

Self “Sensor”ship: An Interdisciplinary Investigation of the Persuasiveness, Social
Implications, and Ethical Design of Self-Sensoring Prescriptive Applications

by

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ABSTRACT

This dissertation research investigates the social implications of computing artifacts that make use of sensor driven self-quantification to implicitly or explicitly direct user behaviors. These technologies are referred to here as self-sensing prescriptive applications (SSPA's). This genre of technological application has a strong presence in healthcare as a means to monitor health, modify behavior, improve health outcomes, and reduce medical costs. However, the commercial sector is quickly adopting SSPA's as a means to monitor and/or modify consumer behaviors as well (Swan, 2013). These wearable devices typically monitor factors such as movement, heartrate, and respiration; ostensibly to guide the users to better or more informed choices about their physical fitness (Lee & Drake, 2013; Swan, 2012b). However, applications that claim to use biosensor data to assist in mood maintenance and control are entering the market (Bolluyt, 2015), and applications to aid in decision making about consumer products are on the horizon as well (Swan, 2012b). Interestingly, there is little existing research that investigates the direct impact biosensor data have on decision making, nor on the risks, benefits, or regulation of such technologies. The research presented here is inspired by a number of separate but related gaps in existing literature about the social implications of SSPA's. First, how SSPA's impact individual and group decision making and attitude formation within non-medical-care domains (e.g. will a message about what product to buy be more persuasive if it claims to have based the recommendation on your biometric information?). Second, how the design and designers of SSPA's shape social behaviors and third, how these factors are or are not being considered in future design and public policy decisions.

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GENERAL INTRODUCTION

Self-quantification, or recording information about one's daily inputs, states, and activities, is used in the healthcare industry to encourage patients to take greater control of managing their health symptoms (Barnett, et al., 2008; Collinge, Yarnold, & Soltysik, 2013), to promote patient self-efficacy (Gleeson-Kreig, 2006; Ngamvitroj & Kang, 2007), to improve diagnostics, and to cut healthcare costs (Marzegalli, et al, 2008; Leong, Sirio, & Rotundi, 2005). In the past, self-quantification was conducted by the patient manually monitoring and recording his or her own physiological signals or behavioral activities (e.g. recording heart rate, testing blood glucose levels at regular intervals, assessing subjective energy level, pain level, affect, etc.) and then transferring these data to the medical provider through note taking, data entry into a computer systems, phoning into an answering service, or reporting to an intermediary care taker (McAdams, et al. (from Bonfiglio and Rossi), 2011 pp180-185). Compared to regular doctor's office visits and/or waiting until symptoms become bothersome, this method of quantification has shown some evidence that it is indeed useful in early diagnosis, improving health outcomes, and reducing costs (Clarke & Foster, 2012; Korotitsch & Nelson-Gray, 1999). Many recent methods of self-quantification have incorporated sensor technology (ambient and wearable) to automatically monitor patient behaviors and biological factors in a way that data is captured in real time with little to no action by the patient (McAdams, et al., 2011; Nangalia, Prytherch, & Smith, 2010; Pantelopoulos & Bourbakis, 2010; Patel, Park, Bonato, Chan & Rodgers, 2012; Song, Wang, Yang, & Li, 2014). Within the healthcare industry, the input of self-sensor data is viewed as a critical component of diagnosis and treatment, especially in situations where some symptoms require frequent and accurate measurement (such as

blood glucose levels) to properly manage (Clark & Foster, 2012). These data are generally being used in two separate but related aspects of health care; diagnostics and prescriptives. In diagnostic applications, medical personnel may use sensor data to identify risk factors or changes in typical behaviors. For example, the ZIO patch heart monitor records the wearer's electrocardiograph information and can detect irregular heart rhythms which can aid in early diagnosis of heart disease and aid in stroke prevention (Barrett, et al., 2014).

In prescriptive applications, medical personnel may use sensor data to generate directives for a patient to follow, such as to change/take medications, change body position, increase the intensity of a work out, stop a particular behavior, etc. These applications are intended to better manage and/or prevent the onset of symptoms. For example, Bachlin, et al. (2014) designed a wearable device for persons with Parkinson's disease who experience freezing of gait (FOG). FOG is a sudden, but momentary "inability" to move and can often lead to a fall. While pharmacological treatments for FOG symptoms have shown limited promise, behavioral treatments using external cues (such as walking to an audible beat) have seen more success. However, behavioral treatments require conscious vigilance, which may be difficult for older patients in the later stages of Parkinson's disease. The wearable designed by Bachlin, et al. detects precursors of FOG symptoms and provides the wearer with an audible sound before the FOG occurs, alerting the wearer that he or she should act to avoid FOG.

Prescriptive application with tangibly positive outcomes, like preventing falls, may seem manifestly unobjectionable, however, the ubiquity and robustness anticipated for the future of wearable devices that use SSD means developers will be able to link biological data to behavior in ways where the prescriptives are far less objectively positive. While the

medical industry's use of self-sensor data and application development and the goals they work toward are arguably guided by government regulations and established codes of conduct (Riddick, 2003), the ethical and regulatory standards guiding the use of self-sensor data in consumer applications are considerably less coherent or transparent. A report from Gartner (2016) projects revenue for SSD devices will reach 28.7 billion in 2016 with the majority of this revenue stemming from consumer wearables for health and fitness, which are projected to sell nearly 200 million units worldwide in 2016 (Woods, & Van der Meulen, 2016). The design and deployment of these consumer products pose unique ethical and regulatory challenges that are not well addressed in literature, especially when contextualized as part of a broader sociotechnical system in which scientific knowledge about the body and understandings of normality are not causal, but co-constructed (Pinch & Bijker, 1984; Foucault, 1977; Ilich, 1976; Rosenberg, 2002).

Project Summary

This dissertation research investigates the social implications of computing artifacts that make use of sensor driven self-quantification to implicitly or explicitly direct user behaviors. These technologies are referred to here as self-sensing prescriptive applications (SSPA's). This genre of technological application has a strong presence in healthcare as a means to monitor health, modify behavior, improve health outcomes, and reduce medical costs (Boulos, Brewer, Karimkhani, Buller, & Dellavalle, 2014; Lewis, Eysenbach, Jimison, Kukafka, & Stavri, 2005; Swan, 2012a). However, the commercial sector is quickly adopting SSPA's as a means to monitor and/or modify consumer behaviors as well (Swan, 2013). This growing industry consists of primarily wearable sensors that monitor characteristics such as movement, heartrate, and respiration;

ostensibly to guide the users to better or more informed choices about their physical fitness (Lee & Drake, 2013; Swan, 2012b). However, applications that claim to use biosensor data to assist in mood maintenance and control are entering the market (Bolluyt, 2015), and applications to aid in decision making about consumer products are on the horizon as well (Swan, 2012b). Interestingly, there is little existing research that investigates the direct impact biosensor data have on decision making, nor on the risks, benefits, or regulation of such technologies. The research presented here is inspired by a number of separate but related gaps in existing literature about the social implications of SSPA's. First, how SSPA's impact individual and group decision making and attitude formation within non-medical-care domains (e.g. will a message about what product to buy be more persuasive if it claims to have based the recommendation on your biometric information?). Second, how the design and designers of SSPA's shape social behaviors and third, how these factors are or are not being considered in future design and public policy decisions.

Primary Objectives

Using an interdisciplinary approach, this research seeks to achieve three primary objectives drawn from the existing body of knowledge on the use of SSPA's in the healthcare industry and their adaptation and adoption by the commercial sector.

Objective 1 (Science, Technology, and Society):

To investigate the social implications of the commercial use of self-sensor prescriptive application technologies (SSPA's) from a Science, Technology, and Society perspective.

Objective 2 (Experimental Psychology):

To conduct an experiment using human subjects that measures perceptions and impacts on persuasion of SSPA use in a non-healthcare scenario.

Broader Purpose

The broader purpose of this dissertation is threefold: to expand and refine basic and applied research in the field of psychology, to contribute to future policy related to governance of emerging technology, and, most broadly, to conduct an interdisciplinary research project that engages different epistemological approaches to knowledge creation and that impacts multiple knowledge domains. The three stated objectives above will facilitate this broader purpose by identifying the risks and benefits as they pertain to the current sociotechnological system in which the technology is embedded, using an experimental approach to investigate persuasive impact of the technology, and developing a value-oriented approach to future regulations related to minimizing risks while maximizing benefits. In a strictly disciplinary approach these questions would more likely be asked and investigated individually by scholars from different domains; however, because each objective relies heavily on the research outcomes of the others, I believe an interdisciplinary approach can more adequately speak to the broad question of how this emerging technology may impact society. Given the recent drive to develop technologies to change health behaviors (Boulos, et al., 2014; Lewis, Eysenbach, Jimison, Kukafka, & Stavri, 2005) and the implications this type of social control might have in political and commercial applications, understanding the impact of emerging SSPA's is both timely and critical.

PART 1 - INTRODUCTION

Competition to be the most influential forces in the lives of individuals for voting, consumer choice, group and personal interactions, etc. is omnipresent. The future Internet of Things (IoT), and all the Big Data it subsumes, is lauded as the ultimate tool for consumer analytics, predictives, and influence (Swan, 2012b). The data provided by wearable biosensors, and the algorithms that drive them, is considered a critical component in designing this truly personalized IoT environment, but an in-depth analysis of how this category of technology could impact society has not been conducted. Attempts to use social, political, and economic persuasion tactics to steer publics to certain courses of action is arguably common place, however, the emerging IoT, and the massive amount of data it will provide access to, creates an unprecedented technosphere of influence that is not yet fully understood. Nonetheless, IoT architects are in a full-throttle race to design new ways to monitor, collect, and share user data through different sensor technologies (Peterson, 2015; Wasick, 2013; Worthman, 2014) and the increasing popularity of self-quantification technologies (such as wearable activity trackers) suggests consumers are willing to provide the data (Lupton, 2014; Lee, Egelman, Lee, & Wagner, 2015). While those interested in the mediators of consumer choice transactions may have previously been restricted to IoT data about geolocation, banking, and other visible demographics, now biological, real-time information tracking about the internal behaviors of the consumer, such as heart rate, metabolic information, genetic markers, and neurological feedback, are also being developed as a means to understand and influence consumer behaviors (Swan, 2012b; Swan, 2013). However, while commercial self-sensoring technologies and applications are predicted to be a cornerstone of IoT development and

success (Swan, 2012a), the ethical standards, goals, and behavioral impacts effecting this consumer industry are much less transparent. The following section attempts to examine the implications of this lack of transparency and highlight potential social impacts of the commercial use of self-sensors to create prescriptive applications for non-medical consumers. These factors are explored by first defining the domain of SSPA and current directions in research and development. Next I examine regulatory and ethical standards for SSPA development and deployment. I then highlight deficiencies in these standards by discussing research in the field of psychology, philosophy, and sociology that suggests a number of, as yet, undiscussed risk potentials of SSPA's.

Self-Sensor Prescriptive Applications (SSPA's)

Self-sensor data (SSD) can be used as a means or as an ends in a technological system. Table 1 lists major types of sensors that are currently used in self-sensing devices and the type of information that these sensors can collect. In some wearables, such as prosthetic limbs, cochlear implants, and speech to text devices, SSD is used as a means of communication between the body and the devices in order to control the action of the device. In this category of wearable, the meaning of a particular quantitative measure of SSD is defined by the design engineer(s) by programming the device to behave in some predictable way when these quantities are present, but these quantities may not necessarily be biologically meaningful or relevant to the user. So, for example, a myoelectrically controlled prosthetic arm is controlled by SSD collected from electrical activity in the residual muscle of the amputated limb. The person wearing the prosthetic limb controls these SSD through intentional engagement of the residual muscle. However, the person need not be explicitly aware of specific quantified measurements of the SSD for the

Table 1

Sensor types used in wearable self-sensor devices.

Sensor Type	Mode	Description	Applications
Accelerometer ^a	electro-mechanical	rate of change of the velocity of an object	orientation, vibrations, location, motion, displacement
Acoustic ^b	electro-mechanical	compression and expansion of solids, liquids, or gases	sound, substrate density, composition
Chemical ^c	voltammetric	energy change as result of interaction between analyte and receptor	composition, movement, speed of processes, flow, force, interaction, temperature, detection
	potentiometric	change in electrical potential	
	optical	change in absorbance, refractive, reflection, luminescence, temperature,	
	piezoelectric	frequency change of quartz oscillator plate	
	magnetic	change of paramagnetic properties of a gas	
Flow ^d	electrical	change of electrical properties	movement of liquid
	thermometric	heat change	
Force ^d	potentiometric	change in electrical potential	force, torque, strain, shock, pressure
	electro-mechanical	change in electrical resistance of chemical polymer upon application of force	
	piezoelectric	frequency change of quartz oscillator plate	
Humidity ^e	physical	changes in shape of elastic material	moisture, leaks, humidity
	psychometrics	changes in electrical capacitance or resistance	
	thermometric	change in resistance of electrical current	
Temperature ^f	gravimetric	mass of an air sample compared to an equal volume of dry air	temperature
	electro-mechanical	voltage of current between dissimilar metals that changes with temp.	
	thermometric	change in resistance of electrical current	

Sources: ^aSparkfun, 2016; ^bMediaLab Robotics, 2008; ^cHulanicki, Glab, & Ingman, 1991; ^dMakkonen, & Laakso, 2005; ^eUpp & LaNasa, 2014; ^fAgarwal, 2016.

prosthetic arm to have value. On the other hand, for some wearables, the quantified measurements of SSD are the ends themselves and value is derived from the user's desire to know what these measurements are. This desire is driven by beliefs about the body and these beliefs are shaped primarily by social, psychological, and political factors. For example, if a wearable is designed to monitor myoelectric activity of a body part so that the wearer can use the data to identify strengths and weakness of the muscle tissue, the value of this device is driven by what the user believes these data do or do not tell him about his body and how important it is to know this information.

The two uses of SSD are not mutually exclusive; a device can use SSD as both a means and an ends whether by intentional design or by the design's affordances (e.g. a person could access the SSD data of a myoelectrically controlled prosthetic to diagnose problems with the residual muscle tissue even if the device was not meant to be used in this way). However, the primary focus of this research concerns devices in which SSD is marketed to consumers as an ends unto itself because of the unique and challenging ethical questions the design and distribution these devices raise have not been well addressed in literature. This is not to suggest that devices that use SSD as a means do not pose equally challenging questions related to moral and regulatory concerns, but a much larger body of research in this field already exists. These are primarily contextualized within the field of disability rights and assistive technologies in relation to issues of fairness, equality, and constructions of normality (Baker, 2014; Allhoff, Lin, & Steinberg, 2011; Erkulwater,

2006; Kass, 2003; Vaughn Switzer, 2003; Conrad, 1992) but a critical analysis of social impacts of devices using SSD as an ends has not been done.

When a device markets SSD as an ends the success rests in the ability to convince the user that these ends have inherent value – in other words there must be some reason the user would want to know what these values are. The underlying theme in all such attempts to construct a value for these devices (whether accurate or not) is that SSD inform the user to act or not act. So a device that monitors heart rate will have little value to a runner unless the runner has a desire to understand the meaning of the heart rate; and to understand the meaning of the heart rate means comparing it to some baseline for normality. The runner can interpret the heart rate as being within a normal range in which case no action is needed, or outside a normal range, in which case action may be needed. Value for this device rests on how important this understanding is to the runner and, through this understanding, an action is always implied (i.e. do something different or keep doing what you are doing). In this dissertation, this is referred to as the “prescriptive” quality of the device. This prescriptive quality may be expressed explicitly through a user interface that provides quantified SSD feedback and informs the user what specific actions they should take to change or maintain these measurements or it may be more implicit by only indicating where SSD feedback is situated to some relative measurement (e.g. higher than your peers, lower than your personal norm, etc.). The user interface that conveys the SSD to the users employing explicit or implicit prescription is called the “application.” Taken together, devices that use SSD as ends are referred to here as *self-sensing prescriptive applications* (SSPA’s).

Consumer SSPA's (and medical SSPA's) figure prominently in the ongoing expansion of the IoT. The perceived intelligence and value of IoT systems will be judged by how data is aggregated to create (a) "cyberinferences," in which completely new information about an individual (or object, group, etc.) is created, and (b) "cyberprescriptives," in which instructions and/or actions are generated for the users or other IoT objects. Cyberinferences and cyberprescriptives will be key in creating intuitive, adaptive systems, and will undoubtedly impact how individuals perceive themselves, make decisions, and interact with their world. The addition of SSD to certain IoT systems will be crucial in generating highly accurate and intimate profiles of individual users and in generating cyberprescriptives that are highly relevant to the user and the context at hand. Producing such an IoT system that could reliably guide user behavior and attitudes through cyberprescriptives (such as purchasing choices, health behaviors, social interactions, movements, etc.) is arguably the Holy Grail for social, political, and economic stakeholders competing for control of user behavior. It is therefore not surprising that the development of SSPA technologies has been met with little opposition. Currently, the healthcare industry is at the forefront in researching and developing this type of behavioral co-piloting technology and research and development (R&D) has so far been relatively transparent in terms of ethical standards, outcome goals, and behavioral impacts (Lewis, Eysenbach, Jimison, Kukafka, & Stavri, 2005). In contrast, R&D policies and regulations for consumer SSPA's are nebulous and far less transparent.

Ethics, Regulation, and Policy. Getting a grasp on regulatory and ethical standards concerning SSPA design is challenging, not only because it is an emerging field, but because it is an interdisciplinary one as well. There are many actors and stakeholders

involved in the design cycle of SSPA's and many points in this cycle at which ethical standards are either unclear, unarticulated, or conflicting. Figure 1 illustrates key aspects of the SSPA design cycle and key factors that require designers to make value-based judgments. Here, "value-based" refers to judgements that can be influenced by personal beliefs and goals. For example, the decision to use a pressure sensor that operates by measuring changes in the volume of a gas substrate rather than one that uses a liquid substrate is based on the designer's beliefs about efficiency, costs, availability of materials etc. in combination with their goals for the "user" which may be the manufacturer, some regulatory body, peers, or an end-user.

Though it is difficult to definitively delineate where one field ends and another begins, the sensor mechanics and infrastructure are primarily the domain of engineering (e.g. mechanical, electrical, chemical, etc.). In contrast, the algorithms (from which cyberinferences and cyberprescriptives are forged) that make SSPA's "meaningful" are shaped by several domains. The algorithm (or set of algorithms) essentially performs as a decision engine from which prescriptives are derived. The task of coding a set of commands based on input from the sensor data (e.g. when heart rate reaches >90 bpm a message should appear on the screen) into syntactic and semantic symbols that can be understood by both the technology and the user is a computer engineering task (e.g. software engineers). But before that can happen, biological interpretation of the sensory data input must be derived from a body of knowledge primarily under the domain of natural sciences. These interpretations are rarely definitive and decisions must be made about which to use. These decisions may be made, for example, by an engineer, a scientist, or an

entrepreneur with access to the internet. Decisions associated with algorithm design of SSPA is at the heart of identifying and understanding the social implications of SSPA and are discussed further in *Algorithmic responsibility*, p 32.

The user interface for SSPA's is another design aspect that falls under multiple domains. The codification of the interface software behavior is primarily within the domain of software engineering, but the aesthetic, messaging, and instrumental goals actualized through the work of the engineer are based on the social, cultural, and economic needs of the actors responsible for producing and ultimately marketing the SSPA. Finally, user

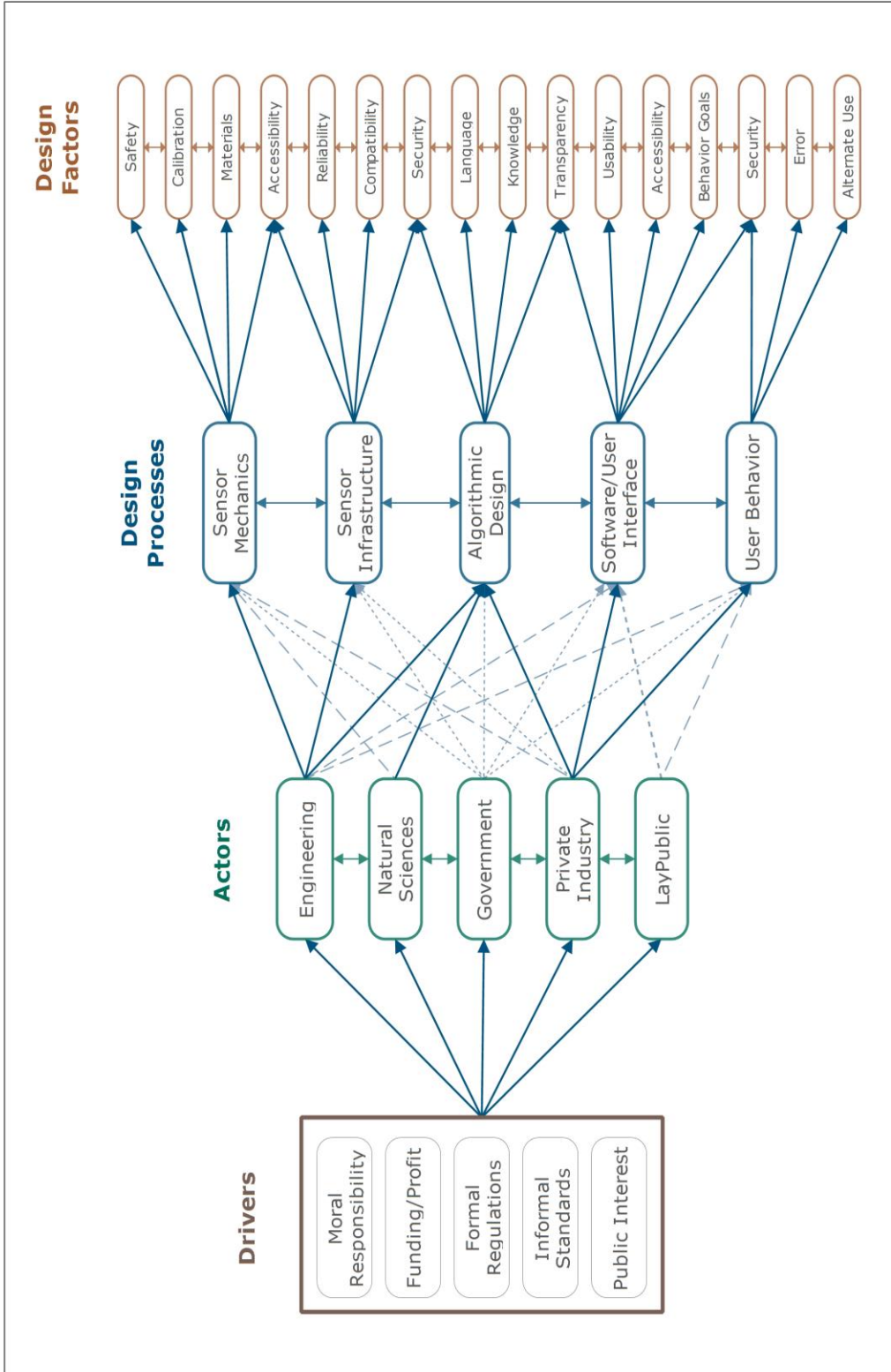


Figure 1. Key SSPA design factors and the drivers, actors and processes that shape them.

behaviors themselves must also be considered as a key aspect of the SSPA design cycle; this factor also falls under multiple domains of ethical and regulatory design considerations. Designers within the engineering domain play a critical role in determining the degree to which users can modify or interfere with the user interface. In order to do this, designers must imagine the various ways in which a user could use a technology in a different manner from which the designer intended and must then decide whether to allow this alternate use or to prevent it by altering the design. (Whether this practice ought to be a required responsibility of the design engineer and the extent to which this type of analysis should be pursued is part of ongoing debate about computer engineering ethics and ethics in technology more broadly (see Herkert, 2001; and van de Poel, 2001)). Users themselves make choices about how and when the interface is used, but whether these choices fully informed or not depends on how transparent the technology's purpose, operating instructions, and risks are. In other words, just as a pharmacy may control user behavior by supplying childproof caps on certain prescription bottles, the patient for whom a prescription is issued is expected to adhere to instructions on how to take the medication, but only when these instructions are clear and meaningful. In its most basic form, engineering related standards apply to the mechanics of SSPA's, science and healthcare related standards apply to the construction of a knowledgebase from which rules about sensor data can be interpreted, private industry standards are used to pick and choose which rules to use, and users decide how the rules will apply to them.

Just as the various components and processes involved in SSPA design fall under multiple domains of informal ethical principles (e.g codes of ethics, industry standards, etc), government oversight does as well. There are several government agencies that

regulate individual aspects of these technologies. For example, if a wearable device makes use of radio wave frequencies, the design would need to adhere to relevant standards set by the Federal Communications Commission (FCC) for that specific factor. Similarly, if the device makes use of chemical reagents, the design would need to adhere to relevant standards set by the Environmental Protection Agency (EPA) for that specific factor. However, many aspects of consumer SSPA design are unregulated; most critically, algorithm design (and the cyberinferences and directives they afford) is not specifically subject to any regulatory oversight so long as the product is not classified as a medium to high risk “medical device” by the US Food and Drug Administration (FDA; US Food and Drug Administration, 2015). This particular issue of algorithm design practices is discussed further in *Algorithmic responsibility*, p 32.

Numerous industry leaders on the medical care side of SSPA development are calling for clarification and oversight from the (FDA) to ensure that applications designed to shape medical related behaviors adhere to some set of quality standards (Strickland, 2012; Boulos et al., 2014). However, the FDA has been slow to respond and has so far only provided narrow guidelines related to specific apps that impact the performance of medical devices that are already regulated (i.e. an app that “transforms” a smartphone into an ultrasound device would need FDA approval before coming to market; US Food and Drug Administration, 2011). Even if the FDA was to take greater control of these types of SSPA’s, it appears that commercial SSPA’s using the same sensor technologies can simply follow a different set rules if marketed as “wellness” or entertainment application.

The FDA released an unofficial, nonbinding set of guidelines for “low-risk general wellness” (LR-GW) products. The very brief document, released for public comment in

January, 2016 was aimed at providing “clarity to industry and FDA staff on the Center for Devices and Radiological Health’s (CDRH’s) compliance policy for low risk products that promote a healthy lifestyle (general wellness products)” (Food and Drug Administration, 2015). The document presents guidelines for defining LR-GW products and clarifies that such products will not be subject to FDA compliance and regulatory requirements.

The characterization of “low risk” is primarily focused on how the physical components of the device interact with the human body. Most of the best-selling wearable devices available today, such as the Fitbit and Apple watch, would be considered “low-risk” under the guidelines so long as they are non-invasive (do not breach skin or mucous membrane of the body), are not known to cause harm if the controls malfunction (eg. laser and radiation damage), and do not damage the skin through biocompatibility issues. Classifying a device as a “general wellness” product is much more subjective and is primarily linked to what the manufacturer *claims* the device can do rather than what it actually does. The guidelines describe “general wellness” products as those with intended use claims solely related to:

1. sustaining or offering general improvement to conditions and functions associated with a general state of health that do not make any reference to diseases or conditions, OR
2. promoting, tracking, and/or encouraging choice(s), which, as part of a healthy lifestyle, may help to reduce the risk of certain chronic diseases or conditions; and may help living well with certain chronic diseases or conditions. (Food and Drug Administration, 2016)

The guidelines do not address the *affordances* of the product, only the “intended use” claims. This could be problematic for a number of reasons. First, while a device might

be marketed as a “general wellness” product according to the guidelines above (and therefore not subject to FDA evaluation), the capabilities of the device may still afford a user access to in-depth symptomatic information unrelated to the intended use claims, and which would normally be used by a physician to diagnose disease or chronic illness. For example, wearable device manufacturer Empatica produces two products that collect similar information but are marketed differently (Empatica, 2016). The E4 Wristband is marketed as a consumer product to provide the wearer with continuous real-time monitoring of blood volume pulse (BVP), electrodermal activity, skin temperature, and motion based activity. It is offered as a data collection device and the manufacturer makes no claims related to diseases or medical conditions. This would (unofficially) be considered a LRGW product. At the same time, the company also offers the Embrace Watch which collects identical information, but is being marketed as an epilepsy monitor and is currently undergoing clinical trials as a tool to prevent Sudden Unexpected Death in Epilepsy (SUDEP). Marketed in this manner, the Embrace Watch would not be considered a “general wellness” product because the intended use claims are directly related to diagnosis of a medical condition. The affordances of the two devices provide the user with the same information from which they can make decisions about their health behaviors, but the manufacturer’s claims about the *intended* use for the data currently dictate whether the device will need to go through any sort of rigorous testing about the accuracy of the data collection or the impact the information has on the user’s actual behaviors and health.

Another potential shortcoming of the FDA’s unofficial guideline is related to a psychological phenomenon referred to as the gatekeeper effect. This phenomenon occurs when an authority (the gatekeeper) exercises some form of implicit or explicit information

filtering before releasing information to a group. Research suggests that information that is *not* excluded by the authority may be perceived as more persuasive even though it is not specifically endorsed (Schweitzer & Saks, 2009). In a legal setting, Schweitzer & Saks found that study participants were less critical of and more persuaded by scientific evidence when it was presented within a trial setting (whether explicitly or implicitly included by the trial judge), compared with the same evidence presented outside of a courtroom context or explicitly excluded by the trial judge. These findings suggest that the judge, or the judicial process more broadly, imbue the scientific evidence with a higher degree of credibility merely by allowing (or not disallowing) access to the information – regardless of the intellectual merit of the information itself. Thinking of the FDA as the gatekeeper, by publishing guidelines through which a manufacturer can avoid review of their product by making only certain kinds of claims about intended use, products that monitor health related information are in some sense “approved” by a process of omission. When thinking about determinations of product safety, *not having* FDA approval is quite different than *not needing* FDA approval. The former is more ambiguous and could imply either a product has yet to seek approval or has been rejected, however the latter implies a degree of risk so low that it could be misinterpreted by laypersons as essentially *having* FDA approval insofar as the perceiver believes the product is within the purview of the FDA. The draft guidelines associate the FDA with product safety for these LR-GW products in a way that didn’t previously exist. Because the affordances of the SSPA are not considered in the draft guidelines, through careful wording of intended use claims, a manufacturer could claim a product, which might otherwise be required to endure clinical testing, is “so safe it doesn’t even require FDA approval.”

The FDA's suggested guidelines for LR-GW wearables also do not address the issue of compatibility and data sharing with other FDA approved self-sensor technologies. The "low-risk" requirement, on the surface, seems to limit a SSPA to a physical design that does not breach the skin and will always be limited to a limited set of sensor types. However, it does not make reference to LR-GW devices that can collect data from other independent FDA approved devices that can transmit data from within the body. This could vastly expand the scope of real-time data available to wearable devices. For example, several ingestible devices that can monitor and transmit physiological, biochemical, and genetic data already have FDA approval (Tolentino, 2013). As it stands now, so long as a SSPA only makes intended use claims related to "general wellness" it could access and provide these types of data to the user and remain outside the FDA's purview. This could expand the scope of data available for "general wellness" assessment to the entire physiological make-up of the human body.

Finally, the draft guidelines also specify that "disease-related general wellness claims should only contain references where it is *well understood* [emphasis added] that healthy lifestyle choices may reduce risk or impact of chronic disease or medical condition," but leaves unsaid from whom this type of consensus must come from and what standards establish it. When it comes to disease-related risk and treatment, the notion that things are ever "well understood," seems overly idealistic and, at the very least, temporary. Users immersed in SSPA's, Big Data, and the IoT will no doubt find it easier to quantify and categorize themselves according to norms and to seek "treatments" to reach those norms when they fall short. But it is critical to recognize that perceptions of what is and what is not normal continually changed over time and things we consider "well

understood” as contributing to a healthy lifestyle (and what we consider to be a “healthy lifestyle”) are intimately tied to culture and power rather than objective interpretation of raw data. Individuals and organizations that control medical knowledge are able to shape these perceptions; however, some of those considered to be “part of” the medical community, such as the pharmaceutical industry, are motivated to create or selectively make available knowledge that most benefits their economic interests, rather than the best interests of the patient (Poitras & Meredith, 2008; Moynihan & Henry, 2006; Goldacre, 2013). Indeed, if we consider the pharmaceutical industry as an example of a private industry borrowing credibility from medical science to sell consumer goods, it stands as an example of how SSPA’s may also gain influence over consumers. No doubt pharmaceuticals are used for decidedly “medical” purpose, but how these purposes come to be considered “medical” is sometimes a chicken-or-egg question (Goldacre, 2013). This issue is discussed further in the context of *medicalization* and control in *Social control*, p 35.

The FDA is not the only government agency struggling with how to address SSPA’s. The Federal Trade Commission (FTC) has also been active in the discussion of health and fitness tracking, and so far, has been just as reluctant to offer official guidance for consumers or manufacturers. Although the FTC’s stated mission is to protect consumers against unfair or deceptive business practices, (US Federal Trade Commission, 2015), their focus in this field has been mainly on data security and not on the impact devices have on actual consumer health. In 2013 the FTC held a public workshop on the Internet of Things, which included a panel dedicated to “Connected Health and Fitness” (US Federal Trade Commission, 2013). The panel moderator began by stating the intended goal of the

discussion is to explore potential privacy and security risks associated with these devices (p 164). During the panel, no discussion took place related to protecting consumers from fraudulent claims made about health and fitness. In a prepared statement released March 22, 2016, the FTC acknowledged that products and services that collect and store health information raise serious privacy and security concerns for consumers, especially when these activities take place outside traditional medical contexts not subject to the Health Insurance Portability and Accountability Act (HIPAA). However, again, the statement characterized consumer protection only in terms of preventing fraudulent access to personal data, with no allusions to protections against bogus health claims (US Federal Trade Commission, 2016).

This is somewhat surprising given that the FTC has taken legal action numerous times against businesses making unsubstantiated health claims related to their product. A recent case charged Focus Education with making false claims about the efficacy of their online “brain training” product without scientific evidence (US FTC V Focus Education LLC, 2014). Also in 2014, the FTC ordered that Genelink could no longer make claims to consumers that their products could treat or prevent particular genetic disease unless these claims were backed-up by “randomized controlled trials conducted on subjects who have that genetic variation” (US FTC v Genelink, 2014). The FTC has made similar demands regarding the requirement that health related claims be backed up by scientific evidence, ordering that one company producing dietary supplements for weight loss to backup their claims with “two randomized, double-blind, placebo-controlled human clinical studies” (US FTC v BEIERSDORF, INC, 2011) and demanding another, selling acne treatment, back their claims up with “competent and reliable scientific evidence” (FTC, 2011).

As described earlier, there are numerous stakeholder groups involved in the design and deployment of SSPA (see Figure 1) and, therefore, numerous stakeholders involved in the activities at each of these levels of ethical analysis. These stakeholders have varying degrees of influence, as well as a range of perceptions about their own moral responsibilities for negative (or even positive) social implications that can be traced back to the technologies. Somewhat ironically, those who are often criticized as being least likely to claim moral responsibility for social outcomes of emerging technologies are the best positioned, both professionally and practically, to do so. Professional engineers have unique expertise and access to the technological processes of SSPA design, and have demonstrated an ability to adhere to formal and informal codes of ethics that are specifically constructed to protect public health and welfare (American Society of Civil Engineers, 2016; American Society of Mechanical Engineers, 2016; Association for Computing Machinery, 2016; Institute of Electrical and Electronics Engineers, 2016; National Society of Professional Engineers, 2016). The critical role that technology plays in shaping human behaviors, as well as the moral responsibilities engineers have in shaping that relationship has received growing recognition in the last few decades (Georgia Tech, Center for Ethics and Technology, 2016). A recent IEEE publication (Baker, Gandy, & Zeagler, 2015) offers a “Proposed Collaborative Policy Design Framework” that serves as a respectable initial step in tackling policy in this domain from the engineering side; however, it falls short in terms of thinking critically about value and risk for the user.

Baker, Gandy, & Zeagler, describe what they call a “design-thinking” approach which begins by defining a technological “object” comprised of the mechanical components, device behaviors, and sociocultural contexts in which it will be used. Once

the object is defined, a policy analysis would be conducted to identify potential barriers to development and distribution. Stakeholder input would then be sought to consider user needs, but it is critical to point out here that “users” in this model are defined as policy makers, regulators, industry representatives, and other standard setting bodies, not end users of the technologies themselves. The final step in this proposed framework is to draft actual policy or return to the initial phase to re-articulate the objectives and outputs of the objects to “creatively address the potentials of new technologies while avoiding pitfalls that could derail progression.”

Baker, Gandy, & Zeagler’s framework emphasizes the need for collaboration between designers of these technologies and the regulatory bodies that govern them. The clearest “benefit” of this approach is that resulting technologies would be much less likely to infringe upon or violate existing regulatory standards. Indeed, they suggest that efficacy will be evident by the “reduced need for regulatory filings, and an expected increase in non-formal industry and multisector collaborative activities.” The clearest benefactors of this approach are the developers of the technologies, in the form of streamlining development and deployment. The framework lays out a process to avoid risk to developers that could stem from regulatory obstacles, but not risk to end-users from potential outcomes not already covered by regulatory standards. It focuses on regulatory avoidance and compliance, while a more robust framework should also incorporate a process to identify new types of risk to end-users that are not addressed by existing standards, so that design can be amended to avoid such risks even in the absence of regulatory obstacles. Also conspicuously absent from the framework is any mention of examining or measuring the value of a technology to the user either before or after deployment. Nor is their mention of

approaching users to identify their problems or needs and evaluating whether a technological approach to addressing the problem or need is even appropriate. A more recent proposal from Lurie and Mark (2016) discusses these types of concerns and why engineers, particularly software engineers, should be responsible for thinking about these factors in design.

The algorithms that drive SSPA's are rendered to the end-user as "software," so it is useful to examine research in the field of ethics and software engineering. In a recent publication in *Science and Engineering Ethics*, Lurie and Mark make the case that the nature of the relationship between the end-user and software engineer warrants a stronger and more formalized emphasis on ethics-driven software development be incorporated within the professional standards for this community. Lurie and Mark point out that end-users are increasingly dependent on computer software packages as technologies become more and more ubiquitous, while at the same time there exists a wide knowledge gap for the user representing how and why these software packages behave the way they do. The researchers argue that the outcomes these engineers facilitate are not merely related to reliability, usability, security, etc., but to the architecture of human interactions with the world, with each other, and with themselves. These interactions can and do have significant ethical implication; choices related to algorithm design and the software it constitutes can impact social norms, freedoms, identity, personal safety, and more. With this in mind, Lurie and Mark lay out an ethics-driven framework for software development that they argue will "raise stakeholder awareness about the ethical considerations and implications relevant to [software development]." They describe five phases of software development and propose a unique set of yes/no questions for each phase that are ostensibly designed to

engage the software engineer and the stakeholder client in a conversation about ethical interventions. However, of the 32 questions they suggest only one that directs the software engineer to consider end-user impacts:

Is there a procedure in place to define the course of action if, during the planning requirements phases, it is discovered that fulfilling the customer's demand will lead to negative consequences and possibly contradictory and illegal outcomes? (Question 4 of "Requirements Phase", p 432).

One other question could be interpreted as being related to ethical implications: "Is a mechanism in place that distinguishes between a quality product versus a correct product?" (Question 2 of "Testing and Verification Phase," p 432). However, the authors are not clear whether the perception of a "quality product" is meant for the stakeholder client or the end-user. As with the Baker, Gandy, & Zeagler framework discussed previously, this framework seems unlikely to promote a user-centered mindset focused on ethical implications, but instead seems more conducive to removing or avoiding boundaries to development and deployment. For example, "Has it been determined who makes decisions on behalf of the client?"; "Has it been determined who approves the budgetary flexibility for project management?" (p 431). While the goals Lurie and Mark lay out are laudable, and the argument software engineers should be more responsible in addressing ethical implications of their craft is well articulated, the framework and sets of questions they propose fall short in addressing substantive issues related to the ethical implications of software design.

In a paper describing a set of rules for moral responsibility and computing artifacts (which includes software and hardware), Miller (2011) made a similar argument to Lurie

and Mark that "people who design, develop, or deploy a computing artifact are morally responsible for that artifact, and for the foreseeable effects of that artifact." He also argues that this responsibility "includes being answerable for the behaviors of the artifact and for the artifact's effects after deployment, to the degree to which these effects are reasonably foreseeable by that person." In terms of developing professional standards for the design of SSPA, it might appear that Miller would argue that a process for considering ethical implications of the technology should fall within the purview of the software engineer; however, Miller adds that moral responsibility for computing artifacts also rests with "other people who design, develop, deploy or knowingly use the artifact as part of a sociotechnical system." Effectively, "The Rules," as Miller describes them, define a shared responsibility in considering the moral implications of computing artifacts, including end-users. However, as Lurie and Mark point out, the end-user may not have the knowledge required to consider and predict the behaviors of SSPA's and the resulting moral implications. This puts users, at least, at a disadvantage in exercising their responsibility; this issues is discussed later in *Engineering discipline*, page 35.

Some researchers have suggested that independent reviewing organizations should engage manufacturers of SSPA's (and technology more broadly) to consider the ethical implications of these devices regarding consumer behaviors when the device falls outside the purview of government regulatory bodies (Boulos, Brewer, Karimkhani, Buller, & Dellavalle, 2014; Sclove, 2010). For example, SocialWellth (formerly Happtique) offers to vet health related applications and devices that are not otherwise evaluated by the FDA. They describe their methodology for vetting as:

“a multidisciplinary review shaped by behavioral science to assess functionality, consumer appeal, usability and design, privacy and security, content quality, clinical evidence, cost and other metrics to deliver value to our healthcare sponsors and end consumers.” (SocialWellth, 2016)

The organization offers a two-year certification for products it evaluates, but the process is voluntary on the part of manufacturer and success of this approach in protecting consumers from risk will rely heavily on educating consumers about the value of the certification process. At the time this research was conducted, the SocialWellth website offered no information to end-users about what type of protections they would be offered by seeking out certified products, nor was there an online process to identify if a product is certified and what that means. The impact of these efforts is difficult to gauge as well; the founder of the company, David Vinson, announced at a 2015 conference that the company had issued 120 certifications out of 600 applications (Vinson, 2015) since launching in 2013, but there are more than 165,000 health related apps currently on the market (McCarthy, 2015). A similar effort by the United Kingdom’s National Health Service (NHS) attempted to create and curate a Health Apps Library in 2013. However, after certifying less than 100 apps and failing to properly vet clinical evidence and app security, the library website was closed two years later (Misra, 2015).

Attempts to guide the design of consumer SSPA’s in a way that protects consumers have been disconnected, schizophrenic, and unable to keep up with the frenetic pace of deployment. It is not only unclear who should be responsible for protecting against unwanted or unintended social impacts, but also who should be thinking about these impacts. The following sections look at some of the broader social implications of SSPA’s that have not been considered in existing literature.

Social Implications

Vision of the future. As described in the previous section, the development of regulations and standards for design and deployment of consumer SSPA's is still in a state of flux. Given the relatively small market penetration of SSPA's like the Fitbit and Apple's smart watch (Patterson, 2016), coupled with as yet unrealized infiltration of IoT systems (Atzori, Iera, Morabito; 2010; Swan, 2012b), and modest inroads into harnessing Big Data (Matzner, 2014), perhaps the existing FDA draft guidelines and the FTC's limited involvement may not seem terrible problematic. However, expectations for all of these technologies are that their use, relevance, and permeation and will grow exponentially in the coming decades, such that ubiquitous, robust data collection will be pervasive and powerful (Patterson, 2016; Gibbs, 2015; Hsieh, Komisar, Jazayeri & Yeh, 2016; Swan 2012b). Although this is certainly not a guarantee, efforts to bring this future to a reality are clear, with government and industry actors working together to pave the way, so it is critical to consider how current policies and standards would hold up if such a scenario came to fruition. The remainder of this paper considers the psychological, and sociopolitical implications of *ubiquitous* LR-GW SSPA's with expanded capacities that are not currently available, but are not prohibited by current standards (for example a LR-GW device that can access sensor data from inside the body from a separate moderate to high-risk medical device such as an implant or consumable).

Self-sensor persuasion bias. To understand the social implications of SSPA's it is critical to understand how SSD impact persuasion from a psychological perspective, as this will no doubt be correlated with commercial industries' efforts to develop the technology. To understand the persuasive value of SSD it is helpful to first consider the instrumental

nature of self-sensor data, i.e. how it is substantively different from other forms of self-knowledge and why is it relevant to decision making? There are a number of sources of self-knowledge that have been well studied; such as social comparison, introspection, reflected appraisal, and self-perception. For example, Daryl Bem's Self-Perception Theory (1972) postulates "Individuals come to "know" their own attitudes, emotions, and other internal states partially by inferring them from observations of their own overt behavior and/or the circumstances in which these behaviors occur." From a behaviorist framework, self-knowledge is gained via observation (by the self or by others) and therefore highly enmeshed in external cues (Skinner, 1974; Bem, 1972). For example, a sensation of feeling low in energy and cognitively depleted can be interpreted as "run-down" or "tired," and so will undoubtedly require the consideration of external factors such as the time of day (e.g. 10 am vs 1 am), social norms (e.g. what others doing the same activities are feeling), and observations about past behavior (is it unusual to feel this way at this time, within this context). The more external information that is available the more likely one can "know" what the feelings of low energy and cognitive depletion mean, but less information can make understanding these feelings more difficult (for example, not being able to articulate the physical feelings, or not being able to remember what activities have been going on recently or how one has felt in this situation in the past). The source of self-sensor data is neither introspection nor external observation, but rather an external representation of internal behavior. In the example referred to above, the interpretation of one's feelings to mean "run-down" vs "tired" could, in the near future, also be shaped by self-sensor data about blood cell count, brain wave patterns, and metabolic data (for examples of existing technologies see Pantelopoulos & Bourbakis, 2010; Patel et al., 2012; and Mukhopadhyay,

2015). It is true that self-sensor data must be represented externally in order to be viewed, but it is not “merely” external at that point. This form of external observation of internal behavior does not easily plug into existing models of decision making, persuasion, attitude formation, etc. In addition, it is not known whether variations in the external representation (e.g. gamified, medicalized, highly branded, etc.) of self-sensor data will impact decision making.

Another front on which SSPA’s pose a risk to users is in the types of attitudes and behaviors SSPA’s can be directed toward. Again, while the development of SSPA’s in the healthcare industry may be arguably guided by beneficence and restricted in scope to addressing attitudes and behaviors closely linked to biological and psychological well-being, the development of consumer SSPA’s is less clearly defined. Consumer SSPA’s aimed at influencing decision making about things users have no strong feelings about (daily tasks, some social trends, low information situations, etc.) will likely be appealing to consumers and, at the same time, are more likely to be based on peripheral cues or heuristics, which require less cognitive resources (Chaiken, 1980). In this case, a consumer model for SSPA design could use SSD to nudge a user toward certain behaviors by targeting decision making that the user is already primed to use peripheral cues for (such as choosing between two unknown brands). This approach harnesses the persuasive value afforded by the attentional effects of self-sensor data (see PART 2, p 51) and, by targeting ambivalent or indifferent attitudes, maximizes the persuasive value of SSD qualities such as expertise, simplicity, etc. The degree to which SSD could unduly bias users is unknown and may, admittedly, even be inconsequential, but given the amount of research being invested in developing effective SSPA’s to influence user behaviors, it seems prudent to

understand if such a risk exists. This issue of the persuasive value of SSD in SSPA design is covered extensively in see PART 2, p 51.

Algorithmic responsibility. Knowing whether SSD may bias a user’s decision making processes is critical in understanding future risks to users who may rely on such information to make what they believe to be informed decisions. However, it is crucial to point out that the risks lie not within the bias to “trust” self-monitoring sensor data alone, nor within the raw data itself of course, but rather, within how sensor data is captured, processed, and presented to each user by other actors. In other words, while raw data collected through my own “sensors” (i.e. eyes, ears, nose, etc.) is made meaningful through my cognitive processing (and the life experiences that have shaped them), raw data from sensors embedded in self-monitoring devices are first processed and made meaningful by someone else –through the engineering of the devices and software used to render the data to me. For example, to produce a digital photograph, many actors are involved in creating protocols to process visual sensor data collected from a scene before it can finally be viewed. At each step, decisions are made about how to achieve the “best” end result, but the connotation and operationalization of the “best” end result may vary from actor to actor – i.e. truest color, lowest energy usage, most profitable, etc. Each goal can shape how sensor data is processed and rendered. For the end user, variations from one group of actors to another mean a picture taken on one camera could look subtly or even drastically different taken on another, even though the same raw data (the original scene) existed for each. As with the design of a camera, the raw data from self-sensor technologies can be captured and rendered to the users in many different ways. This highlights the need to understand the role of “algorithmic responsibility” in SSPA design.

Interestingly, many of the predicted benefits for the use of SSPA's can also be envisioned as risks when contextualized differently. Consider using a SSPA as a basic fitness app meant to guide a user's choices about diet and activity. Assuming the basis on which the prescriptives are derived is reliable, benefits could include increased physical fitness, lower risk of diet related illness, increased longevity, improved sense of well-being, less time off from work, and so on. However, if the SSPA is developed using less reliable information to derive prescriptives, and corporate or organizational goals take precedent over user goals (such as selling products or services, changing employee behavior, etc.) these benefits may be replaced by risks such as poor diet choices, overspending, increase insurance/healthcare costs, etc. (Sadowski, 2014, Swan 2012b). In this example, risks and benefits vary as a function of algorithm design.

An algorithm (or set of algorithms) essentially performs as a decision engine from which prescriptives are derived. There are a number of stakeholders involved in defining the logic, parameters, and function of these decision engines; from the group or individual responsible for initiating the technology, to the final application developer responsible for rendering the prescriptives to the users in a way that is visually appealing. First, the stakeholders initiating the SSPA technology must define how the sensor data input will lead to each inference and/or prescriptive. This means choosing scientific findings that inform what particular sensor readings (or thresholds) mean to the diagnostic or symptom management plan involved and then defining what the outcomes should be when those readings are inputted to the SSPA via a sensor device. While the health care industry is, generally speaking, accountable to standards that encourage these algorithmic designs be based in scientific theory (Lewis, Eysenbach, Jimison , Kukafka, & Stavri, 2005, pp143-

149), there is no similar accountability structure for consumer SSPA's (i.e. LR-GW). This is not meant to imply that consumer SSPA's can only generate positive outcomes if grounded in formalized sciences, but rather to point out that without an authority to oversee the validity of commercial SSPA claims made about what sensor data "mean," there is little consumer protection against fraudulent or harmful claims.

Looking at the development of wearable technologies designed to detect concussions provides an example of how this process can become subjective. Diagnosing a concussion is multistep, complex process that requires a medical caregiver to use their best judgments based on existing knowledge, past experiences, and the totality of the circumstances. Though there are certain best practices that have been put forth by the medical community for diagnosing concussion (Greenberg, M.K. et al. 1997; Randolph, et al., 2009; Scorza, Raleigh, & O'Connor, 2012), the process has not been distilled into a finite and objective set of rules (Scorza, Raleigh, & O'Connor, 2012). More specifically, it is not clear what type and magnitude of force causes a concussion (Hernandez, et al., 2015). Nonetheless there are multiple wearables available (or coming to market shortly) that are being marketed as concussion detectors, such as the Joltsensor[®] and the Hiji band[®]. The SSPA for the Hiji band[®] uses collision force measurements from the wearable and observational data inputted by the users or observer (such as a coach or parent) to "catch any sports related head impacts and allow the injury to be identified and assessed," (Hijiband.com, 2015). The SSPA for the Joltsensor works in the same manner and claims it will "notify the user of a possible concussion," and will help athletes "train smarter and safer" and "make smarter more timely decisions" (Joltsensor.com, 2015). In order to do what these apps claim to do, a decision engine comprised of finite and objective parameters

has to be created (e.g. acceleration speeds between A and B at time of collision result in this action if age is $\leq X$ but $\geq Y$, and weight is more than Z, or more than X items from list A =Y). (Hernandez, et al., 2015). The qualifications of these stakeholders and the quality of the information they make use of may vary wildly from one SSPA to another; not only because there is no regulatory process to guide these decisions, but also because there is disagreement even within the medical community about what exactly these parameters should be.

Social control. Even if a method to determine whether the algorithm design of a SSPA was “ethical” could be developed and research showed that SSD convey just the “right” amount of persuasive power, there are other social implications that may negatively impact the rights and freedom of users that have not been considered in current discourse surrounding SSPA design. The languages and credibilities of engineering and medicine that are used to sell SSPA’s are linked to overlapping phenomena related to social control. On one hand, the invocation of heuristics of wisdom and benevolence related to healthcare and medicine may lead to what is referred to as medicalization of wellness or the social construction of illness. On the other hand, the invocation of objectivity and predictability related to engineering may lead to automaticity of self-awareness. These two aspects are discussed next.

Engineering discipline. SSPA’s have the potential to act as the ultimate tool in self-surveillance of the body – from its location in time and space, to the location of electrons in its brain, and from the construction of muscles to the construction of identity. While some argue that this ability to monitor and observe every aspect of the body creates an opportunity for individuals to control their own health outcomes (Hofmann, 2016),

philosopher and social theorist Michael Foucault's writing about "the political technology of the body" suggests that this ability to know and control the body can be used as a form of subjugation and discipline (Foucault, 1977). He argues:

"subjection is not only obtained by the instruments of violence or ideology; it can also be direct, physical, pitting force against force, bearing on material elements, and yet without involving violence; it may be calculated, organized, technically thought out; it may be subtle, make use neither of weapons nor of terror and yet remain of a physical order. That is to say, there may be a "knowledge" of the body that is not exactly the science of its functioning, and a mastery of its forces that is more than the ability to conquer them: this knowledge and this mastery constitute what might be called the political technology of the body." (p 26)

The emerging IoT and Big Data economies offer unprecedented knowledge about bodies and objects moving in the world, and SSPA's offer unprecedented access to the body qua body; from that knowledge emerges the ability to calculate, organize, and direct—to conquer. Foucault argues that the constitution and control of this political technology of the body is complex, diffuse, and "not localized in the relations between the state and its citizens," (p27). However, as Lurie and Mark (2016) argue, increased dependence on these technologies is correlated with an increased gap in understanding how technologies work; this puts users at a disadvantage in terms of constituting and controlling this political technology of the body. The knowledge gap is related to issues of complexity, as well as issue of access. Numerous strategies exist to ensure citizens do not have access to the algorithmic rules that calculate, organize, and direct the body. Pasquale (2015) argues there are three main approaches to protecting an organization's privacy; *real secrecy* locks up algorithm by preventing users from accessing the code, while *legal secrecy* uses

government sanctioned rules to protect manufacturers and developers from having to share proprietary information. The third approach, *obfuscation*, floods the user with too much information or distracts them from thinking critically about the nature of the claims being made. Langdon Winner (1983) argues that technologies “provide structure for human activity,” and this is intimately true for technologies that construct our understanding of the body and mind. SSPA’s aimed at externalizing internal mechanism of behavior provide a pathway for decisions once based on personal reflection to be based on standardized and automatic processes. The standardization may be constructed with deep reflection about human values and social norms in a good faith effort to improve the human condition –or not. If SSPA’s can be thought of as *forms of life* as Winner argues, users are prohibited or at least significantly impeded from knowing the sociotechnical identity and value systems from which these forms of life are born. Instead, the status quo for characterizing SSPA’s misrepresents these technologies as objective, value-neutral technologies that facilitate some notion of the good life.

Foucault also describes the notion of docility, which is ultimately tied to subjection of the body, and institutional interests in techniques to exploit the body as an object and target of power. Foucault argues that this exploitation of the body has taken place throughout recorded history, but unique changes to approaching docility emerged around the 18th Century (p. 134). What is chilling in his descriptions of these changes is how the affordances of SSPA’s are so well suited to the same purposes in terms of “scale of control” and “modality.”

1. ...there was the scale of the control: it was a question not of treating the body, en masse, ‘wholesale’, as if it were an indissociable unity, but of

working it ‘retail’, individually; of exercising upon it a subtle coercion, of obtaining holds upon it at the level of the mechanism itself - movements, gestures, attitudes, rapidity: an infinitesimal power over the active body. (p. 136)

2. ...there is the modality: it implies an uninterrupted, constant coercion, supervising the processes of the activity rather than its result and it is exercised according to a codification that partitions as closely as possible time, space, movement. (p. 137)

Foucault referred to these methods of “meticulous control of the operations of the body” as “disciplines” and noted their use and legacy in not only penal institutions, but in schools, hospitals, and the military, as well as in non-governmental and commercial organizations such as factories and workshops (p 137). These techniques of discipline are omnipresent and habitualized in our cultural institutions today, and so may go unnoticed. One can see this scale of individuality and the modality of constant surveillance in times of disease outbreaks and terrorist threat when citizens fully expect the state to seek docility and therefore the application of ambient sensors, SSD, and other monitoring technologies are intentionally transparent. When this same approach to docility is used to limit economic choices such as determining which health insurance options are presented to a person based on SSD, it is likely to be much less transparent. (A report from the technology market research firm Gartner, Inc. (2016) estimates that by 2018 more than 2 million employees will be required to wear health and fitness tracking devices as a condition of employment.) A challenge with not only SSPA’s, but much of the monitoring technologies employed today is that citizens often enter into these technological platforms with an expectation of personalized benefit, so rather than docility, it can be “experienced” as empowerment. The difference between the two may or may not be merely perceptual, but again, to the extent

that SSPA's are not currently scrutinized as a political technology of the body, they offer an exceptional opportunity for exploitation by those in positions of power with the privilege of knowledge. Table 2 shows examples of slogan and taglines from popular wearables that position the role of SSPA's as an objective tool that empowers the user to control physical and mental well-being through quantification of the body.

Foucault also argues that in addition to exerting power over life through subjection and docility, a second form of power began to emerge in the late 17th century through the rapid introduction of interventions and regulations to manage populations through quantification and control of biological processes (such as control of birth rates, life expectancy, living conditions, and level of health) (Foucault & Hurley, 1978). Foucault referred to the ability to control these forces as "bio-power;" and argues that as western nation states develop so does the breadth and depth of control over human biological functions and its use as a tool for the maximization of productivity. While discipline is used to direct human behavior at the individual level, "bio-power" is used to direct a population of people (i.e. the residents of a city, state, or nation for example) to behave in a desired fashion. SSPA's present new methods for quantification and control Foucault could never have imagined; with biological and behavioral data constantly being collected then transmitted across networks, returning precise prescriptives for the user or users.

Medicalization and social control. Medicalization is a term used typically in the social sciences to critically describe the process of expansion of medical authority "beyond a legitimate boundary," (Rose, 2007a) "into the domains of everyday existence," (Metzl &

Hertzig, 2007) and “over our bodies through the reduction of social phenomena to individual biological pathologies,” (Fainzang, 2013). Medicalization occurs through an exploitation of knowledge and power. The social control afforded by medicalizations “comes from having the authority to define certain behaviors, persons, and things,” (Conrad, 1979) and subjection of the body (Foucault, 1977). This encompasses the ability

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Slogan and taglines from wearables that connect well-being with self-quantification.

Name	Style	Purpose	Quote
Moov ^a	Bracelet	Fitness Coaching	“You can't improve what you can't measure”
Samsung Gear-S2 ^b	Watch	Fitness Coaching	“Taking charge of your health is easy with Gear S2. Track your daily activity levels, heart rate and water vs. caffeine intake.”
Emotiv Muse ^c	Headset	Neuromonitor	“Monitor cognitive load and discover emotional responses that are preventing you from achieving peak mental performance.”
Emotiv Insight ^c	Headset	Neuromonitor	“Our brains are at the very center of our health and performance. Self assessment and cognitive training is a crucial part of our wellbeing. The Emotiv Insight offers a cost effective and highly powerful solution for self assessment.”
Athos ^d	Clothing	Fitness Coaching	“Smart performance apparel that monitors your biosignals and distills them into meaningful insights.”
Clothing + ^e	Clothing	Fitness Coaching	“When Accurate Data and Every Moment Matters” (overlaid on an image of infant sleeping).
Fitbit ^f	Bracelet	Fitness Coaching	“Fitbit tracks every part of your day- including activity, exercise, food, weight and sleep- to help you find your fit, stay motivated, and see how small steps make a big impact.”

Sources: ^aMoov, 2016; ^bSamsung, 2016; ^cEmotiv, 2016; ^dLiveAthos, 2016; ^eClothingplus, 2016; ^fFitbit, 2016.

to define who can work, who can go to school, who can move around, who can reproduce, who can be held responsible for actions, and who can be considered ‘good’. One of the earliest and most prominent scholars to formalize the notion of medicalization was Ivan Illich, in his book *Medical Nemesis* (1976), in which he attributed the problem of medicalization primarily to physicians. More recent discourse in the field however, argues that private pharmaceutical companies are responsible for the continued expansion of medical authority (Clark, 2014; Goldacre, 2013; Moynihan & Henry, 2006; Poitras & Meredith, 2008) through their efforts to manufacture illness for existing drugs. This same mechanism of medicalization could be used to expand the consumer SSPA industry by applying biomedical models to “general wellness,” and by establishing medical narratives for normativity that don’t explicitly claim to diagnose illness, but rather seek to quantify wellness medically. The economic gains would come not through prescriptions for drugs or medical tests, but through the consumption of lifestyle products aimed to modulate degrees of wellness. For example, the healthy user whose SSPA monitors heart rate, skin conductivity, blood volume, etc. may be advised that his readings are in the second percentile for his age and weight and that following a particular set of actions (determined by the manufacture) will help elevate him to status quo. That might be great; perhaps the SSPA will advise the user to think about exercising more and eating healthier. But, the healthy user has given the SSPA manufacturer the opportunity to evaluate, categorize, and advise his level of healthiness which, even if it is well and good, may have just become subpar based on standards and knowledge that are not transparent. In this case,

medicalization is used to make something real or relevant by identifying it as a biological phenomenon (Clark, 2014), but this may or may not benefit the recipient of this newly constructed reality. Medicalizations and the technological solutions they offer are appealing to consumers because they offer simple and objective explanations and responses focused on the individual (take this pill, apply this paste) for complex, subjective phenomenon. SSPA's offer the ultimate impersonation of personal control.

A classic example of medicalization is the construction of "chronic halitosis" (CH). Bad breath existed as a symptom of underlying disease, poor dental hygiene, or love of smelly food for centuries before the invention of CH. Perhaps more often than not it was simply considered a common, perhaps annoying state that the malodorous owner never even recognized. Mouthwash existed for decade before CH too; however, lackluster sales of Lambert Pharmaceutical's "Listerine" mouthwash, prompted the company's marketing team to embark on an emotional advertising campaign to create the perception of a serious medical problem for which they had the cure. By adding the inherently chilling adjective "chronic" to the Latin word "halitosis" (which loosely translates to "breath disease"), the advertising team created a story of a terrible condition that few people knew they had and others were too embarrassed to tell them; a silent killer of social standing. The increase in sales of Listerine from approximately \$100,000 in 1920 and 1921 to more than \$4 million in 1927 is often attributed to this medicalization of bad breath (Marchand, 1985; Munsey, 2006). This medicalization did not result from physicians overstepping their bounds, or from patient advocacy groups calling for treatment, but rather from private industry motivated by economic interest rather than genuine healthcare concerns, acting with the language and credibilities of the medical field.

An intersection of medicalization and SSPA design that is particularly problematic is within the domain of mental health. While the most highly visible examples of SSPA's are in the fitness industry, developers are making inroads to mental health and acuity. There are already a number of LR-GW SSPA's that claim to monitor and trace biometric data associated with mood. For example, using primarily electroencephalography (EEG) readings the Emotiv Insight headset claims to "6 different emotional and sub-conscious dimensions in real time – Excitement (Arousal), Interest (Valence), Stress (Frustration), Engagement/Boredom, Attention (Focus) and Meditation (Relaxation)," (Emotiv, Inc. 2016). However, the quantitative boundaries of mental states and mental wellness are far from well-defined (Beaulieu, 2002; Ulman, Cakar, & Yildiz, 2014; Uttal, 2012). Even the subjective boundaries of mental health (i.e. observable behavioral symptoms) are moving targets from one iteration of the Diagnostic and Statistical Manual for Mental Disorders¹ to another. There are strong economic interests for pharmaceutical companies to expand the boundaries of mental "illness" through medicalization of social problems, and this is a critical issue in 21st century bioethics discourse (Poitras & Meredith, 2008; Moynihan & Henry, 2006; Goldacre, 2013) that is beyond the scope of this paper. However, huge economics gains could also exist for "lifestyle" related retailers who are able to use the language of SSPA's to implicitly medicalize and quantify mental "wellness" and, in turn, prescribe treatments that control or exploit users by guiding their purchases and activities

¹ The Diagnostic and Statistical Manual for Mental Disorders is currently published by the American Psychiatric Association which lists all classifications of mental disorders. The first official publication in 1921 contained 22 diagnoses. From one iteration to the next, diagnoses of mental illness may be added, expanded, narrowed, and/or dropped. The most current publication contains more than 250 diagnoses (American Psychiatric Association, 2016)

Not every social scientist believes that medicalization is negative, and some see ubiquitous monitoring of physiological data as a way to democratize healthcare. Hofmann (2016) writes that this type of pervasive medicalization, “making ordinary life experiences subject to medical attention to measuring every aspect of life, and thereby making it subject to ‘experience,’ attention and control ... makes persons themselves control their own lives.” However, this is a technocentric view of pervasive ubiquitous self-sensing data – one that ascribe a value-neutral quality that does not currently exist. It ignores the situated and embedded nature of how understandings of these data are constructed. It assumes a level of individual understanding, critical thinking, and attention on behalf of the user that is not practical. This is not to suggest that users do not have the intellectual capacity to understand the terabytes of raw sensor data that they could be faced with on a daily basis, but that all of this information will be useless to the user if they don’t have the time to process it to make meaningful observations. As soon as a technological solution intervenes to assist with this processing (as SSPA’s would do), the designers of that technology automatically, even if inadvertently, infuse their own cultural, political, and economic interests into that interpretation. Hoffman acknowledges that the epistemic challenge in a new frontier of ubiquitous SSD is in this process of validation and selection of relevant data to make sense of it for a particular user. But at least right now, this is most definitely *not* in the control of the users. These limits are not only validated and selected by those who develop SSPA’s, but the subjective definitions and characteristics of “normal” may be constructed through the self-serving story telling of small-time entrepreneurs selling their wears on KickStarter and Peerbacker to multi-layered conglomerates with big marketing budgets.

Free will and prosocial behavior. Even if every SSPA was designed with benevolence and transparency, omnipresent and robust monitoring of the physiological self may still have numerous unintended consequences. One of these is the activation of certain beliefs related to free will and determinism which have been shown to have numerous negative impacts on individual behavior. Definitions of free will vary, but generally tend to refer to an individual's belief in their ability to make deliberate choices and to believe that they are responsible for those choices (Nahmias, Morris, Nadelhoffer, & Turner, 2005; Monroe and Malle, 2010). The following section highlights experimental research as evidence of the possible social impacts of altering individual beliefs through priming and draws attention to how SSPA's may contribute to altering these beliefs.

Research by Mueller and Dweck (1998) was meant to examine the impact of praise on learning and motivation, but their findings also implied that deterministic beliefs could lead to negative behavioral outcomes. The researchers conducted a series of 6 studies in which children completed learning tasks with various degrees of difficulty; designed in such a way to ensure success during the first tasks and failure during a later task. They found that providing praise to the children on the first task that attributed their success to either natural intellect or to hard work, the childrens' effort and attitude toward a subsequent, more difficult task changed in a predictable manner. When faced with the difficult task, children who had been given praise that attributed their earlier success to their natural intellect showed numerous negative effects, including reduced effort, poorer performance, reduced motivation and confidence, and decreased enjoyment. Mueller and Dweck did not attempt to interpret their findings in terms of determinism or free will beliefs, but an argument can be made that the innate qualities associated with "intelligence"

mean that praise for intelligence primes a deterministic world view (at least in so far as it is relevant to the task at hand which was related to learning).

Vohs and Schooler (2008) conducted a more direct examination of the effects of priming deterministic² beliefs on behavioral outcomes. While Mueller and Dweck's study demonstrated that attributing outcomes to innate qualities rather than learned behaviors (such as hard work) had a negative impact on personal effort and motivation, Vohs and Schooler examined whether priming "anti-free-will" beliefs could lead to overt negative moral behaviors. Participants were asked to read a series of statements that either supported a belief in free will, refuted such a belief, or were neutral in nature. Participants then completed a set of problems in reading, math, logic, and reasoning and were told they would receive \$1 per correct answer. In some conditions of the experiment participants were presented with an opportunity to cheat by grading their own answers. Results showed that participants who read the deterministic statements and were given an opportunity to cheat took home more money than all other participants.

In addition to Vohs and Schooler's 2008 study numerous others have explored how beliefs in free will and determinism impact attitude and behavior. Baumeister, Masicampo, & Dwall (2009) found that when participants read a series of statements promoting disbelief in free will they were less likely to provide help in a hypothetical scenario than participants who read neutral statements. They also found that priming disbelief in free will increased aggression against an innocent target. In another study, MacKenzie, Vohs, and

² Vohs and Schooler (2008) did not specifically define the relationship between "free will" and "determinism," but the two terms are treated similarly to antonyms in the paper, such that a prime characterized as "anti-free-will" was also characterized as "deterministic." Some philosophers argue that this is not necessarily the case (Campbell, 1996; Nahmias, Morris, Nadelhoffer, & Turner, 2005).

Baumeister (2014) found a relation between belief in free will and gratitude. Disbelief in free will tended to reduce feelings of gratitude for hypothetical favors, past events, and a real favor. This is likely explained by the foundational role free will is thought to play in determining moral responsibility (Nahmias, Morris, Nadelhoffer, & Turner, 2005).

While research has demonstrated that belief in free will can influence behavior and perception, to understand how this is related to SSPA's it is important to understand what environmental cues may reduce or enhance this belief. The research described so far has typically employed written prompts, but other researchers have demonstrated that less explicit cues play a role as well. For example, Feldman, Baumeister, and Wong (2014) found that belief in free will is related in a number of ways to an individual's perceived ability to make choices. In their study they found that participants who had been asked to recall past choices and the decisions made from those choices during a specific time period had stronger beliefs in free will relative to participants asked only to recall specific actions they had taken during a similar time period. In the same study they found that asking participants to make simple choices (in this case, choosing between different pen types) also increased belief in free will relative to participants who were asked instead to perform a series of simple actions.

Consumer SSPA's monitor and process a user's sensor data and implicitly or explicitly direct their actions based on this data. This research suggests that how these directives are presented to the users could impact that user's belief in free will. Directives presented as a choice between two or more actions would be less likely to reduce the user's belief in free will than directives presented as a single command. For example, a SSPA that

informs a user his potassium is low could suggest the user take one of three actions (e.g. eat a banana, drink a glass of fat free milk, take a supplement) rather than one.

Even more relevant to the discussion of free will and SSPA is research conducted by Ent and Baumeister (2014) regarding physical states of the body and belief in free will. The perception of conscious control over one's bodily actions could be considered a form of "evidence" to strengthen belief in free will (Wegner and Wheatly, 1999), but what happens when control of the body's actions seems difficult or impossible? Ent and Baumeister first compared the strengths of belief in free will between individuals with medical conditions that cause physical symptoms beyond conscious control (epilepsy and panic disorders) and individuals who did not have these medical conditions. They found that participants who had epilepsy and participants who had a panic disorder had weaker beliefs in free will than participants who had neither condition. In a follow up study they found that more temporary states of the body can also affect belief in free will. Participants were first asked about their beliefs in free will and were subsequently asked about the intensity of some of their physical needs at that moment, including urination, sexual desire, fatigue, thirst, and hunger. They found that participants who had reported more intense needs for urination, sexual desire, or fatigue had expressed weaker beliefs in free will. For hunger, they found that this was also the case for individuals who were not currently dieting³. Ent and Baumeister interpret their broader findings as evidence that physical states can influence belief in free will. Further extrapolation suggests that the less control a person has over those physical states, the weaker belief in free will (see Footnote 4).

³ For individuals who were dieting, more intense hunger was correlated with stronger belief in free will. The researchers suggested this is because these participants were more likely to be actively engaging in control over hunger which is an expression of free will (Ent & Baumeister, 2014).

Ent and Baumeister do not specify whether they believe physical states impact belief in free will because the physical sensations create an unconscious awareness of those states (i.e. the stronger the sensation the weaker the belief) or whether reminding a person about their physical state of the past may have a similar effect even in the absence of sensations. In their second study, Ent and Baumeister asked participants about physical states that are typically associated with sensations that the participants could have been experiencing at the time (e.g. hunger pains, fullness of bladder). However, in their first study it is not known whether participants who identified as having a current or past diagnosis of epilepsy or a panic disorders had been experiencing physical sensations at the time they completed the online study or if, instead, the effect was a result of those participants having been reminded about these physical states by being ask to identify as having that particular diagnosis in order to participate. Because of the disruptive nature of seizure disorders and panic disorders, intuitively it seems reasonable to believe that most participants would not have been experiencing major symptoms at the time they completed the study. What this suggests is that reminding participants about physical states that are beyond a person's control may also weaken belief in free will. This is particularly relevant to the discussion of the social impacts of SSPA's, because they are specifically designed to unmask the hidden nature of our internal states. Being reminded (whether through physical sensations or environmental cues) that our free will must sometimes be trumped by our physical needs is an integral part of the human experience and, since most people maintain a belief in free will (Nahmias, Morris, Nadelhoffer, & Turner, 2005; Monroe and Malle, 2010), the weakening effects are likely transitory as these reminders come and go. But ubiquitous SSPA's offer an unprecedented opportunity to remind users of the countless

physiological states of the body that change without willful intent. In this light, SSPA's may serve to continually depress belief in free will, even those that are genuinely meant to improve general wellness.

PART 2 - INTRODUCTION

One of the primary objectives of this dissertation research was to conduct an experimental investigation into the impact of *self-sensing prescriptive applications* (SSPA's) on decision making and attitude formation within a non-medical care framework. Although most of the research dedicated to changing behavior through the use of SSPA has occurred within a healthcare context, commercial use of biosensors is growing rapidly (Research and Markets, 2014; TechNavio, 2014) and little is known about how this form of information will act to guide consumer choices. It is also difficult to make inferences about the persuasive impacts of SSPA's in the consumer industry by simply looking to research from healthcare applications of SSPA, because, relative to the vast quantity of research energies invested in developing self-sensor driven health care technology and infrastructure behaviors (Pantelopoulos & Bourbakis, 2010; Research and Markets, 2014; Song, et al., 2014; TechNavio, 2014), very little research has been dedicated to evaluating and understanding the effectiveness of such technologies in terms of improved medical outcomes and decreased costs.

SSPA's developed for healthcare settings in which the devices would be used to treat or diagnose diseases or medical conditions must be approved by the Food and Drug Administration (FDA) to assure safety, efficacy, and security. This process can be costly and time consuming for manufacturers, with little guarantee of future market share. Recently the FDA released a non-binding set of guidelines for "low-risk general wellness" (LR-GW) devices that would not be subject to FDA oversight (Food & Drug Administration, 2016; also, see *Ethics, Regulation, and Policy*, p 11). Consumer SSPA's marketed to help users with general advice about fitness, relaxation, sleep, etc. may be

considered LR-GW devices and therefore would not need to wade through clinical trials to prove efficacy. This path of least resistance incentivizes developers of sensor technologies and SSPA to focus more on these LR-GW devices. This means more devices entering the consumer market with no regulatory motivations for manufacturers to dedicate resources to understanding how strongly self-sensor data (SSD) impacts attitudes and behaviors. This is particularly important because it is not known whether self-sensor data may bias a user to believe certain claims or advice regardless of the intellectual or scientific merits of the “general advice” produced by this category of SSPA devices. Several theories related to decision making and attitude formation suggest physiological self-sensor data could be particularly alluring in terms of persuasiveness. What follows is a brief overview of four areas of research related to persuasion and what they suggest about the potential impact of SSPA’s on attitude formation and behavior.

Message tailoring. The study of “message tailoring” offers some interesting insight into what we might expect from self-sensor data in terms of persuasion and behavior change. Tailoring a message means that the content, context, or method of delivery is partially determined by specific information about the particular individual for whom the message is intended. This is typically done to enhance the value or persuasiveness of a message and it is found to be more effective than group-targeted messaging or mass messaging (Hawkins, Kreuter, Resnicow, Fishbein, & Dijkstra, 2008; Noar, Benac, & Harris, 2007). While there is no universally accepted theory to explain the persuasiveness of message tailoring, a number of researchers suggest that it is likely related to increased attention and depth of processing (e.g. Hawkins, et al., 2008; Ho & Chau, 2013; Rimer & Kreuter, 2006; Ruiter, Kessels, Jansma, & Brug, 2006).

In a direct examination of attention and tailored messaging, Ruiter, Kessels, Jansma, & Brug (2006) asked participants to read an interventional message about nutrition while simultaneously participating in an auditory attention task. EEG measurements indicated that participants presented with a tailored message (which included personally-relevant information collected from a previous meeting) dedicated less attentional resources⁴ to the auditory task than participants presented with an untailored message. The researchers argue that the decrease in attention to the auditory tasks was most likely the result of increased attention to the tailored message. Participants in the tailored message condition also evaluated the interventional message as being more personally relevant and were more likely to indicate they intended to change their future diet.

There is a strong narrative within the literature surrounding tailored messaging that tailored information increases attention by activating personal relevance, which increases motivation to process the message, leading to attitude change (Hawkins, et al., 2008; Ho & Chau, 2013; Rimer & Kreuter, 2006; Ruiter, et al., 2006). In this narrative tailored information leads to what Petty and Cacioppo (1986) define as a “central processing” or careful thought about a persuasive message. Arguably, self-sensor data is the ultimate form of message tailoring data, so a logical inference might be that it will similarly serve as a central cue, activating the same central route to persuasion. In theory, this should allay concerns that SSPA designers could use self-sensor data inappropriately (e.g. to support a persuasive message that is actually unrelated to the data) because, as a central cue, it should elicit thoughtful, critical thinking about the message that would then undermine the dubious

⁴ Using EEG technology, the researchers measured changes in N100 and P300 event-related potential (which are thought to measure auditory attention) to infer attention reallocation to a secondary task.

persuasive attempt. However, while the notion that tailoring increases *motivation* to process a message deeply may be valid, Petty and Cacioppo also argue that in order for a person to do so he or she must also have the *ability* to process and understand the information being presented.

This ability is moderated by numerous factors including distraction, comprehension, background knowledge, obfuscation, etc. (e.g. Osterhouse & Brock, 1970; Eagly, 1974; Eagly & Warren, 1976). If ability is low, the individual may be unable or unwilling to think deeply about the argument and may defer to available “peripheral cues” instead; cues that are not necessarily related directly to the message (e.g. characteristic of the messenger, etc.). These peripheral cues activate heuristics or mental shortcuts rather than an active thinking process (also referred to as the heuristic approach by Chaiken, 1980) and the attitude changes they create are often temporary and less helpful in predicting future behavior than attitude changes arrived at via the central route (Cialdini, Levy, Herma, Kozlowski, & Petty, 1976; Petty, Barden, & Wheeler, 2002). Research into the efficacy of message tailoring has so far typically made use of individualized data and accompanying arguments that are purposefully easy to understand (e.g. simply restating information that the individual supplied earlier) and directly relevant to the persuasive message (e.g. referencing the individual’s daily caloric intake with his nutrition goals). This makes it difficult to know how novel self-sensor data such as respiration rates, brain wave function, blood cell count, etc. will (or will not) promote a central route to persuasion, especially when the highly tailored information is not clearly linked to the persuasive message (e.g. will personal brain wave data be useful in convincing someone to start taking an antacid?). Arguably, without the ability to understand the biological implications of the self-sensor

data it may merely serve as a peripheral cue that represents something about the message or messenger, (e.g. complexity, expertise, “scienciness”), but one in which the user is particularly motivated to notice because it is highly tailored. Looking to literature related to scientific rhetoric and credibility, there are a number of reasons to suggest that self-sensor data that is perceived to be highly tailored, but is nonetheless difficult for the user to process, may afford it an undue degree of persuasiveness.

Scientific rhetoric and credibility. The language used to describe the way SSPA’s collect and produce information, such as “quantify,” “measure,” “track,” etc. and, perhaps most importantly, the word “sensor” itself, all impart a certain essence of reality. This language allies itself with the language used by many cultures to explain how humans collect “factual” data about the self, others, and the environment; that is, we rely on our own “sensors” such as the eyes, nose, ears, etc. to “know” things. While we also rely on context, the environment, and others to interpret the meaning of these sensory observations, so long as we believe our sensors to be in good working order, we perceive their data to be a “reality.”

In addition to the language used to characterize SSD, framing SSD to users as a “scientific” measure of an internal state may also boost its credibility, whether warranted or not. Dumit (1999) found a number of examples from court cases in which it appeared that laypersons tend to put more faith in information they believe to be obtained from a “scientific mechanism” than information from a more subjective source. Further, Keil, Lockhart, & Schlegel (2010) found that biological explanations of behavior are perceived to be more complex and scientific than psychological explanations. Dumit argues that this bias in thinking is because insight derived from mechanism of hard science are perceived

to be “culturally objective” (Dumit, 1999). If SSD are afforded this characteristic of objectivity, this raises the question of whether this would bias a user to incorrectly believe that prescriptives derived from SSD are also culturally objective.

Beliefs about the perceived messenger conveying the data can also influence persuasiveness. Aristotle argued that an essential factor in any persuasive attempt is the trustworthiness of the speaker (Aristotle & Kennedy, 1991, pp 27-35). Not trustworthiness strictly in the sense that one might trust a computer to consistently calculate correct solutions to a math problem, but in the sense of the speaker’s perceived character traits such as wisdom, virtue, and good will (p 112). Aristotle claimed that a speaker perceived to possess all three of these qualities would be “necessarily persuasive” (p113).

In the case of SSPA’s, a user’s perceptions about who the “speaker” is *ought* to be complex because there are indeed many actors involved in the construction of the message, with many different social and economic goals in mind. This is explored further in *Ethics, Regulation, and Policy*, p 11; also see Figure 1) in terms of the complexity of regulatory policies; in terms of perceptions about the “speaker” the issue is equally nebulous. Some of these players include the engineers who design the sensors, those who design the algorithms, the researchers who construct the “evidence” knowledgebase from which the algorithms are defined, those who fund product development, the benefactors of the behavioral outcomes for the which the SSPA would be responsible for, and so on. The user’s awareness of these actors and his beliefs about what their roles and motivations are will shape the user’s perceptions about the “speaker.” However, without a requisite for transparency in SSPA design, the complexity of how and by whom a message is constructed may be lost. In the field of marketing consumer products, efforts to control and

manipulate beliefs about the speaker is a multimillion dollar industry and users often do not have access to all the relevant information. By promoting the languages and credibilities of engineering and medicine, marketing and design efforts in the field of consumer SSPA's attempt to construct a perception of a speaker who possesses wisdom, virtue, and good when the reality may be entirely different.

Bounded rationality and satisficing. Social Scientist, Herbert Simon (1956) argued that humans have numerous limitations in decision making behaviors and, individuals have a tendency to “satisfice” by seeking a merely reasonable solution rather than to optimize by considering other options that might be more complex, but more valid. Further, many researchers have found a general preference for reductive explanations (Hopkins, Weisberg, & Taylor, 2016; Craver, 2007; Garfinkel, 1981; Trout, 2007) and argue that individuals tend to seek mental shortcuts to decision making (Tversky & Kahneman, 1974) especially in times of uncertainty or high cognitive load.

Commercial SSPA's are likely to appeal to consumers who seek to reduce the cognitive load related to careful, critical decision making. In theory, adding self-sensor data as a new factor in decision making could represent a new layer of complexity especially if that data requires special skills to understand. However, if self-sensor data is presented to a user as a simplification of a number of other complex factors, it may be interpreted as a short-cut to decision making. For example, say a person needs to monitor their level of alertness and anxiety in order to perform their job. To make judgements about their mental state they must make subjective observations about how their body feels and weigh this with memories about how they have slept, what they have eaten, etc. within the last 24 hours or so. Consider a SSPA designed to monitor brainwave sensor data (e.g.

EEG), galvanic skin conductance, sleep data etc. that the user can also use to make judgements about their mental state. These raw sensor data may convey nuanced information about mental state, but understanding the implications and limitations of these data and weighing the differences could be time consuming and stressful and would not reduce the cognitive load of the original task. However, if the raw data is accompanied by an approximation or summary, such as a simplified numeric rating, an avatar's facial expression, or a simple thumbs up or down for alertness and anxiety, this short-cut may be intuitively more satisfying and persuasive than the raw data alone because it conveys a sense of "understanding;" not only of the data, but of the self.

Even in the absence of a deeper understanding of how self-sensor data is relevant to an interventional message, it may still be perceived as adding volume to a body of "evidence." In terms of attitude formation and decision making, researchers find that volume of the arguments can lead to persuasion even when the arguments do not add additional substance (Calder et al., 1974). This poses a risk to users if the designers of a SSPA are able to use self-sensor data to create an air of credibility for a prescriptive that prompts a user to act in a way that is counter to their best interests (for example, claiming that an individual's sensor data indicate he/she needs an energy drink before continuing a workout when, in fact, the energy drink is simply empty calories, and the prescriptive is merely meant to increase sales).

False physiological feedback and persuasion. There are some older studies investigating the role of physiological feedback on attitude change which have demonstrated a persuasive impact. For example, Giesen and Hendrick (1974) had participants watch a film about the use of pesticides while hooked up to a machine

described as an arousal meter and found that subjects led to believe they were experiencing high arousal during the film were more persuaded than participants led to believe they experienced low arousal during the film. In a follow-up experiment using the same methodology and film content, the researchers found that changing the meter label from “arousal” meter to “belief” meter had similar persuasive impacts (Hendrick & Geisen, 1976). Participants led to believe they were experiencing “high belief” while watching the film were more persuaded than the participants led to believe they were experiencing “low belief” while watching the film. Interestingly, in this experiment some participants were told the belief meter was very accurate and others were told the meter was not very accurate, but this did not impact their findings; in other words, participants who were aware they were using a meter that wasn’t very accurate were still more persuaded by “high belief” feedback. Valins (1966) found similar effects by providing false heart rate information to male participants while they looked at photographs of nude women. When participants were led to believe their heart rate increased while looking at particular photos of women, the subjects later judged those photos to be more attractive. Valins found that even when participants were made aware of the deceptions and then rated the photos, they still rate those photos as more attractive.

This early research indicates that physiological feedback does have an impact on persuasion, though it is unclear whether these findings are indicative of the persuasive impact of commercial SSPA given the undoubtedly substantial differences in the level of technological experience these early subjects would have compared to today’s technology consumers.

Present Study

This study tests the hypothesis that participants led to believe a software application is using their self-sensor data to assess the degree to which they like an image will be more likely to agree with that assessment than participants led to believe the application is using only a personalized algorithm. This study also examines whether variations in the way self-sensor data was visually presented to the participant impacts persuasiveness and whether the participant's preexisting attitude toward the image impacts the persuasiveness of the SSD. The experiment uses an actual consumer SSPA, the MindWave Mobile headset by Neuro Sky, to collect neurological SSD.

Persuasion and neuroscience. Although some of the most popular consumer SSPA's are wearables that track heartrate and movement (PwC Health Research Institute, 2016), use of wireless electroencephalography (EEG) for real-time monitoring of electrical activity of the brain is a fast growing market and researchers and manufacturers are motivated to develop "intelligent wearable, wireless, lifestyle EEG solutions," (Mihajlovic, Grundlehner, Vullers, & Penders, 2015). Two primary consumer related markets for wireless EEG's are emerging. First are consumer neuroscience wearables which are primarily used by market research firms to study consumer behaviors related to attention, engagement, and choice. These include devices such as the B-Alert (Advanced Brain Monitoring, Inc., 2016), Mobita (BioPAC Systems, Inc. 2016), Emotiv EPOC (Emotiv, Inc., 2016), and the EEG Module from iMotions (2016). Second are direct-to-consumer wearables which are currently marketed primarily for sleep improvement, meditation, stress management, and brain training, and consumers can buy these directly from the manufacturer or from stores such as Amazon.com. These include devices such as MindWave Mobile (NeuroSky, 2016), Muse (Muse, 2015), Sleep Shepherd (Sleep

Shepherd, 2016) and the Emotiv Insight (Emotiv, Inc., 2016). These direct-to-consumer wearables make no claims related to diseases or medical conditions and the headsets are designed to be about as intrusive as a set of headphones so they would be described as “low-risk, general wellness” devices per the FDA’s recent draft guidelines (Food and Drug Administration, 2016; also see *Ethics, Regulation, and Policy*, p 11). Their intended use claims include non-specific, but impressive statements such as “provides in-depth information on your brain activity” (Emotiv, 2016), “take a snapshot of your brain in an active state (and)...uses this snapshot as a reference to understand your brain signals,” (Interaxon, Inc., 2016), and “interprets meaning of brain signals,” (NeuroSky, 2016.).

Despite inroads into neuroscience and the interpretation of EEG signals, there is substantial debate among neuroscientists themselves regarding what brainwaves can and cannot tell us about human behavior (Beaulieu, 2002; Rose, 2013; Uttal, 2012), and consumers should be particularly skeptical about any behavioral claims or advice derived primarily from this new form of self-sensor data. However, there is a substantial body of evidence that suggest that arguments, especially those pertaining to explanations of human behavior, that use neuroscience information to support them can be unduly persuasive to laypersons.

While investigating the specific impact of neuroimages on juror decision making, Schweitzer et al. (2011) found that mock jurors were more persuaded by a neurological explanation for a defendant’s mental state than clinical psychological explanations. Outside of a legal context, Rhodes, Rodriguez, & Shah (2014) looked at the impact of non-probative neuroscience information on the perceived quality of a fake news article with flawed scientific reasoning. They found that participants who read a news article

accompanied by neuroscience jargon rated the quality of article and the study it described higher relative to participants who read the article without the neuroscience jargon included. In a second study they also found that including superfluous neuroscience information increased perceived understanding of the mechanism described in the article.

In a series of four experiments, Fernandez-Duque, Evans, Christian, and Hodges, (2015) conducted a similar study, this time looking at superfluous neuroscience information paired with science articles that had either low quality or high quality scientific reasoning. The researchers had participants read a set of vignettes, each describing a unique psychological phenomenon. Each vignette including an explanation of the phenomenon using arguments of varying quality, as well as superfluous information that was either neuroscience, social science, or hard science in nature. Participants were asked to rate the quality of the arguments presented. The researchers found that superfluous neuroscience information increased the judged quality of the scientific argument relative to social science information (i.e. that alluded to culture explanations) and the hard sciences information (i.e. that alluded to metabolic and genetic pathways). They found this to be the case for sound arguments and flawed arguments.

Numerous mechanisms have been proposed to explain why neuroscientific information may bias lay judgments. Weisberg et al., (2008) suggested it may act as a seductive detail that distracts laypersons from thinking critically about the other arguments presented. Fernandez-Duque, Evans, Christian, and Hodges, (2015) suggest that the allure of neuroscience may be the perception that allows “neat, tidy attribution to one causal source: the brain.” Rhodes, Rodriguez, & Shah (2014) similarly suggest that it is this reductionist quality of neuroscientific explanations for behavior that may appeal to

laypersons when trying to grasp complex phenomena such as human behavior. In any case, the notion that neuroscience based information may be unduly persuasive to layperson, coupled with the relative novelty of using EEG data in consumer wearables makes this form of SSD well suited to this study. By employing NeuroSky's portable EEG monitor, the MindWave Mobile, in a context in which participant believe their neurological data is being used to interpret their attitudes, the persuasiveness of this form of SSPA can be assessed by examining whether participants' attitudes can be shifted with false neural feedback. In this case, the "argument" being made is a statement about how the participant feels about a particular image (in the form of a suggested rating of likability), and the "evidence" of this argument is represented to the participant as either neural feedback from the MindWave Mobile, or a computer algorithm.

Methods.

Recruitment of Participants. The original sample size consisted of 120 Arizona State University student volunteers recruited primarily from the undergraduate psychology department. All participants were informed they must be 18 years of age or older to participate. Also, because the experiment relied on mild deception about exaggerated capabilities of EEG sensor technology, only students enrolled in undergraduate psychology courses were recruited for participation.

Of those who agreed to participate, two did not complete the study and three failed the manipulation check. The manipulation check included two questions: (1) a multiple choice question about what type of technology was used with four possible answers (e.g. personalized algorithm, neuromonitor) and (2) a multiple choice question about how the

technology worked with four possible answers (e.g previous ratings, brain waves). Participants who got both questions wrong were excluded from the analysis.

The final sample size included 115 participants with a Mean age of 22.66 years, 83% were female, and all had at least some college level education.

Apparatus and materials. The primary equipment used for this experiment was comprised of two components. The first was the MindWave Mobile headset by Neuro Sky (see Figure 2) which is a consumer product (available for approximately \$100 USD at the time of this experiment) that monitors and outputs the EEG power spectrums (alpha waves, beta waves, etc.), propriety measure for attention and meditation, and eye blinks. The data were processed via various free and paid software applications marketed to consumers as brain training and meditation exercises.

The second component was the computer software used to present stimuli to participants. This program was developed using Visual Studio and C#. The program was designed to 1) present instructions 2) present a series of images in random order and record participant ratings of each image, 3) present a second series of images based on participant input from step two, and 4) record participant responses to those ratings.



Figure 2 An image of the MindWave mobile headset by Neuro Sky (2016) that some participants wore during the study.

Three sets of images were used in the study. The first set contained 20 images of water bottles that varied in size, shape, and color and had no visible logos or text. Because participants were rating how much they liked or disliked each image and because a spectrum of ratings would provide more meaningful results, the images were chosen to include both aesthetically appealing and common bottle types as well as less common and less appealing shapes. The second set contained 16 images of homes that were also chosen to provide variety in aesthetic appeal; from extravagant to humble, and from well to poorly maintained. The third set contained images of landscapes that once again were chosen to provide variety in aesthetic appeal, from warm and inviting to cold and unappealing. The bottle images were the only images that were part of the experimental stimuli (the other two sets were included as distractions). Bottles are common objects in US culture with a broad spectrum of uses and associations, so it was expected that participants would have a wide range of opinions about these images, but that they would not be deeply held and therefore would be susceptible to influence by the experimental manipulations. Additionally, because the control condition led participants to believe that they were testing a technology that was similar to those used by online retailers to make product recommendations, bottle images fit well into the experimental narrative.

Design. This study employed a mixed factor design with two independent variables (IV) manipulating the user's beliefs about how the technology functioned (Feedback) and manipulating how the user's ratings toward a set of images at Time₁ were changed for Time₂ (Change). Feedback was a between subjects IV while the Change variable was within-subjects (repeated measures). The primary dependent variable was a measure of the users Agreement with how well the technology deduced their attitude toward each image.

The Feedback dimension manipulated the manner in which the supporting information was rendered to the participant during the experimental phase of the study (Time₂) in which participants were led to believe the software application they were using assessed the degree to which they liked an image. This IV included 4 conditions. In the Control condition participants saw a general statement that the likeability rating was based on their personalized algorithm (see **Error! Reference source not found.3, A**). In the Implicit condition participants saw a statement that the rating was based on their neural feedback data (see Figure 3 B). In the Abstract condition participants saw the same statement as well as a gauge-like iconograph (see Figure 3 **Error! Reference source not found.C**). In the Explicit condition participants saw the same statement as in the Implicit condition as well as a bar graph with numeric readings (see **Error! Reference source not found. Error! Reference source not found.D**).

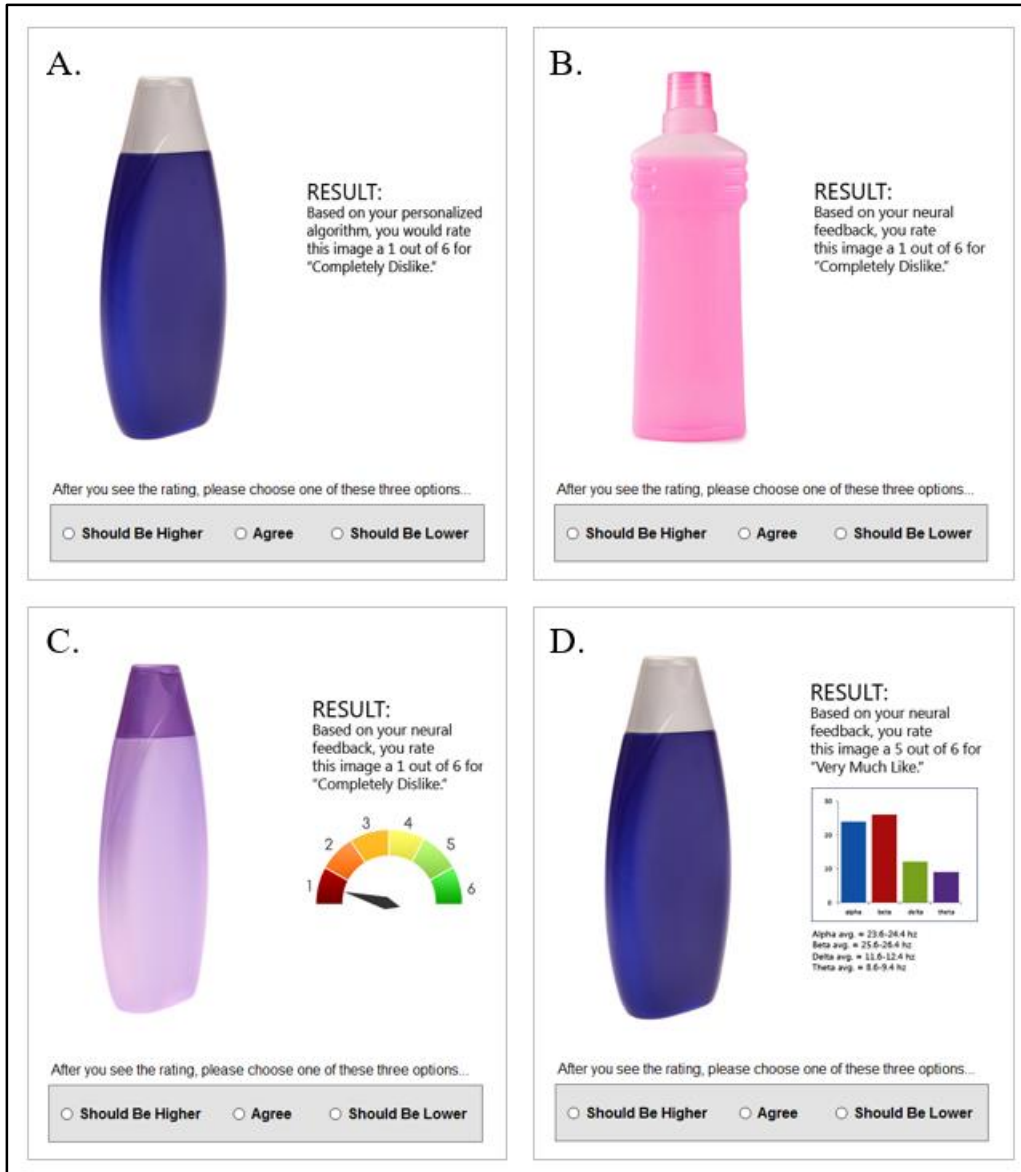


Figure 3. Screenshots illustrating the four different **Feedback** conditions from Time2 during which participants were led to believe the application assessed the degree to which they liked an image. A. Control. B. Implicit. C. Abstract. D. Explicit.

To examine the impact of a participant's preexisting attitudes on the persuasive impact of the neural feedback, some assessments presented by the software application at Time2 were actually based on the participants' earlier responses about the degree to which they liked that image. The Change dimension manipulated the direction in which these

ratings of stimuli from Time₁ were changed (See *Procedure* for detailed explanation) for Time₂.

Each stimulus presented at Time₂ appeared with an assessment of the degree to which they liked an image (ostensibly based on their neural feedback or personalized algorithm per condition). For the primary dependent variable, participants were asked to provide a measure of Agreement for this assessment (See *Procedure* for detailed explanation).

The final design can be represented as a 4 (Feedback: Explicit, Abstract, Implied, Control) x 4 (Change: Same, Higher, Lower, Random) mixed factor design with Agreement as the primary dependent variable.

Procedure. Before beginning the experiment participants were given an informed consent letter outlining the nature of the study and their rights as a participant. Participants were told they would be participating in a study about decision making and technology and that they would be playing a short computer game, looking at some images of homes, landscapes, and consumer products, and answering some brief questions. Finally, participants were told that during some parts of the study they may be asked to wear a small headset that measures brainwaves.

After reading the informed consent letter, participants assigned to one of the three neural feedback conditions participated in a brief warm-up exercise using the MindWave Mobile headset. MindWave users played a short computer game that comes as part of the Mindwave standard software in which they watched a live animated representation of their brain waves and attempted to “blow up” a wooden barrel on the screen by relaxing and focusing on the image. This warm-up exercise was meant to demonstrate that the

Mindwave Mobile device was a functional neuromonitor and to lead them to believe the neuromonitor would be used to generate product recommendations later in the study. Participants assigned to the personalized algorithm (Control) condition watched a brief animated Power Point explaining what a “personalized algorithm” was. The purpose of the Power Point viewing was to ensure that participants in the control condition had a basic understanding of what was meant by a “personalized algorithm” and that their own personalized algorithm would be used to generate product recommendations later in the study.

After the warm-up exercise all participants were asked to complete a “training” phase in which they would rate how much they liked or disliked a series of images and that these ratings would be used to learn about their preferences to either create a personalized algorithm (Control condition) or interpret neural feedback (Implicit, Abstract, and Explicit conditions). During this phase (Time₁) participants rated a series of images. Each image appeared on the screen individually and, after 4 seconds, the participant was asked to rate the degree to which they liked the image using a Likert scale of one-six (with one being “very unpleasant” and six being “very pleasant”). The image series contained 16 images of water bottles (randomly chosen from a pool of 20), followed by a series of 16 images of homes and 16 images of landscapes. The images of homes and landscapes were included as distraction to create a time delay between the participant’s first viewing of the bottle images and their second which occurs at Time₂.

At the end of Time₁, participants were presented with a second set of instructions letting them know that they would now be presented with another series of images and that either their customized algorithm (Control condition) or neural feedback (Implicit,

Abstract, and Explicit conditions) would be used to generate a likeability rating for each image. To enforce the illusion that neural feedback was being used to generate likeability ratings, participants were instructed to focus on each image for a few moments while ratings were generated and the rating did not appear until 4 seconds after the image.⁵

During Time₂ participants were presented with 16 bottle images, 12 of which were selected at random from those the participant had already seen and rated during Time₁ and four that the participant had not seen previously. The 16 images presented during Time₂ were presented in random order. See **Error! Reference source not found.** for an illustration of how bottle images were selected from the pool of 20 at Time₁ through Time₂.

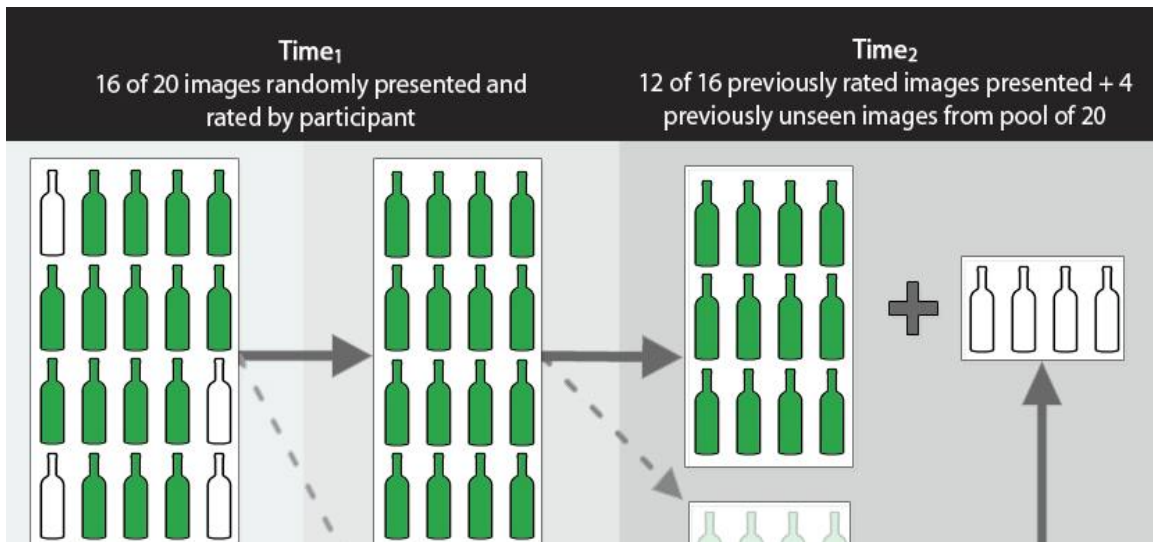


Figure 4. Illustration of how bottle images were selected from the pool of 20 at Time₁ through Time₂. At Time₁ 16 images were selected from a pool of 20 images to appear in random order for participants to view and rate. At Time₂ the participant viewed a second series of 16 images; 12 selected at random from the 16 images rated at Time₁ and the remaining four were those that had not been selected from the original pool of 20 for viewing at Time₁.

⁵ Note, in the Control condition a personalized algorithm would theoretically be able to make predictions about the image without the user ever seeing it and therefore there would be no need for the participant to look at the image for any length of time. However, since participants in all conditions were asked to evaluate how they felt about the image by thinking about whether they agreed with the rating or not, this instruction was kept constant for the control condition to avoid any confounds related to length of time each stimulus was viewed.

After the image was shown for four seconds, a second image appeared alongside the bottle describing what the personalized algorithm or neuromonitor technology calculated the participants “rating” would be for that particular image. The appearance and description of the “rating” varied by condition (see Figures 3 A-D). While participants in all conditions were led to believe the rating was derived by their sensor feedback (or the personalized algorithm in the control condition), the rating was actually derived from the participant’s responses during Time₁. Four images were randomly selected to appear with the Same ratings from Time₁, four were randomly selected to appear with a rating 2 points Higher, and four were randomly selected to appear with a rating 2 points Lower, (see **Error! Reference source not found.**³ for an examples). The remaining four images presented were comprised of those the participant had not seen previously and ratings for these images were generated at Random using the same scale as the other 12. As a measure of Agreement, after each image and its rating were presented, participants were asked to indicate whether they agreed or disagreed with the rating generated by their particular technology by selecting one of three responses: “Should be Higher”, “Agree”, or “Should be Lower”.

After rating each of the 16 images at Time₂, participants were asked a number of additional questions including a manipulation check asking what type of technology they tested and how their technology generated their ratings. Participants were also asked a series of questions about their personal experiences with wearable self-sensor technologies, their attitudes toward the technology they used during the study, and basic demographic information.

Table 3

Example of participant data and average agreement values.

Bottle ID	Eg. Response @ Time ₁	Change Direction	Rating Presented @ Time ₂	Eg. Raw Agreement Score*	Converted Agreement Value**	Avg.
bottle6.jpg	4	Same	4	2	2	} (Same) 1.75
bottle0.jpg	4	Same	4	3	1	
bottle10.jpg	6	Same	6	2	2	
bottle9.jpg	3	Same	3	2	2	
bottle2.jpg	3	Higher	5	2	2	} (Lower) 1.5
bottle4.jpg	4	Higher	6	1	1	
bottle3.jpg	3	Higher	5	3	1	
bottle19.jpg	4	Higher	6	2	2	
bottle14.jpg	5	Lower	3	1	1	} (Higher) 1.5
bottle8.jpg	4	Lower	2	2	2	
bottle11.jpg	5	Lower	3	2	2	
bottle5.jpg	4	Lower	2	3	1	
bottle12.jpg	NA	Random	5	3	1	} (Random) 1.25
bottle18.jpg	NA	Random	1	2	2	
bottle16.jpg	NA	Random	3	3	1	
bottle1.jpg	NA	Random	6	3	1	

Note. *1= "Should be Higher", 2="Agree", 3="Should be Lower"; **1=Disagree, 2=Agree

Quantitative Analysis. As mentioned in the design section, this study used a 4 (Feedback: Explicit, Abstract, Implied, Control) x 4 (Change: Same, Higher, Lower, Random) mixed factor design with Agreement as the primary dependent variable. The first test conducted was a mixed Analysis of Variance (ANOVA) to determine whether any changes in the dependent variable, Agreement, were the result of the between-subjects variable Feedback, the within-subjects variable Change, and/or an interaction between the two. Prior to doing this analysis, note that although participant responses were recorded on a scale of 1-3, responses of 1 and 3 both indicated disagreement (either because the

participant felt the score presented by the program should have been higher (1) or should have been lower (3)). To simplify the analysis the direction of disagreement was disregarded and scores were converted to either 1 for disagree or 2 for agree. These new scores were then averaged across each of the four iterations of each of the four Change directions (i.e. 4xSame, 4xHigher, 4xLower, and 4xRandom), creating 4 average Agreement scores per participant for Change (rather than 16). Table 1 shows an example of participant data to illustrate how responses from Time₁ were changed at each level of the Change variable to produce rating for Time₂ and how Agreement responses were converted to an average score.

Using the average Agreement scores, no main effect of Feedback was found, $F(3,111)=.254, p=.858$, and no interaction of Change and Feedback was found, $F(9,111)=.842, p=.577$. However a main effect of Change was found, $F(3,111)=50.715, p\leq.001, \eta_p^2=.314$. Table 4 shows a series of paired samples t-test for all levels of the Change variable. Subjects tended to agree more with the recommendations made by the program (regardless of whether they wore the neuromonitor or not) when the original score was kept the Same ($M=1.758, SE=.023$), pushed Higher ($M=1.733, SE = .022$), or pushed Lower ($M=1.688, SE=.025$) relative to recommendations made when the image was presented for the first time with a Random score ($M=1.412, SE=.025$, all $ps<.001$). In other words, the presence or absence of the neuromonitor feedback did not have an impact on whether the participant tended to agree with the rating recommendations presented by the program in Time₂; however, participants tended to agree with the recommendation more often when the image was one they had seen before (regardless of whether the recommendation was the same, higher, or lower than their previous actual rating) relative to the random ratings

presented for images they had not seen before. This finding is discussed further in the *Descriptive Analysis* section.

Table 4

Paired samples t-tests for all levels of the Change variable.

Change	Mean		t	df	Sig. (2-tailed)
	Agreement	SD			
Same	1.76	0.24	0.98	114	0.329
Higher	1.73	0.23			
Same	1.76	0.24	1.09	114	0.103
Lower	1.69	0.27			
Lower	1.69	0.27	-1.57	114	0.117
Higher	1.73	0.23			
Random	1.42	0.26	-7.85	114	<.001
Lower	1.69	0.27			
Random	1.42	0.26	-10.11	114	<.001
Higher	1.73	0.23			
Random	1.42	0.26	-10.61	114	<.001
Same	1.76	0.24			
Random	1.42	0.26	-9.92	114	<.001
Different	1.71	0.19			
Random	1.42	0.26	-11.10	114	<.001
Non-Random	1.73	0.16			

Note. Also includes comparison of Random condition to combined mean score of Higher and Lower (labelled as “Different”) and comparison of Random condition to combined means of Same, Higher, and Lower (labelled as Non-Random).

Although the analyses thus far indicate no impact of the Feedback manipulation, it is possible that the manipulation could have had an impact on a subset(s) of participants. To rule out this possibility additional tests were conducted using Agreement as the primary dependent variable. First, a mixed ANOVA was conducted using Feedback and Gender as independent variables to test for an interaction. No interaction was found $F(3,107)=.107$, $p=.956$, but it is important to note that there were very few males in the sample. Second, it

was suspected that individuals who seek out wearables on their own might also be more willing to follow recommendations thought to be derived from the data a wearable monitors. Participants had been asked to indicate if they currently owned or planned to own biometric wearables, so a mixed ANOVA was conducted using this variable and Feedback as the independent variable, but again no interaction was found $F(3,110)=.669, p=.573$.

Descriptive Analysis. Participants tended to agree with the ratings they were led to believe had been derived from either their personalized algorithm or their neural feedback (64.9%). This number increases when looking at rating that were not randomly generated, in which case participant agreed 72.8% of the time (see Table 3 for frequency of Agreement responses for all conditions). As noted in the *Quantitative Analysis* section, participants tended to disagree more often with ratings that had been generated at random. One explanation for this could be related to greater variability in randomly generated ratings away from participants' actual attitudes about the image. Bottle images appearing in Time₂ that had been seen previously were always paired with a rating that was within zero to two points of the participant's original attitude rating (measured during Time₁). However, images appearing in Time₂ that had not been seen previously were paired with a random rating, with unknown variance from the participant's actual attitude. For example, suppose a participant's "actual" attitude rating toward an image is a "one." If the participant sees this image at Time₁ they will rate it a "one" and the image can reappear in Time₂ with any rating between one and three. However, if they do not see this image at Time₁ it would then appear in Time₂ with a random rating of any number between one and six, which could be up to five points higher than the participant's actual attitude. Ratings in the Random condition were not bound to be within two points of the participants "actual" attitudes and

therefore the likelihood that the ratings would be disagreeable were higher for this condition.

When participants who wore the Mindwave Mobile headset were asked if interested in using a similar product to help with consumer purchases, 38.3% said yes, 53.1% said maybe, and only 8.6% said no. There are numerous potential explanations for this. First, participants may have merely been being polite. Second, recalling that participants tended to agree with most of the ratings presented during Time₂, this positive reaction may have been a reflection of a positive experience with the technology.

Table 5

Frequency of Agreement responses for Time₂.

Change	Algorithm (% of N=34)			Neuro Implicit (% of N=25)			Neuro Abstract (% of N=25)			Neuro Explicit (% of N=31)			All Conditions (% of N=115)		
	Should Be Lower	Agree	Should Be Higher	Should Be Lower	Agree	Should Be Higher	Should Be Lower	Agree	Should Be Higher	Should Be Lower	Agree	Should Be Higher	Should Be Lower	Agree	Should Be Higher
	Same_A	11.8	79.4	8.8	12.0	80.0	8.0	20.0	76.0	4.0	16.1	74.2	9.7	14.8	77.4
Same_B	11.8	76.5	11.8	12.0	72.0	16.0	16.0	64.0	20.0	6.5	74.2	19.4	11.3	72.2	16.5
Same_C	8.8	88.2	2.9	24.0	72.0	4.0	16.0	68.0	16.0	12.9	80.6	6.5	14.8	78.3	7.0
Same_D	5.9	79.4	14.7	20.0	68.0	12.0	16.0	80.0	4.0	12.9	80.6	6.5	13.0	77.4	9.6
Mean	9.6	80.9	9.6	17.0	73.0	10.0	17.0	72.0	11.0	12.1	77.4	10.5	13.5	76.3	10.2
Higher_A	20.6	64.7	14.7	12.0	80.0	8.0	8.0	84.0	8.0	3.2	83.9	12.9	11.3	77.4	11.3
Higher_B	23.5	50.0	26.5	16.0	60.0	24.0	24.0	60.0	16.0	6.5	77.4	16.1	17.4	61.7	20.9
Higher_C	2.9	85.3	11.8	24.0	60.0	16.0	0.0	92.0	8.0	12.9	77.4	9.7	9.6	79.1	11.3
Higher_D	8.8	82.4	8.8	4.0	80.0	16.0	20.0	68.0	12.0	16.1	67.7	16.1	12.2	74.8	13.0
Mean	14.0	70.6	15.4	14.0	70.0	16.0	13.0	76.0	11.0	9.7	76.6	13.7	12.6	73.3	14.1
Lower_A	5.9	73.5	20.6	20.0	60.0	20.0	20.0	76.0	4.0	12.9	74.2	12.9	13.9	71.3	14.8
Lower_B	11.8	70.6	17.6	8.0	92.0	0.0	16.0	72.0	12.0	19.4	61.3	19.4	13.9	73.0	13.0
Lower_C	11.8	73.5	14.7	8.0	84.0	8.0	24.0	64.0	12.0	19.4	61.3	19.4	15.7	70.4	13.9
Lower_D	17.6	55.9	26.5	24.0	60.0	16.0	28.0	52.0	20.0	12.9	71.0	16.1	20.0	60.0	20.0
Mean	11.8	68.4	19.9	15.0	74.0	11.0	22.0	66.0	12.0	16.1	66.9	16.9	15.9	68.7	15.4
Random_A	20.6	47.1	32.4	20.0	48.0	32.0	24.0	52.0	24.0	29.0	41.9	29.0	23.5	47.0	29.6
Random_B	17.6	55.9	26.5	36.0	32.0	32.0	24.0	40.0	36.0	19.4	32.3	48.4	23.5	40.9	35.7
Random_C	26.5	41.2	32.4	24.0	28.0	48.0	20.0	36.0	44.0	29.0	51.6	19.4	25.2	40.0	34.8
Random_D	26.5	38.2	35.3	28.0	36.0	36.0	24.0	44.0	32.0	32.3	35.5	32.3	27.8	38.3	33.9
Mean	22.8	45.6	31.6	27.0	36.0	37.0	23.0	43.0	34.0	27.4	40.3	32.3	25.0	41.5	33.5
Grand Mean	14.5	66.4	19.1	18.3	63.3	18.5	18.8	64.3	17.0	16.3	65.3	18.3	16.7	64.9	18.3

Discussion. Despite numerous theoretical findings described earlier that suggested the use of neuroscientific self-sensor data might be more persuasive in altering a user's attitudes than would be a personalized algorithm similar to those often employed to make product recommendations by online retailers such as Amazon.com, this did not prove to be

the case in this study. Because of limitations with the number of participants that could be recruited for the study, a control condition in which participants would be led to believe that their ratings in Time₂ were merely generated at random could not be included in the study design. Therefore, it can only be said that leading participants to believe their brainwave data were used to interpret their likes and dislikes was no more or less persuasive in shifting their attitudes than leading them to believe this was done by a personalized algorithm. However, it cannot be said with certainty that, based on this study, either of these methods is any more or less persuasive than if a participant were led to believe his or her recommendations had been made by a monkey trained to draw cards randomly from a deck. This is not to discount or specifically question the persuasive qualities of technology qua technology, but merely to point out that it would be problematic to make any strong claims that brainwave data is at least “as persuasive” as personalized algorithm data without first understanding the degree to which either is persuasive at all in this particular context.

Another factor that may have contributed to the null findings is the possibility that participants had a tolerance of at least two points on the one-to-six Likert scale that was used to indicate the likeability of each image. In other words, if ratings presented by the program that were within two points of the participant’s original rating were generally perceived as the same score, agreement with scores that were changed up or down did not necessarily indicate successful persuasion. Future research should allow for a wider range in the magnitude of change for scores at Time₁ to Time₂. Including more extreme changes would help identify whether there is a threshold at which users may be persuaded by the neuromonitor data, but not the algorithm or vice versa. This information could not be

determined by looking at the random condition because the participant's original attitudes were not known.

If there was a threshold effect to explain why participants tended to agree with ratings that were within two points of their original score regardless of condition, this does not explain why the neuromonitoring condition was not more persuasive than the personalized algorithm condition for scores that were randomly generated at Time₂. As described in the introduction and study overview, research seemed to suggest that the mere presence of SSD, and specifically the presence of neuromonitoring data, would be more persuasive than non-neuroscience information; however, the data in the present study did not support this hypothesis. It is possible that the context in which neuroscientific information was used in this study was not perceived to be as relevant as in the previously cited research or it is possible that participants in this study, compared to those in previous neurobias studies did not experience enough uncertainty in their decisions to consider additional information that was available. In other words, it is possible that participants in this study simply didn't perceive that the neuroscientific information was relevant enough to their decisions for it to be an influencing factor and/or there was not enough uncertainty to seek additional information cues to make their assessment. This would explain why the neuromonitoring conditions and personalized algorithm conditions did not differ in persuasiveness. Future research should examine whether neuromonitoring data might have a persuasive impact on decision making if the topics, images, or vignettes engage participants in higher stakes decision making or decision making with a higher level of uncertainty.

Given the limitations of this study, as well as the breadth of research related to the effectiveness of tailored messaging, evidence of the persuasive influence of false biological feedback, and other research described in the previous sections, it is premature to suggest that neuromonitoring data, (or SSD more broadly) are not persuasive or even unduly persuasive. In addition to addressing the methodological issues described, to understand the persuasive impact of SSPA's continued research is needed to investigate different sources of SSD (e.g. galvanic skin response, heart rate, etc.), different domains of decision making (e.g. fitness, wellness, consumer choices, lifestyle decisions, etc.), the directness of the causal link between the SSD and the message, the degree of uncertainty or emotional investment in the decision process and so on.

CONCLUSION

The possibility that SSPA's might be unduly persuasive should not be the only risk factor investigated experimentally. Other social implications, such as the degree to which SSPA's may depress belief in free will and promote negative behaviors, should be examined in the future. Furthermore, some of the social implications discussed here are relevant regardless of the persuasive impact of SSD. SSPA's represent a new opportunity for governing people. Whether this will manifest in the future as primarily self-governance as some have argued (Rose, 2007a; Rose, 2007b; Topol, 2011) or as merely a transfer of individual (and collective) sovereignty to industry and state will rest on how these technologies are designed and how persuasive they are. This research has argued that consumer SSPA's pose a unique threat to user autonomy because of qualities that tap into numerous psychological phenomena of persuasion and because of little formal or informal regulatory oversight. The discourse surrounding SSPA standards for avoiding risk through

design and regulation that has taken place has focused on data security, privacy, accuracy, and to some degree, physical harm, while the concerns raised in this research, related to subjection, docility, medicalization, persuasion bias, and erosion of beliefs in free will, have not been widely considered. For SSPA's (and too many other forms of technological innovations) the approach to considering these broader social implications is often "shoot first, ask questions later," i.e. bring these products to market, see what sticks around, and see what the outcomes are. It's unclear how responsibility for accounting for these social implications should be assigned, whose moral authority can be trusted to do it, and what values should play a role. Although engineers are centrally located in reflecting on and responding to ethical implication of SSPA design and deployment, it is critical that government regulatory bodies such as the FDA and the FTC place a higher emphasis on SSPA risk, one that goes far beyond privacy and data security.

The economic success of consumer SSPA's relies on convincing users that their physiological states should not only be monitored, but also controlled. However, numerous factors described in the research presented here suggest that, rather than empowering users to access and unleash the body from some (imaginary) state of ignorance that ostensibly puts wellness at risk, SSPA's invite external actors into the users most intimate activities and allow those actors to define that individual in unprecedented detail. By controlling this knowledge and the standards through which these definitions are constructed, external actors have the ability to remove the very control from the user that they claim to be offering. This is not to suggest that all SSPA's as they exist today necessarily transfer control from the user to an external actor. These technologies can also be used to monitor and control the user's physiological states using only that body's previous state as the frame

of reference for any implicit or explicit prescriptive (such as increasing strength or stamina over past performance). In this case, it is possible that a user could in some sense be empowered to control bodily processes solely on his or her own terms. However, the ability to evaluate and compare oneself to others and against established norms is imperative to a deeply seated drive to understand and control the “self” and its place in the world. SSPA’s that promise this affordance will no doubt be appealing to a broad consumer base and, as described earlier, current approaches to design and marketing of these technologies tap into this drive using language and rhetoric that implies understanding the self can be achieved through subjection of the body. What is critical to acknowledge, however, is that if users are prevented from knowing the values and interests that underlie how these understandings and modes of control are constructed, there is a greater risk that SSPA’s may become not a tool of self-governance, but rather, a tool of social control. One in which understanding the “self” becomes a process of corporate and state reflection to control consumer and population behavior, while ironically lulling users into a sense that they are participating in a process of deep personal reflection.

As a final note, it will be tiresome to some and critical to others that I to point out that the research and arguments presented here, though critical, do not, in fact, constitute a luddite call to ban SSPA’s. Rather, it constitutes a call to acknowledge the deeper social implications of these technologies and to further examine how deficiencies in current ethical analysis and regulatory considerations ought to be addressed in order to avoid unwanted consequences; before, or at least at the same time as, a future of ubiquitous surveillance of bodies and actions is being feverishly constructed. And to underscore that the promises of user empowerment and personalized wellness stemming from advocates

of self-quantification rest not merely in the expansions of the variety and details of SSD data made available to users, but in the design and deployment of the SSPA's that use these data to influence user behavior and define the body.

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