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Algorithmic psychometrics and the scalable subject

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Abstract

Recent public controversies, ranging from the 2014 Facebook ‘emotional contagion’ study to psychographic data profiling by Cambridge Analytica in the 2016 American presidential election, Brexit referendum and elsewhere, signal watershed moments in which the intersecting trajectories of psychology and computer science have become matters of public concern. The entangled history of these two fields grounds the application of applied psychological techniques to digital technologies, and an investment in applying calculability to human subjectivity. Today, a quantifiable psychological subject position has been translated, via ‘big data’ sets and algorithmic analysis, into a model subject amenable to classification through digital media platforms. I term this position the ‘scalable subject’, arguing it has been shaped and made legible by algorithmic psychometrics – a broad set of affordances in digital platforms shaped by psychology and the behavioral sciences. In describing the contours of this ‘scalable subject’, this paper highlights the urgent need for renewed attention from STS scholars on the psy sciences, and on a computational politics attentive to psychology, emotional expression, and sociality via digital media.

Keywords

Facebook, social media, platforms, psychology, psychometrics, big data, affect, emotion, subjectivity, scale

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‘It’s like messing with me. It’s mind control.’

In June of 2014, researchers from Facebook and Cornell University found themselves in the midst of an unexpected crisis. The authors had published an article in the *Proceedings of the National Academy of Sciences* (*PNAS*) describing a 2012 experiment that had subtly changed the content of the News Feeds of almost 700,000 Facebook users (Kramer et al., 2014). The study, as the *PNAS* paper described it, was to assess ‘whether [Facebook] posts with emotional content are more engaging’. The researchers were interested in the ‘positive’ or ‘negative’ emotional valences of a user’s Facebook posts, and how those posts might influence the emotional expressivity of users exposed to them – an effect known as ‘emotional contagion’ (Hatfield et al., 1993). To perform the experiment, the researchers had run what is commonly known in Silicon Valley as a ‘split’ or ‘A/B’ test: the practice, as technologist Ed Felten (2014) describes it, ‘in which a company provides two versions of its service to randomly chosen groups of users [at the same time], and then measures how [each set of] users react’. One group of users had the negative semantic emotional content of posts on their Facebook News Feed algorithmically suppressed, while another group saw the positive semantic content of their feed reduced – a third control group had posts from on their News Feeds reduced at random.

Previous research on emotional contagion via social networks like Facebook had concluded that exposure to emotionally ‘positive’ posts – as determined by the number of words associated with positive feelings – led some users to feel depressed, while increased interactions with the site potentially led to higher levels of personal dissatisfaction (Kross et al., 2013; Sifferlin, 2013). As Kramer wrote (in a Facebook post) after the fact, ‘we were concerned that exposure to friends’ negativity might lead people to avoid visiting Facebook’. Kramer’s framing of the research – as motivated by ‘care about the emotional impact of Facebook and the people that use our product' (Kramer, 2014) – elided the project's concurrent business case: a social media platform whose revenue model is based on the ongoing attention and interaction of its users would be understandably sensitive to, and interested in understanding the emotional reasons why users might avoid the site (Beller, 2006). According to the study's results, there was a small statistical correlation between the numbers of 'positive' or 'negative' posts a user was exposed to in their News Feed and the positive or negative semantic content of users' own posts. The authors took these results as refutation of previous research suggesting an inverse correlation between positive content on Facebook and negative feelings in users (Shakya and Christakis, 2017).

Yet when media outlets began to react to the published results of the *PNAS* study in the last week of June 2014, their framing of the work was almost uniformly negative: 'Facebook manipulated 689,003 users' emotions for science', read a representative headline (Hill, 2014). The firestorm of controversy over the Facebook 'emotional contagion' study played out along two distinct discursive trajectories. One saw the intensification of an ongoing debate over principles of research ethics in the emerging field of data science (Jackman and Kanerva, 2016; Provost and Fawcett, 2013) and the responsibilities social media platforms might hold towards their users as formal experimental subjects (Barocas and boyd, 2017; Metcalf et al., 2016). A second set of anxieties centered on what the study had actually purported to do: manipulate the emotional content of the News Feed. As Bucher (2016) observes, 'the lived reality of the Facebook algorithm generates a plethora of ordinary affects' in the course of everyday use, contributing to an 'algorithmic imaginary'. Users were thus highly exercised when their structures of everyday feeling were disrupted. Emotions, according to their angry reactions, are a category of human expression holding a special, sensitive status, which argues for special protections against manipulation and experimentation. As Hancock admitted to *The New York Times* (Goel, 2014), the users said to themselves: ‘you can’t mess with my emotions. It’s like messing with me. It’s mind control.’ People expressed fears the experiment might have caused them to miss important social or emotional cues in the lives of their Facebook contacts, especially their friends and loved ones. Media outlets, interview subjects, and third-party commentators expressed anxieties around the study’s claims of emotional manipulation by labeling them ‘creepy’: the visceral strength of the controversy stemmed from a widespread belief it was the emotions of individual users which had been manipulated without consent (LaFrance, 2014).

The Facebook emotional contagion study should be understood as a seminal event in the history of digital technology’s social impact: as a moment when the tacit co-development of the psychological and computational sciences became exposed to public view and – for some – a matter of concern (Latour, 2004). The work of Kramer et al. demonstrates how the collection, analysis and manipulation of data about human emotion, affect and mood by social media platforms like Facebook was already both widespread and increasingly central as a component of applied research by social media platforms. The effect size found by Kramer et al.’s particular study was small, but the future implications of such work were vast. The site’s technical affordances, as Davis (2014) observes, ‘affect not just emotive expressions, but [also] reflect back to users that they are the kind of people who express positive emotions’. The emotional contagion study illuminated the subtler, more pervasive ways in which Facebook’s interaction design and analytic practices were already implicated in the day-to-day emotional states of the platform’s users.

In this paper, I argue Facebook's interest in tracking, measuring and manipulating the moods of its users is indexical to a broader integration of the computational and psychological sciences with wide-reaching implications for the social use of digital media. This shared history stretches to the birth of modern electronic computing (Dror, 2001; Kline, 2009; Sengers et al., 2008; Stark, 2016a; Turkle, 2004; Wilson, 2010), but has been understudied by both historians and scholars in science and technology studies (STS): the Facebook emotional contagion study was one of the first incidents to make this *psycho-computational complex* a matter of twenty-first century controversy. For instance, the first, but certainly not the last, in May of 2017, a leaked document from Facebook's Australian division suggested that the company had offered advertisers the ability to target advertisements to teenagers based on real-time extrapolation of their mood (Tiku, 2017).

Facebook is by no means the only digital actor turning to mood tracking as part of a broader effort to collect behavioral and psychological data about users. Exemplified by a number of converging trends in human-computer interaction design, applied psychology, data science and advertising, the extraction, collection and analysis of data regarding human emotion is a bigger and bigger business, part of a broader 'behavioral turn' in digital commerce (Nadler and McGuigan, 2017). Scholars have begun to document the emergence of what Zuboff (2015) terms 'surveillance capitalism' and its reliance on behavioral tracking and manipulation. Affect, emotion, and mood are critical yet curiously under-emphasized elements in this story (Tufekci, 2014). A renewed focus from STS scholars on human emotion as a vector in the intersecting histories of psychology and computer sciences reveals not only how these disciplines have converged in the era of machine learning, big data and artificial intelligence, but how, as some scholars have already noted (Orr, 2004; Pickering, 2010; Wilson, 2010), they were never really separate in the first place.

One field at the center of the contemporary integration of psychology and computation is psychometrics, or 'any branch of psychology concerned with psychological measurements' (Jones and Thissen, 2007: 2). In the spread of these forms of measurement via digital media platforms and systems, psychometrics is a powerful element in what Citron and Pasquale (2014) identify as 'scored societies', in which classificatory artifacts like credit scores, insurance profiles and social media data calculated and analyzed by machine learning algorithms and other computational tools are increasingly determinative of many aspects of our lives. Cheney-Lippold (2017) articulates these categorizing techniques and technologies as the tools of 'soft biopower' and 'soft biopolitics', regulating 'how categories themselves are to define life' and 'the ways that biopower defines what a population is' (Cheney-Lippold, 2011: 175). In this conceptual space, inaugurated by Foucault (2009) and Deleuze (1990), 'a physically embodied human subject is endlessly divisible and reducible to data representations via the modern technologies of control such as via digital systems' (Williams, 2005). Psychometrics is one powerful technique for producing such representations, not only of the human body but also of its intimate associations and expressive energies across space and time.

In light of fracases like the Facebook emotional contagion study, where can the influence of psychological sciences be seen as components of the techniques and technologies of contemporary data science, machine learning, user experience design and massive data analysis? What are the political stakes in these relationships between computation and the psy sciences within systems of digital control? Here I argue the human self as represented by digitally mediated psychometrics should be understood as a *scalable subject*. The 'scalable subject' could be understood as a refinement of the now-widespread notion of the 'data double' drawn from (Haggerty and Ericson, 2000): the digitally articulated person is plastic, perpetually molded from both without and within (see Malabou, 2008). Informed by the history of psychology's intersection with computer science, the subject of digital control is not only plastic but also scalable: shaped and made legible at different orders of technical analysis by those affordances of social media platforms grounded in psychological science, and thrown back to the human person as a model with which to conform or suffer. Moreover, the analysis of affect and emotion as motors of networked digital life reveals these categories of human social experience as volatile, contextually complicated and potentially emancipatory.[1]

The scalable subject's utility as an analytic concept also stems from the flexibility of term 'scale' itself. Scalability is suggestive of the computational logics and mechanisms of what Deleuze (1990) identified as contemporary societies of control. In turn, these mechanisms lead contemporary subjects to perform feelings across multiple types of technologically mediated scales, in ways legible and interpretable by computational tools and algorithmic processes (Dourish, 2016; Seaver, 2017). This subject position has both a discursive genealogy (Giddens, 1991; Illouz, 2008; Rose, 1996, 2013) and a visceral reality as a lived, embodied outcome for individual lives mediated by algorithmic psychometrics – the technical affordances of digital platforms drawn from the psychological and behavioral sciences used to track, classify, and manipulate human thoughts, behaviors, feelings, and actions.

The scalable subject embodies the insuperable and myriad tensions between affect and emotion's capture and control, and their potential as material for resistance and emancipation (Negri, 1999). Facebook's emotional contagion experiment and others like it are logical extensions of a longer scientific genealogy of making emotions legible and comprehensible running from the late nineteenth century up through the present (Alberti, 2009; Dror, 1999a, 1999b, 2001, 2009, 2011). Ian Kerr contends the particular conditions under which we experience digital media shape our ability to develop the practical wisdom of everyday sociality and citizenship (Kerr, 2010). In highlighting the through-lines and contemporary stakes of this history, I show the figure of the scalable subject as foundational to the contemporary 'computational politics' described by Tufekci (2014), in which progressive forces are already at a disadvantage. In our epoch of digital control, the merged norms and design tenets of computation and psychology govern the ordering of people and things. As such, we need a clear articulation of the emotional stakes of this politics and the scalable subjects it has made, if current asymmetries of power, equality, and justice are to be overthrown. 'It's not a question of worrying or of hoping for the best, but of finding new weapons', Deleuze declares (1990: 178). Today, taking up arms *is* a question of worrying, and of articulating how the logics of a psycho-computational complex have developed in tandem with, and reinforced, the techniques and technologies of the human sciences (Stark, 2016a).

Digital phenotyping and algorithmic psychometrics

In the nineteenth century, medical experts, public authorities and organs of popular discourse began to develop what Singer (1996: 72) describes as a 'neurological conception of modernity': how the experience of living under the sociotechnical conditions of modern industrial life 'had to be understood in terms of a fundamentally different register of subjective experience'. The reevaluation of modernity's impact on the subjective experience of individuals living within its flow developed in parallel with new scientific techniques and practices to grapple with and manage modernity's impact on the subject through quantification and metrification (Porter, 1996). In the context of these new 'psy sciences', Rose (1988: 197) suggests, 'social relations, regulatory techniques, and ethical systems' created individuals whose minds could be made calculable and thus explicable, and whose social 'goals [became] identified with personal responsibility and subjective fulfillment'.

Affect and emotion were not spared this paradigm of calculability (Dror, 2001). Alongside physiological measurement of the body, psychometrics was one technique among many for the diagnosis and eventual management of human emotion and personality arising in the medical sciences (Dror, 1999a, 1999b). As Danziger outlines in *Constructing the Subject: Historical Origins of Psychological Research*, experimental psychology in the second part of the nineteenth century was both experimental and reliant on statistical analysis; a methodology grounded in quantifiable phenomena was one way through which the new discipline, initially housed in philosophy faculties, could aspire to the same objectivity, social prestige and status as the other medical sciences (Danziger, 1990; also Daston and Galison, 1992).

Experimental psychology owed much of its theoretical and methodological development to the work of nineteenth-century British scientist Sir Frances Galton. Galton's work on psychometrics was tightly bound to his insistence on the application of numerical values to all possible observable evidence. 'Until the phenomena of any branch of knowledge have been submitted to measurement and number', Galton averred, 'it cannot assume the status and dignity of a Science' (Cowles, 1989: 2). Galton defined psychometrics in an 1879 paper as 'the art of imposing measurement and number upon operations of the mind' (Galton, 1879). While many of his early experiments narrowly involved testing and recording involuntary physical reaction times, Galton saw a wider applicability for statistical quantification and correlation around personality and social affairs (one allied with his interest in heredity and eugenics).

Galton's psychometric experiments should therefore be understood as both a technical precursor and social analogue to contemporary data science projects such as the Facebook emotional contagion study. To some degree, the genealogy stems simply from Galton's work as one of the founders of psychometrics and applied psychology. Yet, as Danziger observes, Galton's methods were challenged by other practitioners of the day. Galton's influence also came from deploying a particular set of techniques already amenable to hierarchies of class, race and sex in Victorian Britain's industrial imperial capitalism. The embryo of the contemporary scalable subject emerged in the size, scale and location of expertise Galton deployed in these early psychometric endeavors, but also in the alliance Galton forged between technologies and techniques of psychological intervention and the dominant social and political narratives of the British Empire.

The technical scope of psychometrics has advanced considerably since the nineteenth century: today, psychometrics has gone algorithmic (Goel et al., 2012; Hu et al., 2007; Marcus et al., 2006; Murray and Durrell, 2000; Rentfrow and Gosling, 2003). In the process, data scientists have brought a variety of psychometric and quasi-psychometric techniques out of the laboratory and into the everyday lives of billions (Dror, 2001), as part of a broader move toward self-tracking and the paradigm of the 'quantified self' (Boesel, 2012; Lupton, 2014; Schüll, 2016). One characteristic of these techniques is their return to the body for information about the mind. In October of 2017, Dr. Thomas Insel, former director of the United States National Institute of Mental Health, published an article in the *Journal of the American Medical Association* titled 'Digital phenotyping: Technology for a new science of behavior' (Insel, 2017). Now an executive of a healthcare technology startup, Insel suggested digital phenotyping, or 'measuring behavior from smart phone sensors, keyboard interaction, and various features of voice and speech', would revolutionize the field of mental health by using the data collected by digital devices to diagnose disorders and engineer 'a fresh look at behavior, cognition, and mood' (p. 1216). In his *The Extended Phenotype*, evolutionary biologist Richard Dawkins (1982) argued for the extension of the phenotype from the set of observable characteristics of an individual 'to include all effects that a gene has on its environment inside or outside of the body of the individual organism'. 'Digital phenotyping' was coined as a term in a 2015 paper by physicians at the Harvard Medical School; according to the authors, the 'digital phenotype' is 'an important extension of Dawkins's theory' through which to consider whether 'aspects of our interface with technology be somehow diagnostic and/or prognostic for certain conditions' (Jain et al., 2015: 462).

In *The Extended Phenotype*, most of Dawkins's examples of phenotypic behavior are of animals, such as beavers building dams. Jain and his coauthors use the term more loosely to mean any manifestation or emanation traceable by a digital sensor (Kerr and McGill, 2007). 'By redefining the manifestation of illness', Jain and his coauthors write, these new techniques of behavioral tracking, 'provide new ways to measure disease and therapeutic response in ways that matter most to patients' (Jain et al., 2015: 463). Yet translating the concept to a digitally mediated human clinical context entailed a number of implicit conceptual jumps by the authors: that the notion of the extended phenotype applies unambiguously to humans, that disease is expressed via regular and recognizable physiological symptoms, that digital technologies are reliable and impartial mechanisms for measuring human bodies and minds, and that these devices can make legible symptoms of disease that are otherwise obscure.

Insel's championing of 'digital phenotyping', and the concept's move from theoretical evolutionary biology to clinical psycho-medical applicability, underscores the ease with which these interconnections have accelerated in the contemporary era of massive data sets and ubiquitous digital tools. Jain and his coauthors do not distinguish between different sorts of data – be it numerical, semantic, or interactional – in testifying to the capacities of digital phenotyping; all these sorts of information can be collapsed into numbers amenable to computational analysis. The authors observed data of use in digital phenotyping was potentially available through 'social media, forums and online communities, [and] wearable technologies and mobile devices'. To Jain and his coauthors, this abundance signaled, 'a growing body of health-related data that can shape our assessment of human illness' (Jain et al., 2015: 462). The scope of these analytic techniques suggests shifts in larger discourse about scientific and social scientific practices in contemporary social worlds (Lazer et al., 2009: 722) – but this volume and variety of data does not solve fundamental problems around correlation as a replicable method of scientific prediction or even of complete description, in psychology and elsewhere (Belluz, 2015; Tackett et al., 2017).

Yet in the view of some technologists, the quantitative results obtained through contemporary large-scale data analysis potentially preclude the need to ask causal questions or make subjective judgments about human behavior at all. This prospect, termed 'the end of theory' by journalist Chris Anderson in a 2008 issue of *Wired* magazine, would, in Anderson's words, entail 'a world in which massive amounts of data and applied mathematics replace every other tool that might be brought to bear' (Anderson, 2008). The ability of companies like Facebook or Google to deploy machine learning techniques to analyze large amounts of data meant, in Anderson's view, modeling and qualitative context were increasingly unnecessary; uncontextualized correlations emerging from the 'raw' data would be sufficient to produce actionable results, even if it was sometimes unclear how these results were achieved computationally. While this epistemological position has been heavily criticized in the decade since (Crawford, 2015; Diakopoulos, 2016; Gillespie, 2016; Introna, 2015; Ziewitz, 2015), it persists in areas ranging from criminal recidivism to workplace hiring to self-driving cars (Barabas et al., 2018; Eubanks, 2018; O'Neil, 2017; Stilgoe, 2018).

In 2009, a bevy of high-profile scholars from both computer science and psychology published a short piece in *Science* titled 'Computational social science'. While less inflammatory than Anderson's polemic, the article's authors also suggested the quantity of available data about social phenomena would have a qualitative effect on research into human affairs: 'Existing ways of conceiving human behavior were developed without access to terabytes of data describing minute-by-minute interactions and locations of entire populations of individuals', the authors wrote, claiming that 'these vast, emerging data sets on how people interact surely offer qualitatively new perspectives on collective human behavior' but lamenting the ways in which 'our current [theoretical] paradigms may not be receptive' (Lazer et al., 2009: 722). Computational social science has since become increasingly represented in the academy alongside its integration into social media platforms. As a participant in this development observes, 'the era of computational social science is co-evolving with theories for governing human behavior through the behavioral sciences', applied through the integration of the latter into the everyday implementation of the former (Matias, 2017: 46).

The continuum of behavioral tests applied via digital systems runs the gamut from quasi-psychological measures to actual psychometric scales. Single variate, split, or 'A/B' testing is a definitive example of a quasi-psychological measure at use in social media experimentation. Facebook and other digital platforms both performatively model user behavior and interactively nudge it in particular directions by deploying these relatively uncomplicated correlation tests, which are used to improve the capacity of a site's interface to garner and hold the attention of users through 'regulation by design' (Yeung, 2017). Social media platforms deploy these tests to adjust their interface design and user experience design to determine which design elements keep users engaged, and collect behavioral data within the context of a user's everyday experience of a platform (Kohavi, 2015; Kohavi et al., 2014; Nolting and Seggern, 2016; Xie and Aurisset, 2016). A/B tests leverage the large number of people using any given website or mobile application at any one time to run simultaneous experiments on multiple variables. A/B testing can therefore suggest both which design features could be better optimized for user engagement, and also how to improve an algorithm's predictive performance: As Geiger (2015: 4) notes, 'an A/B test serves as a kind of popular referendum … but one in which we are never told that we are voting'. This lack of awareness is key to ensure ordinary users continue to contribute behavioral data, to provide Facebook's advertising customers with evidence that their ad placements are having an impact, and to refine the site's ability to run correlations on the data it has already collected.

A/B testing is common to any digital business; the incorporation of statistically verified psychometric tests, scales and models into the everyday work of digital platforms has been less routine, but has taken on an outsize role in public conversations around the extent of what algorithmic psychometrics is and does. Michal Kosinski of the University of Cambridge and his co-authors caused a public stir in 2013 by publishing an analysis using then-publicly available Facebook behavioral data – 'Likes' recorded by users' use of the Facebook's 'Like' button – able to predict many potentially private demographic traits (such as whether a user was gay or straight) with a high degree of statistical accuracy (Kosinski et al., 2013). Kosinski obtained information culled from the public Facebook pages of volunteers via a quiz app called myPersonality, which also subjected his experimental subjects to a battery of common psychometric personality tests. These scales included the well-known NEO or Five Factor psychometric personality test (also sometimes described as the OCEAN model of personality),[2] and the Diener (1985) 'satisfaction with life' or SWL scale.

Kosinski's results were more statistically significant for some measures of demography, behavior, and personality than others. For instance, the analysis was relatively successful at predicting certain demographic categories, such as race or sexual orientation, based on their patterns of Likes. Upon its release, the study caused concern among online privacy advocates; the suggestion individuals could be 'outed' based on their public behavior prompted particular consternation (Kelly, 2013). Yet while the analysis of 'Like' data came close to predicting the scores that the OCEAN personality test subjects self-reported for 'Openness', it was much less successful at predicting where subjects scored on the other axes of the OCEAN model or on the 'satisfaction with life' scale. Kosinski and colleagues suggested that their work's lower predictive accuracy with regard to the SWL scale was 'attributable to the difficulty of separating long-tern happiness from mood swings, which vary over time' (Kosinski et al., 2013: 5804). The results showed that performing psychometrics via massive data analysis was plausible, but would be challenging not only by the work's technical limitations, but also by the potential lack of both quantitative and qualitative data about the whole person over time.

Algorithmic psychometrics is thus exemplary of the ongoing techno-scientific investment in what Ginzburg (2009) has termed the 'conjectural model' of the human sciences. In such a model, technologies and techniques are put to work to determine an interior reality from external clues in a play of correspondences variously defined as causal or correlational, or sometimes both. The integration of behavioral tests, psychological scales and other technical affordances drawn from the psychological and behavioral sciences is both a quantitative and qualitative change in the ways the psy sciences have articulated human subjectivity through technical means; in fact, psychology, as a component of algorithmic psychometrics, should be understood both as a core component of the sociotechnical apparatus of social media, and as a discipline able to make use of those same technologies.

Yet, though social media platforms have solved the problem of all-encompassing and longitudinal data collection, a central epistemological limitation remains: with the exception of behaviorists, psychologists and psychiatrists – especially those in clinical practice – have rarely believed that numbers are able to speak for themselves. Contemporary psychological textbooks, for instance, routinely caution students of the risks that psychological tests, scales and measures will shape and reify the beliefs of both patient and practitioner regarding the epistemological claims of the test itself. One textbook warns of the danger in using rating scales for mental health conditions not as a diagnostic first step, but as a descriptive categorization of the subject, potentially exacerbating a patient's diagnosis as a result (Gregory, 2004). These cautions apply equally to computational analyses of data regarding affect, emotion, behavior, and personality, including data collected via 'digital phenotyping'. If both the subjects of data analysis and those performing it mistake description for prescription, digital technologies risk magnifying this data reification across millions of individuals, with consequences for how we understand and articulate ourselves in relation to our data doubles (Haggerty and Ericson, 2000).

Performativity and the scalable subject

One of the benefits of digital phenotyping articulated by Jain, Insel and others is its flexibility in 'enabling measurement-based care at scale'. In the world of Silicon Valley, the term 'at scale' is often shorthand for 'able to handle a large number of users'. Yet this definition is incorrect. The concept of scale is relational: it implies a set of relative ratios or gradations irrespective of magnitude. The scalable subject of social media platforms and massive data analytics is defined by her embodied, performed relationship to the models of behavior, emotion and personality deployed by these artifacts. By scalable, I mean the ways such a subject can shift herself or be shifted across types or kinds of scale – nominal, ordinal, interval or ratio.[3] As numerous feminist STS scholars have argued, such a performance includes the interrelated correlations, translations and equivalences made both algorithmically by a technical system, and by the subject herself in her social context (Barad, 2003, 2011; Murphy, 2012; Suchman, 2006). '[S]cales contain the conceptual "hooks" for linkages from one to the other, without reduction to a common denominator…[and as such] a specific measure can take on one or another form … according to the situation' (Guyer, 2004: 49). These hooks, which Guyer calls 'tropes', 'linkage points' or 'thresholds', allow different types of scale to interact and yet remain distinct as techniques of classification and evaluation. A/B testing is one such hook or linkage point in the social media context, shifting individual subjects from one scale to another, a technical means through which different types of scale are made relatable to one another.

Psychological and behavioral models incorporated into social media platforms even shape individuals unaware of these models. A model's incorporation into 'algorithms, procedures, routines, and material devices … can have effects even if those who use them are skeptical of the model's virtues, unaware of its details, or even ignorant of its very existence' (MacKenzie, 2016: 19). In the case of social media platforms, the interoperability of binary code allows for multiple, flexible comparisons and linkages between different types of scale: natural language (or symbolic) signifiers of emotional expression or routine behavior can be quantified, just as numerical data about behavior or emotion can, and is, inevitably translated into natural language signifiers or represented in graphic form. By running A/B tests and enabling data collection via personality quizzes, Facebook, as journalist Brian Cristian observes, 'tends to treat users as fungible … testing ad copy [ostensibly] works because man-on-the-street X's reaction is presumed to be a useful guide to man-on-the-street Y's reaction' (Cristian, 2012a, 2012b). Conceptual scale is, by implication, both linked to and potentially an affordance of technical format; numerical data collected from human physiological processes, for instance, is used to extrapolate emotional states as described through language or graphic means (Ahmad, 2011; Picard, 2000; Picard and Klein, 2002; Picard and Scheirer, 2001).

The norms of scalability are motivated by correlation. If the relationships between different variables correlate in the aggregate, there is danger in assuming the same relationship will also correlate at an individual level – an error known as the 'ecological fallacy' (Piantadosi et al., 1988). Tools like computational sentiment analysis of natural language text corpuses are often deployed to chart, and at the same time create, 'an ambient sentiment … productively modulated and manipulated in ways that impact upon the desires, emotions, and preferences of individual viewers and consumers' (Andrejevic, 2011: 615). Yet lost in descriptions of the aggregate are the ways in which individual subjects understand their own scalability in relation to these platforms (Arvidsson, 2012). A lack of accurate descriptive power does not mean the applied psychological techniques within digital systems lack a standardizing, prescriptive or even proscriptive power (MacKenzie, 2016); it is precisely the constructed and performative nature of 'descriptive' models which produces those effects (Hacking, 1999; Isaac, 2009).

Actual social media users are in a bind involving their own configured correlation at different scales: as nominal individuals, ordinal units and profiles composed of numerical data constantly analyzed by a platform. The scaling up performed by the platform is not how human beings perceive and experience the world, and there is a gap between perception at the individual physiological and emotional level (Stark, 2016b), and the platform's view of the mass – or what Foucault (2003) termed the level of 'normation'. What Andrejevic defines as 'ambient sentiment' is both a quantitative aggregation and a scalar translation of individual perceptions of feeling, not a straight description of these latter realities; yet this aggregate category is then represented back to individual users as a norm against which they should perform, in Mackenzie's sense, in correlating their own feelings. The ideal scalable subject preemptively positions herself in the correct scale of the moment, and is fluent in the emotional expressions, behaviors and gestures aligned with a platform's models – conforming to classificatory schemes. Such a subject position is easily added into a larger data set, but in practice a scalable subject is also caught, as matter of lived fact, in the everyday pressure to perform emotional expression at various mediated scales, offline and on (Hochschild, 2003; Illouz, 2007; Raval and Dourish, 2016).

When angry Facebook users accused Cornell's Jeff Hancock of manipulating their emotions as a form of 'mind control' in the wake of the Facebook emotional contagion study, they were intuiting the scalable relationship at the heart of the digital subjectivity constructed and enabled by social media platforms: that the statistical correspondences extrapolated by Facebook's study had the potential to be converted into one-to-one correspondences in their own mediated subjective experience, via the platform's performed affordances and their own subsequent habituated practices (Chun, 2016; Schüll, 2012). This mechanism differs from those of nineteenth century psychological science described and analyzed by Rose. Under Rose's formulation, the psy sciences 'render individuals knowable through establishing relations of similarity and difference amongst them and ascertaining what each shares, or does not share, with others' (Rose, 1988: 197). While these practices of legibility still, of course, take place, the scalability of the digitally mediated subject forces individuals to seek to understand themselves through the examination of algorithmically produced relations of similarity or difference which often seem tenuous or incomprehensible to the individual person, or even the expert at the controls (Pasquale, 2015b).

More broadly, the quantifiable, testable and scalable subject position produced by the incorporation of psychological techniques into social media platforms has become universalized and reified through these platforms' ubiquity (Lee et al., 2015; Rosenblat and Stark, 2016; Scheiber, 2017). As Andrejevic observed as early as 2011, these interventions are the result of, 'the data-driven fantasy of control in the affective economy: the more emotions are expressed and circulated, the more behavior is tracked and aggregated, the greater the ability of marketers to attempt to channel and fix affect in ways translating into increased consumption' (Andrejevic, 2011: 615). Today, digital platforms have capitalized on social and emotional interaction as the engine of the online attention economy: data analysis around behavior, personality, and emotive expression are not only big business, but also examples of applied algorithmic psychometrics on a massive scale.

Emotional psychometrics via social media platforms

The 2014 Facebook emotional contagion study determined the emotional valence of the site's user-posted content through a technique known as 'sentiment analysis', or the tabulation and classification of common words for emotional expression based on their frequency. The tool used by Kramer and his co-authors to perform their analysis was the Linguistic Inquiry and

Word Count (LIWC2007) word counting program, software developed by psychologist James Pennebaker and colleagues at the University of Texas at Austin. Described by its creators as the ‘gold standard in computerized text analysis’, the software, according to the platform’s marketing materials, ‘reads a given text and counts the percentage of words that reflect different emotions, thinking styles, social concerns, and even parts of speech’ (LIWC 2015: How it Works, n.d.). Pennebaker’s particular contribution to the psychometrics of language was to argue that so-called ‘style’ or function words – prepositions, articles, conjunctions and other similar categories – were more indicative of psychosocial states than ‘content’ words such as nouns and verbs, and assessing the two categories together in any written text would provide a more accurate read of its sentiment. The initial purpose of LIWC was to develop an automated means of assessing open-ended written accounts psychometrically – in other words, parsing any text to gauge a person’s psychological state, not simply a standard pre-validated scale or questionnaire. Alongside the *PNAS* study, LIWC has also been used for other well-known social media sentiment analysis experiments, including a 2011 study that tracked the ‘mood’ of Twitter via semantic data and found cross-cultural diurnal and seasonal commonalities around patterns of positive and negative feeling (Golder and Macy, 2011).

As Pennebaker and his co-authors admitted, the psychometric evaluation of large text corpuses is both ‘quite crude’, and not necessarily accurate. In a 2015 paper, LIWC’s creators observed the history of linguistic tabulation and analysis for psychological purposes was a long one, ranging from Freud’s interest in slips of the tongue to the descriptive elements of the Rorschach test (Pennebaker et al., 2015; Tausczik and Pennebaker, 2010); they also noted the ongoing fascination with the ‘conjectural model’ (Ginzburg, 2009). Given that LIWC’s diagnostic results stem from both computational correlation and human judgment (in setting the system's dictionaries and word categories), its finding inevitably reflects evaluative biases grounded in the context of social, historical, and cultural development and use (Nissenbaum, 2015). Pennebaker and his co-authors even admitted that '[t]he imprecise measurement of word meaning and psychological states themselves should give pause to anyone who relies too heavily on accurately detecting people's true selves through their use of words' (Tausczik and Pennebaker, 2010: 29). Nonetheless, the authors observed: 'Psychologists are always looking for measures that reveal the secret, hidden, or distorted 'real' self'. In the context of Mackenzie's notion of performativity, the imprecision inherent in the LIWC model of sentiment should be understood as an active feature of the program's apparatus of subject creation, not a purely incidental limitation.

Alongside natural language sentiment analysis, the extrapolation of psychological states via digital phenotyping is another means to construe and construct a scalable psychometric profile of a digital subject out of patterns in their behavior. Any platform or application can use the sensors built into commercial smart phones – which usually include an accelerometer, gyroscope, linear acceleration sensor, proximity sensor and other sensors – to collect behavioral data. Much of the extant research in the area has so far been tied to applications and services designed to track and manage clinical mental health conditions. This particular expression of the psycho-computational complex was underscored in 2015, when the aforementioned Dr. Thomas Insel, then head of the US government's National Institute of Mental Health, left the organization to take a senior position at Google's parent company Alphabet (Ledford, 2015). While at NIMH, Insel had been an enthusiastic proponent of using digital technologies to monitor patients and personalize treatments (Insel, 2015), and had been a critic of the Diagnostic and Statistical Manual of Mental Disorders (DSM) as a diagnostic tool. Complaining that the DSM was ‘entirely symptom-based and fairly subjective’, Insel suggested one of his primary goals while at Alphabet would be to ‘figure out a better way to bring data analytics to psychiatry’ (Regalado, 2015).

Despite Insel’s departure, the NIMH continues to emphasize digital interventions in mental health management as the future of treatment for mental disorders. ‘Behavioral health apps will need to combine the engineers’ skills for making an app easy to use and entertaining with the clinician’s skills for providing effective treatment options’, suggests a recent NIMH fact sheet (Anonymous, 2017). Smartphone-based collection of behavioral data for psychological treatment is becoming increasingly sophisticated (Burgess, 2012; Lathia et al., 2013; Wang, 2015). Ginger.io is one example of a mobile app designed to translate physiological data into insights about a user’s mood (Buhr, 2014). Developed out of research conducted at the MIT Media Lab, Ginger.io mobilizes and correlates a wide array of passively collected data streams from a user’s smartphone, including patterns of app or text usage, physical movement (captured by the phone’s accelerometer), and location data. The application’s algorithms build a baseline of ‘normal’ activity, and then identify when a user deviates from a pattern – what Sandy Pentland, one of the proponents of ‘computational social science’ and also the company’s co-founder, terms ‘reality mining’ (Eagle and Pentland, 2005). While these developments are often presented as new and novel, it is precisely the long-intertwined history of psychology and computing that has enabled both the discursive paradigms and technical innovations on which such products are based (Gates and Magnet, 2009)

Ginger.io is being marketed as beneficial to patients struggling with mood and behavior disorders such as anxiety and depression, bipolar disorder and schizophrenia, as well as to their health care providers. ‘There’s a lot to learn about how you’re doing from how you use your phone. How you go about your day reflects how you're feeling', the app's website informs potential individual users. While Ginger.io emphasizes the external representation of emotional truth about the self to the patients using it, to providers the application places rhetorical emphasis both on accessibility and cost-containment. 'Our alerts-driven approach directs your team to reach out when patients need it, not when a schedule says they do', the app's website suggests. Whatever the clinical efficacy of Ginger.io's algorithms, the application habituates its users, both doctors and patients, to the idea of a scalable subject intelligible through the sum of and transformation of her data, as well as comprehensive everyday surveillance as a component of clinical care. Meanwhile, wearable devices marketed as mindfulness and wellness aids are pushing techniques of mood management into an ostensibly more direct interface with the body itself while black boxing the scientific and behavioral models underpinning their component technologies (see Littlefield, 2009, 2011; Littlefield and Johnson, 2012).

Digital phenotyping is not confined to clinicians. Facebook and other digital platforms have also increasingly sought ways to structure the behavior of their users so individuals produce their own classificatory data about feelings and behavior. The popularity of informal online tests of all sorts (created by websites such as Buzzfeed.com) and the vernacular use of rating scales like the Meyers-Brigg personality test in professional and business contexts attest to the popular appeal of the conjectural model, and of 'managing intuition' in social and professional contexts (Lussier, 2017). Yet the discourse of human feeling as something to be quantified (Dror, 2001) particularly informs both the computational models increasingly relied upon by data science, and the training of many of the technologists who deploy these technologies on commercial platforms and applications (Boehner et al., 2007). The constellation of techniques and technologies for producing and reinforcing knowledge about the emotional self extends beyond clinical instruments. One key mechanism for encouraging such self-reported emotional data involves enabling users to tag their own activities with graphic objects including emoticons, emoji, animated GIFs, and graphic stickers – a class of now-ubiquitous digital emotive signifiers (Eppink, 2014; Miltner and Highfield, 2017; Stark and Crawford, 2015).

Early blogging and social media platforms such as LiveJournal and MySpace let users set and display their emotional status with a diverse emotional palette of emoticon-like symbols (Boesel, 2013; Kannalley, 2013). In contrast, Facebook initially resisted such tokens of personalized expression, but began to enable users to tag content with simple emotional data through its 2009 introduction of the 'Like' Button (Bosworth, 2014; Gerlitz and Helmond, 2011; Kincaid, 2009). In the spring of 2013 Facebook introduced a LiveJournal-like feature to its users' Status Update fields: the ability to label posts with a wide variety of small graphic icons attached to a wide variety of verbs. In the 'feeling' category, at the top of the pull-down menu, users were given the option of choosing from over 200 simple facial pixel graphics mimicking the popular emoji character set. Individuals could register they felt happy, sad, frustrated, blessed, ill or a variety of other emotions and sensations. While sentiment analysis programs like LWIC and Lexalytics have worked to incorporate emoji into their analytics and business models, the highly allusive nature of emoji use has made their mobilization absent other forms of descriptive text difficult – hence Facebook's interest in pairing the two.

Facebook's designers characterized the addition of these graphics as a way to enable a wider range of emotional expression within the interface design of the site. 'When you talk to someone in real life, you can see their face and have their entire context as to what they mean', Ryan Case, one of Facebook's product designers, told *Fast Company* magazine in 2013 (Wilson, 2013). 'Obviously when you bring it online, you lose some of that context.' Yet media commentators also noted the commercial implications of Facebook's move, often taking the collection and manipulation of emotional data as a given in light of the platform's advertising-based business model. 'By selecting your current activity instead of merely writing it out, you structure data for Facebook', a *TechCrunch* columnist observed when the feature was unveiled, noting the site could 'use that behavior to pinpoint you with ads' (Costine, 2013). Only a small percentage of users have used of the feature since its rollout, though given the size of Facebook's user base even such a proportion was still considerable (Burke and Develin, 2016; Oremus, 2013)

In the fall of 2015, Facebook began to test yet another graphic means to enable users to tag content on the site with emotional data: a palette of six faces signifying basic emotions to compliment the 'Like' button on all user-generated content (Goel, 2015). Facebook's Status Update emotional tagging had allowed users categorize their own words; the site's new Reaction Icons encouraged those same users to categorize other people's content with simple emotional terms. Released to all users in February of 2016, Facebook's reaction buttons drew heavily on the now well-known palette of emoji faces which had gained popularity among social media users, while simplifying user category choice as much as possible: 'With Reactions, Facebook has pared down that most economical mode of communication to its barest of bones', observed *TechCrunch* (Gonzalez, 2015).

Facebook's Like button and Reaction icons are two examples of design features through which a digital platform can push its users toward the performance of particular scales of emotional expression. The site's heavy promotion of pixel graphic 'stickers' in its Messenger application and its incorporation of support for animated GIF images are further examples of Facebook's interest in collecting data gleaned from the emotionally expressive labor of users into its behavioral profiles and its creation of what Andrejevic terms new ‘affective economies’ (Andrejevic, 2011). Facebook’s description of its data usage policy notes the company, ‘can collect the content and other information you provide when you use our Services, including when you sign up for an account, create or share, and message or communicate with others’, in order to make changes to Facebook’s site, and ‘show and measure ads and services’ (Data Policy, 2015). Artists like Ben Grosser have highlighted the heightened ‘emotional surveillance’ enabled by the Reaction icons through interventions like ‘Go Rando’, a web browser extension that randomly chooses an icon for the user to post and thereby obfuscates a user from the site’s collection of emotional data.[4] Yet for the vast majority of users, Reactions, and the heightened emotional surveillance and behavioral tracking they represent, have become a part of their social routines – representing the fading of algorithmic psychometrics into the background of everyday life.

Conclusion: Algorithmic psychometrics and computational politics

In the weeks after the unexpected election of Donald J. Trump to the Presidency of the United States in early November of 2016, articles and opinion pieces began to circulate in both the American and European press ascribing credit (or blame) for the Trump campaign’s victory to a British firm named Cambridge Analytica. In its marketing materials and post-election public statements, the company had bragged that it had been a major factor in the Republican candidate’s unexpected victory through its deployment of ‘psychographic’ data as part of the campaign’s voter analytics. ‘Psychographics’, the company claimed, involved categorizing individuals not simply by demographic qualities, but also by where they stood on the OCEAN personality scale, in order to target advertising and canvassing messages particularly amenable to persuading their particular personality type. In January of 2017, two Swiss journalists published an article making the case in detail. The reporters interviewed Michal Kosinski, the author of the 2013 study on psychometrics via the Facebook 'Like' Button, who revealed that in 2014 he had been approached by a representative of Strategic Communications Laboratories (SCL), the parent company of Cambridge Analytica, seeking access to the analytic methods behind his work. Cambridge Analytica's methods – collecting personality data via Facebook and third-party data brokers, and using them to gauge the personalities of potential Trump voters –closely tracked Kosinski's research. 'This is not my fault. I did not build the bomb. I only showed that it exists', Kosinski told journalists plaintively (Grassegger and Krogerus, 2017). Psychographics via social media had, it appeared to some, helped Donald Trump win the election.

Various parties have disputed the narrative advanced by Cambridge Analytica touting their psychographic profiles as dispositive to the Trump win, dismissing many of its claims as marketing hype (Confessore and Hakim, 2017; Kaye, 2016; Matheson, 2017). The company, despite initially claiming publicly that their psychometric techniques had been decisive, later denied they had even provided those particular analytics to the Trump campaign. In early 2018, reporting from *The Guardian* newspaper, anchored by a Canadian whistleblower, reignited the furor around Cambridge Analytica's data collection practices (Cadwalladr, 2018b, 2018a; Rosenberg et al., 2018), its relationship to Facebook, and its symbolism as a symptom of Zuboff's 'surveillance capitalism'. The story had elements of spy-novel theatrics: Aleksandr Kogan (also known as Aleksandr Spectre), a colleague of Michal Kosinski's at Cambridge University, was purported to have replicated the myPersonality quiz, harvested data from Facebook users without informing either users or the company of his commercial intent, and then sold the data to Cambridge Analytica (Sabri, 2018). At the time of this writing, Cambridge

Analytica has been ensnared in widening probes into Russian social media influence on both the American election and the United Kingdom's 'Brexit' referendum; Kogan's and Cambridge Analytica's ties to billionaire conservative Robert Mercer, the Russian government, and a variety of other nefarious 'psy ops' contracts around the world were all also under investigation by multiple countries around the world (Cadwalladr, 2017).

Yet Cambridge Analytica was only one piece of the Trump campaign's data analytics operation. Headed by a digital marketer, Brad Parscale (Green and Issenberg, 2016), the Trump campaign's close collaboration with Facebook staff was arguably far more decisive in enabling successful voter targeting in multiple ways (Bump, 2018). While Cambridge Analytica has provided a useful conceptual hook for scholars to articulate the dangers of uniting digital advertising and political campaigning, the *de facto* psychometric profiling already being performed by social media platforms long predates Trump's ascension to the presidency. The scope of these networks of data collection, and the ease with which granular behavioral information is available at different scales, can now be leveraged to engage with digital media users directly, interactively, and cheaply for any conceivable purpose. 'Your smartphone', Kosinski observed, 'is a vast psychological questionnaire that we are constantly filling out, both consciously and unconsciously' (Grassegger and Krogerus, 2017). While the efficacy of these forms of targeting remains an open question in the case of the 2016 Brexit referendum and US Presidential campaign, the specter of algorithmic psychometrics underscores Tufekci's 2014 prediction that increasingly granular voter targeting would become a central arena of contestation for the computational politics of the twenty-first century (Tufekci, 2014).

Computational politics are as much about psychology as about computing. In a short essay published in 2015, legal scholar Frank Pasquale cast the Facebook emotional contagion study as exemplary of the ways in which social media platforms shape users' understanding of their own subjectivity and autonomy. Pasquale made an explicit comparison between Facebook's study and its psychological antecedents: he suggested, 'platforms are constantly shaping us, based on sophisticated psychological profiles' codified in a 'new, milder DSM'. If a '[psychological] state is better for business, [perhaps] it will be cultivated and promoted', Pasquale hypothesized (Pasquale, 2015a). Yet the influence of the psychological sciences on digital platforms is, in general, doubly occluded: hidden from users by their baseline incorporation into the technical affordances of platforms, but also often veiled from the designers of those systems themselves. Technologists draw from psychology without much sensitivity to the controversies and contestations which exist within it as a discipline in its own right, and in doing so they risk both reinforcing psychological models of dubious validity or applicability and add new complicating affordances besides (Spellman, 2015; Yong, 2016).

Pasquale's framing of Facebook as a giant psychology experiment conducted primarily for profit is apt. Digital platforms collect behavioral data about affect, emotion and mood – data invaluable for personality modeling – across several different scales: those of natural language, numerical physiological data, and graphic images. The methods and techniques of psychology operationalized via computational systems can use all of these sources of data to construct, stabilize, measure and evaluate any individual as an interpretable scalable subject. Out of these machinations, individuals become made part of what Sweeney (forthcoming) terms 'psychometric publics', groups of 'dividuals' 'imagined as atomized and individually manipulable'.[5] As Sweeney further observes, the centrality of social and emotional interaction in digitally mediated situations is abrogated in such systems. I would add that scalability is precisely why individuals are caught in a double bind with regard to their use of these platforms:

because the scalable subject position can be constituted using any kind of scale and multiple types of individual data, any engagement entails some exposure and contact with scalability's norms, yet failing to engage means social and emotional isolation.

I have laid out some of the data streams through which the subjects of social media platforms are scaled as legible to algorithmically enabled behavioral and psychological science. Through human-computer interaction's indebtedness to psychology, the clinical psychological subject, a figure amenable to testing and experiment, has been transformed into the scalable subject of social media platforms, structured and categorized by companies like Facebook and universalized as a facet of the lived experience of the digital everyday. The increasing centrality of sociotechnical phenomena also suggests we need a re-estimation of the importance of the psy disciplines, and 'soft biopolitics', to the study of digital technologies. Through the application of insights from psychology and the other human sciences and 'sciences of subjectivity' (Shapin, 2012), social media users are scaled and categorized not only for direct commercial gain, but also in the name of public safety, national security, psychological adjustment, political advantage or combinations of all of the above. Such manipulations are already taking place, heralding a new computational politics grounded in our lived experience as scalable subjects. In turn, STS and related disciplines should attend to the human sciences as influenced by and integrated into the fabric of digital media and its uses (Brandt and Stark, 2018; Feldman, 2017; Gates, 2011; Noble, 2018).

If the 2014 Facebook emotional contagion study revealed us to be, whether we benefit or not, scalable subjects, the controversy around Trump's data-driven victory suggests algorithmic psychometrics may have world-historical consequences. I have argued here psychometric models of personality, behavior, and emotion proliferate in the devices and dreams Silicon Valley sell us, shaping our experience of digital technologies and social media platforms – and by extension, our understanding of ourselves (Shaw, 2016, 2017). Human emotions inevitably work as potential levers for human political engagement (Hillis et al., 2015; Papacharissi, 2014). The growth and development of a psycho-computational complex, and of the psychometric analysis and classification of our selves understood as scalable subjects, calls urgently for a computational politics wedded to emancipation and human flourishing. Such a politics, working across multiple scales of online expression, interaction and sociality, must take psychology seriously in its computational context, and must grapple with the reality of our behavioral, affective and emotional suasion by algorithmic psychometrics.

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Notes

[1] For a cogent discussion of the definitional differences between affect, emotion, mood and feeling, see (Gould, 2010). Here I use both 'affect' and 'emotion' to distinguish them as separate forms of experience, and use 'feelings' as a more general term for both terms.

[2] In proposing the NEO scale, Costa and McCrae (1992) argued that most individual differences in personality could be understood as occurring along five basic dimensions: 'Neuroticism (N) vs. Emotional Stability; Extraversion (E) or Urgency; Openness to Experience (O) or Intellect; Agreeableness (A) vs. Antagonism; and Conscientiousness (C) or Will to Achieve'. The authors explicitly noted their scale was not designed, as other more specialized tests had been, to diagnose particular psychopathologies, but was intended as a more general diagnostic aid (Costa and McCrae, 1992; Goldberg et al., 2006; McCrae and Costa, 2004).

[3] 'Some scalar qualifiers may be simply nominal or classificatory, defining this or that phenomenon as part of a semantic domain. Others will be ordinal, defining cognate things along a standard of "greater or lesser". Some may include interval measurement of some kind, where not only the place in the order but the distance between positions on a scale can be expressed. Only those based on number will be ratio scales allowing infinite calculation of the relationship between any item on the scale and any other. These scales presumably form repertoires in all economies, complete with conventional modes of linking one to the other: quality to object classification, quantity in

numbers to money goods' (Guyer, 2004). I am grateful to Max Liboiron and Erica Robles-Anderson for their work on scale, which has also been influential in my own thinking through personal conversations.

[4] Grosser's Go Rando and more recent Twitter Demetricator can be found at https://bengrosser.com/

[5] I am grateful to Patrick James Sweeney for this insight. The term 'dividuals' stems from the work of Deleuze (1990). See also Sweeney (2017).