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Authors

Olshansky, S Jay
Carnes, Bruce A
Yang, Yang Claire
[et al.](#)

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Cover Feature

The Future of Smart Health

S. Jay Olshansky, Bruce A. Carnes, Yang Claire Yang, Norvell Miller, Janet Anderson, Hiram Beltrán-Sánchez, and [Karl Ricanek Jr.](#), Lapetus Solutions

Longitudinal individual and crowdsourced health data from wearable sensors can be leveraged to increase the quality and length of life, giving rise to a new health data economy.

Human health has been tracked using various metrics since the advent of the demographic and actuarial sciences several centuries ago. Epidemiologists, sociologists, gerontologists, and public health experts have since become highly efficient at determining when in the lifespan diseases tend to emerge, what behavioral and genetic risk factors contribute to their onset and progression, how to treat them once discovered, and how basic biology influences both disease expression and length of life. In fact, advances in public health, medicine and science have taught us how to maintain, repair, and “drive” our bodies to maximize health and longevity – generating the first longevity revolution that yielded a 30 year increase in life expectancy at birth during the 20th century.

However, statistics do not capture what is actually happening inside our bodies. This became possible with advanced diagnostic and imaging technologies—including x-rays, positron emission tomography, computed tomography, magnetic resonance imaging, electroencephalograms, electrocardiograms, and laparoscopic surgery—that enable physicians to not only observe disease after symptoms appear but increasingly to detect disease before symptoms are manifest when intervention is most effective. For example, a routine colonoscopy can sharply reduce the risk of death from colon cancer, once a major cause of mortality in long-lived populations.¹ Yet, despite our newfound success in real-time disease tracking, there are still no physiological measures that can reliably and precisely determine biological age.²

The Emergence of Wearable Sensors

As interdisciplinary teams of medical researchers, biologists, and technologists search for the ideal biomarkers of aging, what has emerged in the interim is something that could not have been predicted even a few years ago—the ability to inexpensively and reliably monitor many bodily functions in real time using wearable devices. The wearable device industry has grown rapidly and is estimated to become a \$31.6 billion market by 2020.³ Instead of exclusively relying on invasive procedures such as extracting bodily fluids with syringes or using imaging devices that emanate potentially harmful radiation, we can now choose from a growing array of wearable technologies to keep close tabs on our bodies’ inner workings. The immediate feedback that such technologies provide is somewhat akin to the biofeedback technology that was developed decades ago to help lower heart rate and control brain-wave functions.

Wearable technology currently has three primary applications in the healthcare domain.

The first, driven by profit and demand, is to monitor physiological attributes associated with a specific disease such as diabetes.^{4,5} People with type I diabetes monitor their blood-sugar level frequently over the course of a day to determine when to introduce insulin. This is typically done with a device that draws blood multiple times during waking hours—an intrusive but necessary procedure. Newly developed wearable devices such as GlucoWise (<http://gluco-wise.com>) now make it possible to unobtrusively monitor blood-sugar level in real time. The benefits of continuous blood-sugar monitoring extend well beyond insulin control; the device can discover the body’s unique and precisely measured insulin response to certain foods, and even evaluate personal insulin-based circadian rhythms to identify the best time of day to eat or avoid certain foods. Related uses of wearable technology include real-time collection of data on blood pressure (for hypertension control), resting and exercise-related heart rate, and sleeping patterns.

Another growing use of wearable devices is to enhance physical performance by tracking fitness activities in real time.⁶ This not only creates a biofeedback loop informing users about which training methods yield the best results; it also enables documentation of “personal bests”—fastest time running, swimming, and so on—and the ability to set, measure, and exceed targeted levels of physical activity. Wearable devices that autonomously

measure and track physical performance can be used to learn more about the body's unique functional attributes such as those associated with how certain foods or circadian rhythms influence performance. It is also popular to "gamify" fitness tracking devices to compare a user's physical achievements, such as number of steps taken in a given period of time, with those of friends, family, colleagues, or even strangers to foster competition and thereby improve performance.⁷

A third popular use of wearable devices is as a personal assistant or coach that constantly tracks some variable of interest. For example, the weight-loss industry discovered that keeping a food journal—a list of all foods consumed each day—can serve as a motivational tool and cheating deterrent for those trying to lose weight.⁸ Instead of carrying around a notebook and writing down everything you eat, it is easier and faster to input data into a wearable device (or mobile application) that automatically keeps track of calories consumed or points used. Unlike the first two uses of wearable devices, which are passive data generators, this use of the technology can be either active or passive.

Many other wearable applications are emerging that could extend the quality and length of life in ways never before thought possible.

Translating Health Data into Empirically Verified Metrics

Despite their enormous promise, wearable devices are a nascent technology that we are just beginning to understand. There is no shortage of internal bodily functions to measure; the challenge is what to do with all of the data. The thousands of wearable devices now flooding the market excel at generating information, but most devices are limited to tracking individual physiological parameters and motivating people to engage in more physical activity. However, getting a little buzz on your wrist or a "great job!" emoji from your fitness tracker after walking 10,000 steps doesn't seem like a sufficient reward—in time, a user is likely to get bored with the device and drop it in a drawer. What is needed is some means to aggregate and transmit the data to a third party that can leverage it in a more meaningful way.

Health data aggregation services are now available that collect millions of data points across time from wearable sensors—examples include Human API (<http://humanapi.co>), Welltok (<http://welltok.com>), and Validic (<http://validic.com>). Such crowdsourced data can be translated into empirically verified measures of risk to assist in disease prevention at both the individual and population level. For example, most physicians today rely on samples of bodily fluids taken before or during annual physicals to assess a patient's immediate risk of disease. This information could be complemented with extraordinarily rich data on bodily functions derived from wearable sensors and uploaded continuously between doctor visits. This would not only give the physician a more accurate picture of the patient's health status and risk factors, but could be aggregated with other patients' data to provide the equivalent of a personal longitudinal health survey. Researchers could also use this data, once aggregated, to track health trends at different levels of granularity in real time as well as apply data-mining solutions to develop new insights into the causes of diseases and ways to prevent them.

Example Application

Lapetus Solutions has created several empirically based methods for translating data from wearable sensors into quantifiable measures of risk and benefit that can be used by individuals to measure and enhance their length and quality of life. Here we consider how a person's daily step count can be converted into a quantifiable measure of years of healthy life remaining.

Linking step count to health and longevity

Step count is a popular passive measure of physical activity provided by many wearable devices today, such as Fitbit. Although most researchers acknowledge that walking is a healthy behavior, to our knowledge no one before us had actually translated step count data from wearable devices into empirically verified measures of health benefits. Instead, a somewhat arbitrary threshold of 10,000 steps per day has been held up as a general standard.⁹ However, the complex health benefits of walking cannot be captured by a generic step count applied equally to everyone. Children must walk more steps per day than the average adult to achieve optimum health, while many older people cannot realistically walk 10,000 steps per day. The number of calories burned and operationally defined levels of physical activity are influenced by surface grade—for example, walking uphill is far more taxing

on the body. For healthy adults (with great heterogeneity across the age range), some highly active individuals with the lowest mortality have a step count greater than 12,500.¹⁰

Translating physical activity, including walking, into an empirically verified measure of an individual’s health benefit has been well established in the scientific literature.¹¹ Moderate walking (30 minutes per day most days) reduces the risk of all-cause mortality by 27 percent (risk ratio = 0.73), and vigorous walking (20 minutes per day three times a week) lowers the risk of all-cause mortality by 32 percent (risk ratio = 0.68).¹² These results reveal that walking farther in a shorter period of time (greater exertion) correlates with lower mortality. This benefit, however, peaks at about 4 miles.

One way to translate daily step count from a wearable sensor into an empirically verified health benefit metric is to first translate the level of physical activity into walking speed, then convert walking speed into calories burned, and finally convert calories burned into an operationally defined physical activity measure that can be scientifically linked to observed mortality risk.

Linking physical activity to walking speed

Physical activity can be categorized in many ways—for example, as **Table 1** shows, according to frequency and intensity. Here we focus on walking speed, which typically ranges from 3.1 to 5.6 mph; beyond that speed is a transition into running. This range can be partitioned to define three levels of physical activity: *some*, 3.10–3.93 mph; *moderate*, 3.94–4.77 mph; and *vigorous*, 4.77–5.60 mph. It is also possible to generate fairly precise estimates of walking distance as a function of time traveled, step count, self-reported height, and correlated step length as a function of height. For example, a person who is 5'7" has a typical stride length of 27.5 inches; a person of this height would therefore take 2,307 steps to travel one mile, and 10,000 steps by this person would translate into a distance traveled of 4.33 miles.

Table 1. Operational definitions of different physical activity levels.

Activity level	Definition	Examples
None	Sedentary	Sitting at a desk; conversing with friends; traveling in a car, bus, or train; reading; playing cards; watching TV; using a computer
Some	Activities two or more times per week involving at least 10 minutes of physical exercise that cause a slight increase in breathing or heart rate	Light walking
Moderate	Activities three or more times per week involving at least 15 minutes of physical exercise that cause light sweating and a slight to moderate increase in breathing or heart rate	Brisk walking, bicycling for pleasure, golf, gardening, dancing
Moderate/vigorous	Activities two or more times per week involving at least 20 minutes of continuous cardiovascular exercise that cause heavy sweating and/or large increases in breathing or heart rate	Running, lap swimming, aerobics classes, fast cycling
Vigorous	Activities three or more times per week involving at least 20 minutes of continuous cardiovascular exercise that cause heavy sweating and/or or large	Running, lap swimming, aerobics classes, fast cycling

	increases in breathing or heart rate	
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Converting walking speed into calories burned

The number of calories burned (CB) while walking is a function of walking speed, weight, surface grade, and time spent walking (www.shapesense.com/fitness-exercise/calculators/walking-calorie-burn-calculator.shtml). Assuming a 0 percent surface grade,

$$CB = [0.0215 \times KPH^3 - 0.1765 \times KPH^2 + 0.8710 \times KPH + 1.4577] \times (WKG \times T),$$

where *KPH* is walking speed in kilometers per hour, *WKG* is weight in kilograms, and *T* is time in hours. The CB formula varies as a function of surface grade ranging from -5 percent to +5 percent, and another formula applies to grades ranging from +6 percent to +15 percent. Many step counters have the capacity to measure average grade of surface traveled during a day.

Converting calories burned into mortality risk

Health scientists have developed various mathematical models to associate mortality risk with physical activity. Using “life tables” that estimate how long a typical person of a given age, gender, and with basic measurable physical characteristics (weight, height, and so on) will live based on actuarial and demographic data, they can help people improve their mortality risk profile by measuring and incorporating data related to exercise and other behaviors. These same quantitative models can be applied to wearable sensor data to determine the decreased risk of mortality from walking, running, and other activities.

To illustrate how a measured level of physical activity from sensor data can be converted into health and longevity metrics, consider the example of a 65-year-old US male who is 5'7" and weighs 175 pounds. As Table 2 shows, the medical literature indicates that a male of this age walking at a vigorous pace of 4 mph (2,046 steps/mile) would travel 1 mile in about 15 minutes and burn 109 calories, reducing his risk of mortality by 33 percent if done consistently over a period of time; if the same person walked at 3 mph (2,112 steps/mile) for 20 minutes, he would burn about 105 calories and reduce his risk of mortality by 27 percent.¹² The frame of reference in both cases is a walking speed of 1 mph. The key point is that step counts uploaded daily from a wearable device can be converted into reliable long-term assessments of an individual’s health and longevity. Aggregating such data from millions of device users could lead to a gold standard for such metrics.

Table 2. Relative risk of mortality for a 65-year-old US male who is 5'7" and weighs 175 pounds as a function of step count and walking speed.

Activity level	Walking speed (mph)	Mile time (min)	Stride length	Steps/mile	Calories burned	Calories/step	Relative risk
Minimal	1.0	60	2.17' (26.0")	2,433	198	0.0814	1.00
	1.5	40	2.25' (27.0")	2,347	150	0.0639	1.00
Some	2.0	30	2.29' (27.5")	2,306	125	0.0542	0.81
	2.5	24	2.33' (28.0")	2,266	111	0.0490	0.81
Moderate	3.0	20	2.42' (29.0")	2,182	105	0.0481	0.73
	3.5	17	2.50' (30.0")	2,112	105	0.0497	0.73
Vigorous	4.0	15	2.58' (31.0")	2,046	109	0.0533	0.67

Table adapted from M.F. Leitzmann et al., “Physical Activity Recommendations and Decreased Risk of Mortality,” *Archives of Internal Medicine*, vol. 167, no. 22, 2007, pp. 2453–2460.

Toward a Health Data Economy

The proliferation of passively generated, real-time wearable sensor data opens the door to development of a *health data economy* that will offer consumers novel benefits derived from such data. Here we discuss a few examples of Lapetus-initiated efforts in this area.

Leveraging step-count data

Consider the use of a personal step counter as a self-motivation tool to improve one's health. Instead of simply monitoring the daily number of steps taken and congratulating you upon reaching some target, the device could provide more useful feedback—namely, specific health and longevity metrics directly associated with the steps taken. For instance, the 65-year-old male in the example above would not only receive daily updates of his step count but would also be informed that maintaining vigorous physical activity would reduce his risk of death by 33 percent and increase the probability of living an additional year by 25 percent. In addition to encouraging users to adopt a healthier lifestyle, such information could be used in planning for retirement and deciding whether to purchase long-term care insurance and an optimal age for doing so.

Longitudinal individual health data

Annual personal physicals, also known as physical health evaluations (PHEs), typically include the collection of blood and urine for analysis. These in-depth laboratory-screening procedures detect potentially serious medical conditions that patients can be unaware of, improve delivery of preventive services, and reduce patient worry. While extremely valuable, such assessments are only a snapshot of conditions within the body at a single moment. As such, they are ephemeral and impacted by behavioral and environmental conditions that existed at or just prior to the time the samples were collected.

What these tests fail to reveal is how patients have actually lived their life since the previous physical. Did they exercise regularly? Was their sleep pattern consistent and normal for someone their age? Did they experience periods of inactivity due to an illness or injury? Did their blood sugar or blood pressure ever fluctuate into an unhealthy range? By supplementing lab results with personalized longitudinal data obtained from wearable sensors, physicians would have a much fuller picture of their patients' current health status.

The process might work as follows. Your physician provides you with a wearable device, or you obtain one of many over-the-counter devices recommended for the same purpose, and register it online with the medical practice. The daily data generated by the device to help you monitor your health status or use as a motivational tool to enhance fitness is automatically uploaded to a longitudinal health database maintained by the practice for subsequent analysis.

Longitudinal health data is the gold standard for understanding and evaluating the relationship between various behavioral and environmental risk factors and health. Data from wearable devices can be used to generate charts that track all sorts of health barometers across time—sleep/wake patterns, blood pressure, blood sugar, physical activity, periods of sedentary behavior, and so on.

Figure 1. Hypothetical health chart showing sleep patterns and blood-glucose levels obtained from wearable sensors over a year. Such a chart can give a personal physician insight into hard-to-detect factors contributing to a patient's health problems.

Figure 1 is a hypothetical example of a patient's health chart showing hours of sleep and blood-glucose levels over a year. Such a chart provides a previously unseen look at the patient's overall health since the last annual physical and could prompt the physician to ask the patient during the personal health evaluation, for example, what caused an abnormal sleep pattern in February or why average blood-sugar levels rose to dangerous levels in June and July. With such data, the physician has a much better understanding of hard-to-detect factors contributing to potential health problems in the patient.

Longitudinal crowdsourced health data

Crowdsourced, or participatory, health studies¹³ draw on data from social health networks such as PatientsLikeMe, smartphone health applications, wearable devices that collect health data, and companies that compile health data in different forms and for different purposes such as 23andMe, Quantified Self, and Genomera. The scientific vigor of crowdsourced health research varies widely, but it is clear that a new kind of research paradigm is emerging

based on alternative sources of health data that citizen scientists and trained researchers alike are only now beginning to grasp.¹⁴

One way to ensure progress in this area is to create a longitudinal crowdsourced health database containing freely available anonymized data that meets well-defined standards. This would not only engage the public to accelerate health research, it would also create novel and innovative approaches to improving both individual and overall public health.

BLISS: Better Life and Income Scoring System

It is possible to unite personal health data with other numerically defined attributes, such as net worth and education level, to generate a more complete metric of an individual's relative risk than the FICO score and other credit risk metrics, which are limited to economic measures such as payment history and debt burden. Toward this end, Lapetus is launching the Better Life and Income Scoring System. BLISS weights and combines key financial indicators with longitudinal individual and crowdsourced health data, some of it derived from wearable sensors, to create a single, empirically verified metric—a BLISS score—ranging from 100 to 1,000. A higher BLISS score positively correlates with superior health *and* lower financial risk.

A BLISS score would provide health and life insurance companies with a new, independently verified measure of risk to assess applicants as well as enable consumers to obtain the most favorable pricing for existing or future insurance—a win-win for the insurance industry. In addition, by yielding the most advanced estimates of health and longevity currently available, a BLISS score would give financial planners the ability to fine-tune a retirement plan to an individual's or family's unique attributes. Instead of relying on clients to determine how many years they expect to live in retirement—something most people simply cannot reliably answer—they could use the BLISS score to create a scientifically based plan. Long-term care insurance might not make sense for those with a high estimate of healthy life expectancy, while others' family history might suggest a high probability that such care will be needed.

We foresee the BLISS score becoming the basis of new forms of commerce in the coming health data economy. For example, health and life insurance companies could build different plans around various BLISS score ranges, while enterprises that aim to improve health, physical fitness, and financial well-being might target those with low or middle-range scores. In addition, companies might emerge to facilitate the collection of health data used to compute BLISS scores—for example, to pay consumers to register their wearable devices with them—as well as to develop novel types of sensors.

Wearable devices are being developed at breathtaking speed. The range of physiological attributes and bodily functions that such devices can monitor accurately and in real time is continually expanding, and it is only a matter of time before sensors are routinely implanted within our bodies—temporarily, or perhaps even permanently, becoming part of our identity. While it is impossible to predict which devices, applications, and data aggregation companies will ultimately triumph in the marketplace, the emergence of a new health data economy driven by the flood of data from body area networks seems inevitable.

Sensors can now be plugged into a car to collect data on personal driving habits, enabling auto insurance companies to adjust premiums according to actual behind-the-wheel behavior instead of relying on actuarial data and rare events involving customers such as collisions and traffic citations. This technological advance benefits everyone: those who routinely drive safely are rewarded with lower premiums, auto insurance companies can create more equitable policies, and car manufacturers gain insights that can lead to vehicle safety and performance improvements.

We believe that smart health technologies will evolve along a similar path. People will learn more about their health and be educated on how to take better care of their own body; they will be motivated to do so not just through feel-good rewards but by meaningful financial incentives such as lower insurance premiums. Longitudinal data obtained from wearable and in-body sensors will likely lead to medical breakthroughs that improve individual as well as public health outcomes, reduce healthcare costs, extend longevity and enhance the quality of life, and engender new types of health data commerce. Issues of data privacy will no doubt arise with a health data economy: consumers should always be able to opt out and, more importantly, own their data—making it available to third parties only with permission.

The wearable device revolution is coming, and it will help launch a new era in public health and e-commerce that will benefit consumers and companies alike. It will be exciting to see how this revolution in health

empowerment evolves over the coming years.

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S. Jay Olshansky is the chief scientist of Lapetus Solutions and a professor in the School of Public Health at the University of Illinois at Chicago. A cofounder of the field of the biodemography of aging, he researches longevity forecasting and ways to slow human aging. Olshansky received a PhD in sociology from the University of Chicago. He is on the editorial board of numerous scientific journals and the board of directors of the American Federation for Aging Research, and is a Fellow of the Gerontological Society of America. Contact him at jay@lapatusolutions.com.

Bruce A. Carnes is a senior scientist at Lapetus Solutions and an emeritus professor in the Donald W. Reynolds Department of Geriatric Medicine at the University of Oklahoma Health Sciences Center. A cofounder of the field of the biodemography of aging, he uses statistics to explore the factors that influence longevity as well as their relative importance, and to estimate upper limits for both the longevity of individuals and the life expectancy of populations. Carnes received an MS in population biology from the University of Houston and an MS in statistics

and a PhD in theoretical ecology from the University of Kansas. An author of more than 150 academic papers and numerous book chapters and books, he is a member of the American Association for the Advancement of Science, the Gerontological Society of America, and Sigma Xi. Contact him at bruce@lapetussolutions.com.

Yang Claire Yang is a senior scientist at Lapetus Solutions and a professor in the Department of Sociology and the Lineberger Comprehensive Cancer Center at the University of North Carolina at Chapel Hill (UNC). She specializes in the biodemography of aging, medical sociology, cancer epidemiology, social disparities in health, and quantitative methodology. Yang received an MS in statistics and a PhD in sociology from Duke University. She is a Faculty Fellow of UNC's Carolina Population Center and a member of the American Sociological Association, and has served on the editorial board of many social science journals as well as on the board of directors of the Population Association of America. Contact her at claire@lapetussolutions.com.

Norvell Miller is the president and chief business officer of Lapetus Solutions. A chartered financial analyst, he is the managing general partner of SEInteractive, a general partner of Covestco Seteura, and the managing director of EMS Financial. Miller currently serves or has served on the boards of several privately held companies including Allconnect, Arsenal Digital Solutions, BuildLinks, the MediaSpan Group, Pixel Magic Imaging, and VisionAIR. Previously, he cofounded and worked with numerous growth companies including DentalCare Partners, the Mobius Group, and Affordable Care. Miller received an MBA from Duke University. Contact him at norvell@lapetussolutions.com.

Janet Anderson is the chief marketing officer of Lapetus Solutions. She has more than 25 years of international sales and marketing experience in Europe, Latin America, and North America. Anderson spent most of her career with AEGON, one of the world's largest insurance companies, and most recently served with ReMark, a subsidiary of SCOR, as CEO of their North and Latin American business. Anderson received an executive MBA with an emphasis on international business from Loyola University Maryland. Contact her at janet@lapetussolutions.com.

Hiram Beltrán-Sánchez is a senior scientist at Lapetus Solutions and an assistant professor in the Department of Community Health Sciences at the Fielding School of Public Health at the University of California, Los Angeles, where he is also a researcher at the California Center for Population Research. His research interests include the demography of health and aging, with a particular focus on Latin American countries; biodemographic patterns of health in adult populations; and the development and application of demographic methods to investigate health inequalities. Beltrán-Sánchez received a BS in actuarial sciences from Universidad Nacional Autónoma de México, an MS in mathematics from Northern Arizona University, and a PhD in demography from the University of Pennsylvania. He has published numerous articles on health and aging and collaborated with researchers and institutions around the world. Beltrán-Sánchez cofounded the Latin American Mortality Database, the largest data repository of mortality from 19 countries in Latin America. Contact him at hiram@lapetussolutions.com.

Karl Ricanek Jr. is the CIO and chief data scientist of Lapetus Solutions and a professor in the Department of Computer Science at the University of North Carolina Wilmington (UNCW). A leading expert on facial analytics and facial recognition, he is director of the UNCW Institute for Interdisciplinary Identity Sciences (I3S) and founded its world-renowned Face Aging Group research lab. Ricanek has authored more than 80 scientific articles and multiple book chapters in the areas of machine learning, face recognition, and facial analytics; is affiliated with multiple international scientific working groups on these subjects; and holds numerous patents. He received a PhD in electrical engineering from North Carolina A&T State University. Ricanek is a Senior Member of IEEE and a member of ACM and Intelligence Advanced Research Projects Activity (IARPA). Contact him at karl@lapetussolutions.com.