations to check for relationships between variables and attempt to replicate prior research. Highly correlated social media variables were reduced through factor analysis. Accuracy and ICC of human raters were calculated along with the bias of the raters' decisions at 70%, 80%, and 100% pass rates. Rater ICC estimates were calculated based on a mean rating (k = 7), consistency, 2-way mixed-effects model. Reliability ranged from "good" for age bands (ICC = .87, $F(6,228)$ = 7.59, p < .001) to "excellent" for recommendation to hire or advance the candidate (ICC = .96, $F(6,198)$ = 25.70, p < .001). The thresholds of 70% and 80% rater agreement were chosen to mirror practical cut points in a call center environment. For example, Evolv's selection assessment generates green, yellow, or red scores for candidates where green is the equivalent of a strong hire recommendation, yellow reflects a hire recommendation, and red reflects a do not hire recommendation. In aggregate, between 70-80% of candidates applying for an entry level customer support or sales position typically receive a green or yellow score. The analysis at 100% pass agreement is meant to simulate a more stringent threshold where bias against protected groups, if present, may be more likely to surface. Finally, these personality, social media, and leadership variables were combined with scores from the Evolv pre-hire selection assessment to analyze retention and performance outcomes using multi-level, block-wise regressions. Cox regressions were used for retention and linear regressions for performance.

The retention analysis included multiple dimensions from the Evolv pre-hire assessment, specifically dependability, customer service, customer efficiency, and sales proficiency. All four dimensions were included because the dependability dimension of the pre-hire assessment intended to predict retention was designed and validated to predict early attrition. In the call center industry, this usually means a targeted reduction in attrition during the first 90-180 days on the job, depending on the specific job duties and average time to full productivity. Predictive power declines for that portion of the assessment after the first year of employment. In this study, retention was examined beyond a year, so the knowledge, skills, abilities, and other characteristics (KSAOs) captured in the dependability dimension in the pre-hire assessment would not be expected to be particularly predictive. However, after a year on the job, other pre-hire dimensions relating to ongoing performance show higher predictiveness.

Related batches of correlation analyses were also analyzed for false positives, applying the Benjamini and Hochberg (1995) correction at a .20 rate. This study aimed for a moderate approach in applying the correction, but the .20 cutoff could arguably be set higher or lower – there is no common rule for the threshold. Some correlations in H1 were flagged as possible false positives due to this analysis. For a summary of hypotheses and associated analyses, refer to Table 4.

Table 4

Summary of Analysis Approach by Hypothesis

Hypotheses	Analyses
H1	Correlation with Benjamini & Hochberg (1995) correction for 22 comparisons
H2 & H3	Correlation with correction for 8 comparisons
H4	Block-wise linear regression
H5	ICC and accuracy
H6	4/5ths adverse impact rule of thumb
H7	Block-wise linear regression and Cox regression
H8	Factor analysis and correlation with correction for 32 comparisons
H9	Block-wise linear regression and Cox regression

Results

Hypothesis 1a was partially supported. Number of followers was negatively related to emotional stability (r = -.33, p = .021, n = 48, two-tailed). Number of friends was positively related to openness (r = .29, p = .043, n = 48, two-tailed). Number of groups was positively related to agreeableness (r = .28, p = .05, n = 48, two-tailed). The number of likes was not significantly related to FFM personality (Table 5). However, these three significant relationships were flagged when applying the Benjamini & Hochberg (1995) correction for multiple comparisons, suggesting they may be false positives, and thus should be interpreted with caution.

Hypothesis 1b and 1c were not supported. Contrary to the literature, neither extraversion nor agreeableness were related to the number of friends or followers. The only personality dimension related to the number of friends was openness. Number of group memberships was also not related to conscientiousness. Only agreeableness was related to number of group memberships (Table 5).

Hypothesis 1d was partially supported. Openness was positively related to personal information completion (r = .35, p = .007, n = 48, one-tailed). Agreeableness was not significantly related (r = .21, p = .074, n = 48, one-tailed) however it trended positively, contrary

Table 5

Personal Information Completion and Personality: Correlations and Descriptive Statistics (personality N = 92, social media N = 48)

Variables	1	2	3	4	5	6	7	8	9	10
1. Openness	-									
2. Conscientiousness	.30**	-								
3. Extraversion	.23*	.36***	-							
4. Agreeableness	.50***	.32**	.33**	-						
5. Emotional Stability	.25*	.46***	.57***	.23*	-					
6. # followers	.22	-.04	-.04	.04	-.33*	-				
7. # friends	.29*	.01	-.13	.00	-.19	.71***	-			
8. # groups	.09	.07	-.09	.28*	-.18	.23	.47***	-		
9. # likes	-.03	.11	-.02	.15	.03	.07	.12	.28*	-	
10. Personal profile completion	.35†	.07	-.01	.21	-.05	.02	.11	.12	.19	-
M	23.47	23.15	19.74	23.40	23.01	5.33	608.67	14.15	36.12	.85
SD	3.77	4.29	4.42	4.17	5.36	11.40	674.22	10.72	29.46	.14
Range	9-30	10-30	6-30	11-30	9-30	0-50	35-4,315	0-47	6-211	.50-1.00

* $p < .05$, two-tailed. ** $p < .01$, two-tailed. *** $p < .001$, two-tailed. † $p < .01$, one-tailed.

to the findings from Amichai-Hamburger & Vinitzky (2010). Because so much of the social media and personality literature is inconsistent, the non-hypothesized relationships of extraversion, conscientiousness, and emotional stability were also run, and (as expected) were not found to be statistically significant. Excluding these non-hypothesized relationships from the analysis would have resulted in the correlations for Hypothesis 1a being statistically significant (not flagged by the Benjamini and Hochberg correction), but it was determined important to test the comparisons and share the results, even though they were unlikely to be significant, to support future meta-analytic studies.

Hypotheses 2 and 3 were not supported. Participants higher in conscientiousness were no more likely to report increased self-reported privacy skills using social media (r = .09, p = .220, n = 78, one-tailed), nor were they more likely to have self-limited and configured their main profile to be less publicly available (r = .16, p = .133, n = 48, one-tailed). Similarly for emotional stability, less emotionally stable participants were neither no more likely to report stronger privacy skills (r = -.06, p = .300, n = 78, one-tailed) or self-limit their public profile (r = .01, p = .463, n = 48, one-tailed). Interestingly, emotional stability was significantly related to reported social media usage, such that participants higher in emotional stability reported less frequent use (r = -.25, p = .036, n = 74, two-tailed). Even though this relationship was not a focus of this study, it is reported here as it is consistent with other findings (e.g., Correa, Hinsley, & De Zuniga, 2013).

Hypothesis 4 was partially supported. Examined independently, conscientiousness and emotional stability did not significantly relate to either self-reported privacy skills or the extent to which public personal information fields were completed in social media. Self-reported computer skills on the other hand, were positively correlated with self-reported privacy skills (r

= .22, p = .029, n = 78, one-tailed) and personal profile completion (r = .33, p = .012, n = 48, one-tailed). To check whether computer skills were moderating personality dimensions, multiple linear regressions were calculated to predict self-reported privacy skills and personal profile completion based on conscientiousness, emotional stability, computer skills, and the interactions between personality and computer skills. The regression equation for privacy skills approached significance (F(5,72) = 2.12, p = .072), with an R^2 of .13, and the equation for profile completion was significant (F(5,42) = 2.72, p = .032), with an R^2 of .24.

Computer skills were significantly related to privacy skills at entry (B = 0.61, SE = 0.29, β = 0.23, t = 2.08, p = .024) and the interaction of computer skills and conscientiousness was significant in the final model (B = 0.16, SE = 0.07, β = 1.85, t = 2.09, p = .040), as shown in Table 6. Computer skills were also significantly related to profile completion at entry (B = 0.02, SE = 0.01, β = 0.34, t = 2.42, p = .020) as was the interaction of computer skills and conscientiousness in the final model (B = 0.01, SE = 0.00, β = 2.55, t = 2.36, p = .023, Table 7). The interaction between computer skills and emotional stability did not add significantly to either model. Participants higher in conscientiousness were more likely to rate themselves highly in social media privacy behaviors and complete more of their profile – but only if they also reported higher computer skills. Less conscientious participants were more likely to rate themselves highly on social media privacy behavior and complete more of their profile, but only when their computer skills were lower (Figures 1, Figure 2).

Table 6

Summary of Hierarchical Regression Analysis for Variables Predicting Social Media Privacy Skills (N = 78)

	Model 1			Model 2			Model 3		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
(constant)	23.06***	3.88		16.44**	4.95		51.21*	21.10	
Conscientiousness	0.20	0.17	.15	0.23	0.17	.17	-1.39	0.80	-1.02
Emotional stability	-0.14	0.14	-.13	-0.16	0.14	-.15	0.04	0.45	.03
Computer skills				0.61*	0.29	.23	-2.63	1.94	-1.01
Computer skills × conscientiousness							0.16*	0.08	1.85
Computer skills × emotional stability							-0.02	0.04	-.32
R^2		0.02			0.07			0.13	
F for change in R^2		0.79			4.34*			2.21	

* $p < .05$. ** $p < .01$. *** $p < .001$

Table 7

Summary of Hierarchical Regression Analysis for Variables Predicting Social Media Profile Completion (N = 78)

	Model 1			Model 2			Model 3		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
(constant)	0.82***	0.12		0.58***	0.15		1.56*	0.64	
Conscientiousness	0.00	0.01	.11	0.01	0.01	.15	-0.05*	0.02	-1.48
Emotional stability	-0.00	0.00	-.10	-0.00	0.00	-.13	0.01	0.01	.45
Computer skills				0.02*	0.01	.34	-0.07	0.06	-1.07
Computer skills × conscientiousness							0.01*	0.00	2.55
Computer skills × emotional stability							-0.00	0.00	-.91
R^2		0.01			0.13			0.24	
F for change in R^2		0.28			5.86*			3.22*	

* $p < .05$. ** $p < .01$. *** $p < .001$

Figure 1. Privacy Skills by Computer Skills & Conscientiousness

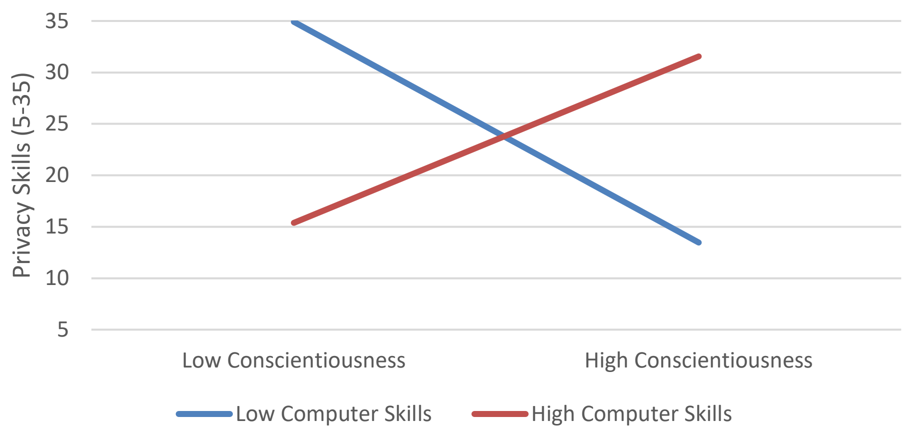
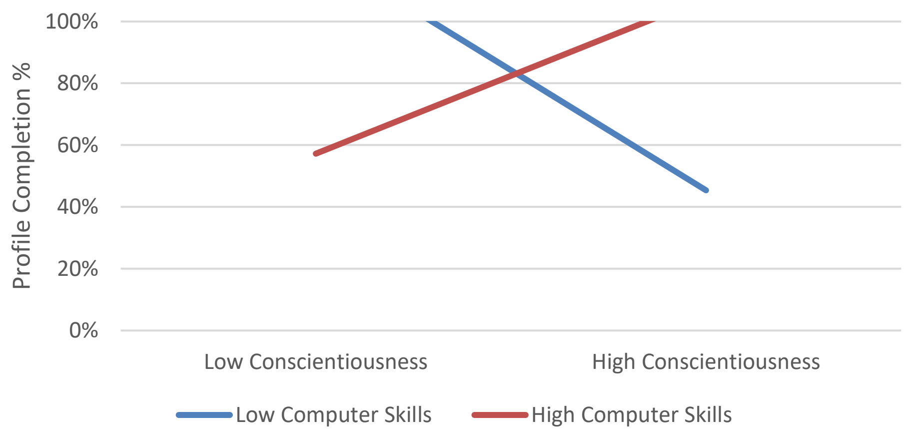


Figure 2. Profile Completion % by Computer Skills & Conscientiousness



Finally, when checking the extent to which profiles had more privacy restrictions, this study also examined the correlations between ratings of profile professionalism with personality. Surprisingly, conscientiousness was negatively related to ratings of profile professionalism (r = -.37, p = .017, n = 40, two-tailed). One possibility is that conscientious users post more often and therefore are more likely to have information on their profile that a hiring manager might flag as inappropriate. However, per Table 4 no significant relationship was detected between conscientiousness and measured social media use. No significant relationship between conscientiousness and self-reported profile activity was found either (r = -.06, p = .614, n = 74, two-tailed). We encourage future researchers to investigate this connection.

Hypothesis 5 was supported. On average, raters accurately guessed the participant's gender 88% of the time (n = 37) and ethnicity 81% of the time (n = 38). Age presented a more difficult challenge. Based strictly on the age ranges presented in the rater questionnaire, rater accuracy at first glance appeared poor (32%, n = 37). However, for the purpose of practical application and potential bias in the selection process, the differentiation of interest is whether the candidate is part of a protected class – in the United States, age 40 or older. When raters' guesses were aggregated into two classifications, under 40 versus 40 or older, rater accuracy improved to 82% (n = 37).

In summary, raters representing a practical, real-world scenario – that of recruiters quickly scanning candidates' publicly available social media profiles – were able to identify the protected class demographic information of social media users with over 80% accuracy. But did this identification matter? It may not be concerning if recruiters can identify protected class information if they also manage to check their own biases and make fair hiring decisions.

To answer this, I examined the pass rates by actual demographic data. Hypothesis 6 was partially supported and had some degree of nuance. Compliance against the 80% or 4/5ths guideline was examined at different pass rates to serve as a check for disparate impact. Compliance with the 80% rule of thumb is typically deemed met when protected classes pass any given selection hurdle (as well as the overall selection process) at 80% of the rate of the highest-scoring or most frequently passing group. In the United States the reference group is commonly white males under the age of 40. However, it can be any group depending on who is passing at the highest rate.

This study looked at increasingly strict pass rates of 70%, 80%, and 100% as defined by rater agreement. That is, if at least 70% of raters said they would move a candidate forward in the process, that participant was determined to have "passed" at the 70% threshold. At the 70% threshold, 95% (*n* = 38 for ethnicity, *n* = 37 for age and gender) of participants who provided demographic data "passed", compared to 66% passing the 80% threshold and only 16% being moved forward in the hiring process by all seven raters (Table 8). At the 100% threshold, the 4/5ths guideline was violated for age and gender but not for ethnicity. This improved at the less aggressive 80% – only ethnicity violated the 4/5ths rule – and the 70% thresholds, where no violations were found. Due to the smaller samples, particularly for ethnicity, these findings must be interpreted cautiously. Regardless, they are cause for concern and warrant further study.

Table 8

Pass Rates at 70%, 80%, and 100% Reviewer Agreement Thresholds (n = 38)

Group	70% Threshold				80% Threshold				100% Threshold			
	NH	H	P%	4/5	NH	H	P%	4/5	NH	H	P%	4/5
Under 40	2	26	93%	93%	10	18	64%	83%	24	4	14%	100%
40+	0	9	100%	100%	2	7	78%	100%	8	1	11%	79%*
Male	0	17	100%	100%	5	12	71%	100%	13	4	24%	100%
Female	2	18	90%	90%	6	14	70%	99%	18	2	10%	43%*
Caucasian	1	13	93%	93%	6	8	57%	69%*	12	2	14%	81%
Asian/Pacific Islander	1	16	94%	94%	6	11	65%	78%*	14	3	18%	100%
Black/African American	-	-	-	-	-	-	-	-	-	-	-	-
Hispanic	0	6	100%	100%	1	5	83%	100%	5	1	17%	94%
Native American/Alaska	-	-	-	-	-	-	-	-	-	-	-	-
Other/Multiple	0	1	100%	100%	0	1	100%	120%	1	0	0%	0%

*NH = No Hire. H = Hire. P% = Pass Rate. 4/5 = Relative Pass Rate. * = violation of 4/5ths or 80% rule.*

Hypotheses 7, 8, and 9 were partially supported. First, the factorability of four social media behaviors (number of friends, number of followers, number of group members, and number of likes) was examined to reduce the number of predictors, as complete data across performance and retention metrics were limited. Social media behaviors were observed to correlate with one another, suggesting reasonable factorability (Table 5). Though the Kaiser-Meyer-Olkin measure of sampling adequacy of 0.53 was lower than the commonly recommended value of 0.6, Bartlett's test of sphericity was significant ($\chi^2(6) = 48.01$, $p < .001$) and communalities were above 0.3, confirming that each item shared some common variance with other items. Given these overall indicators, factor analysis was deemed to be reasonable.

Principal components analysis was used because the primary purpose was to identify and compute composite scores for the factors underlying social media behavior. Initial eigenvalues indicated that two factors explained 51% and 27% of the variance, respectively. The remaining two factors had eigenvalues less than one. An oblimin rotation provided the best-defined factor structure. Only one item had a cross-loading above 0.3 (number of group memberships); however this item had a strong primary loading of 0.62. The factor loading matrix for this final solution is presented in Table 9.

Table 9

Factor Loading Matrix for Social Media Behaviors, Oblimin Rotation (n = 48)

Group	DSMB	ISMB
# followers	0.916	-0.106
# friends	0.910	0.091
# group memberships	0.366	0.621
# likes	-0.159	0.913

DSMB = Dependent Social Media Behavior. ISMB = Independent Social Media Behavior.

The two factors were labeled Dependent Social Media Behavior (DSMB) and Independent Social Media Behavior (ISMB). DSMB is defined here as an activity that is primarily reliant on the actions of other users of the platform. After an individual has signed up to use a social media platform, the decision to have friends and followers is to a certain extent out of their control. Even though the user can find others to connect with and initiate a connection, their total number of friends will be heavily influenced by others. For example, how many people do they know? Do other users choose to accept or reject a friend request? Similarly, follower numbers are often driven entirely by other users choosing whether to follow another user on the platform. Both metrics are dependent on other users.

ISMB is defined as the opposite – that activity in which users control themselves. The decision to like an article or a post is up to the user. Although the presence or absence of rich content will depend on the user's network and interests, the decision to like or respond is primarily up to them. It is also up to users themselves whether to join or remain a member of any given group. There is some dependency on other users to create engaging groups worth joining, welcome or at least tolerate new members, and continue providing something of value to members over time (e.g. connection, entertainment, information), but the decision to join a group ultimately comes down to the user. These factors proved useful when analyzing relationships between social media activity, leadership, and retention.

Hypothesis 8 was supported. Dimensions of transformational leadership were significantly correlated with social media metrics and activity, and aggregate transformational leadership was significantly related to social media profile completion (Table 10). Inspirational motivation was positively related to self-reported social media use, number of followers, number of friends, number of group memberships, and ISMB. Individualized consideration was positively related to the number of friends, the number of group memberships, and DSMB. Intellectual stimulation and idealized influence were positively related to profile completion. Five participants who self-reported that they did not have a Facebook account were excluded from these correlations.

Hypotheses 7 was supported with regard to retention. The analyses mimicked practical recommendations and best practices in selection by searching for incremental prediction in approximate order of the robustness of the methods. It is not sufficient to be predictive – an ideal selection tool should generally also be better than its alternatives with regard to validity and absence of bias. For example, a job related, statistically validated assessment would generally be recommended as superior relative to an individual recruiter or hiring manager's review of a candidate's publicly available social media profile. Along that spectrum, validated pre-hire assessments were examined first, followed by personality, computer and privacy skills, quantifiable social media behavior, and finally, profile reviews from human raters. The relative importance of those predictors in predicting retention was analyzed with Cox regression models. An initial model including all predictors approached significance ($\chi^2(17) = 25.70$, $p = .080$, $-2LL = 50.71$, $AIC = 84.71$) though many individual predictors were not statistically significant. A second analysis dropping the weaker predictors was conducted and resulted in a significant overall model ($\chi^2(9) = 22.07$, $p = .009$, $-2LL = 56.85$, $AIC = 74.85$). Interestingly, only the sales proficiency dimension of the validated pre-hire assessment was predictive of retention in the final model and dependability was dropped early in the analysis (Table 11).

Transformational leadership was then added for the third model ($\chi^2(10) = 25.65$, $p = .004$, $-2LL = 48.62$, $AIC = 68.62$) to check Hypothesis 9, which was also supported. Although leadership is a domain with significant research and job relatedness, in the context of this study it

Table 10

Social Media Activity and Transformational Leadership: Correlations and Descriptive Statistics (variables 1-6 N = 69, variables 7-13 N = 45)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Transformational leadership	-												
2. Inspirational motivation	.90***	-											
3. Intellectual stimulation	.82***	.56***	-										
4. Individualized consideration	.91***	.84***	.65***	-									
5. Idealized influence	.87***	.70***	.72***	.71***	-								
6. Social media activity	.14	.21*	.00	.18	.05	-							
7. # followers	.17	.26*	.03	.21	.03	.27*	-						
8. # friends	-.01	.27*	.04	.26*	-.01	.23	.71***	-					
9. # groups	.21	.26*	.07	.31*	.06	.23	.22	.45***	-				
10. # likes	.14	.09	.08	.13	.21	-.07	.07	.10	.26*	-			
11. DSMB	.19	.30	.04	.28*	.00	.30*	.89***	.93***	.48***	.02	-		
12. ISMB	.20	.17*	.09	.24	.19	.04	.07	.26*	.68***	.88***	.19	-	
13. Personal profile completion	.27*	.16	.26*	.21	.37**	.17	.03	.12	.13	.21	.08	.22	-
M	233.86	67.75	47.94	51.87	56.29	5.16	5.47	633.80	14.80	30.17	.03	.51	.85
SD	26.31	9.55	6.99	7.06	6.29	1.07	11.76	688.15	10.72	30.17	1.02	1.01	.15
Range	160-278	48-84	34-63	36-63	40-70	2-6	0-50	87-4,513	1-47	6-211	-1.07-4.844	-1.15-4.91	.50-1.00

* $p < .05$, one-tailed. ** $p < .01$, one-tailed. *** $p < .001$, one-tailed.

Table 11

Summary of Cox Regression Analysis for Variables Predicting Attrition, Excluding Transformational Leadership (N = 28)

	Model 1			Model 2		
Variable	*B*	*SE B*	*Wald*	*B*	*SE B*	*Wald*
Typing WPM	-0.11	0.09	1.64	-0.11	0.01	3.62
Typing accuracy	0.32*	0.15	4.29	0.35***	0.11	10.09
Pre-hire dependability	-6.14	4.60	1.78	-	-	-
Pre-hire customer efficiency	0.00	0.00	0.89	-	-	-
Pre-hire sales proficiency	-2.97	4.71	3.01	-3.70*	1.62	5.20
Pre-hire customer service	-3.75	5.19	0.52	-	-	-
Openness	0.30	0.25	1.39	-	-	-
Conscientiousness	-0.91**	0.32	8.15	-0.61**	0.20	9.21
Extraversion	-0.12	0.23	0.30	-	-	-
Agreeableness	-0.42*	0.16	6.63	-0.28**	0.11	6.66
Emotional stability	0.01	0.17	0.00	-	-	-
Privacy skills	0.07	0.13	0.29	-	-	-
Computer skills	-0.60*	0.27	4.79	-0.45*	0.23	3.83
DSMB	0.31	0.43	0.53	0.79*	0.33	5.62
ISMB	-0.10	1.01	0.00	-	-	-
Profile professionalism	-3.39	1.77	3.67	-2.00	1.17	2.91
Hire decision	-12.11*	6.16	3.87	-8.36*	4.09	4.18

$^{*} p < .05$. $^{**} p < .01$. $^{***} p < .001$

was not necessarily a job-related construct – the intent was to explore whether it might provide incremental value. Since transformational leadership as a univariate predictor was significant in the third model, it was substituted for its dimensions in a fourth model $\chi^2(13) = 30.20$, $p = .004$, ($-2LL = 41.66$, $AIC = 67.66$) to further refine the prediction (Table 12). The transformational leadership dimensions were then reduced down to only the significant predictor, idealized influence, in the fifth and final model (Table 13) which was also significant overall ($\chi^2(10) = 27.95$, $p = .002$, $-2LL = 44.60$, $AIC = 64.60$).

Across all retention regression models, negative predictor weights indicated a longer tenure at the company (higher retention or lower attrition) relative to other participants, measured in days of tenure. In the fifth and final model, increases in typing accuracy percentage, DSMB, and idealized influence scores were significant predictors of attrition. Conversely, typing WPM, pre-hire sales proficiency score, conscientiousness, agreeableness, computer skills, profile professionalism, and profile advancement recommendation were all significant, negatively weighted predictors – the lower their values, the more likely a participant was to have left the company during the study.

Conceptually it is possible to bucket the pre-hire assessment dimensions into two simplistic retention groups from the employer's point of view. People leaving the company due to lack of performance or failure to show up for work are typically categorized as non-regrettable departures and, regardless of the cause, generally viewed as a negative. People performing well on the job and leaving to pursue new opportunities as they gain experience and skills are categorized as regrettable departures by employers. The pre-hire dependability dimension would fall broadly under the negative header, while sales proficiency falls under the positive. Put

Table 12

Summary of Cox Regression Analysis for Variables Predicting Attrition, Including Transformational Leadership (N = 28)

	Model 3			Model 4		
Variable	*B*	*SE B*	*Wald*	*B*	*SE B*	*Wald*
Typing WPM	-0.06	0.05	1.25	-0.28	0.16	3.11
Typing accuracy	0.44***	0.13	12.06	0.71*	0.29	6.07
Pre-hire sales proficiency	-3.67*	1.69	4.70	-4.69*	2.35	3.98
Conscientiousness	-0.89***	0.26	12.12	-1.61	0.95	2.88
Agreeableness	-0.34**	0.11	9.01	-0.63*	0.29	4.88
Computer skills	-0.74**	0.27	7.53	-1.71	1.15	2.21
DSMB	0.75*	0.36	4.40	2.10	1.28	2.68
Profile professionalism	-3.25*	1.33	5.95	-5.66	3.17	3.17
Hire decision	-12.26**	4.64	6.98	-16.32	9.74	2.81
Transformational leadership	0.05*	0.02	5.23	.	.	.
Inspirational motivation	.	.	.	-0.14	0.15	0.83
Intellectual stimulation	.	.	.	0.33	0.38	0.78
Individualized consideration	.	.	.	-0.22	0.36	0.39
Idealized influence	.	.	.	0.39*	0.19	4.23

* $p < .05$. ** $p < .01$. *** $p < .001$

Table 13

Final Cox Regression Analysis for Variables Predicting Attrition, Including Idealized Influence (N = 28)

	Model 5		
Variable	*B*	*SE B*	*Wald*
Typing WPM	-0.12*	0.05	6.01
Typing accuracy	0.53***	0.15	13.29
Pre-hire sales proficiency	-3.97*	1.74	3.17
Conscientiousness	-1.02***	0.29	12.88
Agreeableness	-0.37***	0.12	10.22
Computer skills	-0.89**	0.29	9.73
DSMB	0.96*	0.38	6.30
Profile professionalism	-3.33*	1.36	5.98
Hire decision	-9.29*	4.59	4.09
Idealized influence	0.25**	0.10	7.11

* $p < .05$. ** $p < .01$. *** $p < .001$

another way, it is typical to see a curvilinear pattern in call centers where the first six months of employment are characterized by many employees leaving voluntarily or "washing out" after completing their initial training. It can be a very challenging job. But after the first 6-12 months, the employees that remain are those more likely to find meaning and purpose in work. Some employees find purpose helping customers solve their issues. Others find purpose exceeding sales goals to bring home a bigger paycheck. Amongst the group that stick it out over the first year are top performers who may start receiving offers from other employers, which then entice them to depart the company.

To examine Hypotheses 7 and 9 with regard to performance, an objective measure of productivity and efficiency was collected. Daily average handle time (AHT) was averaged across a month approximately seven months after participants completed the study questionnaire. Similar to the analysis of retention, linear regressions predicting AHT were conducted, starting with broad and then refined models (excluding transformational leadership) to check Hypothesis 7 (Table 14). Hypothesis 9 was analyzed in models including aggregate transformational leadership, transformational leadership dimensions (Table 15), and finally a refined model including the inspirational motivation and idealized consideration dimensions (Table 16). Across all AHT regression models, negative predictor weights indicated higher efficiency and productivity (less time spent resolving each call) relative to other participants, all else being equal.

Hypothesis 7 was not supported with regard to AHT performance (Table 14). The relative importance of validated pre-hire assessments, personality, computer and privacy skills, social media behavior, and profile review ratings in predicting AHT was analyzed with multiple regression models. An initial model including all predictors was not significant ($F(15,2) = 0.15$, $p = .991$). A second analysis dropped the weakest predictors, based on a combination of statistical, content, and practical implementation criteria. Statistically, predictors with weaker absolute β weights, theoretical backing, or practical rationale were candidates for exclusion. For example, the pre-hire efficiency dimension and typing accuracy measures incorporate elements

Table 14

Summary of Regression Analyses for Variables Predicting AHT, Excluding Transformational Leadership (N = 32)

	Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*
(constant)	-699.25	0.12		740.82	1,398.23	
Pre-hire efficiency	-1,088.01	1,140.13	-.62	-934.74*	418.64	-.54
Typing accuracy	23.46	40.90	.42	13.25	13.79	.24
Typing WPM	-7.53	19.68	-.29	-	-	-
Openness	13.71	48.01	.19	23.52	18.23	.33
Conscientiousness	8.08	46.92	.11	-	-	-
Extraversion	-28.14	44.06	-.45	-13.87	15.77	-.22
Agreeableness	13.58	47.79	.20	-	-	-
Emotional stability	4.76	38.67	.09	-	-	-
DSMB	13.46	208.10	.05	-	-	-
ISMB	-61.47	174.04	-.21	-	-	-
Social media activity	-116.94	169.03	-.43	-90.42	68.54	-.33
Computer skills	33.36	78.27	.26	-	-	-
Privacy skills	0.71	39.02	.01	-	-	-
Profile professionalism	121.07	315.64	.25	-	-	-
Hire decision	-735.03	1,489.14	-.31	-722.60	594.74	-.33
R^2		.54			.42	

* $p < .05$. ** $p < .01$. *** $p < .001$

of conscientiousness, agreeableness, and computer skills. Because a validated pre-hire assessment would be considered a better alternative than self-report IPIP or computer skills questionnaires in a selection context, the latter were dropped in the second model. Similarly, ISMB and profile professionalism could arguable be included based on their β weights, but stronger alternatives (social media activity and hire decision, respectively) were available for both.

The second analysis was also not significant, ($F(6,11) = 1.34$, $p = .319$), though in that model the pre-hire assessment was predictive of AHT in the expected direction ($B = -934.74$, $SE = 418.64$, $\beta = -0.54$, $t = -2.23$, $p = .047$). A better score on the pre-hire assessment dimension of efficiency was negatively related to AHT. This means candidates who scored better on the assessment dimension were more efficient and spent less time resolving each phone call, on average. Social media activity predictors did not significantly add to the model. Transformational leadership was then added to a third and fourth model to check Hypothesis 9, which was partially supported (Table 15). First transformational leadership was analyzed as an aggregated predictor, which did not result in a significant model ($F(7,10) = 1.20$, $p = .384$). Nor was the model significant when transformational leadership was broken into its dimensions ($F(10,7) = 1.45$, $p = .321$). Finally, the two weakest dimensions were dropped and transformational leadership was reduced down to inspirational motivation and individual consideration in the fifth and final model (Table 16). This model was also not significant overall, ($F(8,9) = 2.05$, $p = .153$), though the pre-hire dependability ($B = -1{,}188.43$, $SE = 393.78$, $\beta = -0.68$, $t = -3.02$, $p = .015$) and self-reported inspirational motivation ($B = 28.90$, $SE = 12.12$, $\beta = 0.96$, $t = 2.38$, $p = .041$) dimensions were significant predictors of AHT. Increased individualized consideration ($B = -28.38$, $SE = 15.39$, $\beta = -0.69$, $t = -1.84$, $p = .098$) and social media activity ($B = -127.13$, $SE = 63.61$, $\beta = -0.47$, $t = -2.00$, $p = .077$) also trended towards predicting lower AHT. As inspirational motivation scores increased, participants tended to have higher AHT, translating to worse performance on the job. As pre-hire efficiency, individualized consideration, or social

Table 15

Summary of Regression Analyses for Variables Predicting AHT, Including Transformational Leadership (N = 32)

	Model 3			Model 4		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*
(constant)	410.47	1,482.15		652.02	1,471.85	
Pre-hire efficiency	-1,020.57*	439.41	-.58	-1,258.75*	485.44	-.72
Typing accuracy	15.04	14.21	.27	17.78	13.48	.32
Openness	19.69	19.16	.27	24.37	18.91	.34
Extraversion	-17.34	16.64	-.28	-28.36	17.60	-.45
Social media activity	-102.31	71.33	-.38	-126.41	74.87	-.47
Hire decision	-887.14	622.03	-.37	-1,050.08	655.10	-.44
Transformational leadership	2.36	2.97	.21	-	-	-
Inspirational motivation	-	-	-	31.14	15.20	1.03
Intellectual stimulation	-	-	-	11.40	14.75	.28
Individualized consideration	-	-	-	-31.18	18.12	-.76
Idealized influence	-	-	-	-8.97	20.17	-.44
R^2		.46			.67	

* $p < .05$. ** $p < .01$. *** $p < .001$

media activity increased, participants tended to have lower AHT, meaning they were more efficient on the job.

Across the regression analyses inclusive of transformational leadership, it is also important to note the high multicollinearity among the transformational leadership dimensions. It is no surprise to find transformational leadership dimensions correlated with one another, but it does suggest the analyses with more than one dimension should be interpreted with caution.

Table 16

Final Regression Analysis for Variables Predicting AHT, Including Transformational Leadership (N = 32)

	Model 5		
Variable	*B*	*SE B*	*β*
(constant)	426.11	1,243.24	
Pre-hire efficiency	-1,188.43*	393.78	-.68
Typing accuracy	18.11	12.27	.33
Openness	27.21	16.12	.38
Extraversion	-25.91	14.97	-.41
Social media activity	-127.13	63.61	-.47
Hire decision	-940.38	544.10	-.40
Inspirational motivation	28.90*	12.12	.96
Individualized consideration	-28.38	15.39	-.69
R^2		.65	

* $p < .05$. ** $p < .01$. *** $p < .001$

Although idealized influence was the most predictive transformational leadership dimension and therefore included in the final retention model (Table 13), the other dimensions could have been incorporated instead to build a model that was statistically significant as well, though not as strong. The important consideration here is that idealized influence was not the only useful transformational leadership predictor. Similarly, alternate models (albeit less predictive) could likely be built to predict AHT with different combinations of transformational dimensions than were included in the final performance regression (Table 16). To help guard against overfitting models or selecting suboptimal subsets of predictors, future research should strive to collect a sufficiently large sample to support the use of hold-out data in their analyses.

Discussion

The central concern of this research is: does social media matter in selection? The answer depends on your point of view. From a purely statistical standpoint, yes. Evidence was found pointing to modest incremental validity when including social media variables in models predicting retention. But from a practical and theoretical standpoint, the support is still insufficient, and therefore the answer is no while acknowledging this may change in the future.

Personality and Social Media

This research supported the idea that personality can be gleaned from social media behavior, though the findings were not consistent with prior literature, and several relationships were flagged as possible false positives when calculating the Benjamini and Hochberg (1995) correction. Arguably the relationships predicted by prior research are still worth noting since this study admittedly over-indexed on comparing personality and social media profile variables to inform an area of research where a core set of relationships seems to be consistent, but many others vary from study to study. In this study, several social media variables correlated with personality dimensions; for instance number of followers was negatively related to emotional stability. Social anxiety and a need to accumulate more followers as a means of validation, self-affirmation, or even job security may help explain the link between followers and emotional stability. For some the role of social media influencer has emerged as a career, with influencers in some cases earning thousands of dollars per post. It is also possible that people are attracted to more emotionally unstable personas online, whether that drama is real or perceived. In 2019 a social media influencer who lost her Instagram account was ridiculed online when she posted a tearful video claiming “I am nothing without my following” (Ritschel, 2019). Despite the backlash, or possibly because of the attention generated by it, the video itself successfully went viral and partially rebuilt her following.

Openness was related to the number of friends on social media. Even though it seems intuitive that an individual higher in openness might be exposed to more potential acquaintances or be more interested in searching for new social media connections, this finding is unique. The relationship between agreeableness and the number of group memberships is also unique to this research, although it also seems intuitive. More agreeable individuals may be more willing to join a group, remain in a group, and less likely to be banned from a group for argumentative behavior.

The most consistent personality relationship in the social media literature, the positive relationship between extraversion and number of friends, was not supported in this research. Lack of replication in this study highlights not only a continued challenge in the social media literature but a broader challenge with generalizability of research aimed at the practical application of social media information in the selection process. As with other areas of social science study, too much research continues to focus on college students. Although tools like the MyPersonality repository are a step in the right direction, they may still suffer in terms of generalizability. The MyPersonality social media archive served as a source for multiple analyses and papers and potentially skewed consensus in the field. Outside of college students and individuals willing to opt in to a Facebook personality survey, do working adults represent a unique sub-population? The results of this research certainly raise that possibility. Within this study there are temporal concerns to consider as well, such as range restriction and its effects on measuring employee performance over time, so it stands to reason that similar sampling effects are present outside of this research as well.

Privacy and Computer Skills

That more agreeable individuals would be willing to complete more of their profile seems intuitive, especially when one considers the repeated prompting many sites and apps employ to encourage users to provide additional information. The interactions predicting privacy skills and profile completion are less obvious. The interaction between conscientiousness and computer skills may be a manifestation of behavior relating to confidence and ignorance, respectively. First take confidence – those participants higher in both conscientiousness and computer skills may find it easier to understand the privacy settings on social media platforms, be more likely to read and be aware of feature enhancements over time that grant the user more control over their profile and privacy settings, and put in more effort to learn social media platforms settings and configuration options. Those lower in conscientiousness (even if they are more skilled) may not find the initial effort and subsequent upkeep worthwhile. Similarly, those who are conscientious but lack the skills may still give up quickly or focus their conscientiousness on a hobby or task more likely to reward their time investment. Users lower in both conscientiousness and computer skills may not know or care enough about privacy settings to use them.

The interaction between conscientiousness and profile completion could reflect similar underlying behavior. It is encouraging that those with the skills and determination to actively maintain their profiles appear to be comfortably employing social media. But research has found both beneficial and harmful effects of social media activity (Hu et al., 2017), and participants lower in conscientiousness and computer skills may be a cause for concern. These are users who tend to report sharing more information and who are actively grooming their social media profiles, but who may lack the skills to make full use of all available security and privacy settings. On the one hand, as platforms continue to streamline and simplify their privacy controls, react to legislation like the General Data Protection Regulation (GDPR, 2018) and California Consumer Privacy Act of 2018 (CCPA, 2018), consumer protection groups raise general awareness, and users improve their skills through practice, we might worry less about this group. On the other hand, if users have a false sense of security and efficacy when it comes to their online presence and personal information, they may never take the time to learn about the features available to them for controlling content on their social media profiles or may not be aware of the potential risks in sharing personal information to begin with.

One of the most important privacy-related takeaways of this research is that privacy behavior matters. Social media features and functionality change rapidly. Platforms are shifting their strategies and tools to monitor inappropriate behavior better while simultaneously asking governments and regulators to define what is appropriate behavior and speech. As more social media activity becomes partially or completely closed off to the public, it will be more difficult to collect data. Inconsistent data collection across what remains accessible increases the risk that candidates will not be afforded the same consistent screening opportunities. An inconsistent dataset based on a biased sample is precisely the type of pre-hire indicator most companies would want to avoid.

Transformational Leadership

Transformational leadership as a single, broad factor was not a particularly useful predictor with regards to social media activity, employee retention, or performance, but transformational leadership dimensions were another story. Personal profile completion was positively related to both intellectual stimulation as well as individualized consideration. Individuals who self-rate higher in individualized consideration may engage in more strategic use of social media privacy settings than their peers to consciously target different groups with different messages. They may be more cognizant of how the content they share may be perceived differently by their friends, family, co-workers, or future employers. Inspirational motivation, truly a charismatic dimension, was positively related to the number of friends, followers, and groups. Those higher in inspirational motivation should be able to attract more followers, elicit invitations to more groups (or start groups and attract members), and generally take advantage of the connectivity facilitated by social media.

Idealized influence was positively related to attrition, such that those with higher scores were more likely to leave the company throughout the study. Employees higher in idealized influence, those with strong values and convictions, may be a poor match for entry-level call center roles. Someone who does not like to be bothered by telemarketers but scores low on idealized influence might not be as bothered by a job where cold calling is required.

Inspirational motivation was also a significant predictor of performance in the form of AHT, such that higher inspirational motivation scores were related to decreased performance (more seconds spent on the average call). Individualized consideration trended towards significance in the final model in the opposite direction (higher individualized consideration was related to less time spent on the average call). Inspirational motivation is more about communication and vision, and while that is important in some roles, it may not be beneficial in a call center environment where every second counts. A call center representative who can articulate a clear vision of the product or company may share too much information with a customer who needs to solve a narrow request. Individualized consideration on the other hand, including the ability to quickly identify what motivates a customer, would be directly applicable to help reduce decision overload in the face of many options and direct a customer to a product solution that meets their needs, or to come up with a resolution that solves the customers' issue and leaves them satisfied with the outcome.

The social media profile of one participant stood out with regards to leadership. The participant has a remarkably professional profile, featuring motivational video clips, professional and wholesome profile photos of the participant and their family, and a profile banner highlighting their professional goals. This participant was a small business owner and proud of their work. They also scored just shy of one standard deviation above the mean across all transformational leadership dimensions. They serve as an example of the tantalizing promise of social media as a selection tool – if we can systematically find the professional profiles, why not use social media for screening? One catch is that anyone can post motivational sayings on their social media profile. Even if a meaningful relationship is supported today, it could be diluted if the research findings were to go viral themselves, diluting the effect. Another catch, at least in this research, is that every participant in the study was a good hire, even those with less overtly professional profiles. In a high-volume hiring scenario such as those call centers often face, an automated system brings great promise for efficiency gains but also great risk of false negatives. That brings us to our final consideration.

Traditional Selection vs. Social Media

Social media was not advantageous over traditional methods. It is rather impressive that the pre-hire assessment was still predictive of retention and performance in this study, even after sample and range restriction. ML, data first models can explain incremental validity, but we should not abandon decades of theory-driven research when using them. Validated assessments along with personality and leadership dimensions were stronger predictors of retention than social media activity or a rater's decision upon reviewing a social media profile. Only assessment and transformational leadership dimensions were significant predictors of performance the combined model.

Study Limitations

Personality intercorrelation. It is important to interpret the personality findings with some caution since they were generally correlated with one another. It would not be unreasonable to suspect some degree of measurement or self-presentation bias, but neither would this study be different from the rest of the social media personality literature in that regard. It is reasonable to assume that participants volunteering to take part in a study of social media and share their social media profiles may be sharing a positively skewed view of themselves online (and in a research study). However, results from this research are generally consistent with patterns found in other diverse samples, with extraversion scores lower than the other four dimensions. For instance, Ypofanti et al. reported a similar pattern among Greek adults (2015). Furthermore, other variables in the study were linked to individual personality dimensions, not all of them, suggesting the personality intercorrelations are reflective of true scores.

Pressure to perform. There is also the possibility that participants did not take the study seriously, as there was low pressure to perform. Participation was voluntary and not tied to an employment outcome, so may have clicked through the survey portion of the study without providing thoughtful or representative responses. Examining individual item responses appeared to rule out this concern. First, the IPIP scale used in this study included both positively phrased as well as negatively phrased, reverse coded items. Second, disingenuous response patterns (e.g., all positive, all negative, all neutral) were not present in the survey results. We conclude that participants generally opted in and participated in the study with good intentions.

Sampling issues. There are many advantages of the participant sample in this study. Participants were employed full time and represented a relatively diverse group across age and gender when contrasted with the common college student sample. On the downside, the sample was small, in particular on the analyses with incomplete longitudinal data. Representation for some ethnic categories was also low or non-existent. We do not argue that the sample and findings in this study generalize to all working adults, but that the challenges and recommendations applicable to this dataset and employer are representative of those faced by practitioners regularly. The promise of big data lies in massive, anonymized, aggregated datasets. The reality of small data is felt daily by recruiters, hiring managers, and human resource departments in organizations around the world.

Because participants were employed in call centers means they did not represent the entire adult population, at least in terms of employment status. One would generally expect full-time call center workers to be higher in conscientiousness, extraversion, and emotional stability as they are important, job-relevant traits for those working in such roles. In this study, the selection assessment against which the participants were originally screened included those dimensions as components. Again, this research was not intended to be representative of the entire adult population, it was meant to represent the practical, real-world scenarios facing employers today. Within that context, the personality dimension intercorrelations are not at all unexpected.

Range restriction is also a significant concern in this research, as it is in any selection context. First there are the unrepresented applicants who completed the pre-hire assessment and were not hired. By definition, participants invited to this study scored higher on average on the pre-hire assessment hurdle than the population of all job applicants. Employees who responded to the study invite may have been more curious or had more free time to respond. Those who did not respond may have been too busy to see the invitation or respond, or felt too stressed or disengaged to bother participating. Despite the presence of range restriction, this research was still able to detect the presence of useful predictors across assessments, social media, personality, and leadership in a selection context.

Controls for age and social media tenure. Studies of college students often find strong relationships between the number of friends and various personality outcomes. This study only partially supported this finding, and where relationships were significant, they were not consistent with prior research. The lack of replicability raises the question of why?

There is a possibility that time and age may be important factors. The date at which someone first joins a social media platform will vary depending on factors such the age demographic of the originally targeted userbase or the user's nationality. Products are introduced in new regions in stages and adoption often spreads among cohorts at different rates with younger users acting as early adopters. But in studies of college students, this variable is implicitly controlled as participant age will be generally homogenous. Compared to a random sample of the population, I hypothesize that a cohort of college students are more likely to have joined any given social media at about the same time and therefore have had roughly the same opportunity to find and add friends, join groups, make posts, and generally be active social media users. Unintentionally controlling for the length of time someone has used a social media platform may falsely boost the significance of individual dimensions like personality when predicting social media activity. However, in studies with a more diverse sample, length of time exposed to the social media platform may be a better predictor of the number of friends, groups joined, and activity. It would be important to control for this in future research.

Cultural considerations. This research was based on a sample of North American working adults in one particular role and in one particular industry. The people who seek work and excel in call centers are not representative of the population of all North American adults. Nor do North American working adults necessarily represent all working adults. Researchers need to take into account regional differences in how users communicate online, how personality and leadership dimensions manifest cross-culturally, and consider how their analyses may differ by region or culture. For example, natural language processing benefits from rapid advances and growing availability of open source English language libraries. It is increasingly easy to create tools to parse and classify English text. However, libraries in other languages – if they exist at all – are not necessarily analogous. Inconsistencies across languages reinforce the importance of local validation.

Social Media Profile Reviewers

Raters in this study generally agreed on demographic data and selection scores for candidates simply by looking at an extract of their profile. This study was designed to mimic practical, real-world conditions, and did just that. Raters were able to identify demographic, protected class information rather handily and, despite less consensus on professionalism, still made relatively consistent hire or no hire decisions without necessarily knowing why. The behavior of raters in this study mirrors the behavior of many hiring managers and recruiters. This Decision making in a selection context without clear criteria is often viewed as a greater problem in smaller organizations that may be less familiar with the job selection research and relevant laws, regulations, and industry guidance, but similar anecdotes can be found throughout large multinational corporations as well.

At one point in the study, the raters reviewing social media profiles raised concerns about one of the participant's profiles, which featured a "Remember 9/11" post featuring the photo of a child. Without more information and only a snapshot of the profile to reference, some raters jumped to the conclusion that the child was a victim of the 9/11/2001 terrorist attacks. Additional contextual information gained in the process of gathering and preparing the snapshots for ease of rating made it clear that the child was simply a relative of the participants who they frequently featured in updates around holidays and important events. The post was one of many digital greeting cards that conveyed a message or memorialization (e.g., "Remember 9/11" or "Happy Veteran's Day"), implying it was shared on behalf of their family with the rest of their social media connections. A decision still had to be made weighing the privacy of the participant against potential mental and emotional stress on the part of the raters. The decision was made to reassure the raters that their assumption was incorrect, without providing additional specific details about the profile.

Reviewer well-being is an important consideration that has received little attention in the context of employment-related screening. If an organization asks employees to review social media profiles for employment purposes without sufficient training or forewarning, might a recruiter bring a claim if they unexpectedly encounter disturbing content? Does potential liability outweigh this exposure risk in *not* searching a candidate's social media profile and in the process missing clear, foreseeable indicators of inappropriate behavior (Schmidt & O'Connor, 2016)? These are untested legal waters, but once again the guidance appears to point in the direction of using automated or independent screening tools rather than in-house reviewers who may lack the training or support to review profiles fairly, consistently, and without causing harm.

Research (and the law) also tend to focus on the candidate-employer relationship in the context of selection. But reviewing social media content risks opening up that relationship to include addition willing and unwilling participants. Consider a candidate referred to a job opening by a friend, where the friend had previously consented to have their public profile information reviewed by the employer. At what point has a recruiter overstepped the bounds of consent? If they revisit the original, referring employee's social media profile to look for content involving the referral candidate, unbeknownst to that candidate, they may have trouble defending the validity and job relatedness of that review in the court of public perception. By reviewing data unbeknownst to the referred candidate, has the employer (and perhaps even the friend making an unsolicited referral) potentially crossed a line in data privacy regulations?

The "Remember 9/11" post also underscores the practical concerns regarding accuracy. Justification for excluding a candidate from consideration or taking employment action against a current employee commonly relies on examples of drug use or offensive posts and comments. But it may be difficult to ascertain from a single post or image what is happening. Yet drug use or offensive posts are often presented as the more straightforward examples where social media screening may be appropriate. Image recognition is advancing rapidly and it seems this is one more argument in favor of machine learning screening as a partial solution. ML promises to reduce bias and improve context and accuracy relative to a human reviewer who may quickly scroll through a half-dozen, potentially misinterpreted or unrepresentative posts. However, ML models can still perpetuate biased selection decisions if poorly trained or evaluated – garbage in, garbage out.

Practical Considerations

The core message to practitioners stemming from this research is that they should avoid incorporating social media profiles in their selection process. In this study, social media profiles were at best modestly predictive of retention and did not add significant prediction to performance outcomes, beyond more accepted selection methods. With this comes several highly concerning risks. Raters were able to easily identify age, gender, and ethnicity in seconds while scanning a mere slice of an individual's social media profile. Some (but not all) screening thresholds demonstrated adverse impact. The job-relatedness of a Facebook profile is tenuous at best. Although it is understandable that employers would search for short-cuts to a faster evaluation and less intrusive experience for candidates, traditional selection methods are still preferable for their validity and defensibility.

If you must select based on social media profiles. If an organization decides to forge ahead and incorporate social media profiles in their selection practices, an activity this research does not endorse, there are several practical steps they can take to reduce their legal risk and improve predictive accuracy. Develop clear evaluation criteria based on job analyses and local validation. Monitor adverse impact outcomes in accordance with local laws and regulations. The organization should be prepared to defend its use of social media profile data relative to other selection methods such as assessments or structured interviews. Conduct reviews in a highly structured environment with training for anyone who will be involved in candidate screening, including sourcers, recruiters, hiring managers, and interviewers. Blind review candidates' social media profiles where possible, removing obvious signals of age, gender, ethnicity, and so forth. Employers should be aware candidates may request information relating to a candidate's evaluation under GDPR or similar regulation.

A preferable approach to human raters is to use supervised, validated computer-based screening. As ML algorithms continue to improve and predict personality with better accuracy than human raters (Youyou, Kosinski, & Stillwell, 2015), this will be an opportunity for software products to supplement or replace ad hoc searches. Widespread use will depend on the future legal and regulatory landscape as much as anything, as cases like hiQ Labs, Inc. vs. LinkedIn Corporation (Goldfein & Keyte, 2017) work their way through the legal system and laws similar to GDPR and CCPA continue to be proposed and enacted. Training and interpretation remain critical to ensure scores are evaluated with the appropriate level of context and weighting relative to other selection criteria, even if ML is incorporated to reduce human bias. ML algorithms will also continue to struggle with low volume hiring. Issues of bias and sample size are not new challenges in job selection, but rather a reminder that what is predictive for one role at one company may still need local validity and generalization evidence to support transportability to other roles or organizations.

Even though there is a growing body of evidence that social media can predict personality, this research demonstrates those relationships are still unreliable. From a transportability perspective that is concerning. The findings in this study did not consistently replicate some of the social media and personality correlations more commonly reported in the literature. At this point, we do not have consistent evidence that prior research findings generalize to the workplace. The lack of supporting research suggests any application of social media data in a selection context would be wise to include local validation. The Uniform Guidelines also guide practitioners to consider suitable alternatives. In my opinion, an organization seeking to screen candidates based on one or more personality dimensions should be prepared to answer the question: why are you using social media instead of a validated personality assessment?

Ongoing developments to monitor. The case law and regulations surrounding selection practice tend to lag the rapid pace of technological innovation. Practitioners are advised to monitor the relevant regulatory and judicial bodies in their region for regulations and rulings that may impact their selection process. Definitions of adverse and disparate impact are moving away from the 4/5ths rule. Even though the 4/5ths rule is still a relevant and easily interpreted in courtrooms, judges and attorneys have become more sophisticated in their understanding of statistical methods and significance and expect to see more than just 4/5ths adherence. One appealing aspect of using social media in selection is the ability to scrape vast amounts of data unobtrusively. But trawling for data also creates risks for organizations. Any sufficiently large sample will support statistically significant relationships between variables, including differences between protected groups. Practitioners can stay informed by following the professional organizations like the Society for Human Resource Management (SHRM) and the Society for Industrial and Organizational Psychology (SIOP) that regularly prepare briefs of relevant updates and changes. A push by larger organizations to adhere to the most restrictive regulations (e.g., GDPR) in the absence of consistent laws across countries for the sake of consistency and simplicity is another particularly interesting trend to watch. Only time will tell how lawmakers and case law integrate this shifting landscape.

Social media platforms themselves are also subject to change. New feature development could render the recommendations in this study obsolete. For example, Facebook Dating has launched in the United States (Facebook, 2019). Practitioners have historically been advised to focus social media selection activity on professional networking platforms like LinkedIn, as opposed to truly social platforms like Facebook since professional networks demonstrate greater face validity in an employment context. But if Facebook were to launch a matching service for job seekers, those recommendations would no longer be relevant.

Directions for Future Research

Researchers often lament the pace of technological change in the social media space. However, it may be the biggest opportunity for impactful theoretical work. Technology changes rapidly and knowing that, we as researchers need to stop wringing our hands about the ephemerality of our findings and develop theoretical models less subject to the whims of technology. It is easy to study the number of friends on a social media profile, but we need more thoughtful taxonomies to aggregate findings over the longer term in a way that retains their future relevancy. One example is provided by this research, reducing factors to dependent and independent social media behavior. Another is the incorporation of computer and privacy skills and privacy behavior. A higher-order taxonomy categorizing a broad set of social media and online behavior would facilitate meta-analytic studies and support a more robust, generalizable study of social media in both personal and professional contexts. A stronger theoretical basis would, in turn, help individual studies map to a more consistent, less fluid model while simultaneously enabling them to control for some of the inherent change.

In a similar vein, joining research from the social and information sciences may yield more robust and predictive models. Looking to research on online communities and their dynamics over time may be particularly fruitful. Incorporating a stronger understanding of community dynamics into social media selection research should improve the generalizability of models. For example, early adopters of a platform are typically considered to be younger and more technologically savvy than later adopters. The tendency for younger users to adopt newer platform manifests in the tongue-in-cheek rule of online communities that once your parents join, the platform is no longer cool, and it may be time to move to a new service. Controlling for the relative maturity and mass-market appeal of a given social media platform, as well as demographic characteristics of users such as their age and tenure using the platform, could yield more generalizable models of behavior.

A common complaint about sample generalizability, echoed here, is that academic research may suffer from too narrow a focus on the college student population. This study also raises a related issue: existing literature may have placed too heavy a focus on the broad population of all social media users. We need additional, targeted studies to make more conclusive recommendations regarding work-related applications of social media. But with that call for more research, there comes a caveat – there may not be a useful, unified set of predictors applicable across all social media users. As with most other selection methods, each application may need to demonstrate validity and generalizability. A one-size-fits-all use case for social media in selection, like the research supporting the general predictiveness of cognitive ability, could be a pipe dream. The absence of a one-size-fits-all model is not necessarily a bad thing - at least in the practical case of selection, job analyses should be conducted to determine the relevant KSAOs for a role and the selection process tailored appropriately. A one-size-fits-all solution would be convenient but is not required. A testable null hypothesis here is that working-age adults across different job families exhibit similar social media behavior. That is likely not the case and is a void which future researchers could fill.

I am not aware of studies investigating recruiter well-being while scanning social media profiles. Though one hopes the exposure rate to truly disturbing content is vanishingly low, there is a greater chance that recruiters could encounter and misinterpret content like the 9/11 post in a social media profile, drawing incorrect conclusions about a candidate. Possible exposure to disturbing content is the unlikely but potentially high-profile case that further tips the scale in favor of traditional selection methods. False positives and misinterpretation of posts and content are likely far more common. A researcher might ask recruiters to rate or code a range of representative social media posts, possibly controlling for thoroughness of training and calibration resources. Research demonstrating that tools and training negate concerns about adverse impact and lack of job-relatedness would reduce some of the risks. Training and tools could be compared to the results of ML algorithms trained on social media data. Although properly designed ML selection models would likely be more predictive and less biased than recruiters across large samples, reviewers trained to evaluate social media profiles may have an edge in low volume hiring scenarios that lack sufficient training data for ML applications.

Conclusion

The reality today is that billions of people maintain profiles on social media platforms, and employers often factor what they see on social media profiles into the hiring decision. Working together, I/O psychologists and computer scientists have the potential to elicit deeper, more reliable insight from social media profiles. But like any tool, the information can be used responsibly or irresponsibly. Recruiters can look at profiles, as they do today, and use the information contained therein to make decisions that may be overly reliant on social media information or that may result in adverse impact. On the other hand, automated scanning of profiles for key metrics has the potential to increase the accuracy of pre-employment screening models and as well as decrease the length of pre-hire assessments and job applications. Reducing exposure to legal challenges lowers an organization’s risk and potential costs. Improving the accuracy of pre-hire predictions by even small increments can result in millions of dollars in direct savings for organizations with a large, hourly workforce. A deeper understanding of one's workforce is a true competitive advantage. This research, like the research that precedes it, is mixed. Yes, social media does show some promise in predicting performance and retention. But the process remains fraught and inadvisable. Social media does not appear to be conclusively better at predicting outcomes over more traditional, validated measures, and it carries with it a host of legal and ethical challenges. Just because we could, does not mean we should.

Rather than throw big data at traditional problems, a better question to ask might be what benefits social media can bring to organizations space that is novel and difficult to replicate with traditional methods? Like with online dating sites, social media profile information may help build better workplace relationships. By supplementing research in team effectiveness and team member satisfaction, it may be possible to make team recommendations for new hires or transfers, or better match teams and supervisors, in a way that traditional siloed selection methods cannot mimic. Perhaps by mining a candidate or employee's social media network, particularly socially compatible (or incompatible) personas could be identified. Business professionals love the Myers-Briggs Type Inventory – imagine something similar for organizations backed by rigorous science and data? Match employees to managers whose leadership and management styles are complementary to the employee's work style. Build teams with the personalities of all members factored in. Although this may all sound a little too idealistic to some, Gallup has consistently reported that having a best friend at work is a strong driver of employee engagement (Mann, 2018). Personality matching is not a suggestion that a team must have identical profiles – rather, high performing teams often consist of a blend of diverse and complementary roles (Johnson, Boster, & Palinkas, 2003). But what blend is ideal? Research is necessary to answer these questions. The online dating analogy is not accidental;

many people meet their significant other at work. The possibilities and moral implications are fascinating and only begin to scratch the surface of what is possible with such in-depth tracking.

In the long term, employers and employees may also benefit from periodic profile scans. Historically when an employee has posted a negative comment on a social media site, it has been seen as “a Bad Thing” by the employer, and depending on the severity of the post the employee risks reprimand or termination (IBM Inc., 2008). But who among us has not had a bad day at work? It remains to be seen whether a more positive, proactive response would benefit both the employee and employer. Perhaps it would be of greater benefit to overall organization effectiveness if such online comments were met with a genuine interest in an employee’s well-being by their supervisor or a human resources representative. Social media comments need not be specific to an employer either – an uptick in expressions of stress or frustration may signal an employee who may be at higher risk of attrition or whose productivity is in danger of dropping due to burn-out or stressors outside of the workplace. If an algorithm like the one offered by Humu detects such signals, what then? Should a manager or human resources representative be “nudged” to reach out to the employee? Should the employee receive a reminder that they have unused vacation time or that their employer offers online counseling services as a benefit to all employees? Behavioral nudging is an area with many untapped research possibilities but also much potential for abuse. No doubt some employees will find such services timely and beneficial. Others will see them as invasive and creepy, even when the algorithm is correct. At worst, false negatives and false positives may create an atmosphere of distrust that defeats the purpose of using such tools.

The explosion of big data analytics has opened many doors for researchers that were previously unimaginable. Many people carry a smartphone, a high-powered monitoring device, with them at all times. The union of persistent tracking, cheap computer processing power, and domain expertise is beginning to bridge the academic-practitioner gap in ways we only dreamed of a decade ago. The potential for organizations, employees, and researchers remains huge. It behooves our field to stay abreast of the changes so we can guide organizations with best practices to accurately and efficiently predict applicant performance, protect applicant and employee privacy, and minimize potential abuses.

Appendix A

Participant Survey: Social Media, Personality, & Leadership

Informed Consent Form for Social Media, Personality, Leadership, & Performance research study.

You are being asked to participate in a research project conducted by Tim Lisk, a graduate student in Industrial & Organizational Psychology in the School of Social Science, Policy, and Evaluation at Claremont Graduate University (CGU). I am partnering with The Results Companies and their job application software provider, Evolv, to conduct this research. For more information about my academic research, please visit: http://claremont.academia.edu/TimLisk You are being asked to participate because you have applied to an online job posting at The Results Companies.

PURPOSE: The purpose of this study is to determine:

• If social media use predicts personality, leadership, and job performance

• Whether using social media to predict job performance is discriminatory

PARTICIPATION: This is a two-part study:

• Part 1: You will be asked to complete a survey about your personality and leadership behavior. At the end of the survey, you may choose to participate in Part 2 of the study.

• Part 2: If you volunteer to participate in Part 2, you will be redirected to a software application (app) called "Evolv Social Tools" that was designed specifically for this study. The app will ask for your permission to gather public data from your Facebook profile and you may choose to opt out at any time. You WILL NOT be asked to provide your personal login, password, or other private information. Depending on your Facebook privacy settings and how much information you have chosen to post, the app may gather the following information from your profile: friend list, email address, friend requests, relationships, birthday, groups, interests, photos, religious and political views, follows and followers, personal description, and likes. We expect your participation to take about 20 minutes of your time.

RISKS & BENEFITS: This study poses minimal risks to participants. You may be somewhat inconvenienced by the time it takes to complete the study requirements. You will not receive any direct benefits from this study. We expect this research to benefit society by providing employees and job applicants with a better understanding of how their social media posts may be used during job screening, as well as by outlining possible legal concerns regarding which social media information may be discriminatory & illegal for employers to use in the hiring process. We also expect employers to benefit from improved legal and scientific guidance regarding which social media data is and is not recommended for use in hiring decisions.

Your decision to participate WILL NOT have any impact on performance appraisals, compensation, or any other employment decision.

COMPENSATION: One (1) study participant will receive an iPad Mini. The winner will be drawn in a random lottery of all participants. Odds of winning will depend on the number of participants.

VOLUNTARY PARTICIPATION: Please understand that participation is completely voluntary. Your decision whether or not to participate will in no way affect your current or future relationship with The Results Companies or with CGU or its faculty, students, or staff. You have the right to withdraw from the research at any time without penalty. You also have the right to refuse to answer any question(s) for any reason, without penalty.

CONFIDENTIALITY: Your responses will be confidential and your individual privacy will be maintained in all publications or presentations resulting from this study. Only aggregate results will be reported. Your individual survey responses and your public social media information WILL NOT be shared with The Results Companies and your responses WILL NOT have any impact on performance appraisals, compensation, or any other employment decision.

Your survey and profile information will be stored on a secure, password protected and encrypted computer accessible only by Tim Lisk. For the purpose of this study, your survey and/or social media data will be linked to both your original job application and your current job performance (for example, AHT and CSAT scores) based on your original, system-generated job application ID. The matched data will be stored and analyzed on the same secure computer.

Participant data will be destroyed within two years of the close of the study. The survey is hosted on a secure server with an encrypted (https) connection. No names or other personally identifiable information will be included in the final research findings.

If you have any questions or would like additional information about this research, please contact me at timothy.lisk@cgu.edu, (909) 575-8461, or 201 3rd St, 8th Floor, San Francisco, CA, 94103. You can also contact my advisor Dr. Ron Riggio at rriggio@claremontmckenna.edu. The CGU Institutional Review Board, which is administered through the Office of Research and Sponsored Programs (ORSP), has approved this project. You may also contact ORSP at (909) 607-9406 with any questions. Please print a copy of this consent form for your personal records.

By clicking "Next" I indicate I understand the above information and have had all of my questions about participation on this research project answered. I voluntarily consent to participate in this research.

Background Information

REMINDER: Your individual responses are confidential and WILL NOT be shared with your supervisor or anyone else at The Results Companies. By completing this survey, you will be entered into the drawing for an iPad Mini. If you volunteer to share your Facebook profile data at the end of the study, you will be entered into the drawing a second time.

Thank you for your help!

Sincerely,

Tim Lisk

1) Which of the following best describes your current work role?*

( ) Agent
( ) Supervisor
( ) Other (please describe): ______________________________

2) Which of the following best describes your current work schedule?*

( ) Mostly early morning shifts

( ) Mostly normal business hours

( ) Mostly evening shifts

( ) Mostly late night shifts

( ) None of the above, my work schedule changes frequently

3) Think of a typical day at work. Using the following categories, what percentage of your work is:*

Numbers only, must add up to 100%

________Customer Service (accounts & billing, light up-sell, basic device reset)

________Sales (customer retention, cold calls)

________Collections

________Technical Support (software or hardware troubleshooting)

________Back Office (data entry with no direct customer contact)

4) OPTIONAL: What is your age?

____

5) OPTIONAL: What is your gender?

( ) Male

( ) Female

6) OPTIONAL: What is your ethnicity?

( ) Asian/Pacific Islander

( ) Black/African-American

( ) Caucasian

( ) Hispanic

( ) Native American/Alaska Native

( ) Other/Multi-Racial

Personality

On the following page there are phrases describing people's behaviors. Please use the rating scale below to describe how accurately each statement describes you. Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same gender as you are, and roughly your same age. Please read each statement carefully and then select your response.

Response Options
1: Very Inaccurate
2: Moderately Inaccurate
3: Neither Inaccurate nor Accurate
4: Moderately Accurate
5: Very Accurate

7) Please read each statement carefully and then select your response.*

	Very Inaccurate	Moderately Inaccurate	Neither Inaccurate nor Accurate	Moderately Accurate	Very Accurate
I am the life of the party	( )	( )	( )	( )	( )
I start conversations	( )	( )	( )	( )	( )
I don't talk a lot	( )	( )	( )	( )	( )
I keep in the background	( )	( )	( )	( )	( )
I have little to say	( )	( )	( )	( )	( )
I am quiet around strangers	( )	( )	( )	( )	( )
I am always prepared	( )	( )	( )	( )	( )
I get chores done right away	( )	( )	( )	( )	( )
I am exacting in my work	( )	( )	( )	( )	( )
I leave my belongings around	( )	( )	( )	( )	( )
I make a mess of things	( )	( )	( )	( )	( )

I often forget to put things back in their proper place	( )	( )	( )	( )	( )
I am interested in people	( )	( )	( )	( )	( )
I sympathize with others' feelings	( )	( )	( )	( )	( )
I take time out for others	( )	( )	( )	( )	( )
I feel others' emotions	( )	( )	( )	( )	( )
I am not interested in other people's problems	( )	( )	( )	( )	( )
I feel little concern for others	( )	( )	( )	( )	( )
I get stressed out easily	( )	( )	( )	( )	( )
I get upset easily	( )	( )	( )	( )	( )
I change my mood a lot	( )	( )	( )	( )	( )
I have frequent mood swings	( )	( )	( )	( )	( )
I get irritated easily	( )	( )	( )	( )	( )
I often feel blue	( )	( )	( )	( )	( )
I have a rich vocabulary	( )	( )	( )	( )	( )
I have a vivid imagination	( )	( )	( )	( )	( )

I have excellent ideas	( )	( )	( )	( )	( )
I am quick to understand things	( )	( )	( )	( )	( )
I am full of ideas	( )	( )	( )	( )	( )
I have difficulty understanding abstract ideas	( )	( )	( )	( )	( )

Leadership Experience

The next section will ask you to describe your leadership style. If you have never held a leadership position at work, please think about other times where you may have had a chance to lead others.

8) Have you ever held a formal leadership position in any job, in which you had subordinates who reported directly to you?*

( ) Yes

( ) No

9) How much leadership experience have you had in the following non-work areas?*

	Not Applicable	No Leadership Experience	A Little Bit of Experience	Some Experience	A Lot of Leadership Experience
School (class projects, student body)	( )	( )	( )	( )	( )
Sports (cooperative team sports, team captain)	( )	( )	( )	( )	( )
Volunteering (organizing & leading volunteering projects)	( )	( )	( )	( )	( )
Church (volunteering, fundraising)	( )	( )	( )	( )	( )

Household (parent, caregiver)	( )	( )	( )	( )	( )
Other (extracurricular activities, social events)	( )	( )	( )	( )	( )

Leadership Style

The following statements ask you to describe aspects of your leadership style as you perceive it. Read each statement carefully and decide how strongly each statement describes you.

If you are not currently in a formal leadership position at work, consider times you have acted as a leader in school or in your personal life (sports, church, social events, etc). Do your best, even if a statement does not seem to apply to your experiences.

10) Read each statement carefully and decide how strongly each statement describes you.*

	Very Strongly Disagree	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Very Strongly Agree
My followers would agree that I excel at getting the best out of people.	( )	( )	( )	( )	( )	( )	( )
My followers would say that I am a good mentor.	( )	( )	( )	( )	( )	( )	( )
My followers would say that I bring positive energy to work.	( )	( )	( )	( )	( )	( )	( )

Others seem to easily follow my lead.	( )	( )	( )	( )	( )	( )	( )
My followers would be surprised if I did something inconsistent with our shared mission and values.	( )	( )	( )	( )	( )	( )	( )
My followers would tell you that I check in with them on almost a daily basis to find out how they are feeling and thinking.	( )	( )	( )	( )	( )	( )	( )
Above all else, leaders must serve as a positive role model for those they lead.	( )	( )	( )	( )	( )	( )	( )
My followers would say that they know what I stand for.	( )	( )	( )	( )	( )	( )	( )
Each of my followers would say that	( )	( )	( )	( )	( )	( )	( )

I know them personally.							
It is extremely important to me that my followers are creative.	( )	( )	( )	( )	( )	( )	( )
One of my primary goals as a leader is to support the continuous learning of my followers.	( )	( )	( )	( )	( )	( )	( )
My followers would tell you that I care about their needs and concerns.	( )	( )	( )	( )	( )	( )	( )
Things would be a lot easier if people just do what I say without a lot of complaining.	( )	( )	( )	( )	( )	( )	( )
My followers look to me as a role model for their own leadership.	( )	( )	( )	( )	( )	( )	( )
I would never require a follower to do something	( )	( )	( )	( )	( )	( )	( )

that I wouldn't do myself.							
My followers would never say that they are ashamed of something I have done as a leader.	( )	( )	( )	( )	( )	( )	( )
I have found that motivating people to do their best is the primary key to success.	( )	( )	( )	( )	( )	( )	( )
When a follower has an idea that differs form the rest of the group, it's best to just ignore it and move on.	( )	( )	( )	( )	( )	( )	( )
Things would be a lot easier if people just do what I say without a lot of thinking.	( )	( )	( )	( )	( )	( )	( )
My followers would say that I have an extremely	( )	( )	( )	( )	( )	( )	( )

high level of motivation.							
The only way for our team to be successful is if everyone contributes their own thinking and creativity.	( )	( )	( )	( )	( )	( )	( )
My followers would say that I am very attentive to their individual needs and concerns.	( )	( )	( )	( )	( )	( )	( )
I am quite effective in boosting my followers' self-confidence.	( )	( )	( )	( )	( )	( )	( )
My followers would agree that I challenge them to think creatively when solving problems.	( )	( )	( )	( )	( )	( )	( )
In some cases, I would not want my followers to see how I	( )	( )	( )	( )	( )	( )	( )

achieved results.							
Under many circumstances, it is okay for a leader to say one thing and do another.	( )	( )	( )	( )	( )	( )	( )
All my followers would say that I challenge them intellectually.	( )	( )	( )	( )	( )	( )	( )
I spend a great deal of time getting to know my followers individually.	( )	( )	( )	( )	( )	( )	( )
My followers have told me that my enthusiasm is infectious.	( )	( )	( )	( )	( )	( )	( )
My followers would report that they respect and admire my leadership style.	( )	( )	( )	( )	( )	( )	( )
Although I hate to admit it, I wish my followers	( )	( )	( )	( )	( )	( )	( )

would just do what I tell them to do.							
My followers have often told me that they appreciate my attention to their feelings and concerns.	( )	( )	( )	( )	( )	( )	( )
Inspiring others has always come easily to me.	( )	( )	( )	( )	( )	( )	( )
I work hard to provide my followers with an inspirational vision for our group.	( )	( )	( )	( )	( )	( )	( )
My followers would report that I have cheered them up when they were in a bad mood.	( )	( )	( )	( )	( )	( )	( )
Other people look to me for direction.	( )	( )	( )	( )	( )	( )	( )
My followers would say that I create a	( )	( )	( )	( )	( )	( )	( )

supportive environment.							
My followers marvel at my energy.	( )	( )	( )	( )	( )	( )	( )
I try to set a positive example by always working hard.	( )	( )	( )	( )	( )	( )	( )
My followers would say that I encourage innovation.	( )	( )	( )	( )	( )	( )	( )

Social Media Use

11) On average, how often do you use the following social media sites?

	I don't have an account	I have an account but I rarely check it	I check my account once a month	I check my account once a week	I check my account once a day	I check my account multiple times per day
Facebook	( )	( )	( )	( )	( )	( )
LinkedIn	( )	( )	( )	( )	( )	( )
Twitter	( )	( )	( )	( )	( )	( )
Google+	( )	( )	( )	( )	( )	( )

12) The next few questions refer to your computer skills and privacy on Facebook. Please indicate the extent to which you agree or disagree with the statements.*

	Very Strongly Disagree	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree	Very Strongly Agree
I consider myself a skilled computer user	( )	( )	( )	( )	( )	( )	( )
I can troubleshoot most computer hardware and software issues	( )	( )	( )	( )	( )	( )	( )
I feel knowledgeable about Facebook's privacy settings	( )	( )	( )	( )	( )	( )	( )
Thanks to Facebook's privacy settings, I only share my information with the people I intend to	( )	( )	( )	( )	( )	( )	( )
I frequently edit the privacy settings on my Facebook account	( )	( )	( )	( )	( )	( )	( )
I frequently review the posts on my Facebook Wall	( )	( )	( )	( )	( )	( )	( )
I frequently delete posts from my Facebook Wall	( )	( )	( )	( )	( )	( )	( )

Volunteer for Part 2 of this research

CLICK THE "SUBMIT" BUTTON TO VOLUNTEER FOR PART 2 OF THIS STUDY AND BE ENTERED A SECOND TIME INTO THE DRAWING FOR AN IPAD MINI

The next page will ask you to log in to Facebook and grant permissions to the Evolv Social Tools app. As a reminder, your Facebook login and password ARE NOT collected as part of this study and your profile information will remain CONFIDENTIAL. Information from this research study, including your Facebook information, WILL NOT be shared with the Results Companies. However, for the tool to work you will need to log in to your Facebook account.

If you do not have a Facebook account or you do not want to share your Facebook info, you may simply close your browser window.

This study will determine whether Facebook information can actually predict job outcomes (performance & turnover) more accurately than traditional screening methods. Despite numerous press reports and anecdotal stories of employers using or misusing Facebook during the hiring process, there is very little evidence one way or the other. In addition, this study will also determine whether the use of social media information leads to unintentional discrimination on the basis of race, gender, or age.

If you would like to receive more information about this study or receive a summary of results upon completion, please contact Tim Lisk at timothy.lisk@cgu.edu.

OPTIONAL (not part of the study): To learn more about The Results Companies, you are invited to visit and Like their Facebook page at https://www.facebook.com/pages/The-Results-Companies/427879619376

Thank you! You will be redirected to the Evolv Social Tools app in a few seconds.

Appendix B

Social Media Reviewer Instructions

For this study, you will step into the shoes of a recruiter, reviewing the publicly available social media profiles of 40 job candidates applying for an entry level, customer service position. The customer service position requirements include:

1. Polite attitudes and social skills; the ability to quickly establish rapport over the phone
2. Efficiency
3. Accuracy
4. Dependability and reliability
5. General computer skills

If they're hired, employees can expect their job performance to be measured and evaluated by metrics such as:

1. How well a customer's issue was handled (customer service scores)
2. How much time it takes to resolve a customer's issue
3. Whether or not a customer's issue was actually resolved (i.e. did the custom have to call back again later for more help?)
4. Tardiness and absences

These jobs typically have very high attrition or turnover - it can be stressful answering calls for hours at a time, efficiently, while also maintaining a positive, helpful attitude. The company hiring for these jobs will bring in dozens of new hires every week.

Your task today will be to quickly scan Facebook profiles of the candidates and answer a few follow-up questions for each profile. You should work efficiently – do not spend too much time reviewing each profile. Remember, you have dozens of openings to fill!

For the purposes of this study, you can assume each candidate has also submitted a resume, job application, assessment, and will need to complete a phone interview and background check prior to being hired. So you should really only scan their Facebook profiles for red flags that might make you think twice about hiring someone.

First we'll start with a few questions about you to help calibrate rater responses, and then on to the Facebook profiles.

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