

Health. Care. Anywhere. Today.

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Abstract

What if clinical quality medical equipment were available to every consumer in a form factor that was inexpensive, accurate, and easy to use? What if this equipment provided information that previously was unmeasurable or very difficult to measure? What if the physiological state of individuals, at resolutions measured in thousandths of a second instead of in visits per year, could be measured easily, making it possible to ascertain caloric intake and expenditure, patterns of sleep, contextual activities such as working-out and driving, even parameters of mental state and health. What aspect of healthcare wouldn't change? We present a system that is available today that enables this vision. This award-winning multi-channel wearable physiological monitor has enabled the collection of more than 90 million minutes of data in natural settings from thousands of subjects engaged in diverse activities. Data modeling efforts are resulting in applications that present meaningful and actionable information in real-time to users and their designated collaborators (physicians, family members, counselors, coaches, etc.) We describe the SenseWear system, its design, and a summary of validation studies, current commercial applications, and ongoing research. This discussion will show how the convergence of design for wearability, advances in machine learning, and improvements in wireless technology will manifest the future of health care as personal, ubiquitous, and collaborative.

1. Introduction

In 2005, the United States spent approximately 1.8 *trillion* dollars on healthcare. Of this, approximately 0.6 trillion can be attributed to diseases or conditions caused by the genetic makeup of the patients. Approximately 1.2 trillion is attributed to poor lifestyle choices – people not taking care of themselves. Despite this at most 9 *billion* (0.5% of the total) dollars were spent on helping people better manage their health. Why is this? Certainly, convincing people to change their behaviors is difficult, but a large part of the problem is that you can't manage what you can't measure. You wouldn't try to fly an airplane without instruments, but most people try to navigate their lives without a dashboard for their bodies.

Most traditional devices for measuring physiological signals are large, bulky, and expensive. Polysomnography machines [1] measure how well a patient sleeps, but require a (probably restless) night in a sleep clinic with many wires and electrodes glued to their bodies. Measuring energy expenditure requires an indirect calorimetry machine [2], and although some are becoming more portable, they require breathing into a tube and carting around heavy equipment for the analysis.

Surely, however, the advances in miniaturization and electronics can provide medical devices and computers that are smaller, cheaper, more sophisticated, and more personalized [3, 4, 5]. On the computing side, this push has culminated today in the explosion of handhelds (mobile phones, iPods, gameboys, digital cameras, PDAs, etc.) as the new computing platform—cheaper and more sophisticated enabling smaller and more personal interactions. On the medical side, similar advances have been made. Watches with ambient temperature sensors and glucose monitors, heart straps for joggers, pedometers for dieters, etc. [6, 7, 8, 9]. There are clinical body monitors your doctor can

prescribe and your nurse can administer such as holter monitors and ambulatory blood pressure cuffs. These devices are becoming wireless and less dependent on professionals for their application. More and more they are providing the means to transmit information back to caregivers quickly and seamlessly. So is that all that is required? No. The killer applications are just starting to emerge; applications from weight management to fitness to disease management. But the critical element in all of these areas is the interpretation and presentation of the data.

Wearable body monitoring goes from delivering potentially interesting data to delivering life altering information when it does enough of the data analysis to provide consumable, actionable nuggets of body knowledge automatically to wearers and their overseers. This is the difference between the sheet music and the violin concerto, the difference between the haystack and the needle. In that sense the future of wearable body monitoring will be a story about data and data analysis, as much as it will be a story about form factors and size reduction. The physical monitors are conduits to these distilled facts about our bodies, not the value in and of themselves, just as mobile phones are the conduits for wireless spoken communication between people. But even more than portability for mobile phones, wearability is a requirement for physiological sensors. If you can't stand wearing it, you won't wear it. And that means that the constraints of wearability in the most physical and practical sense, the constraints of where sensors can gather useful information on the human body, and the constraints of wearability, sociology and fashion all need be attended to for this vision to be realized. Fundamentally that means that the lines between design (industrial, mechanical, product, communication) and traditional engineering (e.g. electrical engineering, software engineering, biomedical sensing, and data modeling) will continue to blur as the ubiquitous, pervasive, and collaborative computing revolutions manifest a future of computing and healthcare that is wearable, personal, and sympathetic.

This chapter will discuss the design, current applications, and future of the SenseWear system. The first sections will describe the sensors, hardware, software and the design parameters and capabilities that enable the tracking of multiple channels of physiology at resolutions up to 32 Hz, in natural settings, for extended time periods, with high degrees of comfort. The sociological challenges of introducing physiological devices and new models of human health metrics to medical research and to consumers will be discussed. This will be followed by an introduction to the data-mining prediction and classification that underlie the utility of the SenseWear system, along with a discussion of the value of context for interpreting physiological measurements. Finally, a promising and diverse array of research findings and ongoing initiatives will be summarized.

2. The SenseWear system.

As mentioned in the introduction, a device that can begin to transform health care must meet two difficult criteria. It must provide medically accurate data about a person's life but be designed well enough that it is unobtrusive and easy to wear. The system must be simple enough for the consumer but provide information useful to the healthcare professional. Although BodyMedia, Inc has several wearable body monitoring products, this chapter focuses on its SenseWear system, which includes a wearable armband that senses acceleration, heat flux, galvanic skin response, and temperature and records the data and derived measures over that data for later presentation to the user.

2.1. Designing a physiological computing device for everyday use

The design of a wearable physiological computing device is an effort in finding the synergy among competing criteria ranging from physiological accuracy to comfort, and mechanical

engineering to social acceptability. The design of a product that is to be in continuous contact with the human body twenty four hours a day is to design for an extreme environment. People carry all sorts of devices around with them every day, such as PDAs, cell phones, wallets, wrist watches, etc. BodyMedia first had to ask what makes people comfortable and then design all the electronics, sensors, and packaging around those human needs. Through the creation of a multi-channel, ergonomic and durable sensor hub, individuals who would otherwise be tethered to machines are being granted greater freedom. For others, they opt to wear the device, though they would never have been suffered the annoyance and cost of a lab device, because the device provides them benefits worth the effort to wear it. In the development of SenseWear, BodyMedia prototyped a number of devices ranging from chest straps to smart rings. These prototypes and the development of the design criteria were informed by studies on wearable computing and medical devices such as those used for sleep apnea research, actigraphy measurements, the accuracy of accelerometers for energy expenditure measurements, and on materials such as elastic straps [10, 11, 12, 13, 14, 15]. The criteria for the SenseWear Armband included that it had to: accurately work for up to two weeks under continuous use (24/7); work during active athletic and work situations as well as during sleep; be easy to manufacture and robust enough to survive everyday use in low (0 °C) and high (45 °C) temperature environments; be small enough to keep the overall monitor height and footprint unobtrusive beneath clothing; be non-invasive and non-irritating to the skin and hypoallergenic; have extremely low power consumption; and be cost effective.

To meet these objectives the area of the body where the device would be worn had to be: similar in size and shape on men and women between the 5 and 95% size range; relatively large in surface area (at least 2 in. by 3 in.) to accommodate the required components, including batteries and electronics; low in mobility (non-bending or stretching even during high activity); and have a continuous circumference for easy attachment and detachment. Fig. 1 shows how the upper arm meets many of these criteria. It is unoccupied 'real estate', gender-neutral, least obtrusive and low in the number of collisions, a relatively soft area where a device can be worn comfortably, and is generally concealed by clothing. On the upper arm it is also the case that device weight in this area does not induce fatigue and an adjustable strap accommodates a one size fits all design.

Many of the objectives were met through engineering novel design features. The symmetrical flexible wings (shown in Figure 2) stabilize the device, accommodate diverse arm sizes, and create sufficient pressure for the sensors to function. A proprietary hypoallergenic and non-latex elastic strap was developed for appropriate tension and repeatable attachment. Iterative user testing was conducted with hospital patients, football players, factory workers, rescue workers, firefighters, and the general public.

The goal in making this wearable device was actually to make it as invisible to the user as possible. Very comfortable, very easy to use, something that blends into your life so you forget it is there. In a case study, a high school student wearing the monitor for two weeks said, "You kind of get used to it and don't even know you're wearing it." [16].

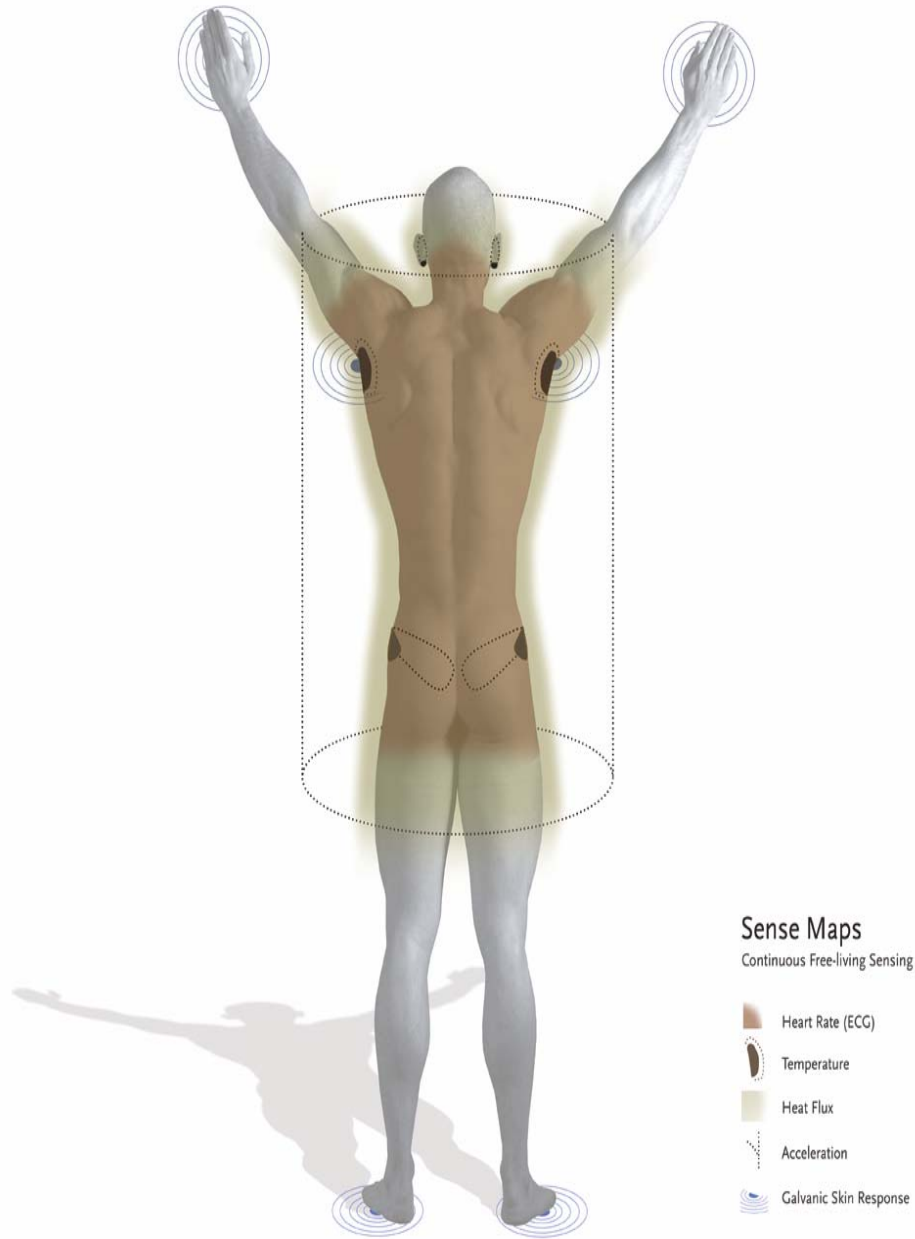


Figure 1. Wearability maps for heat flow, GSR, acceleration, heart rate, and temperature.

2.2. The SenseWear Pro2 wearable body monitor

The SenseWear Pro2 Armband is a sensor hub worn on the back of the upper right arm (tricep area, Fig. 2) [17]. It enables continuous collection of low-level physiological vital sign streams and derives from those accurate statements of human body states and behaviors. The device contains five different sensors. A two-axis accelerometer tracks the movement of the upper arm and provides information about body position. A proprietary heat-flux sensor measures the amount of heat being dissipated by the body by measuring the heat loss along a thermally conductive path between the skin and a vent on the side of the armband. Skin temperature and near-armband temperature are also measured by

sensitive thermistors. The armband also measures galvanic skin response (GSR – the conductivity of the wearer's skin) which varies due to sweating and emotional stimuli. The unit also contains a wireless chip and can communicate wirelessly with scales, blood pressure cuffs, and other medical systems. It can transmit collected sensor data with 916 MHz wireless body-LAN connectivity to a wireless communicator unit with <1 mW power output. The armband is made of flexible ABS, attaches with an elastic Velcro strap (custom designed to have stretch, air/water permeability, and hypoallergenic properties so as to mimic the skin to the greatest extent possible), weighs less than 3 oz., stores 14 days of continuous body data and has enough power for 14 days of continuous wear from a single AAA battery. Using a 4MHz MSP chip from Texas Instruments it transforms the raw physiological data such as movement, heat flux, skin temperature, near-body temperature, and galvanic skin response into snapshots of the user's life.

Each sensor is monitored 32 times per second, and data is tracked over a period of time (typically a minute but this can be adjusted through software). Currently, 41 different features of this multi-dimensional raw data stream are gathered as separate channels. For example, the variance of the heat flux is a channel, as is the average of the heat flux values. Some channels are fairly standard features (e.g. standard deviation) and others are complex proprietary algorithms. Then typically, these summary features for the epoch are stored and the raw data discarded to save memory. The raw data values can be retained (reducing the recording time, of course) through a simple software switch.

Enclosed in a shock and splash proof thermoplastic housing, the monitor straps to the user's right upper arm. At 0.8 in. tall by 3.4 in. long and 2.1 in. wide, the housing squeezes under all but the tightest shirtsleeves with barely a bulge. As it is wearable and unobtrusive, the Armband 'sees' people in the context of their natural daily activities rather than from the constrained viewpoint of a laboratory.

2.3. What SenseWear senses is not what it reports

Having multiple sensors is very important to the success of the armband and its ability to accurately monitor the physiological states of the wearers. Multiple sensors allow for the disambiguation of contexts that might confuse a single sensor. For example, if a wearer's motion is high, it might be due to exercising or to being in a moving vehicle. However, the signatures of temperature, sweat, and heat flux are typically quite different for exercise and being in a car. The algorithms in BodyMedia's software utilize the physiologic signals from all the sensors to first detect the wearer's context and then apply an appropriate formula to estimate energy expenditure from the sensor values. The armband can recognize many basic activities such as weight-lifting, walking, running, biking, resting, and riding in a car, bus, or train. Other activities are classified into combinations of these basic activities; for example, baseball could be broken down into a combination of mostly near-restful activity and running. Key to the armband's utility is that it can be worn comfortably during a person's normal life, and does not require any time in the laboratory for uncomfortable measurements.

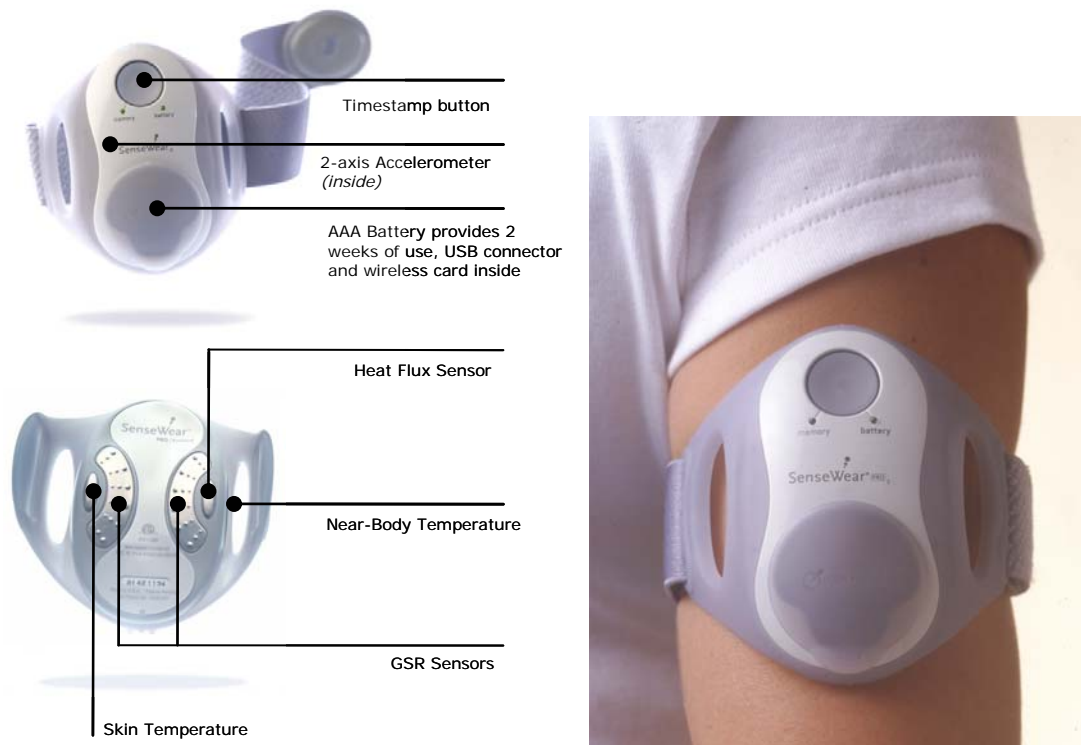


Fig. 2. SenseWear Armband front with time stamp button, back showing sensor interface, and shown on arm.

The algorithms are all created using a proprietary algorithm development process that utilizes a data-driven machine learning approach. Data is first collected at clinical sites with laboratory equipment such as metabolic carts or metabolic chambers. Next, compressed channels are created from this raw data that can be stored on the armband that are useful for determining both the wearer's activity as well as measures such as energy expenditure or sleep state. After this, context detectors are developed that classify the wearer's context. Finally, for each context, a specific algorithm is created using automated machine learning techniques to predict the measure of interest (such as energy expenditure). Section 5 describes the algorithm development process in more detail. At this point, accurate algorithms have been developed for energy expenditure, sleep, physical activity, and the set of activities mentioned above: weight-lifting, walking, running, biking, resting, and riding in a car, bus, or train.

2.4. Wireless technology

The SenseWear system includes a 916 Mhz wireless technology that allows the armband to communicate securely and wirelessly with other devices including computing devices (PCs, PDAs), display devices (watches, kiosks), and other medical devices (blood glucose meters, weight scales, blood pressure cuffs, pulse oximetry meters). BodyMedia has enabled these devices with the SenseWear Transceiver (Figure 3), allowing them to communicate with the armband. Users can take their measurements on these other devices, press the button on the armband, and the measurements are stored in the armband along with the data it records itself. All of the recorded data can then be transmitted to a PC via a wireless communicator (Figure 4) that connects to USB port on the PC. Alternatively, the data can be uploaded to a web-server via a wireless gateway (Figure 5) which contains either a standard or cellular modem, depending on the application.



Figure 3. The SenseWear BioTransceiver that allows medical devices to communicate with the armband.



Figure 4. The SenseWear Wireless Communicator (left) and Wireless Gateway (right) allow communication with a PC or a web-server.

This ability to communicate with different devices allows the user to receive feedback anywhere – whether on the go, at their home, or in their doctor's office. Furthermore, their trusted health advisors (e.g. friends, nurses, nutritionists, coaches, physicians) can look at the information on a printed report given to them by the user, online, or on their own PC. Figure 10 shows a representation of the entire system, with the armband serving as a hub for information that is reported to the web, to a PC, to a custom remote device (such as a baby monitor), to a cellular phone, or to a watch display.

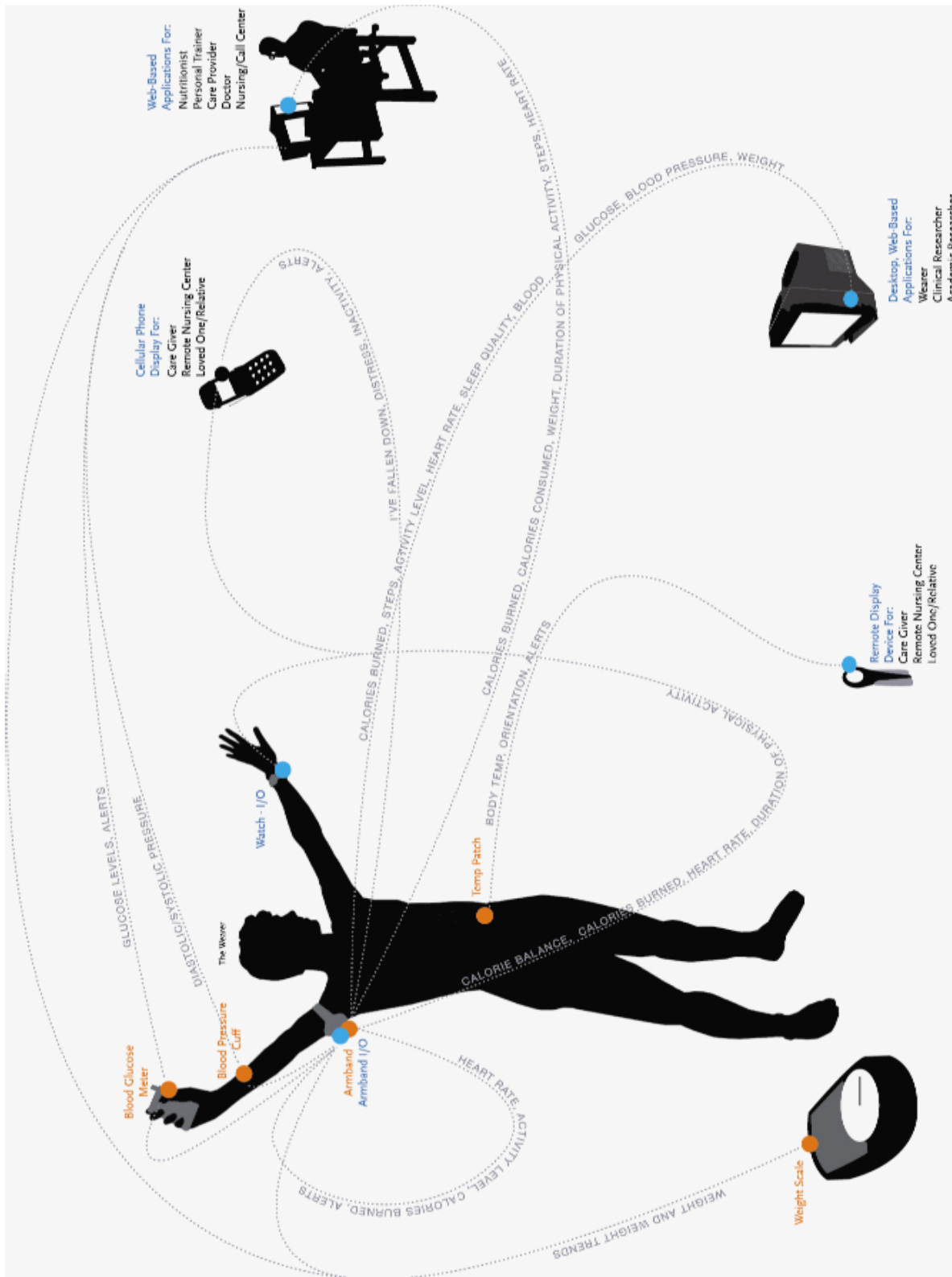


Fig. 5. A platform for immediate and remote body monitoring

3. Current Applications of the SenseWear system

The thing that is really going to change society with respect to health care, wellness and fitness is the ability for people to start to learn about themselves. BodyMedia's design

mantra is, 'make it fun and meaningful to see how you feel.' The BodyMedia platform creates a feedback loop: people want to manage their own health but until now, trying to do it was like dieting without a scale. The feedback loop is the presentation of actionable information that is otherwise unavailable to them (e.g. sleep/awake states each night down to a per minute basis if desired). This information allows people to assess progress toward their health goals. There are numerous applications that can be supported once data is being tracked. People could track elements of their health as closely as they track their financial portfolios. Having baseline data from an aggregate population and from individuals themselves, it is becoming possible to flag individual anomalies and detect potential health problems.

The armband interface is highly customizable. It can be programmed to beep or vibrate when calorie-burn targets are met or as a reminder to take medicine. It is a communications 'hub' collecting and transmitting data from multiple devices worn on the body, all toward the goal of keeping the wearer alert to danger signals and mindful of health necessities. This system provides comprehensive, actionable feedback about a person's body and lifestyle that can be shared with researchers, physicians, dieticians and personal trainers via the Internet (Fig. 7). Internet applications can allow consumers to enter additional data such as calories consumed and body fat measurements to add further meaning to the body data gathered from their armbands. BodyMedia's goal is to help people become more aware of themselves in ways they have never done before and have a fun and engaging time doing that. One opportunity that has significant benefits is to employ a human relationship such as that with a physical fitness trainer. Similarly Debra Tate showed that the combination of online information and regular feedback from a coach along with the ability to self-monitor diet and calorie estimates resulted in preliminary successes [18].

The SenseWear system has been deployed in several applications to date. The first application was a research software package called the Innerview Research Software that was designed for researchers and clinicians to use. This piece of software offers the ability to customize the armband's recording rates as well as reports, summaries, and detailed information about the sensor values that were recorded. Figure 6 shows a report, with one screen showing totals, daily totals of energy expenditure, steps taken, amount of sleep, amount of lying down, and amount of physical activity. For example, you can see that David played soccer on Monday and went snowboarding on Friday from these graphs. The lower part of the figure shows the software's ability to display detailed information. You can see at the top of this part of the figure an auto-journaling of Friday and Saturday, showing when David was physically active, was motoring (in a moving vehicle), sleeping, sedentary, and lying down. The bottom of the graph shows a minute by minute plot of energy expenditure, heat flux, and skin temperature. The sensor values shown in the report are configurable in the software. .

The Innerview Research Software has been used at thousands of sites for a variety of purposes. Some of these include to analyze exercise physiology data, serve as a measure for tracking medical conditions such as pain or physical activity during recovery from surgery, examine skin temperature in soldiers, build emotion-detecting algorithms from the data collected by the armband [19], analyze a person's reactions to architectural spaces [20], and as a variable in longitudinal studies of disease causation.

Other applications have included the study of sleep behaviors, competitive sailing, human computer interactions, and stress response in car and tank drivers. Groups studied range from professional athletes to the elderly to children. The products have survived intact in

Subject David Andre	Age 33	Gender Male	Weight 142.0 lbs	Height 5' 4"	Handed Right	Smoker No	BMI 24.25
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Start Time Fri Feb 4, 2005 07:43 PM	End Time Sat Feb 12, 2005 07:00 PM	Duration of View 7 days 23 hrs 17 min	Duration on-body 5 days 22 hrs 35 min (74%)
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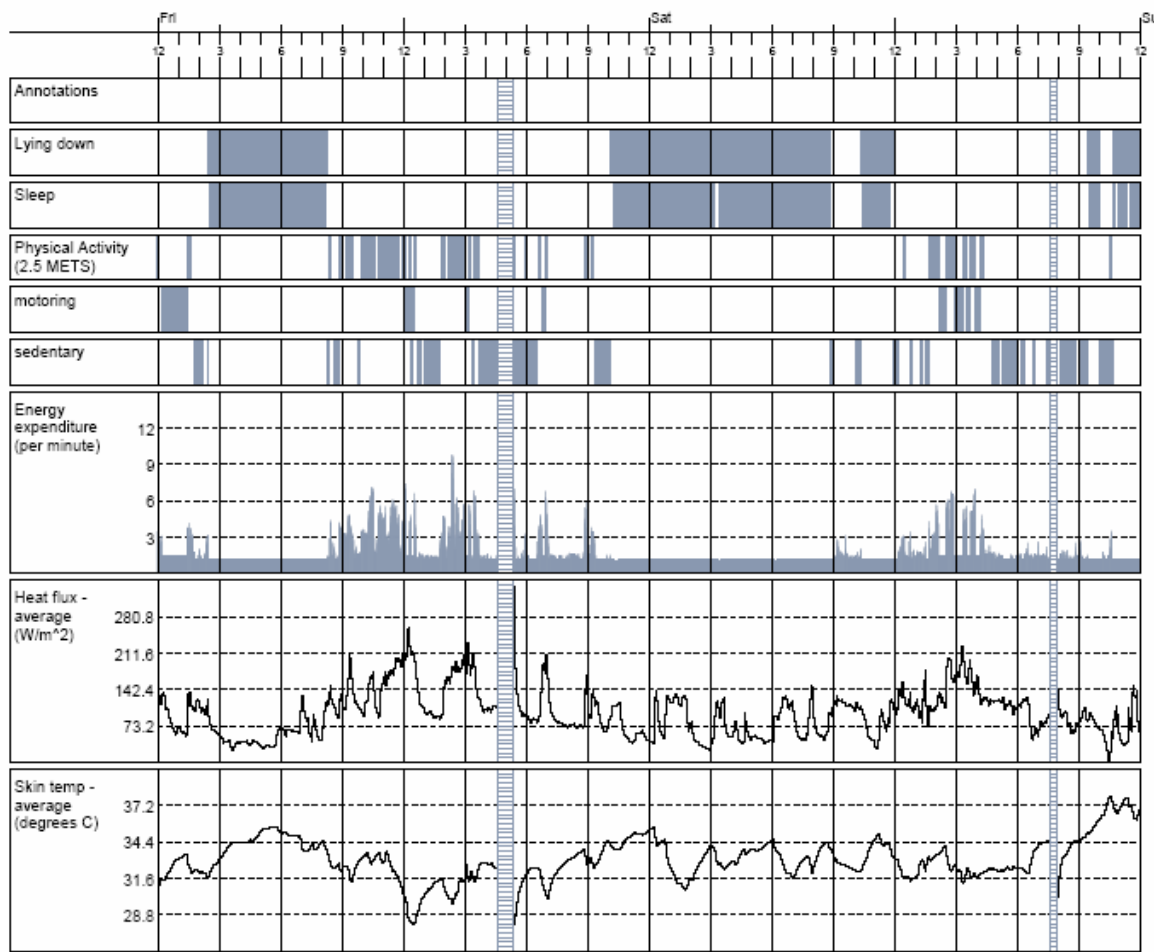


Figure 6. Reports from the Innerview Research Software

extreme environments such as Mt Everest, the North Pole, the South Pole, the highest lake in the world, the Pittsburgh Steelers training camp, and National Guard live firefighter training sessions inside burning planes.

A case study such as the following can help to illuminate the power of this kind of free-living body information. Using the Innerview Research Software, Perini et al [21] investigated the relationship between physical activity estimates and energy expenditure estimates with the recovery of a subject with Sydenham's Chorea. Sydenham's Chorea is a childhood disease that causes rapid and frequent involuntary movements but is benign in that spontaneous recovery will occur in a few weeks. This subject was treated with antibiotics, steroids, and antiepileptic therapy. At the outset, the subject was burning 1910 kcals/day as measured by the armband, with frequent involuntary muscle movements. In the following few days, the subject burned fewer and fewer calories per day as measured by the armband and additionally scored lower on several indices (TAS, flogosis) of the progression of the disease. After six days, the subject was nearly back to normal, with only minimal choreic movements in the limbs. Blood tests revealed normal TAS and flogosis levels and the armband showed only 1400 kcals/day expenditure. At day 10, energy expenditure as measured by the armband increased in conjunction with some reappearance of symptoms. The SenseWear system with the Innerview Research Software is being increasingly used in clinical situations in Europe.

In addition to the Innerview Research software, the SenseWear system is utilized by several commercial web applications to address issues of wellness, weight-loss, and fitness. Apex Fitness and BodyMedia launched bodybugg (a private labeling of the BodyMedia technology) to the general public in the US at the start of 2005. On a daily basis, the bodybugg weight management system (the left side of Figure 7) monitors and calculates a patient's caloric intake and expenditure and returns to both the patients and their care providers the difference between the two as the patient's day-by-day caloric balance. In providing this information, bodybugg is a weight management system that uses the continuous monitoring and collecting of physiological data to show the effect that lifestyle has on weight loss. Depicting calories burned, calories consumed, activity duration, and steps per day, the product strives to increase personal awareness of health and parameters of weight management. The ability for a third-party to view the data (in this case, the personal trainer or Fitness Professional) provides the user with a greater sense of integration and allows the third-party to give significantly better feedback. The bodybugg program (www.bodybugg.com) has thousands of users and is growing quickly.

Other variants of weight-management software have also been developed. One such system, designed for clinical weight management and diabetes management, has been piloted since 2003 with great results, with many subjects losing weight – even as much as 80 pounds. Another related application is The Wellness Project. This variant focuses on meeting calorie burn, step, and physical activity duration goals in the context of an online community setting. Groups can compete amongst their members or among different groups. The right side of Figure 7 shows this web application.

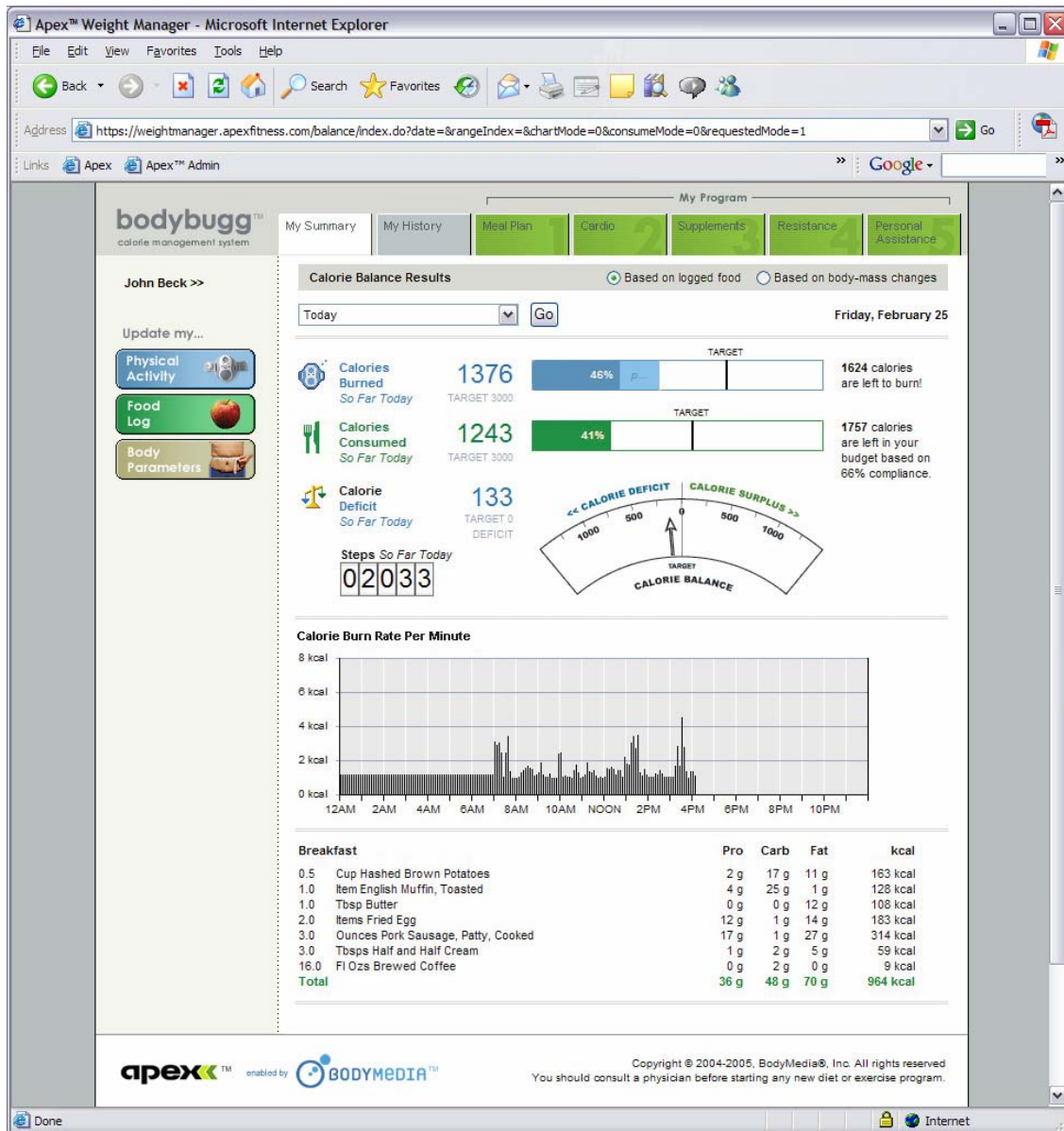


Figure 7. The bodybugg web application.

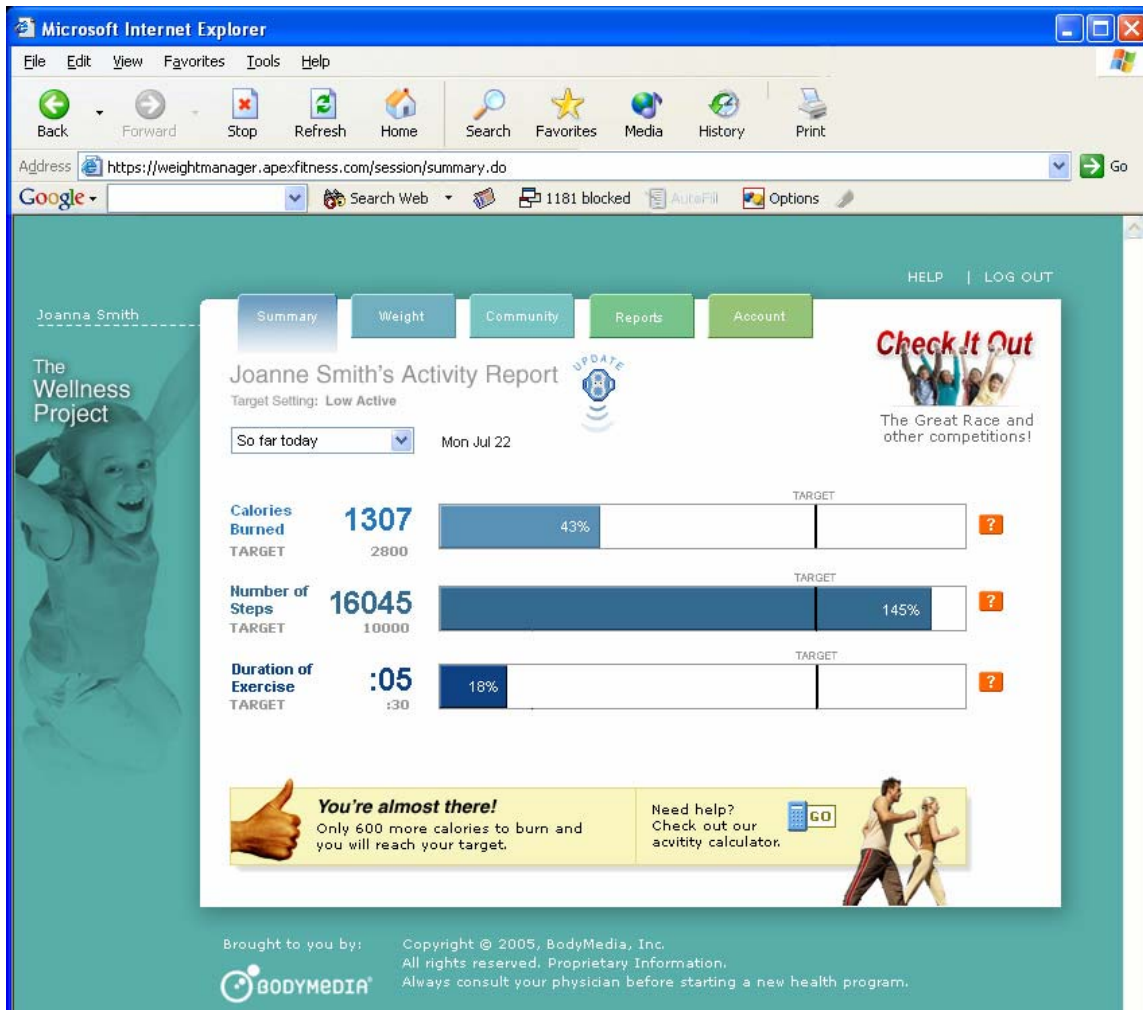


Figure 7a. The Wellness Project web application.

One question many have when first encountering the armband is whether people will actually wear the armband over long periods of time. Fig. 3 illustrates the amount of time users of the device actually wore it. That 83% of users wear it for more than 7 hours a day is a testament to the wearability of the device. To the extent that industry and commercial review is an indicator of reaching the goals for appropriate design, the SenseWear system has won both the Industrial Design Excellence Award and the Medical Device Excellence Award [22, 23]. In fact, it is interesting that BodyMedia is the only company in the world ever to win top honors in both of these awards for the same product platform.

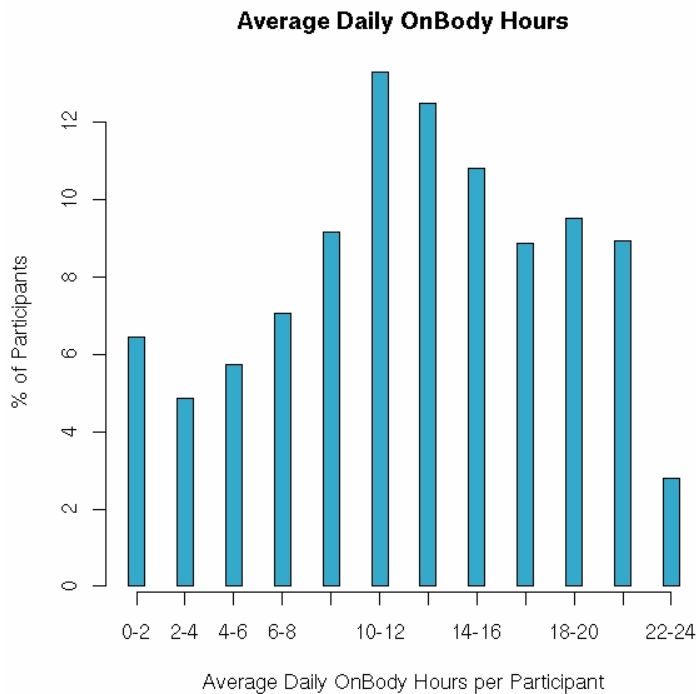


Fig. 7. Daily use patterns from one of Bodymedia's commercial products.

4. The sociological context of the modeling of human health

Traditionally, models of human health have been models of how the human body works. That the previous sentence sounds like a tautology exposes how deep the bias goes that you cannot model human health without modeling how the human body works. This bias is understandable since until very recently there did not seem to be any alternative.

But the ability to put very small high performance computers on the human body in natural environments over long periods of time has opened a new avenue. That avenue is the modeling of human health through the modeling of the data given-off by the human body, often without any initial deep understanding of why that data is what it is. In Section 6, evidence will be presented that this method is accurate in powerful, valuable, and broad ways. But first, asks the skeptic, “Is this even good science?” “Should this even be allowed to count as a model of human health?”

Science is the making of models of the world and the testing of those models to show their predictive value. A model is nothing other than a simplification of the world, ideally reducing non-essential aspects of the world and retaining just those elements that are ‘useful’ (that are required for accurate predictions to be made). The ‘models’ or algorithms that BodyMedia constructs are mathematic simplifications of large amounts of raw data gathered with its devices, gathered in the presence of medical gold-standard lab equipment (such as metabolic carts (Fig. 8) or polysomnography machines) [2, 1]. Ideally, these algorithms have captured the underlying trends in the data so that when worn by a person not in the presence of medical gold-standard equipment, the result a BodyMedia device returns accurately predicts what the medical gold-standard lab equipment would have returned in the same situation. So these are models of human health. They just happen to be models of what the body is doing rather than why it is doing it. These models are tested against the very same yardstick as classic models of human health: their ability to accurately predict what is happening to the body in question.



Fig. 8. Metabolic cart in a lab setting.

The next natural question, once the legitimacy of the method has been satisfied, is the real value of the method. There is a prevalent assumption, in both the medical industry and the general public, that any model built or ‘learned’ by a machine (as all statistical mathematical models are to some degree) could not possibly be as accurate, or as useful as a model built by a person. More specifically, there is often an unarticulated assumption that when these models are wrong they will be wrong in much larger or much more problematic ways than equivalent models built by a person. The first response to these concerns is that real-time or long-term body monitoring in natural environments involves tens of thousands of times as much data as the current models of human health are built upon (periodic readings of blood pressure, cholesterol, bone density, etc.). Kuhn [24] describes the institutional adoption of new paradigms as a 25-year process; and it took the medical community the better part of a century to build a set of models of human health around this data. So waiting for a community, even one as smart and as dedicated as today’s medical community, to build this next generation of models as we move, metaphorically, from physiologic snap shots to physiologic movies, is not realistic.

The second issue is that statistical mathematical models are built by trying to minimize some error function with respect to the predictions that connect the dependent axes (the inputs, which are in BodyMedia’s case the raw data measured many times per second by the SenseWear Armband) to the independent axis (the output, the predicted value, in this case BodyMedia derived values such as sleep state, calories burned in the past day, body position, etc.). Assuming that the data has been properly collected (an assumption that is necessary for verification in all model building exercises) the people and

situations on which these mathematical models are built and tested represent the conditions that happen the most often or are the most important to predict correctly. Models such as the ones built by BodyMedia are constructed explicitly to minimize these errors when applied to unseen subjects. This cannot honestly be said for more traditional models of human health because they have, as an additional constraint, that the model is understandable to the researcher building the model. The case can be made that special cases not seen during the training and testing phase of a statistical mathematical model may be predicted incorrectly in the real world. Of course, when these same special cases are withheld from human researchers building more classic models of human health, the same risk for a model that miss-predicts in these same situations exists.

5. Data modeling, data mining and sensor fusion from multi-sensor streams

‘Bioinformatics,’ is the intersection of life science and computer science. The SenseWear system allows for the gathering and interpreting of multiple streams of vital sign data which is then used to derive statements about the human body, such as calories burned, sleep, and activity type. The fundamental insight for BodyMedia is this—instead of monitoring individual parameters (symptoms) that healthcare institutions are used to looking at—blood pressure, pulse oximetry, cholesterol level and so on—BodyMedia monitors lower level vital signs many times a second, and then builds mathematical models of the data collected. These models are built in the context of the ‘right answers’ from medical gold standard equipment such as metabolic carts for energy expenditure or polysomnography for sleep states. This process of building mathematical models goes by several names in different disciplines, but is most commonly called supervised machine learning in the computer science community.

The process of supervised machine learning is the building of a model in some chosen representation (such as an artificial neural network, a decision tree, or a probabilistic network). Input signals are collected in the presence of the labels to be predicted by the model being learned. This set of input signals and labels is often referred to as the training set. These labels are usually either classifications (e.g. ‘Astro was jogging between 2 and 3 pm’) or regression values (e.g. ‘Astro’s level of energy expended in the past minute was 5.65 kcals’). These labels are treated as ground truth though in practice there is almost always some error in them. Statistical machine learning techniques (e.g. back propagation in the case of an artificial neural network) are then used to create, train, or ‘learn’ a model such that the model accurately relates the inputs to the known outputs (labels). These techniques often search through possible model frameworks to find the best one. The models are compared using methods such as statistical bootstrapping and cross-validation, which measure the ability of the model to generalize to unseen data. After the best model is selected, it is evaluated on a completely unseen set of data.

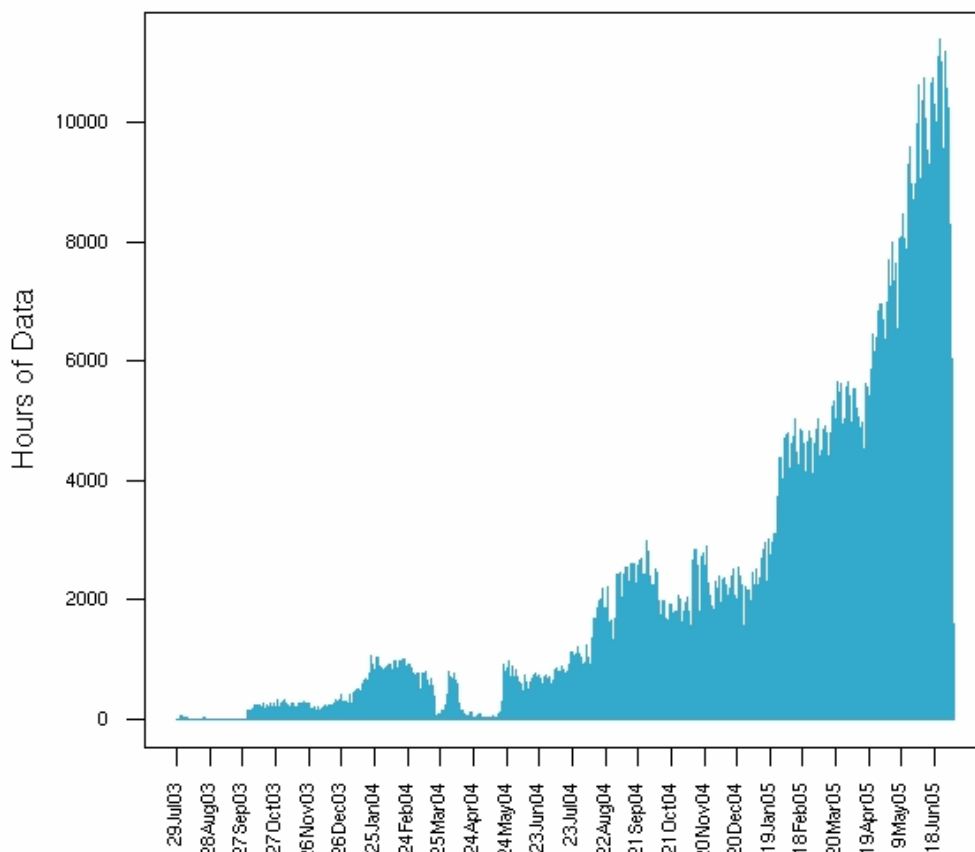
There is considerable science in picking from existing model representations or making a new representation when going through this supervised machine learning process. In addition, it is often the case (as it is with BodyMedia) that the predictions are not made by single classification or regression models, but by hierarchical or networked groups of these models. For example, for a stream of vital sign signals collected by the SenseWear Armband, a first model might attempt to classify the kind of activity represented by these signals (e.g. jogging, biking, resting, sleeping, etc.). Then, for each of these particular activities, a specialized model has been built that is particularly good at rating some prediction problem (e.g. energy expended per minute) for that particular kind of activity (e.g. biking). BodyMedia approaches the data modeling process through a variety of statistical methods including symbolic modeling where expert knowledge exists (e.g. Decision Trees, Production Systems, etc), numeric modeling to fill in gaps in expert

knowledge (e.g. Neural Networks, Bayesian Networks), state modeling for body states such as sleep states that shift in predictable ways (e.g. Hidden Markov Models, Partially Observable Markov Models), and clustering when labels are not available.

The bottom line, however, is that for real world problems, what generally makes the most difference is the quantity and quality of the training data available to the models being learned. To date the combined time that users, researchers, subjects, and customers have worn SenseWear Armbands amounts to over 300 million min over the past 5 years. Data from approximately 100 million minutes, from over 3000 individuals, have been collected by BodyMedia to form a corpus of physiological data. Of those 100 million minutes of physiological data (the inputs in our discussion above), around 10 million min of that data have been explicitly labeled as to their classification (e.g. 'lying in bed') or their level (e.g. stage 2 sleep according to the polysomnography machine). These 10 million min of streaming physiological data have been accrued from over 500 subjects with over 120 different labeled activity types.

Figure 9 shows the rate at which this data stream is increasing. The advantage of receiving all of this data is that even where the data is not annotated or explicitly labeled, the data can be used to improve the algorithms – both by helping in testing the algorithms but also through semi-supervised learning techniques. Exactly because this data improves the algorithms, users have some impetus to provide data, which can improve the information they themselves receive from the system. This creates a virtuous data cycle that encourages the use of the system and the contribution of data toward the general good.

Armband Data by Time



graph includes data from commercial and free living users

Figure 9. Hours of data uploaded to BodyMedia, by day.

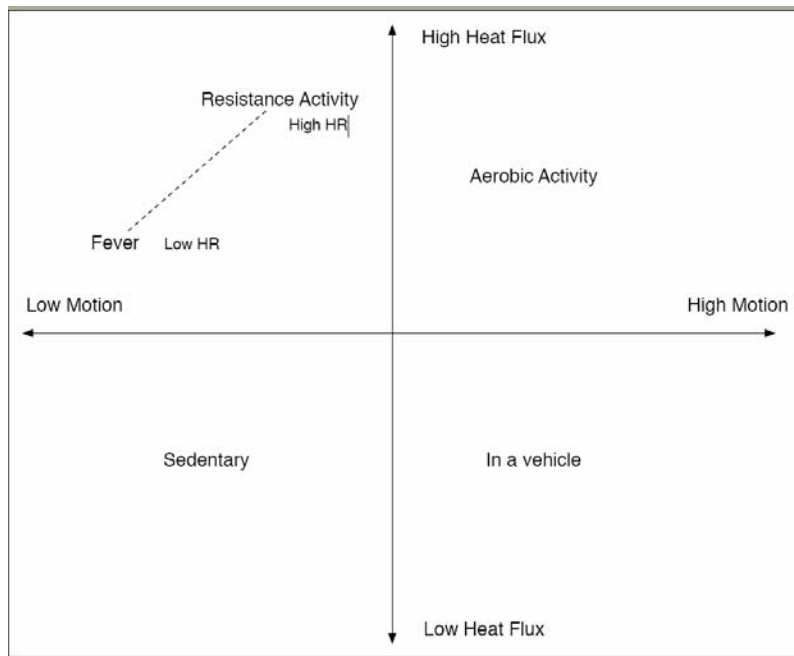


Fig. 10. Activity and condition map: sedentary, vehicle, aerobic, resistance vs. fever characterized by heat, motion and heart rate.

The next question many ask is reasonably, ‘Are all these different parameters really necessary?’ The challenge in real world (i.e. out-of-the-hospital) body monitoring is that there are a lot of states of the human body that are ambiguous when seen from the perspective of a single sensor. By choosing sensors carefully, a higher dimensional space of streaming vital signs can disambiguate these human body states, dramatically increasing what a wearable device can determine; and increase the accuracy of any indirect measurements derived from the lower-level vital signs.

Fig. 10 shows a simplistic example of how multi-sensors can disambiguate human body states that would appear ambiguous to any single sensor. In this example, the challenge is to identify the type of state the human body is currently in. The use of multiple sensors can also help to more accurately capture the correct level from a particular category. For example in Fig. 11, a model that could see only the motion of a person would credit the person with a higher level of energy expended per minute during the ‘walk around the block’ activities rather than during the ‘climbing stair’ activities. This is, it turns out, generally false. And that can be seen by the model built by BodyMedia through the use of multiple sensors. Again in Fig. 11, we see that the rate the person is producing and releasing heat is higher during the stair climbing activities and the models can take advantage of this additional information to more closely approximate what a metabolic cart (one of the medical gold standards on the subject of energy expenditure) would say under these same circumstances.

In practice, these examples do not capture the complexities the models must address. For example, it is possible that if during a period sensor A is increasing and sensor B is decreasing, or vice versa, then the output should be judged to be increasing, but if both or neither of the sensors is increasing, then the output should be judged to be decreasing. This sort of relationship cannot be captured by any first order statistical models as the correlations between A, B, and the output are all zero. This conceptual example highlights the demands on the models being learned to capture arbitrarily complex relationships in the data, not just linear trends. As an example of this, in Fig. 12, examples from four classes of human activity are shown. In all four cases, the two axes represent two orthogonal

dimensions of motion and the points represent a trace in that two dimensional space over two seconds. What we see here are patterns that might be thought of as ‘strange attractors’ that help to identify and differentiate these different activities. These patterns are not just a matter of the amount of motion per minute, but the kinds or patterns of motion that occur in sequences over short (or even over long) periods of time.

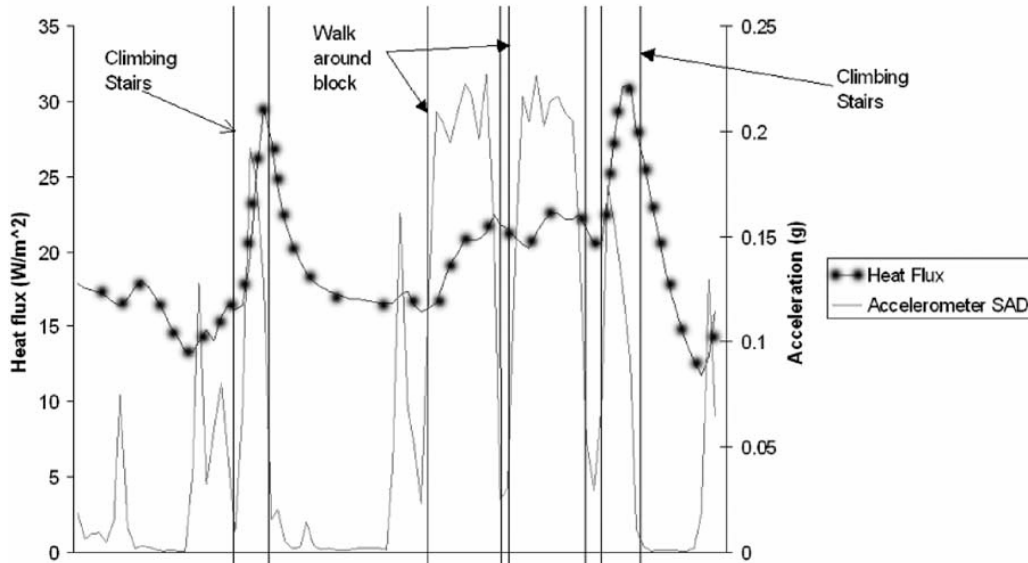


Fig. 11. Sensor data from accelerometry and heat flux comparing flat walking and stair climbing.

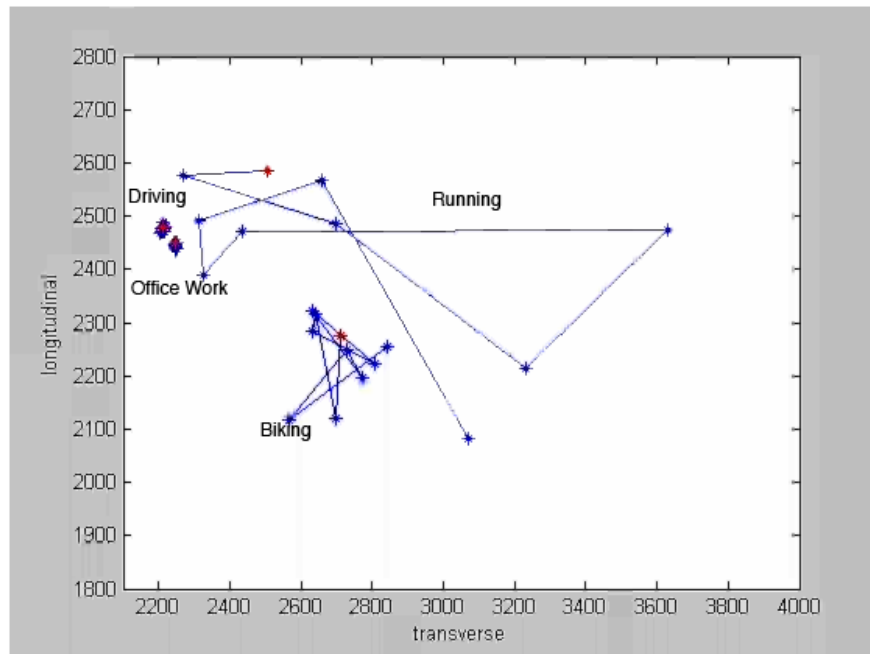


Fig. 12. Longitudinal and transverse accelerometer data from the armband for biking, running, driving, and office conditions (in micrograms per millisecond).

What does all this amount to in the end? These learned models allows BodyMedia, with very high accuracy, to say to a new user who puts on a SenseWear Armband statements such as, “You burned 400 calories over the past hour” or “You were in bed for 8 hours last night, but you only slept for 5 hours and with frequent interruptions.” The

following table shows our current accuracies for a set of new vital signs we derive from the raw data.

Algorithm	Accuracy	Algorithm	Accuracy
Energy Expenditure	Error < 10%	Lying down duration	Error < 1%
Exercise Duration	Error < 3%	Sleep onset	Error < 3 minutes
Exercise type recognition	Error < 5%	Wake Time	Error < 3 minutes
Step count	Error < 2%	Sleep Duration	Error < 5%
Sedentary duration	Error < 3%	Motoring Duration	Error < 5%

Independent researchers have written many validation papers about the SenseWear system, especially with respect to comparing energy expenditure measurements from the system to estimates from gold-standard laboratory equipment. These include tests on normal individuals from 18 to 75 on a variety of exercise equipment comparing against indirect calorimetry, such as Jakicic et al [25], Fruin and Rankin [26], Wadsworth et al [27], and McClain et al [28], all showing significant correlations. Several researchers have examined disease-specific populations, such as cardiac patients [29] and patients with chronic obstructive pulmonary disease [30], finding good results as well. In a very interesting preliminary study, Mignault et al [31] compare the armband to doubly labeled water over a ten day period. The subjects were diabetics examined as part of a larger study. In these patients, the researchers noticed no significant differences between the doubly labeled water technique and the estimates from the armband. The correlations were extremely high (0.9696), with a technical error of measurement of only 104 kcal/day (less than 5%). The authors conclude: "... preliminary analyses suggest that the [...] Armband is an acceptable device to accurately measure total daily energy expenditure in type 2 diabetic patients over a 10-day period".

Human body data, when aggregated, also has tremendous value beyond the value of the individual statements to individual users. The revolution in the financial services industry over the past 30 years came as a direct result of the access to and real-time analysis of the world's minute-to-minute financial vital signs. Wearable physiological computing is just at the beginning of a similar revolution as a natural outcome of pulling additional meaning from the long-term, detailed, objective and accurate views of the physical states of large numbers of people and transforming these into meaningful, desirable, and actionable applications. We envision utilizing this data scientifically for data mining and commercially as a resource for creating and improving algorithms. It will be possible to compare a user's data with similar users, creating empirical definitions of what is the norm and what is abnormal. These data mining challenges and opportunities on large collections of group data are in their infancy, but an active area of effort for BodyMedia.

6. Research and development directions

While there are many exciting on-going applications discussed above, BodyMedia is engaging in continued refinements to the platform and the development of new body monitoring capabilities. These including the integration of new sensors and the ongoing development of data models to extract new physiological features and contextual activities. Some of the areas that BodyMedia is focusing on include: fine-grained sleep detail (e.g. Rapid Eye Movement); personal duress; fatigue, alertness, drowsiness; mental stress, anxiety; hydration, perfusion, homeostasis; surrogates for glucose level; calories consumed (when, and approximate quantity); biometric identification ('finger printing' based on personal biometrics); heart information taken solely on the upper arm; and core body temperature prediction. Efforts to make the device more unobtrusive are also underway.



Fig. 13. A prototype version of a future BodyMedia platform for ambient computing.

For all of these areas, BodyMedia has collected some anecdotal data and discovered, in many cases, compelling signs that significant opportunities for armband-based monitoring exist. For example, in the case of measuring heart signals from the upper arm, BodyMedia has discovered a new, patent-pending, method of obtaining electrical signals from the heart solely from electrodes placed on the upper left arm continuously, and for extended periods of time. This latest BodyMedia innovation can record ECG data from the upper arm, as well as other locations on the human body previously considered impractical by conventional standards, without wires, adhesives, or other equipment. BodyMedia has integrated the technology into prototype versions of the armband using one non-adhesive electrode and one adhesive electrode. Production of a non-adhesive system is underway. Their invention is particularly noteworthy because it challenges conventional wisdom in electro-cardiology that ECG can only be observed using electrodes spaced on "either side" of the heart. Al-Ahmad, Homer, and Wang [32] have presented preliminary results of validating these prototypes, showing that the armband measures heart rate and beat-to-beat variability comparably to a Holter monitor. Preliminary results in incorporating heart rate information into the equations for energy expenditure are supporting McClain et al's [28] finding that the incorporation of heart rate can reduce the error of the algorithms for certain activities. Fig. 13 shows a prototype of a new version of the device that incorporates heart-rate electrodes in a patch version of the armband.

To accomplish many of these research goals for additional body state prediction, further additional sensors may need to be added to versions of the body monitors made by BodyMedia. BodyMedia is experimenting with acoustic sensors; optical sensors, pressure and barometric sensors; GPS digital compass, and gyroscopic elements; ambulatory blood pressure; micro-needles for the administration of medication and sample collection; ambulatory pulse oximetry; bioimpedance [33], and near-body ambient air and environmental sensors. The potential to increase the understanding of human physiology in natural settings and humans' physiological interactions with their environment is substantial.

7. Conclusions

As many pundits have commented, the current state of healthcare is problematic. Costs are skyrocketing and the current institutions are breaking under the load. Consumers are getting saddled with more of the financial responsibility of their own healthcare. Dissatisfied with their options and their care, many patients fail to comply with the treatments and programs that can best help them. Patients and caregivers alike have a hard

time managing that which they can't see – and it is exactly those things that go unmeasured that are costing us the most – 1.2 *trillion* dollars last year alone.

In attempting to address these problems, we must take into account several factors. First, healthcare will increasingly come to be ruled by consumers due to the power of the market. Second, consumers will need personal health care tools to help them manage their health and wellness through helping them manage the root causes of their health and wellness – their choices and behaviors. Nearly all of the tools that consumers end up using will require as inputs physiological information about their bodies. This will require wearable body monitoring that is simultaneously medical-grade and consumer-desirable.

BodyMedia is today addressing this need by following a few simple principles. We strive to find the new vital signs that resonate with consumers and the behaviors they wish to manage. In addition to incorporating our increasing knowledge of the human body, we also directly model the relationship between these new vital signs and the physiological signals we can measure from the body. A fundamental question for us is "how can we get accurate information from the body in a way users will love?" Given that users won't wear twenty different devices, we work to build a single system that delivers value on multiple fronts from the same piece of effort. Finally, we recognize that continuous body monitoring is providing data that science and medicine haven't seen before. We are working to build systems that take advantage of these increasingly large data streams both to better help the consumer and to increase our knowledge of health, physiology, and human behavior.

The SenseWear system and its applications are a first step toward a vision of the future of healthcare that enables users to manage their health and care for their bodies anywhere they choose to do so. The future of healthcare is happening today.

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