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THE NEW TECHNOLOGIES IN PERSONALITY ASSESSMENT: A REVIEW

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This article reviews various new approaches to assessing personality. They are divided into five areas: big data, wearable technology, gamification, video-résumés, and automated personality testing. These are briefly described and the available evidence for their psychometric properties considered. At this stage there is more *absence of evidence* of the psychometric properties of these new approaches than *evidence of absence* of their validity. There is limited, but growing, research on each of these methods that may offer new and improved ways of assessing personality. Test publishers and consultants report that their clients, interested in assessment, are eager to exploit the new technologies irrespective of there being good evidence of their reliability and validity.

Keywords: big data, wearables, gamification, personality

Most people correctly assume that self-reports and interviews are the most common ways to assess personality (Chamorro-Premuzic & Furnham, 2012). The limitation of these methods, specifically dissimulation, impression management, and self-delusion, has meant that researchers have sought other, and better, methods to assess personality. There are also other factors that have led researchers to explore new methodologies to measure personality, including reduced costs, reactions by test-takers, and improved psychometric validity. For instance, studies have shown that personality traits can be predicted from online behavior (Amichai-Hamburger, 2007; Amichai-Hamburger & Hayat, 2013).

It is difficult not to be aware of developments in the psychological assessment of people. Consulting psychologists often lead the trend in developing and using new measures. Some work closely with new start-ups that attempt to exploit the opportunities that new technology offers to assess people more accurately, easily, and cheaply. Many are early adopters, indeed even pioneers, in the field. Others find that it is client demand that causes them to investigate, and then use, new tools and techniques that show that they are at the cutting edge of psychometrics (Furnham, in press). Some will inevitably be in the late majority, while others might even be laggards. The question for many must be the investment of time and money in techniques that in the end fail to

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deliver what they promise and may indeed cause many additional problems. This article sets out to help people navigate this brave new world.

There are plenty of speculators and futurologists in this area, both academic and nonacademic, the latter often being science journalists, practitioners, and consultants. An example is McHenry (2017), himself both an academic and a test publisher. He made five assertions about the future of psychometric tests:

> (1) Smartphones will replace computers for employee assessment. (2) High-quality psychometric testing services will be sold direct to consumers. (3) Advances in the neuroscience of personality will reveal which are the most valid individual differences to measure and how best to measure them. (4) The digital badging movement, coupled to the use of Big Data and new forms of digital CV, will render many of the current applications for high-stakes testing redundant. (5) The basis for employee development will in the near future be derived from the data yielded by wearable devices and not from psychometric tests. (p. 268)

Others have discussed issues such as the use of mobile devices (Arthur, Doverspike, Muñoz, Taylor, & Carr, 2014; Illingworth, Morelli, Scott, & Boyd, 2015; Morelli, Mahan, & Illingworth, 2014) and big data (Guszcsa & Richardson, 2014) for the assessment of individuals at work.

Every generation of personality researchers has attempted to exploit the technology of their time. Two of the most famous personality theorists of the 20th century, Hans Eysenck and Raymond Cattell, were particularly imaginative in trying to invent new ways of measuring personality. Eysenck explored many different methods based in biology (the lemon-drop test) and electricity (electroencephalogram techniques), and he considered mechanical tasks (pursuit-rotor task; Eysenck, 1967); Cattell completed a long book on the "objective" measurement of personality (Cattell & Warburton, 1967). Indeed, for nearly 40 years, there has been an interest in the relationship of personality and salivation (Corcoran, 1964; Deary, Ramsay, Wilson, & Riad, 1988). Current technology, particularly brain scanning, appears to offer even more and better opportunities to study individual differences (Finn et al., 2015).

The majority of research has defined personality based on the five-factor model, which suggests that there are five dimensions (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness) that serve as the building blocks to personality (Furnham, 2008). There is a significant amount of research studying the Big Five in relation to academic achievement, cultural differences, personality disorders, and work success, just to name a few.

For nearly two decades, researchers have noted the possibility of using the World Wide Web to do personality research (Buchanan & Smith, 1999). Chapman and Webster (2003) pointed out 15 years ago that the new assessment technologies (predominantly the Web) have specific goals: improve efficiency, enable new screening tools, reduce costs, standardize the human-resources system, expand the applicant pool, promote the organizational image, and increase applicant convenience. There are now companies that track huge numbers of people on the Web and build various profiles, though not following any classical or modern personality theory.

However, there are also unintended consequences and effects of these developments. Thus, the use of the Internet does expand the applicant pool but also increases the number of underqualified and out-of-country applicants. It is not difficult to be flooded with inappropriate applicants in the sense that many people lacking the required and specified qualifications, experience, or place of domicile apply online because it is so convenient, quick, and easy. There is also the loss of personal touch that both assessor and assessee value and respect. There are further concerns about cheating if timed ability tests are used. In addition, there are still concerns about adverse impact, which means that certain groups simply do not have access to the technology to take the tests.

Current technology, particularly brain scanning, appears to offer even more and better opportunities to study individual differences. The past decade has seen a great expansion of many new technologies in the workplace, some of which have been directed at personality assessment and personnel selection. Ranging from social-media analytics for selection to big-data mining for employee improvement, there has been a great interest in the development of new, valid, and efficient ways to assess both job applicants and holders.

In 2010, Stamper reported, based on a survey in the United States, that 45% of hiring managers were using information found from social-networking sites to inform their hiring decisions. Further, 35% of that group did not hire at least one applicant based on what they found. Moreover, over 70% of Forbes Global 2000 companies (Pew Research Center, 2014) surveyed said they intended to use technologies such as gamification for marketing and customer retention. This article reviews these new technologies and the extent to which they are psychometrically valid and reliable measures of personality and individual differences.

Chamorro-Premuzic, Winsborough, Sherman, and Hogan (2016) recently reported how talent identification in the human-resources world is shifting from the traditional methods of assessment, including job interviews, assessment centers, cognitive-ability tests, personality inventories, biodata, situational-judgment tests, 360-degree-feedback ratings, résumés, letters of recommendations, and supervisors' ratings of performance. They identified the four primary new technologies of talent identification. These are digital interviewing and voice profiling, social-media analytics, web scraping and text analytics, and internal big-data and talent analytics and gamification.

Chamorro-Premuzic et al. (2016) predicted that

> profiling tools will become invisible to individuals and require no deliberate attention from job applicants or incumbents. Most people will be profiled already, and if they aren't, assessment will operate in the form of covert or subtle algorithms embedded in other activities, including fun and interactive, game-like experiences. (p. 39)

Yet it is important to note that they have further highlighted that there is little or no academic research for some of these methods, suggesting that the validity and reliability of these tools are still unestablished (Winsborough & Chamorro-Premuzic, 2016). The aim of this review is to provide an up-to-date review and critique of these tools as well as their implications in the workplace.

Big Data

Big data is defined as anything that is too large for typical database tools to be able to capture, store, manage, and analyze (George, Haas, & Pentland, 2014). However, some researchers prefer to define big data by its "smartness" rather than by its size, for example, the extent to which a dataset is able to provide the material to conduct fine-grained analysis that can accurately explain and predict behavior and outcomes (Mahmoodi, Leckelt, van Zalk, Geukes, & Back, 2017).

Yet it should be noted that lots of sites and environments are not open for analysis, which may create various distortions (Labrinidis & Jagadish, 2012). Indeed this is a problem that involves a number of concerns around such things as privacy, proprietary algorithms, and security data, as well as access by the community of scholars interested in the usual academic pursuits of data sharing, replication, and hypothesis testing.

A fundamental principle in psychology is that past behavior is often a good (perhaps the best) predictor of future behavior. As a result, with the explosion of big data, data-mining techniques (which find patterns in the data) are increasingly used to identify markers of talent. There are four predominant areas that allow researchers to collect data that are explored in this review: social media, smart phones, wearable devices, and existing data sets.

Social-Media Analytics

Arguably, the most-researched tool is the use of social media in the workplace. *Social media* is the term used for Internet-based tools used on computers, tablets, and smart phones to help people interact and share information, ideas, and views. Currently, millions of people organize almost the entirety of their lives online and communicate using social media. Therefore, these people have each left a substantial digital footprint (the trail of personal information that remains online as a result of the use of e-mails, social-networking sites, etc.).

The predominant use of social media would appear to be in recruitment and selection of new employees. By collecting information from an individual's Facebook or Twitter profile, a more selective recruitment can be made because of the growing ability to analyze an applicant's personality from what he or she posts online. This also contributes to understanding the compatibility for a potential job applicant with the organization, which is a growing concern for firms as person-to-organization fit is crucial. A rapid rise of businesses employing this technique has been observed—for example, IBM created Watson, which works by using open text to interpret personality—such as extraverts mentioning "bars," "drinks," and "Miami" significantly more often than introverts do. So a company simply has to paste an individual's Twitter posts into Watson, and basic personality traits can be computed (IBM Watson Analytics, 2017).

However, it should be pointed out that algorithms that count target words can introduce inaccuracy, just as spell checkers often do for spelling. For example, if a person wrote "On our day off, we went to *Miami* and had *drinks* in several *bars*" or "On our day off, our last choice would be to go to *Miami* and have *drinks* in *bars*," both statements may be coded as indicators of extraversion or sociability. All intelligent reviewing systems still struggle with deep structure and syntax. The risks of mechanical algorithms include undetectable but inevitable degradation of validity and virtually undetectable and untraceable adverse consequences for individual job candidates. This can have serious methodological and legal problems and implications.

As with a lot of new technologies, the business world appears to be rocketing ahead of academic research. However, there are a number of studies that have recently been conducted that attempt to assess the use of social media as a new personality-assessment tool (Correa, Hinsley, & de Zuniga, 2010; Park et al., 2015). Table 1 identifies more than 30 studies that have been conducted in the last decade that have evaluated if the different features of social media (e.g., profile pictures, status, number of likes, number of friends) can help predict a user's personality.

The research has grown with social media; the earliest research in this area (before the emergence of social media) focused on the Internet as an entirety or the ownership of websites. Marcus, Machilek, and Schütz (2006) compared a relatively large sample of personal website owners to a group of nonwebsite owners on the Big Five dimensions of personality, narcissism, self-monitoring, and self-esteem based on visitors' self-reports. They found that, compared with the general adult population, website owners scored lower on extraversion, agreeableness, and conscientiousness and higher on openness to experience. Due to the self-report nature of this study, the internal validity of the findings is called into question. However, previously, Vazire and Gosling (2004) reported that observers' identity claims from websites are used to convey valid information about personality and that website observers were generally accurate in their assessments of website authors' personalities.

An emerging conclusion from social-media-based research is that individuals' profile pictures can also say a lot about their personality traits. For example, Hall, Pennington, and Lueders (2014) reported that observers could accurately estimate extraversion, agreeableness, and conscientiousness of unknown profile owners based on profile pictures. More specifically, Celli, Bruni, and Lepri (2014) suggested that people who are more extraverted and stable tend to have pictures in which they are smiling. Further, they appear more with other people. On the other hand, introverts tend to appear alone, and neurotics tend to have images without humans and close-up faces.

Various other features of social-networking sites have been shown to predict personality traits. Some researchers have studied the relationship between Facebook popularity (number of contacts) and personality traits. They found that extraversion predicts the number of Facebook contacts; however these findings were not statistically significant (Quercia, Kosinski, Stillwell, & Crowcroft, 2011). Similarly, Gosling et al. (2011) showcased a positive relationship between extraversion and frequency of Facebook usage and engagement. Parallel to offline behavior, extraverts seek out virtual social engagement, leaving behind a digital trail of behavior such as friendship connections or picture postings. However, their work was based on a relatively small sample of just over 150 participants, again limiting the reliability and generalizability of their results. Overall, it appears that extraversion is one of the more predictable traits with information gathered from social media. This was corroborated by Celli et al. (2014), who reported that agreeableness and extraversion can be

Table 1
Studies Using the New Technologies

Study Authors Year	Type of technology	Findings
1. Chorley, Whitaker, and Allen (2015)	Location-based social networks	Examined the personality characteristics and check-in behavior of volunteer Foursquare users; successfully inferred some elements of the Big Five personality taxonomy by tracking user-location behavior
		Openness correlated with location-based variables (average distance between venues visited, venue popularity, number of check-ins at sociable venues)
		For neuroticism, negative correlations were found (number of venues visited, number of sociable venues visited)
		Conscientiousness is positively correlated with the number of venues visited, check-in diversity, and number of check-ins at sociable venues
2. Pinkser (2015)	Type of Internet browser	Evolv, a human-resources 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; it's hypothesized that the correlations among browser usage, performance, and employment longevity reflect the initiative required to download a nonnative browser
3. Kosinski, Bachrach, Kohli, Stillwell, and Grapel (2014)	Contents of personal websites and Facebook activity	Data collected from over 350,000 U.S. Facebook users (and their personality assessments) showed that there are psychologically meaningful links between users' personalities, their website preferences and Facebook profile features
		Website audience-personality profiles were developed such as of deviantART.com, which showed that this website attracts an audience that tends to be liberal and artistic rather than conservative and traditional (i.e., with high Openness), shy and reserved rather than outgoing and active, etc.
		Found significant correlations between Facebook profile features and psychological traits; for instance, liberal and open-to-experience individuals tend to "like" more items on Facebook, post more status updates, and join more groups, and extraversion relates to the number of Facebook friends
4. Celli, Bruni, and Lepri (2014)	Facebook profile pictures	Bag-of-visual-words technique was used to automatically predict personality and interaction styles from profile pictures in Facebook
		Agreeableness and extraversion can be more easily predicted among personality traits, while dominance and affect achieve performances slightly above $f(1) = .6$; emotional stability is the most difficult trait to predict
		Extravert and stable people tend to have pictures in which they are smiling and they appear with other people; introverts tend to appear alone, neurotics tend to have images without humans and close-up faces, etc.

(*table continues*)

Table 1 (*continued*)

Study Authors Year	Type of technology	Findings
5. Lima and de Castro (2014)	Tweets	Developed PERSOMA, a multilabel classifier based on the algorithm-independent approach; its objective is to identify the personality trait of groups of Tweets based only on the information contained in the Tweets themselves, thus not relying on profile data
		The extraversion trait is accurately predicted by all classifiers, whereas the traits of agreeableness and neuroticism also present high accuracy, precision, and recall levels; openness was the most difficult trait to predict, followed by conscientiousness
6. de Montjoye, Quiodbach, Robic, and Pentland (2013)	Phone metadata (e.g., call frequency, duration, location)	Produced fairly accurate descriptions of users' personalities from phone metadata and whether users were low, average, or high on each of the Big Five from 29% to 56% better than random (extraversion and neuroticism were the traits that were best predicted)
7. Kosinski et al. (2013)	Facebook "likes"	Based on the myPersonality database and used relatively straightforward methods (singular value decomposition and linear regression); showed that Facebook "likes" are highly predictive of personality and number of other psychodemographic traits, such as age, gender, intelligence, political and religious views, and sexual orientation
		There are examples of "likes" most strongly associated with given personality traits. For example, users who "liked" Hello Kitty brand tended to have high openness, low conscientiousness, and low agreeableness
8. Schwartz et al. (2013)	Facebook statuses	Applied differential-language analysis to uncover features distinguishing demographic and psychological attributes to 700 million words, phrases, and topic instances collected by myPersonality from Facebook status updates of 75,000 participants; findings showed a striking variation of language driven by personality, gender, and age; this work confirmed existing observations (such as neurotic people's tendency to use the word *depressed*)
9. Hall, Pennington, and Lueders (2014)	Facebook profile pictures	Findings indicate that observers could accurately estimate extraversion, agreeableness, and conscientiousness of unknown profile owners; profile pictures were useful for estimating extraversion and agreeableness
10. He, Glas, Kosinski, Stillwell, and Veldkamp (2014)	Facebook Wall posts	Concluded that the textual posts on the Facebook Wall could partially predict users' self-monitoring skills and that the typical networking language, emoticons, and Internet slang are robust predictors to classify high and low self-monitors
		Expressions related to family topics were found more likely used by low self-monitors
11. Wang and Stefanone (2013)	Location-based social networks	Examined the personality characteristics that lead individuals to share their location-based check-ins with other Facebook users
		Found that extraversion and narcissism did not necessarily relate directly to location-based check-ins but did contribute to exhibitionism and showing off

(*table continues*)

Table 1 (*continued*)

Study Authors Year	Type of technology	Findings
12. Sumner et al. (2012)	Twitter profiles	Focused on attempting to predict the dark-triad personality in social media using machine-learning algorithms and identified significant correlations between the dark triad and Twitter users Found that in linguistic terms, psychopaths and Machiavellians tend to use more swear words and words associated with anger
13. Quercia et al. (2012)	Facebook popularity	Studied the relationship between Facebook popularity (number of contacts) and personality traits Found that extraversion predicts the number of Facebook contacts No statistical evidence for the relationship between popularity and self-monitoring—a personality trait describing an ability adapt to new forms of communication, present oneself in likeable ways, and maintain superficial relationships
14. Qiu, Lin, Ramsay, and Yang (2012)	Linguistic content of Tweets	Found that Tweets contain valid linguistic cues to personality; in particular, extraversion was found to be positively correlated with positive-emotion words and social-process words, agreeableness was found to be negatively correlated with negation words, and openness was found to be negatively correlated with second-person pronouns, assent words, and positive-emotion words (however, weak correlations)
15. Chittaranjan, Blom, and Gatica-Perez (2011)	Smartphone data	Extraverts were more likely to receive calls and also spend more time on them Agreeableness among women was associated with an increase in the number of incoming calls; agreeable men were found to communicate with more number of unique contacts through voice calls Conscientiousness was associated with higher usage of the mail app, which could be used in a professional context, and with lower usage of the Youtube application High openness was associated with increased usage of video/audio/music apps in women and also with the usage of nonstandard calling profiles
16. Quercia, Kosinski, Stillwell, and Crowcroft (2011)	Twitter	Found that both popular users and influentials on Twitter are extraverts and emotionally stable (low in the trait of neuroticism). Popular users are also “imaginative” (high in openness), while influentials tend to be “organized” (high in conscientiousness) Also, accurately predicting a user’s personality could be simply based on three counts publicly available on profiles: following, followers, and listed counts; knowing these three quantities about an active user, one can predict the user’s five personality traits with a root mean-squared error below .88
17. Golbeck, Robles, and Turner (2011)	Facebook profile	Attempted to predict personality from Facebook profile information; they used a very rich set of features, including both Facebook profile features and also the words used in status updates; results showed that using the profile data as a feature set, they were able to train two machine-learning algorithms—m5sup′Rules and Gaussian Processes—to predict each of the five personality traits to within 11% of its actual value

(*table continues*)

Table 1 (*continued*)

Study Authors Year	Type of technology	Findings
18. Gosling et al. (2011)	Facebook activity	Revealed several connections between personality and self-reported Facebook features; e.g., they showed the positive relationship between extraversion and frequency of Facebook usage and engagement in the site; as in offline contexts, extraverts seek out virtual social engagement, leaving behind a behavioral residue such as friendship connections or picture postings; however, their work was based on a relatively small sample of 157 participants, again limiting the reliability and generalizability of their results
19. Ryan and Xenos (2011)	Time of total Internet usage	Showed that certain personality traits are correlated with total Internet usage and with the propensity of individuals to use social media and social-networking sites Facebook users tend to be more extraverted and narcissistic, but less conscientious and socially lonely, than nonusers
20. Zhong et al. (2011)	Time of total Internet usage	Identified the personality profiles of heavy Internet and Facebook users but shed little light on the issue of how a person's Facebook profile reflects personality
21. Woolley, Chabris, Pentland, Hashmi, and Malone (2010)	Tracking badges	Used tracking badges to follow employees' behaviors at work and record the 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; it also identified the individuals who are a central node in the network
22. Amichai-Hamburger and Vinitzky (2010)	Facebook activity	Found several significant correlations—they found that extraversion was positively correlated with the number of Facebook friends but uncorrelated with the number of Facebook groups Additionally, they found that high neuroticism was positively correlated with users posting their own photos but negatively correlated with uploading photos in general
23. Correa, Hinsley, and de Zuniga, (2010)	Time of total social-media usage	Extraversion and openness to experiences were positively related to social-media use (defined as use of social-networking sites and instant messages) while emotional stability was a negative predictor
24. Back et al. (2010)	Facebook profiles	Data gathered from various online social-network sites showed that online profiles reflect the actual personalities of their owners rather than idealized projections of desirable traits; accuracy was strongest for extraversion and openness and lowest for neuroticism
25. Ross et al. (2009)	Facebook profiles	The study proposed a number of hypotheses but reported only one significant correlation—between extraversion and group membership; a relatively small ($N = 97$) and homogeneous sample (mostly female students studying the same subject at a single university) and a potentially unreliable approach to collecting data (participants' self-reports of their Facebook profile features rather than direct observation) may have prevented the authors from finding more significant connections and make it difficult to extrapolate findings to a general population
26. Schrammel, Köffel, and Tscheligi (2009)	Time of total social-media usage	Extraversion was shown to correlate with the size of a user's social network in several studies Openness to experience was found to be positively related to number of friends and time spent online, whereas agreeableness was not related to the number of friends in online communities

(*table continues*)

Table 1 (*continued*)

Study Authors Year	Type of technology	Findings
27. Kluemper and Rosen (2009)	Social-media analytics	Examined the ability of social-media assessments to measure personality and general mental ability; 63 undergraduate students (judges) from an upper-level business course assessed the Facebook pages of six other students from a lower-level course; the judges filled out standardized questionnaires to assess Big Five personality factors and intelligence; the six students whose Facebook pages were assessed filled out similar Big Five questionnaires; correlations between self-reported personality traits by students and ratings based on judgments from Facebook pages were often in the range of .3 to .5
28. Butt and Phillips (2008)	Mobile-phone use	A total of 112 mobile-phone owners reported on their use of their phones and completed the NEO-FFI and the Coopersmith self-esteem inventory Extraverts reported spending more time calling, and changing ring tone and wallpaper, implying the use of the mobile phone as a means of stimulation Those with higher levels of neuroticism/extraversion and low levels of agreeableness/conscientiousness spent more time messaging using SMS
29. Khan, Brinkman, Fine and Hierons (2008)	Keyboard and mouse use	The results suggest that some of the main traits and subtraits of personality can be measured from keyboard and mouse use; significant correlations were found between personality main traits and subtraits and the use of keyboard and mouse Specifically, a significant positive correlation was found between the trait extraversion and speed of movement on a keyboard and mouse
30. Back, Schmukle, and Egloff (2008)	E-mail addresses	Using 599 e-mail addresses of young adults, their self-reported personality scores and the personality judgments of 100 independent observers showed that there is some valid personality-related information even in users' e-mail addresses E-mail perceptions were significantly correlated with e-mail owner self-reports of personality for five (neuroticism, openness, agreeableness, conscientiousness, and narcissism) of six personality dimensions
31. Evans et al. (2008)	Facebook profiles	Examined what aspects of the Facebook profile individuals use to form personality judgements and showed that certain features are difficult to grasp for people; e.g., although the number of Facebook friends is clearly displayed on the profile, people cannot easily determine features such as the network density (whether a user's friends know each other)
32. Guadagno, Okdie, and Eno (2008)	Blogging	Found that people who are high in openness and high in neuroticism are likely to be bloggers. Additionally, the neuroticism relationship was moderated by gender, indicating that women who are high in neuroticism are more likely to be bloggers as compared with those low in neuroticism, whereas no differences were found for men
33. Rosen and Kluemper (2008)	Social media	Found that extraversion and conscientiousness positively correlated with the perceived ease of use of social-media websites; extraversion was also shown to have a positive correlation with perceived usefulness of such sites

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Table 1 (*continued*)

Study Authors Year	Type of technology	Findings
34. Wehrli (2008)	Profiles on Swiss social-networking site (StudiVZ)	Study found that extraverts show a higher probability in joining StudiVZ, adopt the technology faster, and accumulate more friends on their contact lists—they also take more central positions in the friendship network
		Also found that highly conscientious people tend to refrain from participation on social-networking sites
35. Gill, Oberlander, and Austin (2006)	E-mails	Studied the accuracy of personality judgements based on e-mails
		Found that even with minimal textual cues there is relatively high agreement, for ratings of author extraversion
36. Marcus, Machilek, and Schütz (2006)	Contents of personal websites	The average website owner reported being slightly less extraverted and more open to experience; compared with various other samples, website owners did not generally differ on narcissism, self-monitoring, or self-esteem; as Internet browsing is to a large extent a private activity, relationships between website choices and personality might be unaffected by peer pressure and the tendency to present oneself in a positive manner
37. Vazire and Gosling (2004)	Contents of personal websites	Found that website observers were generally accurate in their assessments of website authors' personalities
		Website authors tended to enhance their extraversion and agreeableness
		These findings suggest that identity claims are used to convey valid information about personality
38. Machilek, Schütz, and Marcus (2004)	Owning a website	Compared a relatively large sample of personal-website owners to various groups of non-website owners on the Big Five dimensions of personality and narcissism, self-monitoring, and self-esteem. They found that, compared with the general adult population, website owners scored lower on extraversion, agreeableness, and conscientiousness and higher on openness to experience
39. Wolfradt and Doll (2001)	General Internet usage	Found a high interest of using the Internet for communication for those with high levels on neuroticism

Note. NEO-FFI = NEO Five-Factor Inventory.

more easily predicted among personality traits, while emotional stability (low neuroticism) is the most difficult trait to predict.

Other features include an individual's Facebook likes, which was discovered by pioneering researchers at Cambridge who developed the myPersonality database (Stillwell & Kosinski, 2013). This database includes over 6 million Facebook users who have been able to take a variety of personality and ability tests by installing myPersonality. Alongside this, the majority of users have also given consent for access to their Facebook information including "likes." Based on this wealth of information, Stillwell and colleagues (2013) showed that Facebook "likes" are highly predictive of personality and a number of other psychodemographic traits, such as age, gender, intelligence, political and religious views, and sexual orientation. For example, they found significant correlations between Facebook profile features and psychological traits; for instance, individuals who are more liberal and open to experiences tend to "like" more items on Facebook, post more status updates, and join more groups.

However, there are some reports that point toward big data (particularly, Kosinski's model) as the "culprit" behind Brexit and Trump's presidential win. Kosinski's previous company, Cambridge Analytica (CA), allegedly sold its information to an election-influencing company. By December 2015, CA claimed to have collected up to 5,000 data points on over 220 million Americans. In September, the Trump campaign spent $5 million with CA to target potential voters. The company has denied the claims but, regardless, it highlights the potential danger big data has (Doward & Gibbs, 2017).

Another commonly used method in research to assess personality is a linguistic-analysis technique used on information gathered from social media. This method is extremely useful when it comes to understanding an individual's personality based on the words he or she uses. For example, Qiu, Lin, Ramsay, and Yang (2012) concluded that Tweets do contain valid linguistic cues to personality. In particular, extraversion was found to be positively correlated with positive-emotion words and social-process words, agreeableness was found to be negatively correlated with negation words, and openness was found to be negatively correlated with second-person pronouns, assent words, and positive-emotion words. Furthermore, Schwartz et al. (2013) applied differential-language analysis to uncover features distinguishing demographic and psychological attributes of 700 million words, phrases, and topic instances collected by myPersonality from Facebook status updates of 75,000 participants. Their findings showed a striking variation of language related to personality, gender, and age. This work confirmed existing observations such as neurotic people's tendency to use the word *depressed*.

Nevertheless, despite some organizations believing that information gathered from social-media sites are more well-rounded and uncovers an individual's true personality, this does not always appear to be the case. The issues that occur with traditional methods remain true for newer methods. For example, individuals may intentionally or unintentionally misrepresent themselves online as they formulate a profile that showcases their ideal selves rather than what truly symbolizes their actual personality (Green, 2013). Research has emphasized that personal accomplishments and positive attributes are more likely to be advertised online rather than the negatives (Qiu, Lin, Leung, & Tov, 2012). This can have great implications for the selection process, and recruiters must use social media with caution. Indeed the social media may paradoxically be much more prone to impression management than either interviews or standard personality questionnaires (Buffardi & Campbell, 2008).

It has become apparent that some people have more than one social-network identity. Further, as it becomes more widely known that social-network identities are being used for selection, it is possible and likely that impression management and self-editing will increase, which in turn lowers reliability and validity. Indeed there are reputation-defending and -restoring organizations that, for a fee, try to enhance a person's public face and profile, which would lead the data analysis to be incorrect. Thus it might be possible to create personal websites designed specifically to make the person look like an ideal citizen and employee, namely, high on conscientiousness and agreeableness as well as being socially self-conscious and concerned.

Wearable Technology

Although big data may offer a great opportunity to understand behaviors and identify patterns that were previously impossible to uncover, there can still be limitations—in particular, gathering the data in the first place. Wearable technology provides the solution to this problem because, every day, an individual's digital footprint can be tracked and recorded. In the workplace, employees have wearables such as smart watches and fitness trackers that have sensors and are leaving large digital footprints that can be analyzed to understand patterns of behavior.

A growing trend is the use of tracking badges in the workplace. These allow employers to follow employees' behaviors at work and record the frequency of talking and turn-taking and where in the office they are the most. For example, a Massachusetts Institute of Technology laboratory has developed a new technology called SocioMeter, a wearable sensor to measure face-to-face interactions between people with an IR transceiver, a microphone, and two accelerometers (Choudbury & Pentland, 2010). The data that can be gathered from these emerging technologies have been demonstrated to be extremely useful in social-network analysis by identifying a central node in a network (Woolley, Chabris, Pentland, Hashmi, & Malone, 2010). It has also shown where people go for advice and how ideas and information spread within an organization, which has in turn predicted team effectiveness.

One important issue here is how and when employees provide consent for the use of their wearable data to be collected, analyzed, and stored. For instance, consent may be buried in lengthy and complex legal documents that employees are asked to sign at the beginning of their employment period. Many employees may not read or fully understand these documents and click to accept without comprehending their implications. Few people have considered the ethics of these techniques and employee attitudes to surveillance (Furnham & Swami, 2015).

Mobile Phone Logs

The predominant item of wearable technology that the majority of the population owns is a mobile device. Mobile-phone data sets have logs of calls, texts, and location-tracking, among other dispositional information. De Montjoye, Quoidbach, Robic, and Pentland (2013) showed how standard phone logs can easily predict how extraverted, agreeable, conscientious, open to experience, and neurotic a user is. Their findings were that motion indicators, such as distance traveled, significantly correlated with neuroticism, whereas social-life indicators, such as the size of the social network, correlated with extraversion. These findings are consistent with previous research using social-media profiles, illustrating greater reliability for this conclusion.

Personality can also be assessed based on the calls that people make. Chittaranjan, Blom, and Gatica-Perez (2013) highlighted that extraverts were more likely to receive calls and also spend more time on them. Agreeableness among women was associated with an increase in the number of incoming calls, whereas agreeable men were found to communicate with more unique contacts through voice calls. Conscientiousness was associated with higher usage of the mail app, which could be used in a professional context, and with lower usage of the Youtube application. High openness was associated with increased usage of video and audio applications in women and also with the usage of nonstandard calling profiles.

Gamification

Another rapidly growing trend is the use of gamification in the workplace as well as in the education sector (Attali & Arieli-Attali, 2015; Dichev & Dicheva, 2017; Fetzer, McNamara, & Geimer, 2017; Kim & Shute, 2015; Landers, 2015; Mavridis & Tsiatsos, 2016; Nacke & Deterding, 2017; Seaborn & Fels, 2015). Gamification can be defined as the use of game design elements (e.g., adaptation, assessment, conflict, challenge, immersion, rules/goals, feedback) in nongame contexts (Deterding, Dixon, Khaled, & Nacke, 2011). Gamified elements in the workplace have exploded as a result of more adults playing games during their personal time. For example, in 2014 consumers in the United States spent $22.4 billion dollars on video games (Entertainment Software Association, 2015). Games are fun and dynamic and are therefore the perfect tool for motivating employees in various situations in the workplace, such as employee training (Collmus, Armstrong, & Landers, 2016). Gamification can also be employed during recruitment and selection of new job candidates by gamifying selection and personality tests, making them more enjoyable to complete. The central question for researchers is whether this affects test validity, while for developers and test-users it is whether it is worth the development costs.

Organizations can influence the quantity and quality of applicants that apply for a job by utilizing gamified elements. For example, gamification can increase intentions to accept job offers due to increased organizational attractiveness (Collmus et al., 2016). Firms that use gamification during their recruitment process may exhibit the image that they are technology-focused and forward-thinking and have a good organizational culture. Gamification also helps enhance the selection process for firms by providing new tools to establish job-performance predictors such as cognitive ability, personality, and person-organization fit.

Although there is little academic research in this area, organizations have demonstrated the impact of gamification. PricewaterhouseCoopers (PwC) in Hungary, for example, developed Multipoly, which allows potential job candidates to virtually test their readiness for working at the firm by working in teams to solve real-world business problems (PwC, 2015). Since launching this program the firm has reported a 190% growth in job candidates with 78% of users reporting they are interested to learn more about working at PwC, showcasing the influence of organizational attractiveness from gamification. In addition, the successful hires with Multipoly experience also found onboarding at PwC easier, as they had already gained a sense of the firm's culture through the game.

Another gamification example has been identified by Mekler, Bruhlmann, Opwis, and Tuch (2013), who have highlighted the use of points and leader boards as a popular gamified element. This has been exemplified by LinkedIn, a website that allows people to upload their online résumés. Users can endorse others on their skills, thus increasing their rating in a particular area such as leadership ability. This tool can be likened to the gamelike element of score points, where the higher the score, the better.

Gamified selection tests for organizations are arguably more beneficial than traditional methods of assessment because of their potential for improved criterion-related validity. Some researchers have suggested that gamified assessments such as PwC's situational-judgment test are more predictive of future behavior than simple selection questionnaires, highlighting the usefulness of gamified tests (Lievens & Patterson, 2011). Another example of how gamification makes assessments more valid is that it is harder to fake or cheat (Armstrong, Landers, & Collmus, 2015). A number of researchers have shown that scores on standard, but complex, computer games are good measures of cognitive ability as measured on standardized IQ tests (Sin & Furnham, 2018).

During traditional assessments, individuals are often susceptible to social-desirability bias and may change their responses to what they believe their employers are looking for, which does not reflect their true traits. However, in tests that are gamified and well designed, it is often difficult to identify the behaviors or traits that are being assessed, thus reducing this bias.

Video Résumés

Face-to-face interviews and résumés may be still the most common and traditional methods for job selection, but the online world has changed the landscape of recruitment and selection. Websites such as LinkedIn have replaced traditional résumés with over 300 million users (Smith, 2017). More recently, video résumés have become a more common tool in selection because of the arrival of inexpensive webcams and online video platforms such as YouTube. Video résumés are defined as short messages recorded by potential job candidates about their skills and experience. Video résumés have great potential for improving the selection process; their use bypasses the issue of an individual's personality face-to-face not matching his or her written résumé. Thus employers can now analyze an individual's communication skills and personality traits more cheaply, easily, and conveniently.

Academic research has found that employers using paper résumés tend not to accurately infer the personality traits of job candidates. Cole, Feild, Giles, and Harris (2009) studied 244 recruiters' ability to infer personality from paper résumés and found that with the exception of extraversion the reliability and validity of Big Five personality inferences were low. This finding has been attributed to the reduced amount of information provided by paper résumés compared to video résumés, which are rich in information.

Apers and Derous (2017) experimentally compared the accuracy of personality judgments between paper and video résumés. They concluded that, with the exception of extraversion, personality traits were equally inaccurately judged by recruiters across all types of résumés and, interestingly, that applicants' perceived attractiveness did not affect accuracy judgments. More importantly, it was found that information-rich video résumés did not result in more accurate estimations of personality traits. Therefore, recruiters should be cautious making any judgments based on résumés, even video résumés. Furthermore, Hiemstra and Derous (2015) reviewed the use of video résumés and highlighted that they also have the potential to instigate discriminatory hiring practices; thus future research should focus on assessing the extent of this.

Automated Personality Testing

Ultimately, it can be argued that all these new advancements in technology have resulted in a more automated approach to personality testing. The growth of artificial intelligence and big data is changing the way personality assessments are conducted. Kosinksi et al.'s (2013) research in social-media analytics, for example, has gone on to be developed into a machine-learning algorithm that can now predict human personality types using nothing but what people like on Facebook (Youyou, Kosinski, & Stillwell, 2015). Their research suggests that computer-based judgments of personality (based on an individual's digital footprint) is more accurate than an average human's judgment and is almost as accurate as a person's spouse (the best of human judges).

A similar machine-learning system was developed by Lima and de Castro (2014). Called *PERSOMA*, it is essentially a multilabel classifier based on an algorithm-independent approach. Their objective is to identify the personality trait of groups of Tweets (from the social networking site, Twitter) based only on the information contained in the Tweets themselves, thus not relying on profile data. Like previous research, the trait extraversion is accurately predicted by all classifiers, while the traits of agreeableness and neuroticism also present high accuracy and precision. Openness was the most difficult trait to predict, followed by conscientiousness.

Despite the numerous studies that have reported the usefulness of social media for personality testing, it is still limited in its use because the constructs are still unstable. Machine-learning approaches that have been taken to social-media sites such as Facebook have shown great accuracy, though as noted above there are still problems with the use of these algorithms. Nevertheless, it is likely that in a few years Facebook will become obsolete, following its predecessors such as Bebo or Myspace, which were highly popular a few years ago but are now no longer used.

Moreover, 10 years ago, social media consisted of only a few websites that people used. However, currently social media are everywhere, including regular websites where people can comment and share across different social networks. Social media can also be accessed by numerous devices including desktops, smartphones, and tablets. Given the extremely rapid growth of social media over a relatively short period of time, it is difficult to predict where it will be in another decade. Therefore, future research may benefit from focusing on understanding behavior through the affordances of social media such as its ability to befriend or follow other people rather than concentrating on a specific platform.

Furthermore, accurate prediction of an individual's personality traits is dependent on large amounts of data gathered. The greater accuracy that is associated with this means that potential job candidates could be matched more accurately, which could lead to improvements in job turnover rates and retention. However, although there is a rapid increase in online users, there still remain individuals who do not utilize the full potential of social media or mobile phones—for instance, some baby boomers. Moreover, many users on social media are listeners more than talkers, resulting in fewer posts. Therefore, caution must be taken before using these emerging technologies in predicting personality traits or behaviors.

A Note on Ethics

Both consultants and researchers are required to abide by a number of ethical guidelines in the assessment of people. Every so often there are very high-profile, and thus well-known, litigation cases where people attempt to sue test publishers, test administrators, organizations, and consultants because of decisions based on judgments and test scores. They are usually, but not exclusively, people from minority groups of many types who feel the tests unfairly discriminated against them. There is also the question of what meaning should be given to low-frequency users of social media. Are they disadvantaged in some way? Do these tests discriminate against older and poorer people who may reside in rural settings? What about users of older, outmoded systems compared to those using the latest competing system? These problems could lead to many unintended consequences and legal cases.

Hence, it is argued that various test scores may not be valid. In response psychological societies such as the American Psychological Association and British Psychological Society have laid down long prescriptive and proscriptive rules and guidelines for testers.

However, the new technologies present a range of new problems. The first is obtaining data about an individual without his or her consent. How would candidates feel about organizations that were scraping a great deal of data from the web and other open sources about them? There are important questions about the accuracy of these data and who indeed is supplying this. Next, there are many potential issues around wearables and issues around surveillance (Furnham & Swami, 2015). What if people refused to put on these wearables? How would individuals feel about employers that have electronic daily maps of whom they were in contact with? What if the wearables developed a minicamera or a recording device that gave some idea about what was occurring during interactions? Wearables can give physiological data as well as contact data. In this sense they provide data on wellness and physical fitness, which may be considered an inappropriate and unethical way of assessing people.

It seems sensible that two things be done concerning the ethics of the new technologies. First, ethics committees need experts and specialists on these new technologies to inform other committee members. Second, the committees could also benefit from the insight of users and researchers who themselves do not have any financial interest in the development or sale of those technologies.

The advent of the new technologies have provided a whole new research area for ethicists, a potential field day for lawyers, and considerable problems for consultants and others who use these technologies. To a large extent this is virgin territory.

Conclusions and Future Directions

Emerging technologies open a whole new world for organizations and will change the way people recruit and train employees as we know it. Consulting psychologists in this enterprise need to constantly update themselves on what is available as well as the evidence for reliability and validity.

Many have argued for an integrative online–offline package for personality assessment (Amichai-Hamburger, Brunstein Klomek, Friedman, Zuckerman, & Shani-Sherman, 2014). Alongside the technologies mentioned in this article, there are more novel tools being built; for example, the Internet of Things is set to increase the amount of data gathered about individuals (Atzori, Iera, & Morabito, 2014). The Internet of things involves everyday items such as household appliances, cars, and clothing items becoming computerized and connected to the Internet. These provide new opportunities for organizations to collect information about potential employees, including past history.

There are frequent press reports about high-technology companies developing, for their own use only, new techniques for the assessment of their people. These are employed primarily in selection and appraisal. They believe, it seems, that this gives them significant competitive advantage. This is often difficult to evaluate but evokes considerable public interest.

There are, however, numerous justified concerns for future work in this area. For instance, there is some evidence that suggests potential inconsistencies/mismatches between personality at home and personality at work. Although these differences may not be great in a larger context, it is possible that someone who is perhaps gregarious with friends but much more restrained at work is going to be misclassified by big data.

It is also important to note that job selection is essentially an arms race. For every improvement on the employer side (e.g., online personality assessments), there can/may/will be a reactive step-up on the applicant side. Thus, savvy applicants clean their Facebook profiles and photos in anticipation of an upcoming interview. Therefore, the question is whether it is widely known that your social media will be scraped for employability data. Many people will either create a dark social-media presence or go off the grid with information that might be coded in a negative fashion.

Psychometricians know how long and arduous the validation process for any technique is. To establish various kinds of reliability (test–retest, alternative forms, internal) and validity (concurrent, construct, discriminant, incremental, predictive), it is necessary to collect considerable amounts of data (Furnham, 2008). They also observe that the two types of data that are most desirable are also the most difficult to acquire: longitudinal data tracing people over time, and accurate and valid dependent measures of actual work behavior and successes. The validation of these new techniques is essentially the same as that for the old and established techniques. This takes considerable time and effort from dedicated and hopefully disinterested researchers, less interested in sales and proselytizing than in the validation of the product (Chamorro-Premuzic & Furnham, 2010; Furnham, in press).

It has been said about some psychological tests that they are techniques in search of a theory or solutions to nonexistent problems. There is always the danger when exploiting the possibilities of new technology that insufficient evidence is collected and assessed to show incremental validity over existing and established methods. The history of psychology is littered with examples of how the primary technology of the time shapes not only theories and technology but also how many promises were never delivered.

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