Sensing is Believing: What People Think Biosensors Can Reveal About Thoughts and Feelings

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ABSTRACT
Biosensors—devices that sense the human body—are increasingly ubiquitous. However, it is unclear how people evaluate the risks associated with their use, in part because it is not well-understood what people *believe* these sensors can reveal. In this study, participants ranked biosensors by how likely they are to reveal what a person is thinking and feeling. We report quantitative and qualitative results of two survey-based studies, one on Mechanical Turk workers (n=100), and one on participants in a longitudinal self-tracking study (n=100). Our findings imply that, in the absence of information about particular sensing technologies, people rely on existing beliefs about the body to explain what they might reveal. Highlighting mismatches between perceived and actual technical capabilities, we contribute recommendations for designers and users.

Author Keywords
biosensing

CCS Concepts
•**Human-centered computing** → *Empirical studies in HCI;*

INTRODUCTION
Shall we be sensed? Implicitly or explicitly, consumers must ask themselves this question when they purchase or encounter any number of sensors inside the home, at their job, or on their body [32, 5, 34]. Nafus [23] terms this process biosensing—the pervasive digital monitoring of human bodies, driven by sensors. Such devices may offer convenience, such as a smartwatch with a GPS for navigation. However, even this ubiquitous modality may yield surprising, and intimate, predictions; a recent study related smartphone location traces to symptoms of depression [3].

Disclosing sensor data comes with some known risks to user privacy, as well as uncertainty about future risks. It is currently unclear how people evaluate the risks of sensor-based disclosure, in part because it is unclear what people think biosensors can currently reveal about them. Do they believe that these sensors can detect their moods, identities, or emotion (more so than non-commercial sensors such as medical devices)? How do these beliefs relate to existing beliefs about the body, or existing habits of disclosing sensor data?

In this study, we conducted two separate survey-based studies on two different sample populations: 100 Mechanical Turk workers, and 100 participants from a large (n>10,000) longitudinal study of participants who currently own a self-tracking device and agree to upload their data to help with health-related science. We asked people in both samples what they *believed* a broad base of biosensors can reveal about what a person is thinking and feeling. We compare and contrast responses from those who currently use biosensors to benefit science with a broader sample of individuals who have varying levels of interest, knowledge, and use of biosensors.

We find that people do believe biosensors can reveal their thoughts and feelings. These beliefs vary a lot by sensor, but are remarkably consistent across participants. However, these beliefs do not always match empirical realities. For example, people believe electroencephalography (EEG), or brainwaves, to be particularly revealing, even though work in brain-computer interface (BCI) has found these data difficult to interpret [21]. Meanwhile, we found that virtual reality (VR) headsets and sensor-derived geographic location seem less revealing, even though such devices have been and are increasingly outfitted with biosensors [18, 3].

Our qualitative analyses enrich and complicate these observations by providing evidence that these preconceptions arise in part from people's beliefs about the body. These analyses suggest that beliefs about the body, along with social context and the perceived capacities of particular sensors, play a fundamental role in shaping beliefs about what sensors can know. We discuss how these beliefs may structure and inform what people expect, what kinds of biosensing they are (un)willing to put up with, and what claims they are willing to accept. This contribution motivates two main warnings from our study: that designers must beware of the seemingly creepy, and that users must beware of the seemingly innocent.

BACKGROUND & PRIOR WORK
Why would anyone want to wear a biosensing device (e.g. a Fitbit) if it sends data back to a company, who may use the data internally for unknown purposes, or even share data with unknown third parties? Early work has described sensor adoption as a process of weighing trade-offs between risk and

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reward [12]. However, later work broadened these claims considerably, implicating users' systems of belief around data, and the social practices that surround it, as the primary factor behind their adoption of biosensing [34, 29, 23, 31]. In her early studies on biosensing, Nafus describes the work of marketing biosensors at a large corporation: "Figuring out whether a consumer market for biosensors was even thinkable had everything to do with whether the data they produced cohered with a cultural and social imaginary, such that users stood a chance of making sense of them" [23]. Past work in HCI has corroborated this assertion, revealing that the meanings of biosensor data are largely defined by social context. For example, in their study of sensing devices in the home, Tolmie et al. noted how a family used sensor readings from a home's bathroom to help them tell stories about visiting relatives and mischievous cats [34].

Past work more directly implicates interpretations about thoughts and feelings in the interpretation of biosensor data. In a controlled experiment, [19] found that participants believed an elevated heartrate signaled anxiety, and affected trusting behavior in a simulated partner. Prior work at DIS, a more contextual study with color-changing fabrics [14], found that people's beliefs about the body (moist skin, as measured by skin conductance) met with social contexts to produce "authoritative" accounts of what wearers were feeling. Earlier work at DIS has also relied on this property to produce emotionally meaningful interactions with biosensors [16]. Together, this work indicates that the contextual meanings of sensor data may congeal around the mind, particularly mood and emotions. However, it does not shed light on how or why particular meanings are formed (e.g., what relation, if any, these meanings have to the specific biosensors employed).

These and other past studies of meaning-making around sensors tend to look at one or two sensing modalities, typically via interactions with particular technologies. These studies reveal a rich texture to the social and contextual interpretation of biosensory data. However, studies of specific technologies cannot examine the similarities and differences in what users believe that many different sensors can reveal about them to others.

In this study, we seek to examine the mind-related meanings people might build around a broad range of different sensors. We trade the focused, contextual analysis of prior studies for a comparative, mixed-methods survey of sensing modalities. Participants in our survey may not have a shared understanding of sensing modalities grounded in a specific application context, and our survey does not aim to provide one. Instead, our study seeks to evaluate what people *believe* about the biosensors' capabilities, even if those beliefs are inconsistent between participants. Their beliefs, however diverse, may impact the way sensors are deployed, or understood as meaningful. In the following sections, we describe our research question, methodological design, and key findings.

RESEARCH QUESTION

Our study design was motivated by one main question: To what degree do people believe wearable sensors can reveal about their thoughts or feelings?

To help answer this question, we included a wide selection of sensors in our survey study (Table 1). This selection includes both sensors commonly found in wearable and mobile devices, and sensors more commonly associated with the medical industry. We sought to achieve a mix of modalities found only in medical devices, found only in commercial devices, and found in both commercial and medical devices. We aimed to understand how participants ordered these sensors, to view how relatively revealing devices seem compared to less commercially-common biosensing modalities.

To understand how these determinations relate to beliefs about both the body and a sensor's technical capabilities, we chose a subset of these sensors around which to build qualitative questions. Finally, to better understand how existing practices around sharing biosensor data relate to these determinations, we ran two studies with two, different populations: one population that already shares data from biosensing devices, and one general population.

METHODS

Samples

For our first study, we sought to capture a population who already use, and share data from, biosensing devices. Such participants may be on the forefront of adopting biosensing technologies, and may act as a harbinger for the characteristics of future electronics consumers. Thus, we chose as our sample for this study participants in Health-e-Heart (HeH), a large (n>10,000) longitudinal study in which participants volunteer to share data from wearable sensors longitudinally so that researchers may monitor health outcomes [8]. We obtained permission from the administrators of that study to email participants a link to partake in our study. We recruited 100 participants, 63 who identified as women and 47 who identified as men, with a median age of 48.

For our second study, we sought a population with no specific orientation toward biosensor disclosure. Thus, we chose as our sample for this study Mechanical Turk workers in the United States. We recruited 100 participants from Mechanical Turk. We created a Mechanical Turk task for our study, and limited the task to workers in the US. We recruited 100 participants for this sample, 23 who identified as women, 76 as men and 1 as transgender. Participants had a median age of 29. We followed Dynamo's Guidelines for Academic Requesters in requesting tasks from Mechanical Turk [7].

Survey

Our survey consisted of a question in which participants ranked various sensors: "Please rank the following sensors in how likely you believe they are to reveal what a person is thinking and feeling." Sensor order was randomized in the ranking UI. We chose the terms "thinking" and "feeling" to center explanations on mind-related meanings, while providing a degree of ambiguity to not overly guide participants toward particular answers. For example, "thinking" could be interpreted as specific thoughts or general topics, and "feeling" leaves room for emotions, moods, or even mental health. Joining the two words with "or" allows participants flexibility in responding to either or both concepts.

Data	Medical?	Commercial?
Facial expression	No	Yes (camera)
Body language	No	Yes (camera)
Brainwaves (EEG)	Yes	Yes
Eye movement	No	Yes
Heartrate/pulse	Yes	Yes
MRI/fMRI	Yes	No
Blood pressure	Yes	No
Skin conductance	Yes	Yes
Blood oxygenation	Yes	No
Step count	No	Yes
GPS + accelerometer	No	Yes
VR headset	No	Yes

Table 1. Sensors referenced in the survey.

In addition to the main ranking question, we also sought free-response text that we could analyze through qualitative methods. We chose three sensors for these qualitative responses, asking about each modality, "Why did you answer the way you did?" From these responses, we sought qualitative data to deepen our perspective on participants' quantitative ranking decisions. First, we chose GPS, a common sensing modality present in almost all smartphones. Second, we chose brainwaves (EEG), an uncommon modality in a small (though growing) number of consumer devices. Finally, we chose VR, an emerging modality familiar from advertisements and popular media, and one which manufacturers are attempting to outfit with an increasing variety of sensors [18]. These sensors aimed to solicit diverse views, and allow us to better understand how and why people evaluate sensors as revealing or not. We performed an "issue-focused" analysis of the free-response questions [38], allowing topics and themes to emerge during analysis of qualitative responses. These emergent themes served to organize our qualitative results in the following section.

RESULTS

In our quantitative rankings, brainwaves (EEG) are seen as among the most revealing biosignals, just below body language and facial expression in their capacity to reveal the inner workings of a person's mind. More common sensors such as GPS and step count are seen as less revealing (despite empirical evidence suggesting such data can be quite revealing [3]). A one-tailed t-test indicated that Mechanical Turk participants found virtual reality headsets (mean=2.65) significantly more revealing than Health-e-Health participants (mean=1.58, t=2.31, p<.05). Conversely, Health-e-Heart participants believed fMRI (mean=6.32) to be significantly more revealing than did Mechanical Turk participants (mean=5.0, t=2.50, p<.01) in a one-tailed t-test.

To better understand why participants rated the sensors in this way, we turn to our qualitative data. We focus our analysis on two sides of the disclosure spectrum. First, we investigate why EEG was believed to be the most revealing as to what a person is thinking or feeling. Second, we investigate why participants believed VR to be less revealing, despite its increasing popularity as a consumer device, and a medium for sensing user behavior [18]. Finally, we discuss participants' responses around GPS, which was ranked among the least revealing sensors despite its use in predicting intimate mind-related meanings such as mental health diagnoses [3].

Referring to the body

When we asked participants to reflect on why they answered the way they did during the ranking task (Figure 1), many participants referred to their beliefs about the body in explaining the capacities of sensors. For example, participants in both samples generally believed EEG to reveal various details about the mind, mood, emotions, and identity, referring to the brain in their explanations for these beliefs.

> I assume some information can be gleaned from brain wave activity in various parts of the brain related to rewards or executive control, but without accompanying information, it may be difficult to discover my thoughts. *(HeH)*

> I would rate this relatively high on the list because science has shown that we can detect a lot about which areas of the brain are accessed and at which times. This can tell a person a lot about what they might be thinking and especially how they are feeling. *(HeH)*

> Brain activity can pinpoint exact emotions by monitoring certain areas on the brain. *(MTurk)*

While these explanations range somewhat in their specificity and confidence, they express a shared belief that EEG is revealing *because* of the modality's relationship to the brain. Specific language referring to scientific concepts, such as "executive function" or "areas of the brain" reveal the degree to which these explanations are rooted in concepts of the role the brain plays in cognition, rather than the specific capabilities of EEG devices. Similarly, interpretations of VR often centered around the parts of the body with which VR is associated.

> Because by closely observing the person virtually you can read facial expressions and body movements *(HeH)*

Responses to GPS also related relevant bodily states to their emotional correlates.

> staccato movement for agitation, can't stand still, for excitement - different rates and amplitudes of movement. *(MTurk)*

This same participant expressed no specific hypothesis for EEG. In this case, the absence of a reasonable hypothesis could make certain sensors seem less revealing than others. Interestingly, among the vast majority of participants who ranked EEG highly, most had no specific hypothesis for how its signal would yield insights. The relative rarity of hypothesis-driven judgments among our respondents highlights the extent to which many participants' beliefs stem from their beliefs about the body, rather than from beliefs about specific mechanisms. Meanwhile, one participant who ranked VR, but not GPS, more highly than EEG referenced overall uncertainty about what devices can reveal.

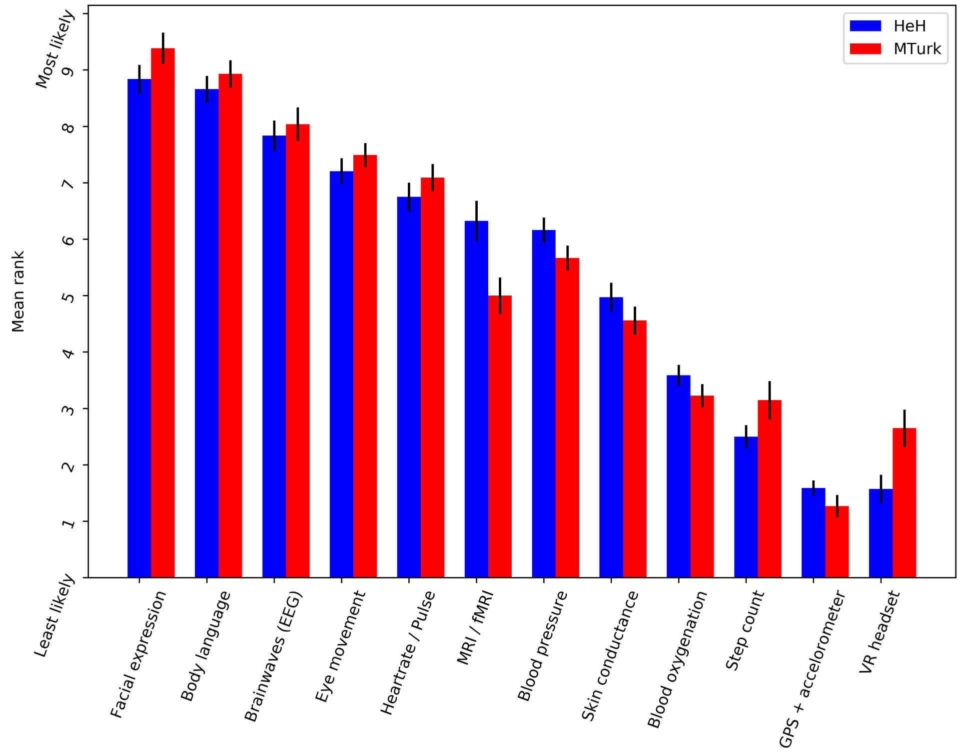

Figure 1. "Please rank the following sensors in how likely you believe they are to reveal what a person is thinking and feeling." Higher bars indicate higher rank, or higher likelihood of being revealing.

Referring to context and behavior

Many responses also referred to context and behavior in explaining how sensing modalities may become revealing. For example, responses around VR very often hinged on social context.

> It would depend on the environment in which you were placed and your actions therein. *(MTurk)*

> I think this is more likely for someone to express themselves when using it, which may give away what someone is thinking or feeling. I'm not sure that it could directly do it, but given context clues it might be possible to find out some information. *(MTurk)*

> Because what they do when wearing that headset is what they want to be doing in real life which can tell you a lot about what they are thinking / feeling. *(MTurk)*

The third participant here reveals a latent assumption that VR is specifically for playing out fantasies. Thus, the users actions show their desires, which in turn reveal their thoughts and feelings. In this quote as well, participants do not have beliefs about the capabilities of VR devices *per se*, but about the behaviors and bodies that these devices interact with. A similar trend emerged in responses around GPS.

> If, for example, GPS shows I'm at a therapist's office, one may conclude I am or have in the past struggled emotionally. Or if I am at a funeral home, chances are I am sad. But GPS would give limited information. I could be at a grocery store, but that location wouldn't point to any emotions. *(HeH)*

> It would solely depend on the location in which you are present or a pattern of locations. *(MTurk)*

> while the location could tell what you are thinking.. ie. if you were in a live volcano.. it usually would only give location and nothing else. *(MTurk)*

These responses, which vary in skepticism, share a reliance on context in explaining how GPS may reveal thoughts and feelings. By the same token, some participants noted that context may well obfuscate the meaning of GPS signals as much as reveal them.

> You can feel good or bad in many different places *(HeH)*

> GPS only tracks location and not the reason behind the location *(HeH)*

The questions of context here, and particularly of "reasons," gestures toward the themes of causal inference that plague much of the contemporary debate around machine learning, particularly in its ability to provide actionable "predictions." In the specific case of GPS, much existing empirical results on using location to track moods, emotions and mental health is indeed correlative [3, 17]. Future work should continue to examine how people reason about "reasons" in sensor-driven inferences, and in their interactions with machine learning systems broadly [34, 29]. Finally, individuals' life experiences might shape the way they engage (or refuse to engage) with brain-sensing devices.

> My son has absence seizures, so his brainwaves change. *(MTurk)*

This quote, among others, motivates the need for a rich, qualitative understanding of people's first-hand experiences with brainscanning devices and data collection to better imagine what role BCI applications could play in day-to-day life, and what barriers may exist to their wider adoption. We return to this topic in our implications for design.

Referring to sensors

While the majority of participants' explanations referred to either the body or context in explaining sensors' capabilities, a few responses referred directly to the perceived capability of sensors themselves. In the case of EEG, three participants indicated a general sense that EEG as a sensing modality was unable to capture specific thoughts and feelings.

> I don't think we have the ability to translate brainwaves into thoughts or emotions. *(HeH)*

> EEG is very nonspecific and rarely can tell details reliably. *(HeH)*

> Possible but not accurate. *(MTurk)*

These responses range from a fundamental skepticism to caveats about possible accuracy or specificity. In the case of VR, one participant referred to the possibility of future developments in producing more nuanced or accurate observations.

> We have no idea what we can pull out of our brains yet - A VR headset is just the beginning *(HeH)*

Although this participant is specific about the brain, she is open to the possibility that new data, and new theories, will yield new ways of knowing about thoughts and feelings from existing data. While this observation is a crucial component of academic discourse on sensor disclosure [32, 5], it is notable that this belief surfaced only once among subjects in our study; the infrequency of this observation highlights the degree to which users may undervalue the role of ongoing technical development in making data more revealing in the future. We discuss this point further in the following section.

BROADER IMPACTS

Throughout our qualitative results, we found participants mobilizing their beliefs about the body, about broader context, and about sensors themselves, to reason about what sensors can know or reveal about thoughts and feelings. This finding expands ongoing discussions about presumed authority of data [13, 19, 11] by questioning how perceived authority varies depending on folk beliefs about what, where, when and how sensing occurs.

Crucially, we find that perceptions about sensing modalities may not match empirical realities. As a result, designers may struggle against devices seen as creepy, while users may fall victim to devices perceived as innocuous. We express the broader impacts of these findings as two warnings, the first for designers, and the second for users.

Designers: Beware of the seemingly creepy

Some sensors were consistently rated as revealing by study participants. Most notably, EEG seemed revealing to study participants, even though the modality presents notorious difficulties to engineers (the signal is noisy, and dynamic over time) and to users, who may struggle to make sense of the data [20]. Why does EEG seem more sensitive than the other devices, even fMRI, another brain-sensing device? One possibility, supported by some prior work in psychology, is that people may ascribe near-magical abilities to brainscanning beliefs about the brain, and brainscanning [6, 2, 30]. Though some past work in HCI has investigated beliefs about EEG-based BCIs [20, 9], little work has looked at how user perceptions of EEG may compare to other sensing devices.

Our observation presents a possible challenge for the design of near-future BCIs. Future makers of these devices (e.g. Facebook [25] and Elon Musk's BCI startup, Neuralink) [36] must actively contend with users' perceptions of brain-scanning (i.e., that these machines can read or decode thoughts and feelings). Brain-computer interface designers should actively engage with technology probes, ethnographic studies of use in context, and other tools from HCI and design research to accompany the deployment of BCIs.

In general, these challenges may extend beyond EEG and brain-computer interface, as well. Emerging sensing modalities should be screened, analyzing users' beliefs about what these modalities might reveal about them, to better anticipate aversions that stem from popular perceptions of the modalities' capabilities.

Users: Beware of the seemingly innocent

Meanwhile, more common sensing modalities, or ones more common in popular dialogues (such as VR), seemed less revealing than they really are. VR headsets, seen as "a movie on your head" may in fact collect intimate data about users [18]. The same is true for GPS: the signal was widely seen as innocuous by participants in our study, yet past work has used location traces to detect mental health issues [3].

The perceived passivity of devices such as VR headsets, and perhaps the ubiquity devices such as GPS, could allow nefarious designers to take advantage of users' naivete, surreptitiously tracking intimate details such as their mental health [3, 22] or sexual preferences [35]. Emerging sensing modalities beyond GPS and VR may also be more revealing than they seem, and existing sensing modalities may find unexpected new uses in the future. Designers must familiarize themselves with users' beliefs about sensors. Devices should *seem* as revealing as they are: labeling and marketing may all play a role in what devices are understood to collect.

The perceived innocuousness of common sensors may either explain their ubiquity, or stem from it. In either case, the impact of these perceptions for consumer protection is clear: end-users may not be able to make informed decisions about privacy, as they do not (and likely cannot be expected to) have all relevant facts about what sensors might reveal about them. Future regulation should consider common beliefs or conceptions about sensing modalities embedded in devices, or require clear statements at the time of consent about how these data will be used by the parties collecting them. As prior work at DIS has revealed, such notices themselves require serious design consideration [26]. However, without such protections, data that users give willingly may be repurposed to draw inferences to which users would not have consented.

DISCUSSION

Sensors do not passively reveal the world. They enact ways of knowing it [10, 33, 5]. To sense the body, designers must embed claims about the body in particular technologies, *and* users must believe these claims (or supply their own). Designers should be careful in what notions of body they embed, as such notions may "trickle down" to users through interactions and artifacts [19]. By the same token, users' beliefs are not simply misconceptions. They are folk theories [34]: impactful, insightful in their own ways, and consequential for discourse and design [24, 39, 15].

How do data-driven insights claim their authority [11]? Who has the power to encode and reinforce beliefs about the body through the design of technical artifacts [1]? On one hand, the beliefs we see in our study could disappear, merge with the claims of technical tools. On the other, they could resurface in artifacts that perform and embody these folk theories. This latter possibility points not just to a design space for creative applications, but a way of preserving and passing forward alternative ways of knowing the world.

Future work

As participants discussed the capabilities of sensors, they tended to mobilize beliefs about the body to support their claims. How do beliefs about sensor capabilities relate to beliefs about the body, and how do they intersect with the perceived technical capabilities of particular devices? Perhaps, when people lack knowledge about specific new technologies and their capabilities, they rely on existing beliefs about the body to explain what these technologies might be able to reveal. Future work may examine this question more deeply, and in more diverse social contexts (for example, among researchers who build emotion recognition systems using biosensors).

Our study does not address how culture, gender, religion may affect the perceptions, adoption and acceptance of a sensor-driven life. Social position shapes what we may see, and thus what we may accept [37, 28]. It also affects how we view ourselves as data participants; this work did not deeply investigate the effect of race, class, gender, or other immutable characteristics on attitudes about sensing devices. Future work should maintain a sensitivity to how these devices produce differential vulnerabilities along conduits of social power [27].

As emerging devices (such as VR and EEG) become more familiar to users, future work should monitor beliefs about sensing modalities as these technologies develop. Sensors such as GPS and accelerometer are now ubiquitous, but attitudes around them have likely changed since their introduction. Future work could track attitudes as they change, or attempt to replicate past work on sensor disclosure practices (e.g. location disclosure [4]). Through longitudinal studies, we stand a chance at observing changes in attitudes, thus putting us in a position to anticipate changes in privacy attitudes and privacy-preserving behaviors.

One latent assumption in our study is that Mechanical Turkers would function as a "no-surveillance" sample. However, it is unclear if this assumption is well-founded: Mechanical Turk participants may already be subject to monitoring, as the human-intelligence tasks they perform on the platform may participant them to various types of surveillance (e.g., clicks, timing activity, browser fingerprinting, etc). Future work should examine more deeply Turkers' knowledge of, and response to this sort of tracking, issues which connect to to broader questions of digital surveillance in the workplace.

CONCLUSION

Biosensors promise to produce increasingly high-resolution models of bodies in space. Our results indicate that users will fill in details missing or unclear from these models, perhaps falling back on beliefs about the body to explain their social relevance. Our findings raise potential pitfalls for designers, whose devices may seem creepier than they are, and for consumers, whose seemingly innocuous devices may in fact be used to infer intimate details such as emotions, proclivities or mental health. Both users' and designers' knowledge claims—reified in technical artifacts, and reinforced through their use—will play an important role in shaping how pervasive sensing will come to matter in the course of life.

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