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Performance, Well-Being, Motivation, and Identity in an Age of Abundant Data: Introduction to the "Well-Measured Life" Special Issue of *Current Directions in Psychological Science*

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Abstract

Our lives are being measured in rapidly increasing ways and frequency. These measurements have beneficial and deleterious effects at both individual and social levels. Behavioral measurement technologies offer the promise of helping us to know ourselves better and to improve our well-being by using personalized feedback and gamification. At the same time, they present threats to our privacy, self-esteem, and motivation. At the societal level, the potential benefits of reducing bias and decision variability by using objective and transparent assessments are offset by threats of systematic, algorithmic bias from invalid or flawed measurements. Considerable technological progress, careful foresight, and continuous scrutiny will be needed so that the positive impacts of behavioral measurement technologies far outweigh the negative ones.

Keywords

measurement, well-being, bias, life-logging, gamification

New technologies for measuring mood, learning, behavior, and performance have created an ongoing, unintended social experiment of immense scale. Society has not adequately stopped to assess the impacts, both positive and negative, of this experiment. Every day, citizens of the modern world face a multitude of devices that are measuring, logging, analyzing, and assessing their behavior. Some examples of these behavior measurement technologies (BMTs) include technologies that measure individual performance (Fitbit, mobile health apps, brain-training software, and standardized tests), technologies that promote social connection and comparison (Facebook, scholarship metrics such as Google Scholar, student in-class comparisons), and technologies for aggregating data from many people for research or commercial purposes (23andMe, National Assessment of Educational Progress, PatientsLikeMe).

The rapid development of BMTs risks outstripping our understanding of their psychological and behavioral consequences. In addition, the life-logging and Quantified Self movements raise a number of questions for which theories and studies in social psychology, development, communications, human-computer interaction, sociology, and health behavior are directly relevant. The overall goal of this special issue of *Current Directions in Psychological Science* is to review what psychologists know about the individual and social consequences associated with the increasing prevalence of technologies that let lives be recorded, measured, logged, and shared.

As shown in Figure 1, we are surrounded by a mob of devices measuring our actions and decisions. Instruments of surveillance, including street cameras, browser trackers, ambient audio recording devices, face-recognition software, and movement trackers are being introduced into communities at an alarming rate, with negative impacts on well-being and feelings of freedom (Acquisti et al.,

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Fig. 1. Pictorial representation of the increasing measurement of our lives, which is due in large part to technological advances. Devices make recordings of our audio and visual behavior, but also of our choices, movements, and writing. (Designed by Robert L. Goldstone and Joe Lee; illustrated by Joe Lee.)

2015; Zuboff, 2019). Although being surveilled is often not under our direct control, we willingly subject ourselves to still more scrutiny in the form of "sousveillance" systems—devices we choose to use that measure ourselves. Consider just a single device, the modern smartphone. It is startling to realize how many ways it measures us—via camera, microphone, light sensor, cell-tower strength, Wi-Fi, Bluetooth, vibration, sites visited, texts sent and received, GPS position, gyroscope, and accelerometer.

New Measurement Opportunities for Transforming Psychology

BMTs let psychologists unobtrusively study the everyday activities of people. This potential has been sufficiently compelling to entice many psychological scientists out of the comfort zone of their laboratories. These researchers are willing to replace clean, well-controlled data with much larger scale, sometimes messier, data collected from people in everyday contexts. In some cases, modern BMTs allow researchers to combine the real-world relevance of field experiments with the control of experimental manipulations (Mosleh et al., 2022, this issue). Table 1 presents some examples of new BMTs as they have been employed by psychologists working in a few selected subfields. For clinical psychologists, automatic text analysis of writing samples by people using social media can be used to predict mental disorders, such as depression, anxiety, and suicidal ideation (Coppersmith, 2022, this issue). For example, depressed individuals are likely to exaggerate the importance of negative events, engage in black/white dichotomous reasoning, and discount positive experiences, and these tendencies can be revealed by automatic natural language processing tools (Bathina et al., 2021). If performance on online cognitive-training games is measured at many separate times (see Stafford & Vaci, 2022, this issue), a marked decline in performance can potentially be used as an indicator of worsening dementia, signaling the potential need for intervention or a checkup. When provided as input to machine-learning methods

Table 1. Examples of the Use of Behavioral Measurement Technologies in Subfields Within Psychology

Subfield	Measurement	Use
Clinical psychology	Analysis of the sentiment expressed in messages on social media	Assess suicide risk, onset of a manic episode, or emotional changes
Life-span development	Performance on cognitive-training games	Detect worsening dementia, memory, or language proficiencies
Child development	Automatic recognition of child-directed speech	Determine relations between language input and ensuing language facility
Educational psychology	Logging interactions with pedagogical materials	Infer a detailed model of what a student currently knows and is prepared to learn next
Positive psychology	GPS tracking, media consumption, social-media posts	Measure activities as both the causes and the consequences of well-being and life satisfaction
Neuroscience	Electrocorticography (ECoG)	Create individualized maps of cortical function, predict epileptic seizures, develop brain-computer interfaces

for detecting patterns, eye gaze and electrophysiological measures can be used to detect likely cases of frustration or mind wandering in learners (D'Mello et al., 2022, this issue). In all three of these applications, the ability to distinguish cases requiring versus not requiring intervention need not be perfect. As long as the cost of false alarms is not too high, there can be significant benefits even if only a small percentage of cases that would otherwise not have been detected are flagged as concerning, much as the use of smart watches that flag irregular heart rhythms that might be suggestive of atrial fibrillation can bring significant health benefits if they identify users who had never before considered that they might have this disorder.

Modern BMTs allow developmental and educational psychologists to assess learning in children, and even fetuses (Reid & Dunn, 2021). BMTs that register large swaths of a child's environment provide a normally missing but necessary ingredient for a full model of learning (de Barbaro & Fausey, 2022, this issue; Kachergis et al., 2022, this issue). After all, to predict learning, one needs to know not only the learning algorithm but also the input provided to that algorithm (Roy et al., 2015; Warlaumont et al., 2022, this issue). The major payoff for an in-depth understanding of a whole learning situation (learner + material to be learned + context) is the ability to know what material a learner is prepared to learn next, and the most effective way of presenting that material (Doignon & Falmagne, 2012; Stafford & Vaci, 2022, this issue). In the domain of positive psychology, a similar perspective can be adopted toward improving well-being. Both group-level and idiosyncratic determinants of well-being can be identified from social-media interactions, media consumption, physical activity level, and dynamically changing geolocation (Hinds et al., 2022, this issue). In neuroscience, chronic neural recordings can be taken from electrodes placed on the brain's surface, allowing the measurement and management of disorders such as epilepsy. With much more easily deployed wearable sensor and smartphone technologies, disorders such as Parkinson's disease, Huntington's disease, multiple sclerosis, and strokes can be treated (Dorsey et al., 2018). For all of these technologies, a natural developmental sequence has been to first use the technology to detect environment-behavior patterns and then use those patterns to predict and intervene on future behavior.

Promises and Perils

The psychological stakes for the use and misuse of these BMTs are so high that speaking of "advantages and disadvantages" seems too restrained. The promises and perils of BMTs can be organized in the 2 × 2 design shown in Figure 2, which distinguishes positive and negative impacts at the individual and societal levels.

Promises for the measured individual

As articulated by the Quantified Self (Lupton, 2016; Swan, 2013), life-caching (detailed recording of one's life events, often with sharing on social media) and life-logging (Gurrin et al., 2014) movements, a wide range of wearable sensors and apps can be used to track life activities with the hope of understanding and improving human performance. As anyone who has unhappily stepped on a scale after a Thanksgiving weekend of indulgence can attest, measurements can act as useful catalysts for change. Oftentimes, in fact, it is hard to know how to improve our performance

	Promises	Perils
For the Measured Individual	• Rich Feedback on Performance • Multifaceted Assessment of Progress Toward Goals • Personalized Interventions and Education • Coaching • Increased Connection to Other People • Gamification of Serious Work • Monitoring Mental Health and Well-Being • Greater Self-Knowledge	• Choking • Self-Consciousness and Performance Anxiety • Potential for Violations of Privacy • Narcissism • Threats to Self-Esteem From Upward Social Comparison
For Society	• Discovery of Interactions Between Individual Factors and Interventions • Plentiful Data on Naturally Occurring Behaviors • External Validity of Observed Patterns • Reduced Bias	• Exacerbated Influence of Systematic Biases • Commodification of Users • Reduced Diversity • Focus on Behaviors Measured by Flawed Instruments • Neglect of Things That Matter if They Cannot Be Measured

Fig. 2. Promises and perils of behavioral measurement technologies, for the individual being measured and for society in general, including research communities.

without quantitative information about how we are doing. The goal of improving performance is not reserved for elite athletes and musicians, but is increasingly shared by people who would like to improve their sleep, weight, fitness, second-language skills, emotional regulation, game play, or general health. People are endlessly interested in themselves, and so systems that track our screen time, driving habits, productivity, and performance quality provide valuable data that can be used to help us shape our own behavior. As these systems become more sophisticated, they often advance from simple, single-measurement devices to richer, multifaceted assessments. Even for something as seemingly straightforward as running, there is a growing appreciation that there is value in measuring not simply the time it takes to run 5 miles, but also pace consistency and cadence, breathing efficiency, stride timings, joint flexibility, and motivation.

Designed to do more than measure performance, many systems provide measurement-based personalized interventions and education. There are often learning benefits when materials are presented in a way that is personalized to a learner's interests, demographics, and choices (Reber et al., 2018). A particularly powerful version of data-driven interventions is adaptive learning, in which individual differences in interests, goals, affective states, strategic behaviors, and, crucially, current knowledge states are used to determine the next materials and problems to give learners (Aleven et al., 2017).

Currently, there are far more systems that measure and report performance than there are complete personal-coaching systems that provide detailed recommendations on how to improve performance and psychologically savvy encouragement. Coaching systems based on principles such as making users aware of discrepancies between how they want to behave and how they actually are behaving, recruiting social support from friends and family, encouraging reflection, and emphasizing putting goals into behavioral practice offer promise in attaining notoriously challenging psychological goals, such as changing one's personality (Allemand & Flückiger, 2022, this issue). Motivational psychology can play a valuable role in developing automatized, metric-based personal trainers that provide apt feedback and motivation without frustrating or stressing their users. There are large individual differences in how people respond to negative feedback, nonspecific motivational messages like "You're doing great; keep it up," and challenges to push performance beyond current levels. Accordingly, effective automatic personal trainers of the future will need to adapt their feedback to their users, who will typically be weighing the goal to improve against the goal to feel good about themselves now (Grundmann et al., 2020).

Given the difficulties in automatizing effective personal coaching, it is reassuring that BMTs can also be used to increase connectivity among people. Intimate partners can choose to share their fluctuating mood, stress, health, activity, and productivity information with each other, thereby allowing them to provide better support. Systems such as Strava, Peloton, Parkrun, and Nike+ track and share human exercise activities. They tap into deep human motivations to be competent and autonomous, but also connected to family, friends, and even people pursuing the same activity who would otherwise be strangers (Bitrián et al., 2020). Through a combination of shared goal pursuit, social support, and competition, these systems can motivate challenging activity far more effectively than people would be able to do on their own.

A key component of many progress-monitoring systems is the gamification of activities that are good for the individual or group but are insufficiently rewarding in the short term. One potent gamification ploy is to bestow badges, levels, certificates, ranks, points, or objects (real or virtual) on users when they engage in beneficial activities. These perks tap into people's natural drive for upward mobility and progress, and can be delivered more quickly and frequently than "real-world" rewards typically arrive. One interesting possibility is to gamify serious pursuits, as *Chore Wars* (http://www.chorewars.com) does for housework. Given increasing interest in training over years in a workplace (Beier, 2022, this issue), many employers also increasingly use gamification. Motivational principles gleaned by game designers can be applied to make jobs more fulfilling, and this may prove necessary if societally important jobs are going to effectively compete against games for people's "brain cycles" (Castronova, 2007).

People are not always good judges about what makes them happy. When correlated with environmental and social contexts, measurements of mood and behavior can help people better understand what makes them happy, productive, healthy, and fulfilled (Singer, 2011). Broadly construed, the promise of well-measured lives is greater self-knowledge. By tracking and analyzing our lives, we can better remember our lives and devise evidence-based ways to improve them. By incorporating adaptive feedback and coaching, these insights can be translated into lasting changes.

Perils for the measured individual

The sanguine conclusion of the last paragraph needs to be tempered by acknowledgment of real psychological threats from constant, often distracting, measurements. The very act of measuring performance can negatively affect that performance by making people overly self-conscious and unhelpfully converting automatic, well-honed behaviors into ones that are consciously, if awkwardly, controlled (Beilock, 2011). Many people experience performance anxiety when monitored, and this anxiety is not evenly distributed within a population. People are particularly likely to feel anxiety, and show resulting performance decrements, when they perceive themselves to be at risk of conforming to negative stereotypes about their social group (Spencer et al., 1999). In addition, the presence of surveillance systems makes people feel more inhibited, paranoid, and threatened.

Plentiful measurements tied to individuals open up a myriad of privacy abuses (D'Mello et al., 2022, this issue). Consider a smartphone's accelerometer data, which might be thought to be relatively innocuous. A review (Kröger et al., 2019) has shown how these data can be used to provide information about a user's passwords, inebriation, age, gender, weight, smoking, driving behavior, and sleep quality. Our naturally evolved impulses toward self-protection, rooted in ownership, personal space, and reputation management, are often not triggered by modern measurement devices because the measurements are taken without users' awareness (Shariff et al., 2021). Consequently, users may not take steps to protect their privacy despite the value they place on it. One general concern about privacy is that the more information others know about you, the more influence they can exert on you. Targeted advertisements, misinformation tailored to an individual's fears, and highly accurate purchase predictions are all examples of this often unwanted and covert influence.

Habitual self-measurement risks narcissism and threats to self-esteem. Self-reflection on how to improve oneself can be positive, but exaggerated focus on oneself can lead to diminished concern with the well-being of others. Absorption with their own measurements can make people have a sense of self-worth that is fragile, become overly competitive, and be less likely to feel a shared human experience. The sharing of measurements and achievements on social media is particularly concerning because of the possibility of feedback loops in which people with threatened self-esteem post more positive life events to make others regard them more favorably, which makes other people see more positive life events and, in turn, feel worse about their comparative worth

(Verduyn et al., 2022, this issue). Large amounts of social-media use is associated with negative well-being, and studies in which social-media use is experimentally manipulated suggest that it causally affects well-being in a negative direction (Mosleh et al., 2022, this issue; Twenge, 2019). It is often demotivating to observe other people doing better than oneself, and on large social-media platforms, users may encounter many such skewed samples.

Promises for society

Transcending impacts on individuals, BMTs offer opportunities for benefiting communities as well as society at large. People choosing to measure and analyze their own data are naturally interested in how to improve their own lives, but when their measurements are aggregated with others, robust patterns can be extracted. Sites such as PatientsLikeMe offer a way for people who share a health condition to learn from each other's symptoms and treatments. Researchers can explore crowdsourced data archives to detect reliable patterns relating contexts to behaviors. Sufficiently large crowdsourced databases can reveal not only main effects but also reliable differences between subgroups in what interventions are most effective.

In contrast to laboratory studies, widely aggregated BMTs provide plentiful data on naturally occurring behaviors. Compare, for example, studying motivation by measuring how long participants in the lab spend trying to spell words by taking subsets of 10 letters with studying motivation by analyzing games played on an online chess site. The latter approach offers data on natural behaviors from highly motivated and proficient players (Stafford & Vaci, 2022, this issue), and individual players provide potentially hundreds of hours of data reflecting the fluctuations in their motivation and performance (Goldstone & Lupyan, 2016). In many cases, the data from BMTs offer notable advantages for external validity, generalizability across groups, and robustness.

A final promise of BMTs for society is that they will reduce bias. Human judges show large systematic biases in their judgments as well as unacknowledged variability due to seemingly extraneous environmental factors. For example, an analysis of 207,000 immigration court decisions found that when it is relatively hot on the day of an asylum hearing, judges are less likely to grant asylum (as reviewed in Kahneman et al., 2021). By providing open and transparent data to aid decisions, and inputs to consistently applied decision algorithms, BMTs can prevent people's judgments from being clouded by their momentary disposition, in-group allegiance, prejudice, or self-interest.

Perils for society

Despite their promise of bias-free judgments, BMTs often exacerbate biases by systematizing them (D'Mello et al., 2022, this issue). A study (Angwin et al., 2016) on the use of a risk-assessment tool used in U.S. criminal sentencing decisions found that the undisclosed algorithm, incorporating factors such as the education level and job of the defendant, was almost twice as likely to falsely predict that a defendant would perpetrate crimes in the future when the defendant was Black rather than White. Biases can be introduced by the selection of populations to study, the choice of variables to measure, and the application of analysis operations that filter, transform, and manipulate data. To take one example (from D'Ignazio & Klein, 2020), because crash-test dummies were originally constructed to resemble only men's, not women's, bodies, women had a 47% higher chance of car injury than men. A person or group that is not adequately represented in the data may be left out of consideration in new policies and innovations. This lack of representation is also a risk when people try to protect their privacy by opting out of being measured.

It has been observed that when users do not pay for a Web product, it is because they themselves are the product. Companies profit from the detailed measurements they take on their users by delivering narrowcasted advertisements, providing personalized premium content, and selling data collected to other companies. The interests of companies do not always coincide with the well-being of users, and it should come as no surprise when BMTs are used by companies to optimize the former, potentially at the expense of the latter (Zuboff, 2019). It is worth bearing this in mind before you spend half an hour preparing a Twitter response to a tweet that infuriates you. Even without nefarious intentions, machine-learning algorithms that optimize the time users spend on Twitter could be learning to present the users with materials designed to provoke a strong negative reaction. In fact, false news spreads many times faster than the truth, in large part because false news is more surprising and emotionally charged (Vosoughi et al., 2018).

When a single measurement system has wide deployment and impact, there is often a deleterious reduction in the diversity of the people being measured, their behaviors, and the institutions to which they belong. For example, the highly competitive world of law-school admissions has led to law schools emphasizing LSAT scores over applicants' unique credentials, at the same time that applicants are incentivized to choose their school on the basis of quantitative media rankings of law schools rather than a unique fit between student and school values (Espeland & Saunder, 2016). The end result is that the highest-ranking schools end up with students who have rather similar skills and backgrounds, and the schools themselves become less distinctive. Diverse groups typically outperform more homogeneous groups, and the advantage for diversity grows as the tasks facing the group become complex and multifaceted (Page, 2019). The resilience afforded by diversity within and between groups is undermined by procrustean gateway metrics of success.

Systems often imperfectly measure what they are designed to measure. Healthy skepticism is appropriate for claims that a machine-learning system can automatically and with high accuracy use a social-media post to measure the author's sentiment or use a student's essay to measure the student's understanding of a text. Progress is rapidly being made on both fronts, but genuine understanding of text by machine-learning systems remains a distant goal (Mitchell, 2019). A particularly important cause of mismeasurement is that when a measurement becomes high stakes, such as when a student's achievement-test result partly determines whether the student will be admitted to an elite college (Koretz, 2009) or when universities are rank ordered in terms of their quality (O'Neil, 2016), then there is increased incentive for individuals and institutions to game the system by trying to improve how they look according to the specific measurements in a way that does not generalize to different measurements. An ironic outcome of incentives to game high-stakes assessments is that as an assessment becomes more important, it is oftentimes likely to become less externally valid and predictive (Koretz, 2009). As Goodhart's law (named for the British economist, Charles Goodhart) states, "When a measure becomes a target, it ceases to be a good measure."

A final, broad peril of BMTs is that society will overemphasize things that are measured, and underemphasize valuable things that are hard to measure (Johnson, 2022, this issue). Graduate programs tend to overemphasize GRE scores despite their low accuracy in predicting graduate students' success because they offer the apparent precision of quantitative scores that can be easily compared across students. Even though most longtime researchers have strong impressions about the worth of their peers' research, these rich, expert appraisals are often neglected, overshadowed by an overly facile focus on Google Scholar citation numbers. Even people who should know better need to be reminded that not everything that counts can be counted with existing BMTs.

Conclusions

Although there are both exciting opportunities and disturbing threats emerging from trends in behavioral measurement, there is no denying that the trends are rapidly rising. Accordingly, psychological scientists need to turn their attention to improving measurement technologies for individual and collective benefits. Expertise in critical assessment needs to be applied to behavioral assessments themselves so that they continue to improve, and the attention directed at a given assessment should be proportional to its impact. The goal should be that when teachers teach to the test and students learn to the test, learning of value will still take place, and that when our individual and social behaviors are tracked and shared, well-being increases. This will require developing and testing measurement systems that are more multifaceted, diverse, and sophisticated than those currently available, and also the wisdom to know when subjective judgment should be trusted more than any existing measurements.

Transparency

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