

Review

## Sensor Mania! The Internet of Things, Wearable Computing, Objective Metrics, and the Quantified Self 2.0

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Received: 4 September 2012; in revised form: 31 October 2012 / Accepted: 31 October 2012 /  
Published: 8 November 2012

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**Abstract:** The number of devices on the Internet exceeded the number of people on the Internet in 2008, and is estimated to reach 50 billion in 2020. A wide-ranging Internet of Things (IOT) ecosystem is emerging to support the process of connecting real-world objects like buildings, roads, household appliances, and human bodies to the Internet via sensors and microprocessor chips that record and transmit data such as sound waves, temperature, movement, and other variables. The explosion in Internet-connected sensors means that new classes of technical capability and application are being created. More granular 24/7 quantified monitoring is leading to a deeper understanding of the internal and external worlds encountered by humans. New data literacy behaviors such as correlation assessment, anomaly detection, and high-frequency data processing are developing as humans adapt to the different kinds of data flows enabled by the IOT. The IOT ecosystem has four critical functional steps: data creation, information generation, meaning-making, and action-taking. This paper provides a comprehensive review of the current and rapidly emerging ecosystem of the Internet of Things (IOT).

**Keywords:** Internet of Things; sensors; objective metrics; quantified self; personal metrics; high-tech hardware; integrated sensor platforms; multi-sensor platforms; information visualization; health Internet of Things

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### 1. Introduction: The Rapid Approach of the Internet of Things

#### 1.1. What is the Internet of Things?

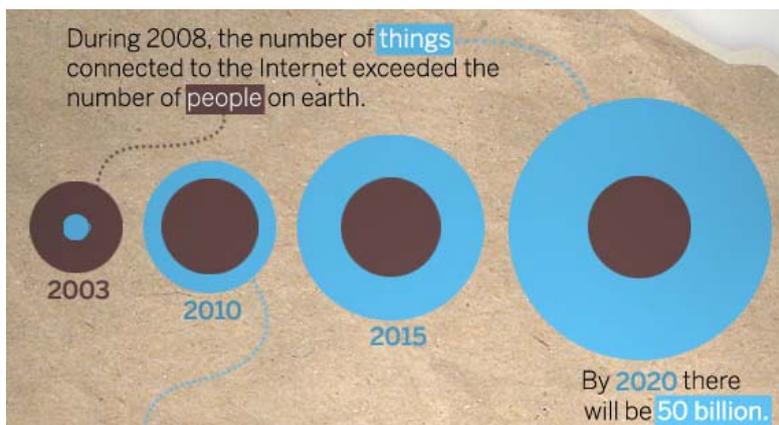
There are several definitions of the Internet of Things (IOT). One that is salient for how the term is currently in use is provided by the U.S. National Intelligence Council: “The “Internet of Things” is the

*general idea of things, especially everyday objects, that are readable, recognizable, locatable, addressable, and controllable via the Internet - whether via RFID, wireless LAN, wide-area network, or other means [1].*” A key point is that while the most familiar Internet-connected devices are computers such as laptops, servers, smartphones, and tablets (e.g., iPads, etc.), the IOT concept is much broader. In particular, everyday objects that have not previously seemed electronic at all are starting to be online with embedded sensors and microprocessors, communicating with each other and the Internet. This includes items such as food, clothing, household appliances, materials, parts, subassemblies, commodities, luxury items, landmarks, buildings, and roads. It is estimated that 5% of human-constructed objects currently have embedded microprocessors [2]. These tiny microprocessor chips and sensors record and transmit data such as sound waves, temperature, movement, and other variables. Other terms for the Internet of Things include Internet-connected devices, smart connected devices, wireless sensor networks, machines and devices communicating wirelessly, ubiquitous computing, ambient intelligence, and smart matter.

One way of characterizing the IOT is by market segment where there are three main categories: monitoring and controlling the performance of homes and buildings, automotive and transportation applications, and health self-tracking and personal environment monitoring. Some of the basic IOT applications underway in the connected home and building include temperature monitoring, security, building automation, remote HVAC activation, management of peak and off-peak electricity usage, and smart power meters. Worldwide smart power meter deployment is expected to grow from 130 million in 2011 to 1.5 billion in 2020 [3]. Some of the many automotive and transportation IOT uses include the Internet-connected car (syncing productivity, information, and entertainment applications), traffic management, direction to open parking spots, and electric vehicle charging. It is estimated that 90% of new vehicles sold in 2020 will have on-board connectivity platforms, as compared with 10% in 2012 [3]. In industrial transportation, train operators like Union Pacific use IOT infrared sensors, ultrasound, and microphones to monitor the temperature and quality of train wheels [4]. One of the biggest IOT growth areas is measuring individual health metrics through self-tracking gadgets, clinical remote monitoring, wearable sensor patches, Wi-Fi scales, and a myriad of other biosensing applications. Two high-profile prizes in this area are designed to spur innovation, the \$10 million Qualcomm Tricorder X Prize for the development of a handheld device to non-invasively monitor and diagnose health conditions in real-time [5], and the \$2.25 million Nokia X Challenge for sensor technology that can bring about new ways to monitor, access, and improve consumer health [6].

The rapid growth of the IOT is pictured in Figure 1, comparing the number of devices on the Internet to the number of people on the Internet. Connected devices surpassed connected people in 2008. Cisco estimates that by 2020 there will be 50 billion connected devices, 7 times the world's population [7]. Similarly, the Connected Life initiative sponsored by the GSMA (GSM Association, an industry-association for worldwide mobile operators) found that in 2011, there were 9 billion total Internet-connected devices (compared to the total human population of less than 7 billion), two-thirds (6 billion) of which were mobile, and estimates that in 2020, there will be 24 billion total Internet-connected devices, 12 billion mobile [8]. Moreover, these 24 billion Internet-connected devices are estimated to have an economic impact of over \$4.5 trillion in 2020 [8].

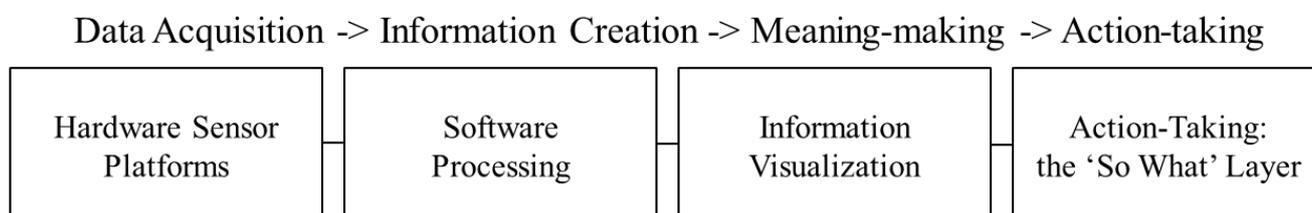
**Figure 1.** The accelerated growth of Internet-connected devices [7].



### 1.2. The Internet of Things Ecosystem

The IOT is connecting real-world objects to the Internet with tiny sensors. A number of functional layers are starting to be visible in the developing ecosystem as pictured in Figure 2, starting with data generation, and moving to information creation, and then meaning-making and action-taking. The broad brush categories are the Hardware Sensor Platform layer, the Software Processing layer, the human-readable Information Visualization layer, and the human-usable Action-Taking layer.

**Figure 2.** Processes and Layers in the Internet of Things Ecosystem.



## 2. Hardware Sensor Platforms

One of the biggest drivers of the IOT is the increasing number of low-cost sensors available for many different kinds of functionality. Some of the standard sensors include movement (via accelerometer), sound, light, electrical potential (via potentiometer), temperature, moisture, location (via GPS), heart rate and heart rate variability, and GSR (galvanic skin response or skin conductivity). Other sensors include ECG/EKG (electrocardiography to record the electrical activity of the heart), EMG (electromyography to measure the electrical activity of muscles), EEG (electroencephalography to read electrical activity along the scalp), and PPG (photoplethysmography to measure blood flow volume).

These sensors are included in a variety of devices and solutions. The trend is moving towards multi-sensor platforms that incorporate several sensing elements. For example, the standard for the next-generation of personalized self-tracking products appears to be some mix of an accelerometer, GSR sensor, temperature sensor, and possibly heart rate sensor (from which heart rate variability may be calculated). Some recognized first-generation quantified tracking devices and applications include the Fitbit, myZeo, BodyMedia, MapMyRun, RunKeeper, MoodPanda, Nike Fuelband, The Eatery,



health, fashion, finance, consumer electronics, and other applications. The Sony SmartWatch, offering Twitter, email, music, and weather information is currently available (\$175, <http://www.sonymobile.com/gb/products/accessories/smartwatch/>). In a potential extension of Google's Project Glass (augmented reality eyewear), Google has patented smartwatch technology for an augmented reality smartwatch with two flip-up screens, a touchpad, and wireless connectivity [9].

**Figure 4.** Smartwatches: A New Product Category of Programmable Watches: the Pebble Watch (from Pebble Technology Corporation), the Basis Watch, the Contour Watch from Wimm Labs, and the Sony SmartWatch.

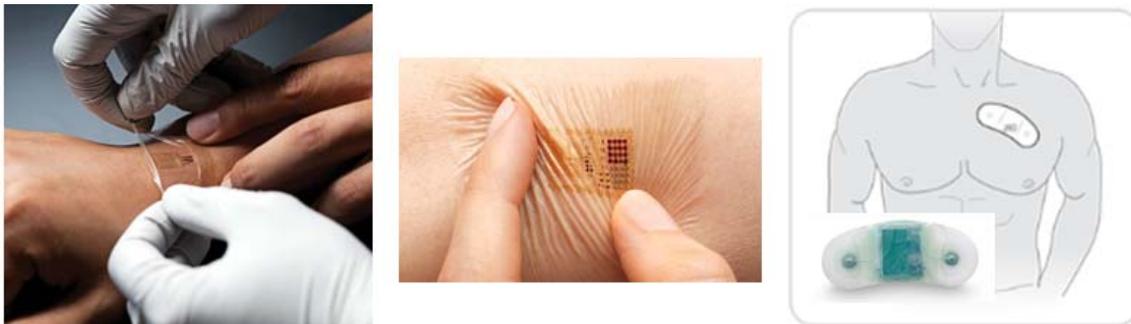


Wristband sensors are a predecessor to smartwatches and remain a successful product category on their own. One of the first examples of wristband sensors was using accelerometers to measure steps taken with products like the Nike Sense. Current examples continue to feature accelerometry and include the Nike Fuelband (\$149, monitoring steps taken), the Jawbone UP wristband and iPhone app (\$99, tracking steps taken, distance, calories burned, pace, intensity level, active *versus* inactive time, and GPS), the Adidas MiCoach (\$70, providing heart rate monitoring, real time digital coaching, interactive training, and post-workout analysis of pace, distance, and stride rate). Three next-generation products add new functionality to the standard metrics of total steps taken, distance, and calories. The Mio Active (\$119, <http://www.mioglobal.com/>) adds heart rate, either with or without a chest strap. The LarkLife (\$149, <http://www.lark.com/>) identifies type of activity, allows single-button press diet tracking, measures sleep, and uses the combined metrics to make personalized recommendations about changes a user can make to feel better [10]. The Amiigo (\$119, <http://www.amiigo.co/>) wristband and shoe clip also measure the type of exercise, plus body temperature and blood oxygen levels through an infrared sensor [11]. Other sensor platforms also focus on fitness and athletic training, for example Somaxis ([www.somaxis.com](http://www.somaxis.com)) with ECG and EMG muscle and heart sensors and GolfSense (\$130, <http://www.golfsense.me/>) where users attach a wrist-based sensor unit to a golf glove. The unit has two accelerometers and other sensors that collect and transmit data wirelessly for real-time feedback. Multi-sensor wristband devices are also in development for clinical use, for example in epilepsy. One team created a wristband to detect convulsive seizures through electrodermal activity and accelerometry, a useful improvement over lab-based EEG methods as the device can be worn continuously [12].

## 2.2. Wearable Sensors and Monitoring Patches

Another new product category that could quickly become commonplace is wearable sensors, low-cost disposable patches that are worn continuously for days at a time and then discarded. It is estimated that 80 million wearable sensors will be in use for health-related applications by 2017, an eight-fold increase over today [13]. The concept is not new, nicotine patches for smoking cessation are a familiar concept, but the extended on-board sensor functionality is an important innovation. The next generation of patches moves away from standard transdermal passive diffusion technology, and instead uses rich sensor technology to enable patches to transmit information wirelessly, and possibly engage in two-way communication for real-time adjustments. One of the most exciting potential developments in wearable patches is Sano Intelligence's continuous blood chemistry monitoring patches, characterized as a \$1 API for the bloodstream, and estimated to be available in mid-2013. The disposable patch (one-week use) has been demonstrated to measure blood glucose and potassium levels, and aims to measure a full metabolic panel, including kidney function and electrolyte balance. Further, there are enough probes on the wireless, battery-powered chip to continuously test up to a hundred different samples [14].

**Figure 5.** Continuous Wearable Sensor Patches for Blood Chemistry and Vital Signs (mc10) and Cardiac Rhythm (iRhythm's Zio Patch).



A promising concept pioneered by mc10 is stretchable electronic tattoos for the continuous monitoring of vital signs with flexible electronics patches as shown in Figure 5. These stretchable electronics track and wirelessly transmit information such as heart rate, brain activity, body temperature, and hydration level, and may be available to athletes in the fall of 2012 [15]. Wearable sensor patches are also useful for heart monitoring and have again allowed an improvement over current methods. The Zio Patch from iRhythm (two-week use) can be worn to monitor cardiac rhythm and warn of arrhythmias (Figure 5). Another interesting example of new patch technology is a continuous blood pressure monitoring patch from Sense A/S. Instead of the cumbersome pressure cuff, there is a small arm patch with electrodes that sense the changing impedance of tissue around a vessel and convert it into a blood pressure reading via a waistband sensor unit [16].

One of the classic use cases for wearable patches is the continuous glucose monitor (CGM) worn by diabetics and other self-trackers. New developments mean that the current state-of-the-art technology is available in several CGM solutions where an under-the-skin continuous glucose monitor uses a sensor and transmits glucose readings every 1–5 minutes to an external receiver or insulin pump [17].

Also promising is the idea of using the glucometer as a platform. Chemists have developed a method to bind short segments of DNA to a large number of potential molecules that might be present in blood, water, or food. The DNA segments also bind to the enzyme invertase so that glucose is produced if the target molecules are present, and could then be read easily with a \$20 drugstore glucometer. So far, this glucometer-as-a-platform method has been used to detect cocaine, interferon, adenosine, and uranium [18,19].

### 2.3. Continuous IOT Monitoring and Advances in Blood Testing 2.0

A key expectation of IOT devices is that they allow for continuous monitoring and connected real-time data transmission, ideally with real-time feedback and personalized recommendations. The continuous remote monitoring of patients is a significant market here, estimated to be \$21 billion in 2016 as compared with \$9 billion in 2011 [20]. One example of a multi-sensor remote monitoring platform is the FDA-cleared BodyGuardian from Preventice which integrates ECG, heart rate, respiration rate, and physical activity data. Another example of continuous monitoring wearable sensors is the FDA-cleared Visi Mobile from Sotera Wireless (Figure 6) which continually monitors vital signs such as ECG, heart rate, respiration, and temperature.

Another example of the now-expected continuous monitoring and automated data transmission and feedback functionality is available in the AgaMatrix iBGStar blood glucose monitoring system. This was the first traditional glucometer to connect directly to an iPhone app (Figure 6), to allow transitory readings to be recorded, stored into longitudinal profiles, and shared. The Proteus digital health system is another example of the now-expected continuous transmission functionality, effectively defining a new category of medical device. Here, a biodegradable ingestible sensor is attached to a pill that transmits data regarding the body's interaction with the medication to a wearable patch (Figure 6).

**Figure 6.** Continuous Monitoring: Sotera's Visi Mobile, AgaMatrix iBGStar Smartphone-Connected Glucometer, Proteus Digital Medicine Pill Consumption Tracking System, and Next-Generation Dried Blood Spot Testing from ZRT Laboratory.



Blood testing is another area where sensor technology and other innovations are speeding progress. A key advance in user-friendly direct-to-consumer blood testing is dried blood spot technology. Instead of going to a lab, consumers can prick their fingers at home with a lancet, put a series of blood spots on a laboratory card, mail in the card for analysis, and view the results on the web (Figure 6). One company offering dried blood spot testing is ZRT Laboratory (<http://w3.zrtlab.com/>), however given the lack of available alternatives like the announced \$1 Sano Intelligence API-for-the-bloodstream

patches, pricing is still commensurate with lab-drawn blood tests. This could change quickly as new market entrants have their eye on the \$65 billion lab testing market (where the direct-to-consumer segment is growing 15%–20% per year [21]). One recently-launched consumer proteomics startup, Talking20 (referring to the 20 amino acids that make up the proteins in the body, [www.Talking20.com](http://www.Talking20.com)), is offering dried blood spot testing at a significant discount, \$10 per card, testing five markers, vitamins B1 and B9, and hormones: testosterone, estradiol, and progesterone.

For clinical diagnosticians, there is a new point-of-care blood testing solution, the i-STAT System from Abbott Labs (<http://www.abbottpointofcare.com/>). This is a handheld blood analyzer that provides real-time lab-quality results in minutes and measures 25 different blood markers including hemoglobin, hematocrit, glucose, potassium, calcium, pH, urea nitrogen (BUN), creatinine, and lactate. Results can be used immediately onsite and transmitted to physicians for real-time consultation. Another innovative direction in blood testing focuses on developing tests for pathologies that were not previously measurable. One example is the newly available Ridge Diagnostics blood test for depression, measuring the serum levels of nine biomarkers (alpha1 antitrypsin, apolipoprotein CIII, brain-derived neurotrophic factor, cortisol, epidermal growth factor, myeloperoxidase, prolactin, resistin, and soluble tumor necrosis factor alpha receptor type II) [22]. The test is expensive, available on the market for \$745 (<http://www.ridgedx.com/>). While the test is intended for depression diagnosis, it might be interesting to measure the same markers in a predictive progressive manner to see if pathologies like depression might be detected earlier and prevented. Blood markers are predictive of other conditions. For example, with diabetes, hemoglobin 1AC levels are predictive of condition onset by ten years, and could be a target for early preventive intervention [23]. Depression tendency or pre-onset might possibly be similarly detected and managed.

#### 2.4. Brain-Computer Interfaces (BCIs), Neuro-Sensing, and Emotion-Mapping

In the coming era, it may be possible to have a much greater understanding of the brain. There could be numerous useful applications from this, for example mental performance optimization techniques and a variety of emotion reading, mapping, and management programs. An early sensor technology for obtaining brain data is the consumer EEG (also called the brain-computer interface (BCI)). Some of the first-generation consumer EEG rigs are pictured in Figure 7 and include the 14-node EEG Emotiv (\$299, <http://www.emotiv.com>), the single-node EEG NeuroSky (\$99, <http://www.neurosky.com/>), and the sleep quality tracker myZeo, also essentially an EEG (\$99, <http://www.myzeo.com/>). The Emotiv and the NeuroSky have been used for different applications such as improving attention and meditation, and video game performance. At least one academic study has validated the performance of consumer EEGs, finding that for 6 of 8 participants, the responses to the traditional EEG and the Emotiv were similar [24]. Emotions were mapped to a standard four quadrant diagram of arousal and valence (reflecting the intensity and positive or negative charge of the experience). An established image research library (IAPS) was employed, although the researchers noted that both methods were still close to baseline error rates, in other words that emotion mapping remains a challenging problem. Another single-node EEG, the iBrain from NeuroVigil, is available to academicians and claims to be better than current clinical EEG methods due to a clustering software

algorithm, SPEARS (Sleep Parametric EEG Automated Recognition System), the company has developed for sleep analysis (<http://www.neurovigil.com/spears/>).

**Figure 7.** First- and Second-Generation Consumer EEGs: Emotiv, NeuroSky, and myZeo, and InteraXon and Axio.



The next generation of consumer EEGs may take advantage of a variety of sensor technology improvements particularly in Bluetooth low-energy data transmission and battery technologies. This could mean that more comfortable, unobtrusive, and visually-attractive wearable electronic brain monitors could be available to be worn 24/7 to continuously collect data and package it into useful real-time applications. At least two companies have planned second-generation consumer EEG products as pictured in Figure 7, InteraXon (<http://www.interaxon.ca/>) and Axio (<http://www.axioinc.com/>). Another company, Veritas Scientific (<http://www.veritasscientific.com/>), has developed a lie-detection device, the TruthWave, based on consumer-available EEG technology. A standard neuroscience technique is used to detect brain activity when a person's face is recognized, registering the P300 response from a type of brain activity known as event related potentials (ERPs). Having access to continuous neural data could significantly open up the field for the development of interesting applications, for example in image recognition, emotion detection and intervention, and flow state performance management.

A number of companies and academic labs are working to measure emotion, also known as affect. This is in some sense a digital implementation and extension of work by emotion research pioneer Paul Ekman (<http://www.paulekman.com/>), who developed the FACS (Facial Action Coding System), now known as FACE (Facial Expression, Awareness, Compassion, Emotions), to taxonomize every human facial expression. Two companies, Affectiva (<http://www.affectiva.com/>), and Affective Interfaces (<http://www.affectiveinterfaces.com/>), use computer webcams and eye-tracking technology to read facial microexpressions, mainly for the purpose of neuromarketing (e.g.; determining the biophysical response of participants to consumer brands or entertainment products like TV shows or movie endings). Affectiva uses a multi-sensor wristband that captures GSR, temperature, and accelerometry in addition to the webcam eye-tracking technology.

Some other interesting applications of eye-tracking, not directly related to emotion sensing, are from Cardiio (<http://www.cardiio.com/>), who calculates heart rate from the camera on a mobile phone, and EyeTribe (<http://theeyetribe.com/>), who has created portable eye-tracking—software for controlling mobile devices with eye movements. Even without EEGs or eye-tracking, some degree of emotion-mapping such as stress levels may be detected with other measures obtained from sensors like GSR [25]. Academic labs are also using the expanding range of neurosensing technologies to extend emotion research, in particular, the Interdisciplinary Affective Science Laboratory at Northeastern

University (<http://www.affective-science.org/>) and the Neurophysiology and Empathy research group at the University of Parma (<http://www.unipr.it/arpa/mirror/english/staff/gallese.htm>).

### 2.5. Smartphone and Smartphone Plus Peripheral

Mobile is the platform, for many activities, initially for communication, then also for computing, and now for quantified tracking. As of October 2012, smartphone penetration was 78% in the US, which lags other countries such as Singapore (92%) [26]. One reason for this is that some markets have leapfrogged technology roll-outs to have continuous Internet access for the first time via smartphone. Even just basic voice functionality coupled with automated algorithms is resulting in useful next-generation IOT predictive applications, for example Parkinson's disease detection. The Parkinson's Voice Initiative has a phone-based voice diagnostic that they claim is 98% effective. The user places a call and says 'aaaaah.' A machine learning program analyzes different voice qualities in the sample such as vocal tremor, strength, breathiness, and fluctuations in the jaw, tongue, and lips to assess the presence and severity of Parkinson's disease [27]. Smartphones are also being used with external peripherals to be part of the IOT. Many devices have been attached to smartphones for novel applications as illustrated in Figure 8 such as AliveCor's electrocardiogram (ECG) recorder for heart monitoring (<http://alivecor.com/>), MobiSante's smartphone-based ultrasound imaging system (<http://www.mobisante.com/>), and the CellScope (<http://cellscope.com/>). The CellScope has a series of clip-on modules for the smartphone such as an otoscope (to look into the middle ear), and a dermascope (to capture magnified images of the skin). Relatedly, there are many examples available on the Internet for how to add a lens to a smartphone camera to turn it into a microscope.

**Figure 8.** Internet of Things (IOT) Smartphone Peripherals and Next-Generation Wearable Computing: Consumer ECG, Mobile Ultrasound, CellScope, and Google's Project Glass (per Antonio Zugaldia).



As the trends in sensor miniaturization and functionality improvement continue, it is easy to envision that for some applications, the next-generation of sensortech could involve the direct integration of sensors into the smartphone platform instead of being an alongside hardware peripheral. One example of this is the LifeWatch V, an Android-based smartphone with the usual suite of sensors to measure ECG, body fat, heart rate, stress, temperature, blood saturation, and blood glucose levels [28]. The idea of sensors built directly into hardware is also exemplified in Google's Project Glass, projected for launch in late 2012. Project Glass defines a new category of wearable computing with augmented reality glasses (Figure 8) where a small camera and computing node mounted on the corner of the glasses can search the Internet and display real-time results right in front of the eyes. In the

future, there could be special editions of Project Glass or other similar multi-sensor platforms with microprocessors embedded to merge a range of functionality like EEG, eye-tracking, heart rate, GSR, accelerometry, temperature, GPS, and Internet search and results display into a category-defining human augmentation platform for real-time information, communication, and personal feedback and performance optimization.

### 2.6. Environmental Monitoring and Home Automation Sensors

Quantified tracking in home automation and environmental monitoring is more established as a sector, but here too IOT innovations continue. Some are pictured in Figure 9 such as the Sensordrone from Sensorcon (<http://www.sensorcon.com/>), a successfully-funded Kickstarter project. The keychain-based sensor monitors the environment and transmits data via Bluetooth to any connected device. Applications are envisioned such as investigating air quality, carbon monoxide levels, potential gas leaks, and measuring a child's temperature. More detailed applications include using the capacitance sensor as a stud finder, a liquid level monitor, or a proximity monitor [29]. More generally, it is now possible to use environmental sensors to measure a range of concerns including air quality, barometric pressure, carbon monoxide, capacitance, color, gas leaks, humidity, hydrogen sulfide, temperature, and light. Another project (supported by Cosm) is Flexibility Internet Sensors (<http://www.flexibility.com/>), an open sensor toolkit and Internet-connected platform for wireless home and environmental monitoring. Each sensor has a unique IPv6 address and can be accessed with a standard web call or via web services like Twitter.

Other new home and environmental sensing solutions include the Air Quality Egg (<http://airqualityegg.wikispaces.com/AirQualityEgg>), also successfully funded with Kickstarter. This sensing device measures the air quality in the immediate environment, and offers the now-expected social layer to users—the ability to share data with an on-line community in real-time. In home automation, there is an active development community, one example of which is a Google-sponsored project, openHAB (the open Home Automation Bus <http://code.google.com/p/openhab/>). The project attempts to provide a universal vendor-neutral platform for integrating multiple hardware devices, bus systems, and interface protocols. A related solution is the Android appliance SmartyHome (<http://www.mysmartyhome.com/>), for home automation and music and sound system coordination.

**Figure 9.** IOT Home Automation and Environment Monitoring Innovations: Sensordrone, Flexibility Internet Sensors, Air Quality Egg, and openHAB on Android.



### 3. Software Processing and Data Transmission

Now having an idea of the different kinds of sensor hardware, and quantified self, home, and environment applications, this section looks more closely at the software processing tools and the technical landscape of the developing IOT ecosystem. Data streams collected from the underlying hardware sensors and circuit boards may need to be processed in a variety of stages. Some data processing may occur locally, where the hardware is based geographically and the data is collected, and then additional processing may take place after the data has been transmitted to the Internet, and still more for eventual end-user consumption. For the data transmission portion of the process, any variety of standard communication protocols may be used including Wi-Fi, Bluetooth, ANT, ZigBee, USB, and 2G, 3G, and 4G. An important recent innovation is Bluetooth low-energy (BTLE) which allows mobile devices to send data more efficiently with much greater battery efficiency than traditional Bluetooth, essentially enabling the regular ongoing if not continuous transmission of relevant data.

The volume of IOT sensor data being generated is already significant and could grow in an accelerating manner. Most of the data may be stored in the cloud, e.g., on the Internet somewhere, and it is important to consider data privacy, security, ownership, and access concerns. Cloud services vendors like AT&T and Qualcomm (with the 2net Platform, an FDA-listed Class I Medical Device Data System) are developing services specifically for biosensor and health data collection and storage. Salesforce.com’s Heroku and Microsoft’s Azure are other examples of cloud platforms-as-a-service (data collection and analysis services) which run on either public or private clouds like Amazon Web Services, Joyent, and Rackspace.

There are discussions but no action yet regarding the development of an IOT data commons, where consumers could contribute personalized data streams from their activities. Some individuals are open-sourcing their data flows already, but they have not yet been collected in a central accessible and usable location. A data commons, a biobank of user-contributed publicly-available data could be a significant public resource. Like the Wikipedia model, even if only 1% of the population is interested and able to contribute, it is enough value to create a public resource that can be used by all.

**Table 1.** Selected Examples of Emerging Solutions in the IOT Landscape.

Name	Sensor Hardware Platform	Sensor Operating System	Software Processing and Development Environment	Sensor Data Integration Platform
<i>DIY Hardware and Software Components (for programmers)</i>				
Arduino <a href="http://www.arduino.cc/">http://www.arduino.cc/</a>	X	X	X	
Electric Imp <a href="http://electricimp.com/">http://electricimp.com/</a>	X	X	X	
Flexibity Internet Sensors <a href="http://www.flexibity.com/">http://www.flexibity.com/</a>	X	X	X	

Table 1. Cont.

Name	Sensor Hardware Platform	Sensor Operating System	Software Processing and Development Environment	Sensor Data Integration Platform
<b>DIY Hardware and Software Components (for programmers)</b>				
Contiki <a href="http://www.contiki-os.org/">http://www.contiki-os.org/</a>		X		
Tiny.os <a href="http://www.tinyos.net/">http://www.tinyos.net/</a>		X		
Processing.org <a href="http://processing.org/">http://processing.org/</a>			X	
Cosm <a href="https://cosm.com/">https://cosm.com/</a>				X
Sen.se <a href="http://open.sen.se/">http://open.sen.se/</a>				X
Singly <a href="https://singly.com/">https://singly.com/</a>				X
Sympho.Me <a href="http://sympho.me/">http://sympho.me/</a>				X
Fluxstream <a href="https://fluxstream.com/">https://fluxstream.com/</a>			X	X
<b>Consumer-ready IOT Sensing Solutions (Minimal Setup Required)</b>				
Current Cost NetSmart meter <a href="http://www.currentcost.com">http://www.currentcost.com</a>	X	X	X	X
Twine <a href="http://supermechanical.com/">http://supermechanical.com/</a>	X	X	X	X
Ninja Blocks <a href="http://ninjablocks.com/">http://ninjablocks.com/</a>	X	X	X	X
knut <a href="http://www.amperic.com/">http://www.amperic.com/</a>	X	X	X	X
Beesper <a href="http://www.beesper.com/">http://www.beesper.com/</a>	X	X	X	X
Green Goose <a href="http://www.greengoose.com/">http://www.greengoose.com/</a>	X	X	X	X
Bubblino <a href="http://bubblino.com/">http://bubblino.com/</a>	X	X	X	X
Good Night Lamp <a href="http://goodnightlamp.com/">http://goodnightlamp.com/</a>	X	X	X	X

Table 1 shows some examples of how the IOT ecosystem is developing. At its most basic, the IOT value chain can be divided into the categories of sensor hardware platforms, sensor operating systems, software processing and development environments, and sensor data integration platforms. The table lists exemplar solutions being offered in the different value chain categories, in the areas of both DIY (do-it-yourself) hardware and software components for programmers, and consumer-ready IOT sensing solutions for end-users, with minimal setup required.

### *3.1. DIY Hardware and Software Components (for Programmers)*

#### 3.1.1. Sensor Hardware Platforms, Operating Systems, and Software Processing and Development Environments

Some examples of DIY sensor hardware platforms include the Arduino and Electric Imp circuit boards, and the Raspberry Pi single-board computer to which Arduinos and sensors may be attached. The Arduino and Electric Imp are single-board microcontrollers that come with basic software suites for programming them. Some sensors are already attached to the boards and other standard sensors can be ‘plug-and-played’ directly into boards, for example, temperature, sound, light, potentiometers, and moisture sensors [30]. Sensor operating systems may be already on-board the sensor hardware platforms, or may be separate. Some of the best-known examples of separate operating systems for IOT sensors that run on a variety of hardware platforms are Tiny.os and Contiki. These operating systems allow IOT devices and other small battery-operated low-power systems to communicate with the Internet. For more robust software processing beyond the operating system, other development environments can be used such as processing.org, an open-source tool for creating interactive programs. Sensor data integration platforms as discussed below may also offer more extensive software processing and development environments in standard programming and scripting languages. The sensor hardware landscape is changing quickly and there is at least one resource, OpenYou (<http://www.openyou.org/>), which maintains a list of open source development tools related to sensors and health hardware, including pointers to libraries, drivers, and projects.

#### 3.1.2. Sensor Data Platforms

Once data has been collected, transmitted, and processed, it can be brought into another set of tools for making applications from the real-time data sources, either directly or via API (application programming interface). One sensor data platform for this is Cosm where diverse sensor data feeds can be brought into the same platform using the OAuth login standard, for example looking at different information displays of Arduino temperature data, Current Cost NetSmart energy data (<http://www.currentcost.com/product-netsmart.html>), and Twitter feeds from other IOT-connected devices as illustrated in Figure 10. Another integrated sensor data platform is Sen.se where infographic ‘senseboards’ of different data streams can be displayed on any website (Figure 10). Sen.se is perhaps the first to offer critical multiviz functionality—combining data from multiple sensors into one graph. Sen.se also provides a suite of sensor data processing tools. ‘The Funnel’ process can be used to obtain data from different sources, process it in real-time and output desired values, for example, the average of home-based temperature sensors or other predefined calculations. ‘The Calculator’ can perform simple operations such as converting energy consumption to dollars, and the ‘Text Mashupper’ can be used to write real-time text messages out from the data. ‘The Multiviz’ tool can be used to graph up to three data streams, for example, combining power consumption and average temperature in every room of a house, or a person’s weight with the number of steps taken daily. Another platform with very basic functionality for tracking multiple quantified tracking data streams is TallyZoo (<http://www.tallyzoo.com/>).

**Figure 10.** Examples of the Infographic Sensor Data Displays from Cosm and Sen.se.

### 3.1.3. Platforms for Integrated Data, Integrated APIs, and Personal Data Web Services

A new category of web service is emerging to integrate data flows from different IOT quantified tracking devices, web services, and social networking activity. This may include a unified data platform, a unified API platform, and possibly personal data-based web services built on top of these.

Regarding unified data platforms, one example is Showwme (<http://showw.me/>), a platform for unifying social network and news feeds in one place. Another example is platforms providing online cloud storage of personal data, such as the Locker Project (<http://lockerproject.org/>) and Personal (linked with Dropbox, <https://www.personal.com/>). These services retrieve and consolidate personal data such as email, phone calls, social network posts, photos, utility bills, purchase receipts, health monitoring devices, text messages, and browser activity, and let the user control how it is stored and shared. A third example is unified self-tracking, where there are several mobile applications such as Daily Tracker (<http://www.thedailytracker.com/>) and Track and Share (<http://www.trackandshareapps.com>) that facilitate the unified tracking of a number of data streams [31]. These applications have unified tracking, respectively, of to-do list, health, fitness, sleep, and expenses, and habits, happiness, and bowel health. A significant barrier however is that nearly all tracking applications still require manual input.

Next considering unified API platforms, this an important and emerging service where developer APIs are themselves integrated into a platform to support the design of applications using integrated data streams. A leading example is Singly, ‘an API for the self,’ which provides a developer-friendly way to obtain and integrate social and health-tracking data streams such as contacts, photos, locations, and fitness data from other platforms into the creation of new applications. As of October 2012, APIs for approximately twenty web services were available on Singly including Overview, Dropbox, Facebook, Fitbit, Flickr, Foursquare, GitHub, Google Contacts, Instagram, LinkedIn, Meetup, RunKeeper, Tumblr, Twitter, Withings, Wordpress, Yammer, and Zeo, and multiple programming languages were supported: Android, iOS, Node.js, Python, and Ruby. Singly’s unified API platform articulates a critical underlying enabling technology in the emerging multi-data stream IOT ecosystem – completely modular format-compatible data manipulation platforms.

Personal data dashboard services are starting to be constructed on unified data platforms and unified API modules. One example is Sympho.Me (<http://sympho.me/>), which aggregates data into a calendar format so that users can see steps taken, computer-use productivity, nutrition metrics, and money spent. Another example is Fluxstream (<https://fluxstream.com/>) which uses the Singly platform to

visualize data from the BodyTrack project (<http://www.bodytrack.org/>). More specifically, Fluxstream provides an open-source personal data visualization framework for sensorviz (e.g., visualization of sensor-based data) with the goal of creating actionable infographic visualizations from inputs like amount of sleep, steps taken, calories burned, temperature, heart rate, and GPS. BodyTrack is an ongoing CMU (Carnegie Mellon University) project building and integrating open-source and open API tools from a variety of quantified tracking devices. The project incorporates data streams from existing self-tracking devices such as Fitbit, BodyMedia, WiThings, and Zeo, and has also developed two unified hardware platforms of its own. The BodyTrack chest strap measures ECG, respiration, and accelerometry, and the BodyTrack Indoor Environmental station measures indoor air quality, temperature, humidity, barometric pressure, and sound and light levels. The Fluxstream project joins BodyTrack and Singly to create data dashboards of IOT data streams that can be viewed infographically to make environment and health interactions more readily identifiable.

#### 3.1.4. Tools for Operating Quantified IOT Experiments on the Self, Home, and Environment

Experimentation is an important dimension in the IOT landscape, and another branch of the IOT sector is arising to provide support and facilitation tools. The Quantified Self community (with approximately 5,000 members in nearly 70 worldwide meetup groups as of October 2012) has always been the venue for self-experimenters to present their projects in a simplified version of the scientific method, answering three questions: ‘What did you do?’ ‘How did you do it?’ and ‘What did you learn?’ One recent trend is the emergence of tools explicitly for the conduct of quantified self experiments. These tools offer the rapid design and launch of experiments, and some degree of automated operation, data analysis, and recruitment. On the mobile platform, there is PACO, the Personal Analytics Companion for the conduct of private or shared personal science experiments (<https://quantifiedself.appspot.com/>). Another tool is studycure, an online platform that allows users to create and run interactive experiments (<http://studycure.com/>) using simple if/then logic to design study parameters. Community self-experimentation networks also exist, such the health collaboration community Genomera (<http://www.genomera.com/>) where professional researchers, non-profit groups, and individuals run studies examining a range of issues such as sleep quality, vitamin deficiency, microbiomic profiling, empathy-building, and how the memory works, and Curious, Inc. (<http://wearecurio.us/>), a personal data discovery platform in beta testing as of October 2012 that intends to look for correlations across big health data streams.

#### 3.2. Consumer-Ready IOT Sensing Solutions (Minimal Setup Required)

There are many consumer-ready applications of IOT sensor technology, perhaps the most familiar is the smart meter, used to measure home electricity, natural gas, or water consumption. Smart meter deployment is growing exponentially, from less than 4% of the global installed base of 1.5 billion electricity meters in 2008 to an expected 18% in 2012, and 55% by 2020 [32]. Beyond power meters, there is a new generation of IOT sensors designed to empower end-user creativity and ingenuity in their deployment. Consumers may place sensors in venues around the home or other locations to track a variety of measures with sensor platforms such as Twine, Ninja Blocks, knut, Beesper, Green Goose, and Bubblino, some of which are pictured in Figure 11 and listed in Table 1.

**Figure 11.** Consumer-ready IOT Sensor Platforms and Gadgets: Twine, Ninja Blocks (an early prototype), knut, Green Goose, and Bubblino.



There are several interesting consumer IOT platforms. Twine is a 2.5" flexible square with Wi-Fi connectivity and internal and external sensors powered by two AAA batteries. Temperature and vibration sensors are included with an expansion connector for other sensors. A simple web app allows the sensors to be setup with human-friendly rules (no programming required), and the connected sensors communicate information from real-world objects via email, text, Twitter, or Pebble watch. For example, one Twine can send a tweet when the laundry is finished (the dryer stops vibrating), and another can send a text if the basement floods (moisture sensor). A related platform, Ninja Blocks ('the API for atoms') provides an Internet-enabled console block plus five home sensor units (distance, temperature, motion, camera, *etc.* sensors (\$200)). Similar to Twine, knut provides a small, battery-powered, Wi-Fi enabled sensor unit for real-time monitoring in the home environment for temperature, humidity, vibration, and the opening of doors or cabinets (\$80). Another related sensor platform, Beesper, offers temperature and humidity sensors and online visualization graphs to measure the condition of garden soil, and beer and wine storage areas.

Even easier to use is another class of consumer-friendly IOT gadgets. Green Goose offers a family of products using sensors to record dynamic behavior such as pet movements, bicycle wheel turns, drinks from a water bottle, toothbrushing activities ('Did the kids brush their teeth today?'), and whether the toilet lid is up or down. Bubblino, a Twitter-monitoring, bubble-blowing Arduino-bot, is another fun and informative use case for sensors. The robot blows a bubble every time pre-specified key words appear on Twitter. The Good Night Lamp is another interesting use of IOT functionality which is designed to improve the feelings of human connectedness. A family of lamps is made up of a Big Lamp and Little Lamps that are Internet-linked to it. The Little Lamps are distributed to anyone in the world so that when the main user turns on the Big Lamp, the Little Lamps turn on as well.

#### 4. Information Visualization (Infovizzy) Layer

Ultimately the large volumes of IOT sensor data need to be translated into something human-readable and human-usable. The first two steps in this process are data acquisition from hardware sensor platforms, and information creation through software processing. Then the information needs to be made accessible so that meaning-making can happen. The usual way is through graphical presentation. The current expectation is that IOT sensor platforms, quantified tracking devices, and monitoring tools have web interfaces and mobile applications to display beautifully designed easily-readable infographics of the data. Thinking of good examples of

information display as a model, data visualization pioneer Edward Tufte's infographics come to mind, for example, the chart of Napoleon's march (<http://www.edwardtufte.com/tufte/posters>). Here the information is high-resolution, multi-dimensional, and intuitively understandable. An analogous example in the quantified tracking world is the Eatery application for keeping a photo-based nutrition diary as pictured in Figure 12. Information and possible actions are clear (first screen), the positive/negative valence is obvious on the 1-100 scale as are present and historical time views (second screen), and community ratings are intuitively apprehended (third screen).

**Figure 12.** Infoviz Expectation: Intuitively-Understandable Graphics like in the Eatery App.



#### 4.1. Tools for Data Visualization

There are a variety of online tools for conducting data visualizations, many of which are freely available. One tool that claims to be the largest data visualization showcase in the world and also understand the importance of design ('Data—say hello to design') is visual.ly (<http://visual.ly/>). This is a community platform for data visualization and infographics where users are encouraged to create stories from their personalized data. Another tool, IBM's Many Eyes visualization platform (<http://www-958.ibm.com/software/data/cognos/manyeyes/>) allows large data corpuses to be pasted into the interface for upload (note, all information becomes publically available). Many Eyes then has a range of visualization tools for the aggregated display of both qualitative and quantitative data. Qualitative data may be visualized in formats such as word trees, tag clouds, phrase nets, or word clouds; quantitative data may be visualized in formats like bar charts, histograms, bubble charts, scatterplots, matrix charts, network diagrams, or pie charts. Another tool was discussed in the previous section, Fluxstream (<https://fluxstream.com/>), an application specifically aimed at creating visualizations from multi-stream sensor data. Other online tools are provided by Google, in a suite of three free information visualization tools, starting with Google Refine (<http://code.google.com/p/google-refine/>) for accessing, aggregating, and processing messy data [33]. The second tool is Google Drive Fusion tables (<http://www.google.com/fusiontables/Home/>), an experimental data visualization web application that tries to make large data tables meaningful. Finally, the Google Prediction API attempts to derive insights from data sets (<https://developers.google.com/prediction/>). A related prediction tool is p(k) Prior Knowledge's Veritable API (<https://www.priorknowledge.com/>) which is in beta testing as of October 2012 and allows prediction-making from tabular data.

#### 4.2. Continuously Updating Real-Time Sensor Data Visualization

One of the most valuable uses of ubiquitous sensor technology is the ability to deliver real-time ambient suggestions from the passive data climate to the user in unobtrusive ways. For this, the ability to continuously update data visualization displays with real-time sensor data is critical. One existing tool for doing this is LiveGraph (<http://www.live-graph.org/>), a real-time data graph plotter. In Figure 13 is an example of real-time LiveGraph output being fed from real-time sensor data for temperature, GSR, and energy expenditure. Another tool for real-time graphing is RRDtool (<http://oss.oetiker.ch/rrdtool/>), a high performance data logging and graphing system for time series data which is good for monitoring continuous data streams. Other real-time graphing tools include a MATLAB library matplotlib (<http://matplotlib.sourceforge.net/>), and Grapher for OSX [34].

**Figure 13.** LiveGraph Continuously Updating Adjustable Graph from Real-Time Sensor Data.



### 5. Action-Taking Layer, the ‘So What’ Interface

What is even more challenging to develop than meaning-making through the human-readable information visualization layer, and which arguably has been mostly nonexistent to date, is the ‘So What’ layer that impels action-taking. This is the information presented in context, in such a way where it would be obvious and intuitive which actions to take as a result of seeing the information. The ‘So What’ layer makes sense of the data, and allows action items to be derived based on real information. Data can be seen more scientifically, relating what might have seemed not to be related with what is actually related. There are several reasons why the reaction to some of the new IOT data flows might be ‘So What?’ A lot of these data flows are completely new—they are being created for the first time, and have not been previously available, especially on a consumer basis. In the past, individuals did not interact directly with a lot of data or unprocessed data. Moreover, not only are there new data flows now available, there are also new *kinds* of data flows. The new kinds of data flows are forcing conceptual and behavioral changes in how humans interact with data. As usual, there is typically a lag time between the availability of new technologies, and the individual and societal

maturation process around them. It is just starting to be realized that there are these new data flows available, that they are new *kinds* of data flows, where perhaps a change in mindset is required to understand them, and further, that a deeper contemplation of the appropriate uses of the different kinds of data flows is also required.

### *5.1. Not Just More Data—New Kinds of Data!*

#### 5.1.1. All Data is Salient

From the human perspective, there is mainly just one traditional concept and mode of behavior regarding data, the binary filter of important or non-important. Any data element streaming across the transom of comprehension could be tossed into the saliency category or discarded. This is even how the brain works, essentially acting as a massive hierarchical filtering system for relevancy. Consequently, the data that populates the human world has been primarily of the type where every element is salient. A quintessential example is the calendar. Each appointment noted is relevant. One advantage of this model, where every data item is relevant, is that the ‘So What,’ action-taking is implied and clear. For example, the meaning of appointments to the calendar user is clear: a 2 pm appointment means leaving the office at 1:30, and preparing for the meeting before that if necessary. A birthday means ordering a gift a week ahead, or calling on that day. The related actions to take are implicit to the user from the information display. On the other hand, the disadvantage of data displays where all items are salient is they are high-cost as the information has to be input, and possibly validated, which is usually done by humans.

#### 5.1.2. Anomaly Detection

The era of big data means that almost every industry now routinely handles petabytes of data on a regular basis and crunches through it to find meaningful insights. One basic technique for data analysis in an IOT environment where 99% of the information may be irrelevant to meaning-making and action-taking is anomaly detection and exception reporting. Some of the classic examples of anomaly analysis include fraud detection, credit scores, seismic data analysis, and weather prediction. What is new is that individuals are now more readily interacting with large data streams, where tools for meaning-making are not fully present. One example of consumers wondering about the immediate utility and applicability of big data is personalized genomic testing [35]. What exactly does it mean to be at slightly above average risk for a certain condition, colorectal cancer, for example, and what should one do about it? Another example is when self-trackers become frustrated and put aside the activity after seeing that many metrics do not have a lot of variability on a short-term basis (e.g.; day-to-day or monthly), or seem to warrant action-taking, for example, constancy in sleep quality (measured by myZeo), glucose levels (measured by glucometers), and blood pressure ratings. On the other hand, anomalies to these normal data flows could be quite valuable, as well as data seen in different time frames, like longer-term and more longitudinally. Human social and biological processes may trend and change on more of a seasonal, annual, or decadal time frame where it would be possible to have predictive and prescriptive visibility as harbingers of other issues that would not be clear in the time frame of months and days.

There is an opportunity to make better tools (particularly since humans are more disposed to think in terms of story narratives than statistics as The Black Swan and other resources have noted [36]), and also to educate and set expectations about the salience and immediate utility of big streams of quantified IOT data. One of the issues with big data is that maybe it is useful, but not at its current time frame, scale, or resolution. Also any single data flow may be more useful when combined with other data streams, for example, personal genetic risk together with blood serum levels, and lifestyle data creates a more salient and actionable risk profile. Other examples would be mood-tracking data combined with social interactions and exercise logging, or a unified data visualization dashboard combining Fitbit steps taken, WiThings weight, exercise levels from heart rate data, and food consumption data from grocery store and restaurant loyalty programs and ePayment mechanisms. The killer app of quantified IOT tracking data is determining and linking multiple related information inputs related to a desired outcome.

A benefit of the big data era is that petabytes of information may be passively and inexpensively collected and stored, and used as a background monitoring environment for predicting issues ahead of time. It is precisely this passive background layer of continuous monitoring that could be helpful in improving physical and mental health. Preemptive activity could be facilitated to realize preventive medicine during the 80% of the lifecycle of health conditions while they are still pre-clinical [37], and mental performance could be optimized on an ongoing unobtrusive basis, for example through microcommunications [38]. The passive background data becomes useful when there is an anomaly, for example, letting an individual know that their pulse is off on a certain day, and that a telemedicine consultation with a physician has been pre-booked. This action-taking step might be accomplished with the contemplated next generation of functionality in mobile health applications like BetterDoctor (<https://betterdoctor.com/>) where it might be possible to see which doctors are available online right now.

### 5.1.3. Correlations

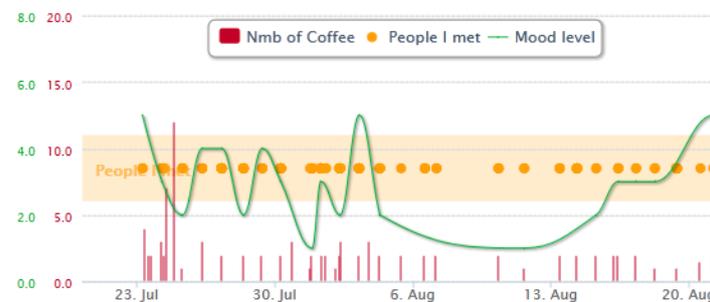
Another behavior and practice evolving from the new data flows of the IOT is looking for correlations in the quantified data streams. In Figure 14, there is an IOT data stream example where correlation is quite clear. At the top of the home power meter is the watts consumed and below it the price. The two items are clearly correlated, and moreover, like in the calendar example, the potential action-taking as a result is also intuitively clear—if you want to lower the bill, reduce energy consumption.

**Figure 14.** The SmartR Power Monitor from Current Cost.



Other data correlations are not as obvious. In Figure 15 there is a plot of one month of daily data regarding coffee consumption, social interaction, and mood level. There may be meaning at different levels of the data, first at the level of single data flows, where here for example it can be seen that mood varied considerably. Second and possibly more importantly, there may be meaning derived from correlations between the data streams. Here, mood was elevated when there were more social interactions and cups of coffee consumed. However, it is not clear whether the links between mood, caffeine consumption, and social interaction were due to correlation or causation, and so this self-tracking project could be moved into a self-experimentation phase for further testing. For example, it might be helpful to distinguish what kinds of social interaction took place, having different sizes or colors of dots to indicate closeness, friends and family, or some other parameter.

**Figure 15.** Example of Multiviz Data Stream Infographing Available on the Sen.se Platform.



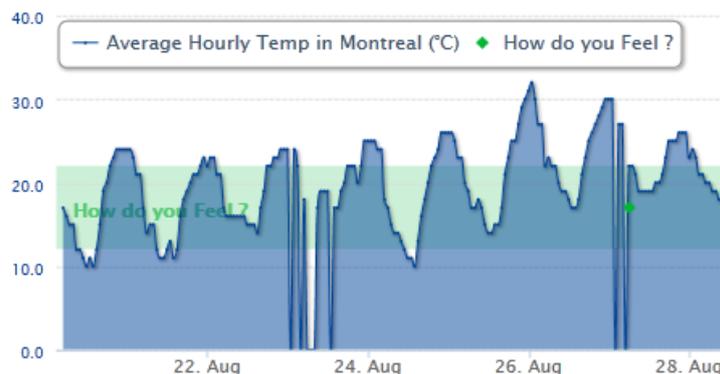
One benefit of having more kinds of data streams that can be manipulated on demand is that the velocity of question-asking and experiment iteration can be much greater. Indicative of this is a recent study of quantified self-tracking projects, the DIYgenomics epistemology study ‘Knowledge Generation through Self-experimentation.’ The study found that the key reason individuals conducted some sort of project was to resolve or optimize a specific lifestyle issue such as sleep quality, and that they often iterated through many different solutions, and kinds of solutions, before finding a resolution point [37]. Other study findings were that sleep quality was the biggest factor in work productivity for several participants, where for one individual, raising the bed mattress was the resolution to the problem, and for another, reducing caffeine consumption helped the most [37]. This new generation of quantified-self experimentation allows individuals to heal, fix, optimize, tinker, and engage in curiosity-driven research in new ways than were possible previously, and which may have deeply meaningful solutions. A further benefit of greater numbers of data flows being available is that many different elements and dimensions can be analyzed, both those hypothesized to be related and those seemingly unrelated. Machine learning algorithms and other techniques can be used to seek patterns in large data sets.

#### 5.1.4. Higher-Frequency Data Points

A fourth dimension of IOT data flows is new data in the form of more data, at very high sampling frequencies which leads to having a continuous information climate. One example is in Figure 16, showing the average hourly temperature for a week in Montreal Canada. Many individuals may be used to ‘consuming’ temperature data as the two-node phenomenon of daily high and low, or perhaps

through the more vague notion of being ‘hotter or colder than usual’ for this time of year. Hourly average temperature is higher resolution and therefore different from just having the daily high and low. Quantitatively, it is more data points. Qualitatively, it feels different intuitively too; more is more. To grasp the meaning of this, other analogous examples could be reviewed where more granular data took the place of the previous heuristics, for example population composition before census-taking, voter composition before targeted polling, and television viewership before Nielsen ratings.

**Figure 16.** Example of Data Stream Infographic Available on the Sen.se Platform.



One benefit of having more detailed IOT data is the possibility of individuals and communities learning more about their bodies and the worlds in which they live. For example, someone could adjust their schedule to be more in rhythm with the world and their own biological cycles, having a specific ramp up or ramp down time frame, for example, finding out specifically that watering the yard any time after 5 pm in certain months and 6 pm in others produces low stress on the electricity grid, rather than thinking it is always good to wait until 8 pm. Further, this metric could be available (and priced) in real-time on a day-to-day basis. Individuals and communities could operate more harmoniously in cycle with their internal and external environment. Other examples of newly available high-frequency data being used to surface previously undetectable patterns include projects from the MIT SENSEable City Lab, in one case visualizing spending in Spain during Easter of 2011 in partnership with the bank BBVA (<http://senseable.mit.edu/bbva/>). Interesting cyclical and timing of expenditures becomes visible in the 4 million transactions when they can be analyzed easily in a visual format.

Other useful correlations between IOT data streams might be found, for example average hourly temperature overlaid with crime maps. Unified data stream analysis might allow phenomena that are not time-linear to be detected, such as episodes and their triggers or event-based situations. Additionally, in the big data era, algorithms from other fields like information compression, topology, complexity, chaos, and turbulence may be applied to illuminate new patterns in IOT data and investigate the universal applicability of these algorithms.

## 5.2. Interpreting the New Kinds of IOT Data Flows

What starts to emerge in the plethora of IOT data streams is that not every data stream has the same value. There are higher-valence and lower-valence streams. Some of the high-valence data streams already identified and discussed are mood (with its tight link to happiness), and price. These streams

are familiar and deeply resonant, and most people are aware of some of the basic actions to take to regulate them. Applications that tie IOT data flows to high-valence human values are immediately more meaningful than those that do not. For example, average hourly temperature may have less meaning until mood is correlated. Linking data streams to things that are known to be relevant, particularly on a personalized basis, is of higher value. Quantified data streams need to be correlated and processed into action recommendations. Therefore, to close the ‘So What’ gap between the information being available but individuals not knowing what to do as a result, it is necessary to make the meaning and action-taking possibilities more explicit. Some ways to accomplish this could be by putting the data dimensions together in ways that are clearly communicated, where action-taking is obvious, and where a causal relationship is explored or made explicit. To the degree possible, information should be personalized to have high value and meaning to the individuals or groups viewing it.

### *5.3. Producing Lasting Behavior Change*

Perhaps the most challenging end goal (the ‘holy grail’ outcome) of IOT tracking is lasting behavior change. One possible progression of the events required for behavior change with IOT tools is as follows: start tracking, obtain data, look at the data in infographics, determine the meaning, try a behavior change, maintain the behavior change through the three week cliff for new habit instantiation, and ultimately produce a long-lasting change. Strategies can be developed to explicitly target different components of this value chain. In particular, the IOT allows for a social engagement and gamification layer to be incorporated in every part of the process, including for some of the trickiest parts like new habit formation and maintenance.

One issue with IOT devices so far is lack of sustainable usage. Eager early adopters purchase solutions and try them briefly but do not find them enduringly useful and they become shelfware (e.g., stored unused on a shelf). One way to avoid this could be completely redefining the notion of consumer products, now conceptualizing products and services, and the vendor relationship as an ongoing dialogue rather than a one-off purchase. Social networks for consumer products and services could facilitate the dialogue, allowing ongoing communication between the solution user, the solution provider, the solution recommenders (such as peak performance coaches and preventive medicine counselors), and other ecosystem members in a light-to-heavy layer of social engagement. Some of the kinds of communication involved could be feedback on the service (users give to providers), personalized recommendations (providers and recommenders give to users), and best practices sharing and gamification (amongst users). Coaching regarding performance improvement and behavior change is an emerging growth industry, for example, a new site, coachup (<https://www.coachup.com>) has recently launched to provide athletic tips from personal coaching experts. This model could be extended to other areas of personal peak performance management using IOT tools. For example, IOT-related coaches could include power-use footprint analysis and reduction consultants, environmental burden assessment coaches, genetic counselors, wellness program managers, preventive medicine strategy experts, and specialists in productivity and mental state optimization.

The most successful IOT solutions vendors will likely be those that give consumers a clear path for action-taking and behavior change with their products and services. Consumers can be directed

through a road map designed to increase their engagement as the solution continues to benefit them. This road map could include the steps of getting the consumer to try quantified tracking with the solution, see the value provided by the solution, continue engagement, change behavior, and maintain the behavior change. Since even the simple act of tracking has been shown to have an impact, individuals can start with this light-touch behavior. Some of the benefits of self-tracking alone in affecting behavior change have been seen in weight loss diary-keeping [39] and home power consumption. Electricity consumption was reduced when individuals could self-monitor and obtain feedback about their resource use: 7%–10% reductions with smart meters or other feedback [40,41], and a 32% reduction with feedback plus incentives [42]. If IOT tracking can be made extremely easy (ideally automated), fun (with gamification and social engagement), and even remunerative (with rebates and cost-savings), then there could be significant growth in the types of things individuals are willing to track, and IOT data streams as a result.

One example of harnessing financial incentives in the IOT economy for behavioral change is GymPact (<http://www.gym-pact.com/>), an application in the RunKeeper suite of activity tracking applications (<http://runkeeper.com/apps>). Users commit a monetary amount for planned gym workouts ahead of time which are later confirmed by mobile check-ins at athletic facilities. The site claimed that 90% of the 45,000 GymPact users as of August 2012 had been successful in going to the gym on committed days [43]. Financial rewards are paid to those that complete workouts from the pool of money generated by those that do not, averaging \$0.50–\$0.75 per workout per the company’s website. Another successful example of behavior change, or at least crowd participation, even without financial incentives, is the Global Corporate Challenge (<http://www.gettheworldmoving.com/>) where corporate employees compete to walk at least 2,000 pedometer-measured steps every day. Enrollment has grown from 130,000 participants in 2011 to 185,000 in 2012. Some reasons for the program’s success could be that it is easy to use, has a fun visualization graphic plotting aggregate steps taken on the world map (‘You have walked from London to Mt. Kilimanjaro!’), and has lightweight social engagement and competitive elements.

### 5.3.1. Light-Touch IOT Microcommunications: Ambient Notification, Micropractices, and SMS Coaching

Behavior change can be a deliberate top-down commitment with explicit actions, but it does not have to be. Repetitive light touches over time from one’s IOT personal data climate may also produce a lasting impact, perhaps exactly because changes can be slowly and sustainably brought into daily practice. Ambient notification is a leading example of light-touch communication from the IOT that is becoming standard. Here, sensors capture data and notify individuals (including the user, and if permissioned in, family and physicians) via SMS text message, phone call, Tweet, email, smartwatch, email or other communication of certain events or reminders. For example, the AgaMatrix glucometer texts the user a reminder if a glucose measurement is missed. The Vitality GlowCaps medicine dispenser bottles have wireless reminder lights on the bottle cap notifying pill-takers when it is time to take or refill medication, and also send notifications by text, phone call, or email. The new concept of ‘consumer product services’ discussed in Section 5.3 is developing with the Vitality GlowCaps as the vendor has an ongoing dialogue with users by providing progress reports of ‘scores’ related to

medication adherence (sent by email or accessed on the company's website). These light gamification techniques (*i.e.*, progress reports and scoring) provide an incentive to complete simple tasks by tapping into the human desire to compete and be the best. The market for medication reminders could be a lucrative case-proving demonstration of IOT technology as the World Health Organization estimates that 50% of patients fail to take medicine correctly [44].

IOT technology and ambient notification can also support other activities for peak performance and behavior change. One example is micropractices, the idea of 30–90 second context-shifting activities such as meditation, yoga, or breathing exercises. In compressed schedules with time constraints, exercise and relaxation activities can become deprioritized, and can be re-introduced in the smaller quantized packets of micropractices. Ambient reminders could notify users of micropractice recommendations, particularly when synched with biosensor input, neurobiofeedback, attention-measurement, accelerometers, and appointment calendars to ensure that the micropractice notifications come at a propitious moment in natural cycles (like the example of ambient alarm clocks that wake users at natural moments in the sleep cycle). Again, progress-reporting, scoring, and other gamification techniques could be used to encourage different tiers of micropractices, initially 1–10 per day, and progressing to 25 or 100 per day. An integrated neurobiofeedback, calendaring, accelerometry, and GPS platform could allow micropractice notifications to adapt when someone has a heavier schedule than usual or is traveling to allow for optimum rejuvenation given dynamic circumstances. The participant could still earn a high-score (and a hardship badge) despite not being able to do as many micropractices as when schedule commitments are lighter. The quality not the quantity of micropractices is important. Another potential benefit of micropractices is their attribute of real-time cognitive stimulation as the individual is not just going through a pre-learned mechanical practice (like doing a repetitive gym workout), but is actually responding in an ongoing way to new suggestions and challenges which requires cognitive engagement.

Light-touch IOT communications can also be used for other kinds of applications and behavior change, for example in preventive interventions, messaging to interest groups, and SMS coaching. One example is the SMS group messaging interventions delivered by Infield Health over the Twilio platform (<http://www.infieldhealth.com/>) in areas such as smoking cessation and improved cardio health. Another example is in the DIYgenomics empathy-building study (<http://genomera.com/studies/social-intelligence-genomics-empathy-building>) where a Siri 2.0-like personal virtual coach sends participants a few messages per day designed to evoke empathy, such as “Are you going to ask me how I’m doing today?” “Who could you reach out to today?” and “I understand how you feel right now [37].” These light-weight modules could be expanded to include training in other peak performance areas such as athletics, leadership, charisma, influence, creativity stimulation, team-building, and any other new ideas that might take advantage of microcommunications as a platform.

### 5.3.2. Access to Core Drivers of Human Behavior—New IOT Data Flows

What could make a significant difference in behavior change is having access to the more fundamental drivers of human behavior, both at the individual and overall human level. In the near-term it may be possible to have 24/7 access to more rigorous neural data streams,

emotion-mapping information, motivation triggers, productivity determinants, and other transformative new data flows. Even if these data flows do not reveal immediate causal information or a phenomenal understanding, they may be quite useful in training desired states and other applications. There are at least two levels of training behaviors that could arise from IOT services. First is at the simple behavior and task execution level as previously discussed with ambient reminders and other light-touch IOT communications. Second is at a more complex behavior level involving cognition, for example, using IOT sensors to train mastery practices like athletic performance, getting into peak mental performance states such as focus, flow, creativity, and relaxation, and achieving peak emotional states such as gratitude, joy, optimism, and anticipation. IOT sensors may be useful for detailed feedback in the biophysical discovery and training phases of mastery practices, and then as skills develop and become internalized, used less frequently and eventually only for periodic maintenance and refreshing of the acquired practices.

## 6. The Enablement Layer (Supporting Infrastructure)

Underlying the development of the IOT ecosystem (sensor hardware, software processing, information visualization, and action-taking) are some important enabling mechanisms. Some of these include new business models like crowdfunding, software developer community formation, and structural changes.

### 6.1. The New Business Model: Maturation of Crowdfunding

In the last few years, crowdfunding (open calls on the Internet to thousands of potential supporters to invest or donate small amounts of the overall capital needed for a project) has arisen as a new means of raising capital. Some leading crowdfunding websites are Kickstarter, indiegogo, PetriDish, RocketHub, and MedStartr. Crowdfunding started in the US and is becoming a global phenomenon. As one example, the German crowdfunding website startnext (<http://www.startnext.de/>) has successfully funded projects like the iCrane (a crane positioning system for the iPhone, <http://www.startnext.de/icrane>).

In the last year, some high-profile success stories from Kickstarter are proving crowdfunding as an increasingly valid funding possibility. Not only is Kickstarter an excellent financing alternative from a purely economic perspective (using the efficiency of large liquid communities on the Internet to find the backers with the highest affinity for the project and eliminating venture capitalists and other middlemen), but crowdfunding has even higher-order benefits. Historically, only one in ten startups succeeded, not because they failed to deliver a product, but because they failed to deliver a product that anyone wanted. Now the issue of finding real life customers and iteratively incorporating their feedback is greatly improved through crowdfunding mechanisms like Kickstarter where producers and consumers are directly connected. The Kickstarter model takes advantage of the rampant demand for early adoption of new technology gadgets as project backers are themselves the first customers, purchasing their own early version of the product by making a cash pledge to the project.

Some recent Kickstarter success stories include the Pebble watch, which was initially turned down by traditional funding sources but later had to cap its Kickstarter fundraising at over \$10 million on an originally-sought \$100,000 (<http://www.kickstarter.com/projects/597507018/pebble-e-paper-watch>).

for-iphone-and-android). A similar success story is Twine, raising \$556,542 from 3,966 backers after seeking \$35,000 in pledges (<http://www.kickstarter.com/projects/supermechanical/twine-listen-to-your-world-talk-to-the-internet>). Other similar funded IOT projects include Sensordrone (discussed in Section 2.6), raising over \$170,000 from an initial goal of \$25,000 (<http://www.kickstarter.com/projects/453951341/sensordrone-the-6th-sense-of-your-smartphoneand-be>) and NODE, a handheld multi-sensor environmental monitoring platform with radiation, carbon monoxide, and other sensors, raising \$76,340 (<http://www.kickstarter.com/projects/108684420/node-a-modular-handheld-powerhouse-of-sensors>).

### 6.2. Software Developer Community Formation—New Era of IOT Hacking Inspired

One way the growth of the IOT sensor market can be seen is through the growth in the accompanying IOT software developer community, and in hardware hacking more generally. Numerous user groups, meetup group, hackathons, local MAKE facilities, TechShops, biolabs, IOT incubators, and online learning tools (for example, <https://www.manylabs.com>) are popping up to support the growth in IOT sensor technologies. Hardware incubators have arisen like Lemnos Labs (<http://www.lemnoslabs.com/>, San Francisco, CA, USA) and HAXLR8R (e.g., ‘hack + accelerator,’ <http://haxlr8r.com/>, San Francisco, CA, USA and Shenzhen, China) [45]. As of October 2012, the group meeting listing service, Meetup.com, featured 18 worldwide groups focused specifically on hardware, and 30 in Silicon Valley alone with hardware as one of their keyword tags. Moreover, there are large numbers of participants in the existing hardware meetup groups (another indication of interest), for example London’s IOT group has almost 800 members (<http://www.meetup.com/iotlondon/>). Different vertical meetup groups within IOT hardware include automotive, open-source, hardware engineering, application development, hacks, and gadgeteering. Health tech incubators supporting IOT sensor-related innovation have also arisen including Rock Health (<http://rockhealth.com/>, San Francisco, CA, USA) and Blueprint Health (<http://www.blueprinthealth.org/>, New York, NY, USA).

### 6.3. Structural Change as an Enabler

Simultaneous with the bottom-up foment of entrepreneurial innovation in the IOT sector are at least three important top-down structural changes in the US health care sector (possibly reflective of broader global change) that could impel quicker adoption of IOT-related technologies. The first structural change is a shift in mindset towards acknowledging that the majority of diagnoses (perhaps 18 out of 20 cases) are straightforward, and that perhaps 70% of physician consultations could be handled by phone, which could mean a huge cost savings for the industry [46]. One obvious question is why telemedicine is not a norm given that the majority of physician consultations and diagnoses are routine. The answer is structural—as of March 2011, only 12 states offered reimbursement for telemedicine services (e.g., telephone, email, video consultation), and at lower rates than in-office visits [47]. The situation is shifting, albeit slowly, for more payers and states to approve telemedicine reimbursement.

The second structural change is a number of economic programs that start to place the consumer at the locus of medical decision-making, health services shopping, and preventive medicine solutions. The consumer is charged with making health care purchasing decisions directly, which is hoped may

force more price rationalization and transparency into the industry, and lead to improved health outcomes, including that consumers take more responsibility for monitoring and maintaining their own health. One program is the ‘Obamacare’ health insurance exchanges that are legislated to be in effect by 2014 and have price comparison of health services as an integral feature [48]. Another program is the widespread adoption of health savings accounts (HSAs) by employer-funded health plans in the US [37], where consumers purchase health services more directly. Two other programs are the reduction or elimination of capitation (e.g., the per-person amount paid by health insurers to physicians), and the trend towards higher deductible insurance plans.

The third structural change is a shift in mindset to realizing that new models may be needed for health data sharing and privacy. Traditional mechanisms for providing health data privacy have become impractical and irrelevant in a modern era that includes transferable web-based personal health records, online data sharing and social network activity, and large public data sets of health-related information. For example, only a few data points are needed to identify an individual and medical records may have ~500,000, which means that it could be impossible to protect the underlying identity of individuals whose data have been shared in open health databases. Simultaneously, many consumers are starting to have access to a variety of their own health data streams (for example, genomics, IOT sensor data streams, and electronic health records), and would like to share these resources in comfortable ways that accommodate different levels of privacy preferences. In response, there are at least two proposals for standards in individual data-sharing to support a new era of health data rights with updated privacy, usage, and security provisions. One is an academic proposal for a revision of HIPAA (the U.S. Health Insurance Portability and Accountability Act) with principles more in line with the data contribution and consent models pioneered by the Creative Commons [49]. The other is the We Consent project (<http://weconsent.us/>) for portable genomic data-sharing consent. Regulatory proposals are not the only sign of a new era in health data sharing, pharmaceutical leader GSK surprised the industry by announcing in October 2012 that the company would publicly release patient-level experimental clinical trial data [50].

Even the slow advent of a few elements of these structural changes could have a significant impact in the movement towards preventive medicine and the greater use of IOT technologies.

## **7. Conclusion**

### *7.1. Limitations*

Despite the excitement and potential transformative power of the IOT, there are a number of potential limitations. First, since the IOT industry is in the early stages of development, it may be too soon for a comprehensive review of the sector. The specific direction and impact of the IOT economy is not yet clear. How the market develops in actuality may be quite different than the trajectory suggested by the current level of activity in new startup companies. Second, there are barriers to the immediate and ubiquitous adoption of IOT products and services for several reasons. Sensors are still expensive, battery life remains an issue, data transmission is not a seamless problem, wireless coverage is not ubiquitous, location data is problematic, and in most cases large data streams cannot yet be analyzed instantly, and it is not trivial to convert these data stream into meaningful real-time

personalized recommendations. Third, although currently proposed IOT solutions may sound feasible for implementation, the timing might be too early and it may be necessary to wait for subsequent ratchets down the price/performance curve of technology advance to catalyze widespread adoption. One or more significant innovations, for example, in microprocessor chip miniaturization, battery improvement, or the automation of self-tracking could trigger extremely fast uptake, as similarly helped drive the iPod and iPhone revolution. Despite these and other limitations, there is already significant growth and interest in IOT solutions, and if vendors are able to tangibly demonstrate the benefits of the early applications, this will bring more resources to the field to resolve challenges and work towards mainstream implementation.

*7.2. Defining an Internet of Things Research Agenda*

As an emerging field, a research agenda may be defined for the IOT. The context of research could be structured in different ways, looking at time frames, for example, reviewing the nexus of current activity, and what may be expected in the short-term *versus* the medium and longer-term. A research agenda could be organized around core enabling technologies and technical roadblocks. Figure 17 sets forth a proposed research agenda that is organized per the functional categories discussed in this analysis of hardware sensor platforms, software processing and data transmission, big data processing and information visualization, human impact, and extended infrastructure.

**Figure 17.** Internet of Things Research Agenda.

<p>Hardware Sensor Platforms</p> <ul style="list-style-type: none"> <li>• Building and Home Automation</li> <li>• Automotive and Transportation Applications</li> <li>• Environmental Monitoring</li> <li>• Biophysical Sensors and Health Tracking</li> <li>• Mobile Computing</li> <li>• Wearable Electronics</li> </ul>
<p>Software Processing and Data Transmission</p> <ul style="list-style-type: none"> <li>• Data Format and Transmission Standards</li> <li>• Integrated Hardware and Software Platforms</li> <li>• Operating Systems</li> <li>• Software Processing</li> <li>• Development Environments</li> <li>• Integrated Data, API, and Web Services Platforms</li> <li>• Consumer-ready IOT Sensing Solutions</li> </ul>

Figure 17. Cont.

<p>Big Data Processing and Information Visualization</p> <ul style="list-style-type: none"> <li>• Data Aggregation, Hygiene, Validation, Structuring, Management, and Analysis</li> <li>• Algorithm Application (e.g., Machine Learning, etc.)</li> <li>• Information Presentation and Data Visualization</li> <li>• Continuously Updating Real-Time Data Flows</li> </ul>
<p>Human Impact: Reaction and Action-Taking</p> <ul style="list-style-type: none"> <li>• Interpretation and Meaning-making of IOT Data Flows</li> <li>• Data Literacy and New Kinds of Data</li> <li>• Behavior Change</li> <li>• Microcommunication</li> </ul>
<p>Extended IOT Ecosystem Infrastructure</p> <ul style="list-style-type: none"> <li>• Business, Revenue, and Financing Models</li> <li>• Customer Group Needs Assessment</li> <li>• Adoption Strategies</li> <li>• Key Problem Area Definition</li> <li>• Limitations, Barriers, Social, Ethical, Legal, and Technical Concerns</li> </ul>

7.3. Internet of Things Vision and Roadmap

7.3.1. Short-Term Applications: Biophysical Monitoring, Performance Fitness Training, 24/7 Unobtrusive Wearable Electronics, and Biometric Recommendation Engines

While realizing the problematic aspects of making predictions, it is nevertheless a useful exercise to contemplate what may be coming in the near-term. Several applications are already in development. One area with demand, financial resources, and an existing pain point is improved biophysical monitoring. There are many job functions such as astronauts, pilots, military personnel, and fire fighters where exhaustion, fatigue, and physical and mental performance monitoring is critical. Biosensor IOT solutions may offer a significant improvement over current methods. A new level of biophysical monitoring also allows for a second application area in the redefinition of peak performance fitness training for a large market ranging from professional and amateur athletes to anyone who is exercising. One opportunity is for more granular real-time performance feedback, moving from the familiar target heart rate zone readout to a more detailed stratification of output levels such as warm up, aerobic exercise, anaerobic exercise, and VO2 max integrated with a real-time exhaustion meter.

A third application area is the many forms of wearable electronics that could become the norm, including smartwatches, wearable sensor patches, and augmented reality glasses. This could be further extended to comfortable, unobtrusive ubiquitous wearable computing through the next nodes of data processing and transmission improvement, hardware miniaturization, and new battery technologies such as energy-harvesting through heat, vibrations, and light [51]. A fourth and more distant application area is the notion of a Biometric Recommendation Engine, using the objective metrics

collected from multi-sensor IOT platforms such as wearable electronics and home monitoring systems as inputs for real-time personalized recommendations. Personalized recommendations could be made in a broad range of areas including which work-related project to work on next, what exercise, nutrition, and entertainment options to consider, and which social interactions, stress-reduction practices, or other microinterventions might be applicable at any moment. Biometric recommendation engines could be relevant in both clinical patient treatment, and personal performance optimization. One concrete example is a music-recommendation engine (like Pandora) driven by personal biometrics for entertainment, athletic training, and music therapy purposes.

### 7.3.2. Long-Term Possibilities: Continuous Passive Information Climate, Big Data and Machine Learning, and Data Literate Populations

In the longer term, the IOT could bring a ‘Cambrian explosion’ in the number and types of sensors, devices, hardware platforms, software programs, and end-user applications. Whole new classes of devices and capabilities could be enabled. The ubiquitous sensor hardware layer could start to provide a continuous information climate of passive data collection and background analytics. It could become expected for personal information climates to provide real-time recommendations such as “You are 10% more dehydrated than usual right now, how about a drink?” The increasingly routine 24/7 information flows could greatly extend the kinds of data available, the characterization of biophysical, environmental, and social phenomena, and ability to quantify, measure, and track anything. The availability of baseline norm, variability, and anomaly statistics for a wide range of dynamic contexts—home, building, automotive, environmental, and the self could mean a much greater understanding and capability for action-taking. Rather than only having access to the traditional data climate (a few targeted snapshots) and experimental methods (trial and error hypothesis testing) in IOT-related applications with real-world everyday objects, a much more robust big data era is facilitated. Here the method is running fairly simple algorithms over very large data corpuses, which has allowed unprecedented progress in formerly intractable problems such as digital vision processing (for example, getting computers to recognize pictures of cats [52], Internet-based translation [53], and cultural analysis (via the Google books nGram Viewer project (<http://books.google.com/ngrams/>))[54].

There could be an adjustment period as humans adapt to an IOT landscape with more kinds of data and different mindsets, activities, behaviors, and perspectives when interacting with these data. Whole fields of study previously limited to self-reported information such as psychology could be radically supplemented and transformed with objective metrics obtained from the IOT. The IOT is in the early stages of modulating data onto the world of existing artifacts. Increasingly objects may be able to collect their own data and act on it autonomously with pre-set limits and degrees-of-freedom algorithms. Eventually, the IOT label could become a redundant demarcation as all human-manufactured matter in the future could have integrated sensors and microprocessors. A next generation of sensors and microprocessors is already being developmentally fashioned from organic, inorganic, and hybridized material, using cutting-edge technologies for manipulating organic and inorganic matter such as synthetic biology and molecular nanoelectronics. Distinctions between man and machine, and subject and object could blur further as IOT appliances eventually create a layer of exosenses to greatly extend current human capabilities and the ability to integrate with the outside world.

## Acknowledgements

The author would like to acknowledge helpful dialogues, information, and suggestions from the following individuals: Jeremy Baron, Forrest Bennett, Alex Grey, Beau Gunderson, Malek Houlihan, Shule Houlihan, Tito Jankowski, Rachel Kalmar, Sean O'Grady, and David Orban.

## Conflicts of Interest

The author is affiliated with two collaborative health organizations mentioned in the text, DIYgenomics and Genomera.

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