New Talent Signals: Shiny New Objects or a Brave New World?

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RUNNING HEAD: New Talent Signals

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Abstract

Almost 20 years after McKinsey introduced the idea of a war for talent, technology is disrupting the talent identification industry. From smartphone profiling apps to workplace big data, the digital revolution has produced a wide range of new tools for making quick and cheap inferences about human potential and predicting future work performance. However, academic I/O psychologists appear to be mostly spectators. Indeed, there is little scientific research on innovative assessment methods, leaving HR practitioners with no credible evidence to evaluate the utility of such tools. To this end, the present article provides an overview of new talent identification tools, using traditional workplace assessment methods as the organizing framework for classifying and evaluating new tools, which are largely technologically-enhanced versions of traditional methods. We highlight some opportunities and challenges for I/O psychology practitioners interested in exploring and improving these innovations.

Keywords: talent identification, technology, big data, social media, gamification

Friedrich Hegel thought conflict and war were the major engines of progress (Black, 1973). McKinsey & Company's notion of a war for talent (Chambers, Foulon, Handfield-Jones, Hankin, & Michael III, 1998) has created considerable interest in the development, validation, and application of innovative tools for quantifying human potential (Chamorro-Premuzic, 2013). Like other forms of warfare, the talent war has spurred an explosion of digital tools for identifying new talent signals – i.e., non-traditional indicators of work-related potential. As a result, not only are talent identification practices rapidly becoming more high-tech, but they are evolving faster than I/O psychology research (Roth, Bobko, Iddekinge, & Thatcher, 2016). This leaves academics playing catch-up, and HR practitioners with many unanswered questions: e.g., how valid are these methods; are new technologies just a fad; can new tools disrupt traditional assessment methods; what are the ethical constrains to adopting these new tools? This article attempts to address some of these questions by reviewing recent innovations in the assessment and talent identification space. We review these innovative tools by highlighting their link to equivalent old school methods. For example, gamified assessments are the digital equivalent of situational judgment tests, digital interviews represent computerized versions of traditional selection interviews, and professional social networks, such as LinkedIn, are the modern equivalent of a resume and recommendation letters. Thus our paper draws parallels between the old and new worlds of talent identification, and provides an organizing framework for making sense of the emerging tools we are seeing in this space.

If it ain't broke, don't fix it: The old world of talent is alive and well

Although definitions of talent vary, four basic heuristics distinguish between more and less talented employees. The first is the 80/20 rule (Craft & Leake, 2002) based on Vilfredo Pareto's (1848-1923) observation that a small number of people will generally create a

disproportionate amount of the output of any group. Specifically, around 20% of employees will account for around 80% of productivity, while the remaining 80% of employees will account for only 20% of productivity. Who, then, are the talented individuals? The *vital few* who are responsible for most of the output. The second heuristic concerns the principle of maximum performance (Barnes & Morgeson, 2007), which equates talent to the best an individual can do; that is, people are as talented as their best possible performance. The third heuristic equates talent to effortless performance, emphasizing its relation to innate ability or potential. Because performance is usually conceptualized as a combination of ability (talent) and motivation (effort) (Heider, 1958; Porter & Lawler 1968), talent can be defined as performance minus effort. Thus, if two individuals are equally motivated, the more talented person will perform better. Similarly, if people want to perform as well as those who are more talented than they are, their best bet is to work harder than them. The final heuristic equates talent to personality in the right place. That is, when individuals' skills, dispositions, knowledge and abilities are matched to a task or job, they should perform to a higher level. This definition is the core of the so-called Person-Environment Fit theory of I/O psychology (Edwards, 2008). Thus, a major goal of any talent acquisition venture is to maximize fit between employees' qualities and the role and organization in which they are placed.

With these heuristics in mind, it is possible to classify individuals as more or less talented. People who are part of the vital few, who have displayed higher levels of performance, or achieved high levels without trying hard or having much training, and who seem to have found a niche that fits their dispositions and abilities, will generally be considered more talented. Consider the case of Lionel Messi, the Barcelona soccer star. Although Messi's teammates are usually considered the best soccer players in the world, he is consistently the best player in the

team and in some seasons he is individually responsible for over 60% of the critical goals and assists in his team. This makes Messi not just part of the vital few, but also the vital one, in the team. Furthermore, as hundreds of YouTube compilations show, Messi's maximum performance is matched by none, and it is also effortless – he has been dribbling and scoring in the same way since his early teens and, unlike Cristiano Ronaldo, is not known for training particularly hard. However, while Messi's qualities are certainly in the right place at Barcelona – where he plays with his lifelong friends and shares the values of club and supporters – he has struggled to show a similar form when playing for the Argentine national team. Thus even for an extraordinary talent like Messi, fit matters.

The next step in talent identification concerns two critical questions: what to assess and how (Ployhart, 2006). The "what" question involves defining the key components of talent. This question is important because if you don't know what to measure, there is no point in measuring it well. In other words, you can do a great job measuring the wrong thing, but that will not get you very far. The "how" question concerns the methods that can be used to quantify individual differences in talent – in effect, these are the tools used by consultants, recruiters and coaches to help organizations win the war for talent. We see test designers and publishers as arms merchants in the war for talent. We ourselves provide scientifically defensible "weapons" that help organizations win the talent war by better understanding and predicting work-related behaviors, particularly in leaders. There are, of course, many other key players in the war for talent: from CEOs, who represent the generals, to HR managers, who are the lieutenants, to coaches and consultants, who are the soldiers, hit men or mercenaries, respectively. We all share a common goal, which is to help organizations attract, engage, and retain more talented individuals, who are the commodity being fought over.

To provide a more granular answer to the "what" question of talent identification, we can examine the qualities that talented individuals tend to display at work. As argued earlier in this journal, the generic attributes of talent can be described with the acronym RAW (Hogan, Chamorro-Premuzic, & Kaiser, 2013). First, talented people are more *rewarding to deal with* (R)—they are likable and pleasant. Interpersonal and intrapersonal competencies such as EQ, emotional stability, political skill, and extraversion capture this core element of talent, which enables individuals to get along at work (Van Rooy & Viswesvaran, 2004). And in a world where the employees' direct line manager tends to determine career success, it is unsurprising that perceptions of talent will be largely driven by being pleasant and rewarding to deal with. Second, talented people are more *able* (A), meaning they learn faster and solve problems better. This is a function of experience, general intellectual ability (Schmidt & Hunter, 1998), and the domain-specific expertise which the Nobel laureate Herbert Simon described as a person's "network of possible wanderings" (Amabile, 1998). The more able employees are, the easier it is for them to make sense of work-related problems, translate information into knowledge, and quickly identify patterns in critical work tasks. Third, talented people are more *willing to work hard* (W), thereby displaying more initiative and drive. This theme, which concerns how employees get ahead, is reflected in meta-analytic studies highlighting the consistent positive effects of ambition, conscientiousness, and achievement motivation on job performance and career success (Almlund, Duckworth, Heckman, & Kautz, 2011). Although the labels vary, these universals of talent comprise fairly stable individual differences that have been studied and validated extensively in I/O psychology, as well as social, educational, and differential psychology (Kuncel, Ones & Sackett, 2010). A great deal of conceptual confusion about talent arises because organizations prefer their own labels, and they devote significant time devising

"original" competency models – as the saying goes, "a camel is a horse designed by a committee."

As for the "how" question, it is noteworthy that traditional methods for talent identification are alive and well. Indeed, 100-years of research in I/O psychology provide conclusive evidence for the validity of job interviews (Levashina, Hartwell, Morgeson, & Campion, 2014), assessment centers (Thornton & Gibbons, 2009), cognitive ability tests (Schmitt, 2013), personality inventories (J. Hogan & Holland, 2003), biodata (Breaugh, 2009), situational judgment tests (Christian, Edwards, & Bradley, 2010), 360-degree feedback ratings (Borman, 1997), resumes (Cole, Feild, & Stafford, 2005), letters of recommendations (Chamorro-Premuzic & Furnham, 2010), and supervisors' ratings of performance (Viswesvaran, Schmidt, & Ones, 2005). Unfortunately, HR practitioners are not always aware of this literature, or remain attached to their amateurish competency labels and meta-models, which explains why they often prefer to rely on their intuition to identify talent (Dries, 2013), and also why the face and social validity of these methods are often unrelated to their psychometric validity (Chamorro-Premuzic, 2013a). Similarly, shiny new talent identification objects often bamboozle recruiters and talent acquisition professionals, with no regard for predictive validity.

For example, employers and recruiters have used social media to evaluate job candidates for several years. Intuitive examinations of social media profiles are a popular, albeit clandestine, method for "discovering the applicant's true self." Informal assessments of candidate's online reputation, called "cyber-vetting" (Berkelaar, 2014), are often preferred to reviewing the more formal but overly polished resume. Yet, most people spend a great deal of time curating their online personae, which are burnished by the same degree of impression management and social desirability as their resumes (Back, M. D., Stopfer, J. M., Vazire, S., Gaddis, S., Schmukle, S. C.,

Egloff, B., & Gosling, S., 2010). Burnishing has even been taken as a right, seen in the ability of European Union citizens to limit access and hide links to images or posts that do not fit the reputation they want to portray online (Warman, 2014). When social media users decide what images, achievements, musical preferences, and conversations to display online, the same self-presentational dynamics are at play as in any traditional social setting (Chamorro-Premuzic, 2013b). Consequently, people's online reputation is no more "real" than their analogue reputation; the same individual differences are manifested in virtual and physical environments, albeit in seemingly different ways. It is therefore naïve to expect online profiles to be more genuine than resumes, although they may offer a much wider set of behavioral samples. Indeed, recent studies suggest that when machine-learning algorithms are used to mine social media data they tend to outperform human inferences of personality in accuracy because they can process much bigger range of behavioral signals (Youyou, Kosinski, and Stillwell, 2015). That said, social media is as deceptive as any other form of communication (B. Hogan, 2010); employers and recruiters are right to regard it as a rich source of information about candidates' talent – if they can get past the noise and make accurate inferences.

For their part, candidates seem to expect that their digital lives will be examined for hiring purposes (El Ouirdi, Segers, El Ouirdi, & Pais, 2015). Although studies suggest that candidates may find cyber-vetting unfair (Madera, 2012), most seem habituated to the idea that their social media activity will influence potential staffing or promotion decisions. Indeed, one study found that nearly 70% of respondents agreed that employers have the right to check their social networking profile when evaluating them (Vicknair, Elkersh, Yancey, & Budden, 2010). Job applicants may therefore face a "posting paradox" (Berkelaar & Buzzanell, 2015), torn between sharing authentic personal information – and risking inappropriate self-disclosure – or

creating a professional but deceptive online persona that appeals to potential employers. Yet

humans always regulate their social behavior to conform to others' expectations and social rules,

even when the environment tolerates narcissistic indulgences in self-presentation, such as on

Facebook. This is the fundamental skill that enables people to live in harmony and reflects

individual differences in social competence (Kaiser, R. Hogan, & Craig, 2008).

The new kids on the blog: Talent in the digital world

Most innovations in talent identification are the product of the digital revolution, enabled

by the application of innovative tools designed to evaluate massive data sets. As the human need

for connectedness met digital and mobile technologies, it has generated a wealth of data about

individuals' preferences, values, and reputation. These traces of behavior, also known as the

online footprint or digital breadcrumbs, may be used to infer talent or job-related potential. For

example, M.I.T. researchers used phone metadata (e.g., call frequency, duration, location, etc.) to

produce fairly accurate descriptions of users' personalities (de Montjoye, Quoidbach, Robic &

Pentland, 2013). Similarly, Chorely, Whitaker, and Allen (2015) successfully inferred some

elements of the big five-personality taxonomy by tracking user location behavior. Although data

has turbo-charged analytics in fields as diverse as medicine, credit and risk, media and

marketing, HR generally lags behind. Despite all the talk about a big data revolution in HR and

the rebranding of the field as "people analytics," novel talent identification tools are still in their

infancy, and user-adoption is relatively low even in industrialized markets. One notable

exception is the use of professional social networking sites, such as LinkedIn, for recruitment

purposes. However, these sites are simply the modern equivalent of a resume and phone

directory, with the option of including personal endorsements (the modern version of a

recommendation letter). Inferences based on these signals are mostly holistic and intuitive; and

the focus is on hard skills rather than core talent qualities, e.g., ambition, EQ, intelligence (Zide, Elman, & Shahani-dennig, 2014). Nonetheless, demand for recruitment-related networking sites is estimated to be growing at around 15%-20% per year (Handler, 2014), with hundreds of startups offering technologies to screen, interview, and profile candidates online (Davison, Maraist, Hamilton, & Bing, 2012).

Insert table 1 about here

These new ventures are predominantly based on four methodologies which have the potential to disrupt and perhaps even advance the talent identification industry; they are: (1) digital interviewing & voice profiling, (2) social media analytics & web scraping, (3) internal big data & talent analytics, and (4) gamification. As shown in Table 1, each of these methodologies corresponds to a well-established talent identification approach. We discuss the new methodologies below.

Digital interviewing and voice profiling

Although pre-employment job interviews are generally less valid than other assessment tools, they are ubiquitous (Roth & Huffcutt, 2013). Furthermore, job interviews are often the only method used to evaluate candidates, and when used in conjunction with other methods they are generally the final hurdle applicants need to pass. Technology can make interviews more efficient, standardized, and cost-effective by enhancing both structure and validity (Levashina et al., 2014). Some companies have developed structured interviews that ask candidates to respond via webcam to pre-recorded questions using video chat software similar to Skype (thus *digital interviewing*). This increases standardization and allows hiring panels and managers to watch

the recordings at their convenience. Moreover, through the addition of innovations, such as text

analytics (see below) and algorithmic reading of voice-generated emotions, a wider universe of

talent signals can be sampled. In the case of voice mining, candidates' speech patterns are

compared to an "attractive" exemplar, derived from the voice patterns of high performing

employees. Undesirable candidate voices are eliminated from the context and those who fit

move to the next round. More recent developments use similar video technology to administer

scenario-based questions, image-based tests, and work sample tests. Work samples are

increasingly common, automated and sophisticated. For example, Hirevue.com, a leading

provider of digital interview technologies, employs coding challenges to screen software

engineers for their software writing ability. Likewise, Uber uses similar tools to test and evaluate

potential drivers exclusively via their smartphones (see www.uber.com).

Based on Ekman's research on emotions (Ekman, 1993), the security sector has

developed micro-expression detection and analysis technology to enhance the accuracy of

interrogation techniques for identifying deception (Ryan, Cohn, & Lucey, 2009). The recent

creation of large databases of micro-expressions (Yan, Wang, Liu, Wu, & Fu, 2014) is likely to

facilitate the standardization and validation of these methods. Beyond using automated emotion

reading, new research aims to correlate facial features and habitual expression with personality

(Kosinski, 2016). Although effect sizes tend to be small, this methodology can provide additional

talent signals to produce more accurate and predictive profiles.

Social media analytics & web scraping

Humans are intrinsically social, and our need to connect is the driving force behind

Facebook's dominance in social networking – it is estimated that nearly 25% of all the people in

the world (and 50% of all internet users) have active Facebook accounts. Unsurprisingly,

Facebook has become a useful research tool – and ecosystem – to evaluate human behavior (Kosinski, Matz, & Gosling, 2015). Research finds that aspects of Facebook activity, such as users' photos, messages, music lists, and "likes" (reported preferences for groups, people, brands, and other things), convey accurate information about individual differences in demographic, personality, attitudinal, and cognitive ability variables. Michal Kosinski and colleagues have shown that machine-learning algorithms can predict scores on well-established psychometric tests using Facebook "likes" as data input (Kosinski, Stilwell & Graepel, 2013). This makes sense, since "likes" as the digital equivalent of identity claims: "likes" tell others about our values, attitudes, interests, and preferences, all of which relate to personality and IQ. In some cases, associations between Facebook "likes" and psychometrically derived individual difference scores are intuitive. For example, people with higher IQ scores tend to "like" Science, the Godfather movies, and Mozart. However, other associations are less intuitive and may not have been discovered without large-scale exploratory data mining. For example, one of the main markers – strongest signals – of high IQ scores was "liking" Curly Fries (a type of French fry, popular in the U.S., characterized by a wrinkly, spring-like, shape). Somewhat ironically, media coverage of this finding led to an increase in "liking" Curly Fries, presumably without causing a global rise in IQ scores. However, unlike the static scoring keys used in traditional psychometric assessments, machine-learning algorithms can auto-correct in real-time. Thus, when too many unintelligent individuals "like" Curly Fries, they cease to signal higher intelligence. This point is important for thinking about validity in the digital world: some talent signals may not generalize from particular contexts, or may change over time (like Curly Fries). Facebook is allegedly interested in using personality to understand user behavior, and incorporates a wide range of personal signals, such as hometown, frequency of movement, friend count, and educational level

to segment its audience for media and marketing purposes (Chapsky, 2011). Perhaps the same information will soon be used for talent management purposes, especially in recruitment or pre-hiring decisions. Social media analytics has turned up several such counterintuitive associations, which big data enthusiasts and HR practitioners care little about because their main goal is to predict, rather than explain, behavior. I/O psychologists on the other hand – and psychologists in general – may fret about the a-theoretical, black box, data-mining approach, which has created somewhat of a gap – and tension – between the science and the machine approach.

Some estimates suggest that 70% of adults are passive job-seekers (i.e., not actively searching for new jobs, but open to new opportunities), and companies like TalentBin and Entelo identify potential job candidates outside the pool of existing job applicants (Bersin, 2013). Entelo claims that it can search (scrape) 200 million candidate profiles from 50 internet sources and identify individuals likely to change jobs within the next three months (Entelo Outbound Recruiting Datasheet). If these claims are accurate, then it raises the possibility of placing workers in more relevant roles, and lowering the proportion of disengaged employees, the economic value of which should not be underestimated.

Another unexpected talent signal concerns the language people use online. Psychologists from Freud and Rorschach onwards have argued that people's language reveals core aspects of their personalities (Tausczik & Pennebaker, 2010). Linguistic analysis is a promising methodology for inferring talent from web activity, and it can be applied to free-form text (Schwartz, Eichstaedt, Kern, Dziurzynski, Ramones, Agrawal, Shah, Kosinski, Stillwell, Seligman & Ungar, 2013). This methodology has been around for 25 years, but modern scraping tools and publicly available text have made it applicable to large-scale profiling. Indeed, work with the Linguistic Inquiry and Word Count application (LIWC; Pennebaker, 1993) has shown

that some LIWC categories correspond to the big-five personality traits (Pennebaker, 2011). For

example, for both males and females, higher word count and fewer large words predicted

extraversion (Mehl, Gosling, & Pennebaker, 2006), which itself correlates with leader

emergence (Grant, Gino, & Hofmann, 2011). Other work (Schwartz et al., 2013) shows that

gender, religious identity, age, and personality can be identified from linguistic information.

Unlike other areas of assessment-related innovations, peer-reviewed studies provide

evidence for the links between word usage and important individual differences. For example,

the words that neurotics use in blogs include "awful," "horrible," and "depressing" whereas

extraverts talk about "bars," "drinks," and "Miami" (Schwartz et al., 2013; Yarkoni, 2010). Less

intelligent people mangle grammar and make more frequent spelling errors. There are free tools

available to infer personality from open text (IBM's Watson does it for you here:

http://bit.ly/1OjlkuR). These tools allow us to copy and paste anyone's writing into a web page

and generate their personality profile. New applications analyze email communications, and

provide users with tips on how to respond to senders, based on their inferred personality

http://bit.ly/1lkv5gB; others use speech-to-text tools, and then parse the text through a

personality engine (e.g. HireVue.com).

What is unknown is whether these types of talent signals are additive in terms of the

predictive power. For example, does biodata and Facebook likes and voice profiling improve

prediction of work related outcomes? This is an area ripe for large scale research.

Big data and workplace analytics

In-house data is another source of information about talent. Because so much work is

now digital -- recorded or being logged and transmitted via the internet-of-things --

organizational performance data is both vast and fine-grained. Mining these data for critical

signals of talent is consistent with the traditional I/O psychology view that past behavior is a good predictor of future behavior. For example, big data may be used to connect aggregate sales staff personality variables, LinkedIn use, engagement scores, and sales activity (including number of calls, frequency, length of time spent with customers, and net promoter scoring) to customer ordering data and future revenues. Once the data are recorded, models can be developed and tested backwards in time to create predictions (as is the case when modelling sharemarket behavior).

Sandy Pentland and his MIT colleagues have used tracking badges to follow employees' behaviors at work and record frequency of talking, turn taking, and so on. This showed where people go for advice (or gossip), and how ideas and information spread within an organization. These data predicted team effectiveness (Woolley, Chabris, Pentland, Hashmi & Malone, 2010) as well as identifying the individuals who are a central node in the network (presumably because they are more useful to the organization, or because they have more and stronger connections with colleagues).

One critical ingredient in talent identification is the criterion space – the empirical evidence of talent. In the I/O field, the well-known criterion problem (Austin & Villanova, 1992) remains problematic. Bartram noted that traditional validation research has been predictor centric (Bartram, 2005) and despite the development of competency frameworks (e.g. Lombardo & Eichinger, 2002), criterion data remains noisy, dependent on supervisor ratings, and unsatisfactory. Although more data may not help conceptually, finer understanding of performance is possible in principle, although this issue has not been addressed to date. Emergent tools and products suggest that this inevitably will happen.

For example, an important area in organizational big data is the case of peer-evaluations or open source ratings. Glassdoor, a sort of Yelp of workplaces, is a good example. The site enables employees to rate their jobs and work experience, and has manager ratings for nearly 50,000 companies; anybody can retrieve the ratings. This enables employers to see how employees perceive the company culture and how individual managers have impacted workers and workplaces. With these data organizations can effectively crowdsource their evaluations of leadership, looking at the link between employees' ratings and company performance.

So long as organizations have robust criteria, their ability to identify novel signals will increase, even if those signals are unusual or counterintuitive. As an example of an unlikely talent signal, Evolv, an HR data analytics company found that applicants who use Mozilla Firefox or Google Chrome as their web browsers are likely to stay in their jobs longer and perform better than those who use Internet Explorer or Safari (Chow & Blumberg, 2014). Knowing which browser candidates used to submit their online applications may prove to be a weak but useful talent signal. Evolv hypothesizes the correlation between browser usage, performance, and employment longevity reflects the initiative required to download a non-native browser (Chow & Blumberg, 2014).

Gamification

More Americans play games than do not, half of all gamers are under the age of 35 (Statista, 2015), and parents mostly think video games are a positive influence on their children (Big Fish Games, 2015); therefore, it seems obvious to look for talent signals via this medium. For instance, HR Avatar conducts workplace simulations in the form of interactive cartoons aimed at customer service or security roles. Or consider the personality assessments developed

by Visual DNA which present users with choices in the form of images and pictures, an intuitive

and engaging experience with validity comparable to other questionnaire formats.

Gamification is now mobile. One company, Knack, claims to evaluate several different

talents ('knacks') from playing puzzle-solving games on mobile phones. What is interesting is

that Knack has completely taken on the gamified persona, awarding players badges that they can

share with friends. Another company, Pymetrics, gamifies some of the assessment principles of

neuroscience to infer the personality and intelligence of candidates (Noguchi, 2015). Whether

and to what degree it is useful to share this information with others, is yet to be seen. But this

approach represents a shift in the relationship between test providers, test takers, and firms: from

a B2B to a B2C model, and from a reactive to a proactive test taker. We predict that the testing

market will increasingly transition from the current *push* model--where firms require people to

complete a set of assessments in order to quantify their talent--to a *pull* model where firms will

search various talent badges to identify the people they seek to hire. In that sense, the talent

industry may follow the footsteps of the mobile dating industry. Consider the case of Tinder, a

popular and addictive mobile dating app. First, users agree to have some elements of their social

media footprint profiled, when they sign up for the service. Next, their peers are able to judge

these profiles and report whether they are interested in them or not by swiping left or right (a

gamified version of hot-or-not). This is consistent with research showing that personality traits

can be accurately inferred through photographs and that these inferences drive dating and

relationship choices (Zhang, Kong, Zhong, Kau, 2014). Finally, if the algorithm determines a

match both parties receive instant feedback on their preferences. This model could easily be

applied to the talent identification and staffing process. In fact, it is easier to predict job

performance and career success than relationship compatibility and success.

The enablers of new tools

The World Wide Web has made it possible for workers to leave digital footprints all over the Internet, perhaps most prominently on social networking sites. However, without devices to examine these footprints, these novel talent signals would be of no use. Technological advances in three key areas have made the new tools of HR professionals possible: data scraping, data storage, and data analytics.

Data scraping involves gathering data that is available on websites, smartphone and computer networks, and translating these data into behavioral insights. Gathering data on potential workers is a first step towards understanding what they are like, and some of the most powerful devices for gathering and manipulating data are open source and free to use (e.g., Python, Perl), making them quite flexible and readily available. Because many data scraping devices require working with and/or developing Application Program Interfaces (i.e., programming skills), HR professionals are enlisting computer programmers to develop customized devices for their data scraping needs.

The availability of large amounts of useful data has increased demand for data storage. As a result, devices for data storage and centralization have emerged; they include cloud-based storage systems (e.g., iCloud, Dropbox) and advanced HADOOP clusters, which allow for massive data storage and enormous computer processing power to run virtually any application.

Finally, advances in data analytics have created interesting new HR tools. For example, software for text analysis and object recognition can rapidly transform purely qualitative information into quantitative data. Such data can then be submitted to a variety of new analytic techniques such as machine learning. In contrast with traditional data analytic techniques, machine-learning techniques rely on sophisticated algorithms to: (a) detect hidden structures in

the data (i.e., unsupervised learning); or (b) develop predictive models of known criteria (i.e., supervised learning). Once again, some of the most powerful tools for conducting these analyses are open source and free (e.g., R: R Core Team, 2015) making them available to anyone.

The future is here, but be careful

As William Gibson pointed out, the future is already here; it's just not yet evenly distributed. In a hyper-connected world where everyday behaviors are recorded, unprecedented volumes of data are available to evaluate human potential. I/O psychologists need to recognize the impact our digital lives will have on research methods, findings, and practices. We believe that these vast data pools and improved analytic capabilities will fundamentally disrupt the talent identification process. There are several key points to be derived from our review. First, many more talent signals will become available. Second, even if these emerging signals are weak or noisy, they may still work additively and be useful. Third, new analytic tools and computing power will continue to emerge and allow us to improve and refine the prediction of behavior in a wide range of contexts, probably based on the additive nature of these signals. Alternatively, if they do not prove to be additive, we anticipate that subsets of these signals will allow more specific prediction of performance. That is to say, computing power and the vast number of data points will allow for much greater alignment between the criterion and predictor, which is a fundamental tenet of validity (J. Hogan & Holland, 2003).

The datification of talent is upon us, and the prospect of new technologies is exciting. The digital revolution is just beginning to appear in practice, and research lags our understanding of these technologies. We therefore suggest four caveats regarding this revolution.

First, the new tools have not yet demonstrated validity comparable to old school methods, they tend to disregard theory, and they pay little attention to the constructs being assessed. This

issue is important but possibly irrelevant, since big data enthusiasts, assessment purveyors and

HR practitioners are piling in to this space in any event. Roth and colleagues (Roth et al., 2016)

point out that construct validity is lacking when using information from social media for

employment purposes, which does not seem to worry big data enthusiasts who are simply

interested in finding relationships between variables. In our view, predicting behavior is clearly

a key priority in talent identification, but understanding behavior is equally important. Indeed,

scientifically defensible assessment tools provide not just accurate data – they also tell a story

about the candidate that explains why we may expect them to behave in certain ways. Until we

have peer-reviewed evidence regarding the incremental validity of the new methods over and

above the old, they will remain bright, shiny objects in the brave new world of HR. Though, as

we have pointed out, shiny objects interest HR practitioners regardless of their demonstrated

validity and reliability.

Three additional issues may constrain the implementation of new assessment tools in

talent identification processes. First, privacy and anonymity concerns may limit access to

individual data, a point that has been raised repeatedly in earlier scholarly articles (Brown &

Vaughn, 2011; Davison, et al., 2012; Roth, et al., 2016). On the other hand, scholarly concern

has not stopped recruiters, HR, or managers from using individuals' digital profiles, nor has it

slowed the development of tools designed specifically to do this. Individuals may provide

consent for their data to be used without understanding the implications of doing so, or may

simply be unaware. Governments and privacy advocates may step in to regulate access or

control usage, but it would be better if consumers fully understood what can be known about

them and how that information might be used. Note, however, that in other fields of application,

such as programmatic marketing, predictive analytics appear to operate without many ethical

concerns, even though they offer relatively less to consumers – e.g., the promise of a relevant ad is arguably less enticing (and likely) than the promise of a relevant job.

Second, in order to match or surpass the accuracy attained by established tools, the cost of building new tools may be prohibitive. For example, developing a valid and comprehensive gamified assessment of personality costs much more than a traditional self-report or situational judgment test. Thus there is a natural tension between price, accuracy and user-experience: e.g., when you increase the user-experience, you increase price but decrease accuracy; when you increase accuracy, you increase price; and if you want to maintain the same level of accuracy while improving the user-experience, you increase price substantially.

Third, new tools are extremely likely to identify individual's ethnicity, gender or sexual orientation as well as talent signals. Certainly in the U.S., and throughout much of the industrialized world, EEOC guidelines concerning adverse impact must be considered; even a fundamentally solid assessment tool *should* come under additional scrutiny if it is seen to contribute to adverse impact. This issue strengthens the case for more evidence-based reviews of any emerging tools, in particular those that scrape publically available records of individuals (e.g., Facebook or other social media algorithms). Clearly, emerging tools enable employers to know more about potential candidates than they probably should, and ethical concerns – as well as the law – may represent the ultimate barrier to the application of new technologies.

In short, people are living their lives online. By doing so they make their behavior public, and that behavior leaves more or less perpetual traces – often inadvertently. The ability to penetrate the noise of all this information and identify robust talent signals is improving, but merging today's fragmented services with scientifically proven methods will be necessary to create the most accurate and in-depth profiles yet.

Last Thoughts

In the context of overall enthusiasm for these adventures in digital mining as applied to talent identification, we have two last thoughts. First, although it is clear that most of the innovations discussed in this paper have yet to demonstrate compelling levels of validity, such as those that characterize academic I/O research, from a practical standpoint that may not be too relevant. As most I/O psychologists will know, there is a substantial gap between what science prescribes and what HR practitioners do, especially around assessment practices. In particular, the accuracy of talent identification tools is not the only factor considered by real-world HR practitioners when they make decisions about talent identification methods. And, even when it is, most real-world HR practitioners are not competent enough to evaluate accuracy – this enables vendors to make bogus claims, such as "the accuracy of our tool is 95%." In a world driven by accuracy, the Myers-Briggs would not be the most popular assessment tool. It seems to us that organizations and HR practitioners are more interested in price and user-experience than accuracy.

Second, the history of science is much more one of adventitious and serendipitous findings than many people realize. Raw empiricism has often produced marvelously useful outcomes. So we are not at all worried about the fact that this explosion of talent identification procedures are uninformed by any concerns with well-established personality theory and what we know about the nature of human nature. As discussed, there are two fundamental questions underlying the assessment process: (1) What to assess? and (2) How to assess it? Virtually all of the innovative thinking in the digital revolution in talent identification concerns the second question. Having scraped and collated the various on-line cues, the next question concerns how to interpret the data. As Wittgenstein (an Austrian proto-psychologist) once observed, "In psychology there are

empirical methods and conceptual confusions." The most thoughtful of the data scrapers have provided evidence that their data can be used to predict aspects of the Five-Factor Model, an idea at least 65 years old. Going forward it would be nice to see as much effort put into re-conceptualizing personality as is being put into assessment methods. In the end, true advancements will come if we can balance out data and theory, for only theory can translate information into knowledge. As Immanuel Kant famously noted: "Theory without data is groundless, but data without theory is just uninterpretable".

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Table 1: A comparison between old and new talent identification methods

Old methods	New tools	Dimension assessed
Interviews	Digital interviews Voice profiling	Expertise, social skills, motivation, intelligence
Biodata **Supervisory ratings**	Big data (internal)	Past performance Current performance
IQ **SJT** **Self-reports**	Gamification	Intelligence, job-related knowledge, big five personality traits or minor traits
Self-reports	Social media analytics	Big five personality traits and values (identity claims)
Resumes **References**	Professional social networks (LinkedIn)	Experience, past performance, technical skills and qualifications
360s	Crowdsourced reputation / peer-ratings	Any personality trait, competencies, reputation