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Computer

QUALITY-OF-LIFE TECHNOLOGIES

Enterprise IT Standards, p. 70

Truth in Timestamping, p. 78

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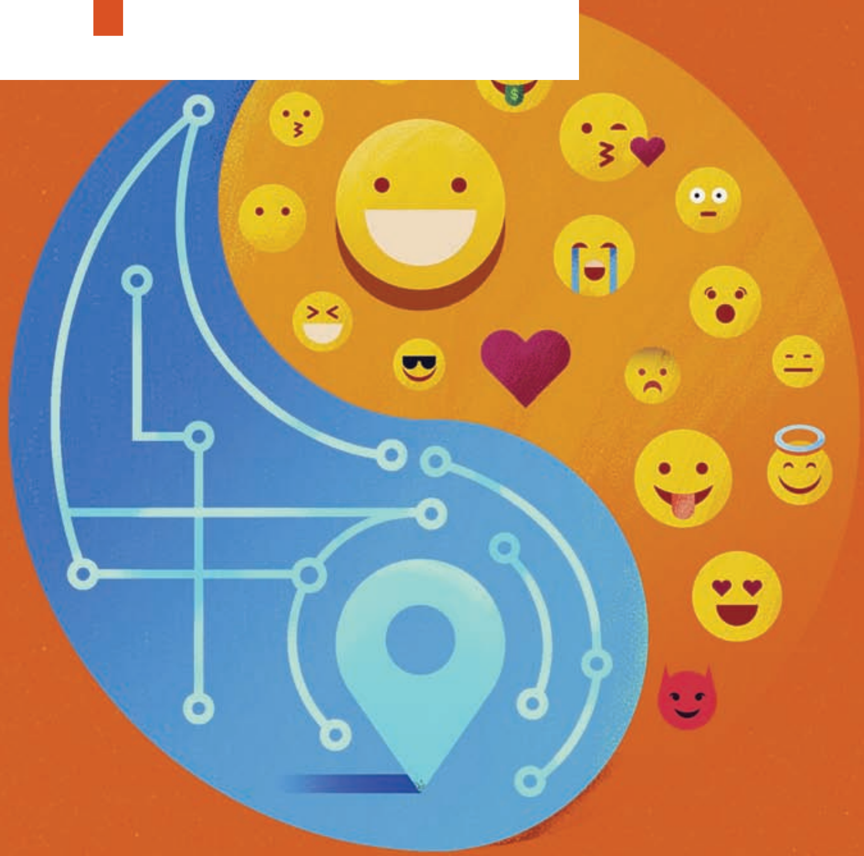

MARCH 2017
FEATURES

MARCH 2017

CONTENTS

ABOUT THIS ISSUE

QUALITY-OF-LIFE TECHNOLOGIES

The world of QoL technologies promises improved health and wellness, while presenting serious challenges for technologists.

FEATURES CONTINUED

RESEARCH FEATURE

COLUMNS

Membership News

Departments

See **www.computer.org/computer-multimedia** for multimedia content related to the features in this issue

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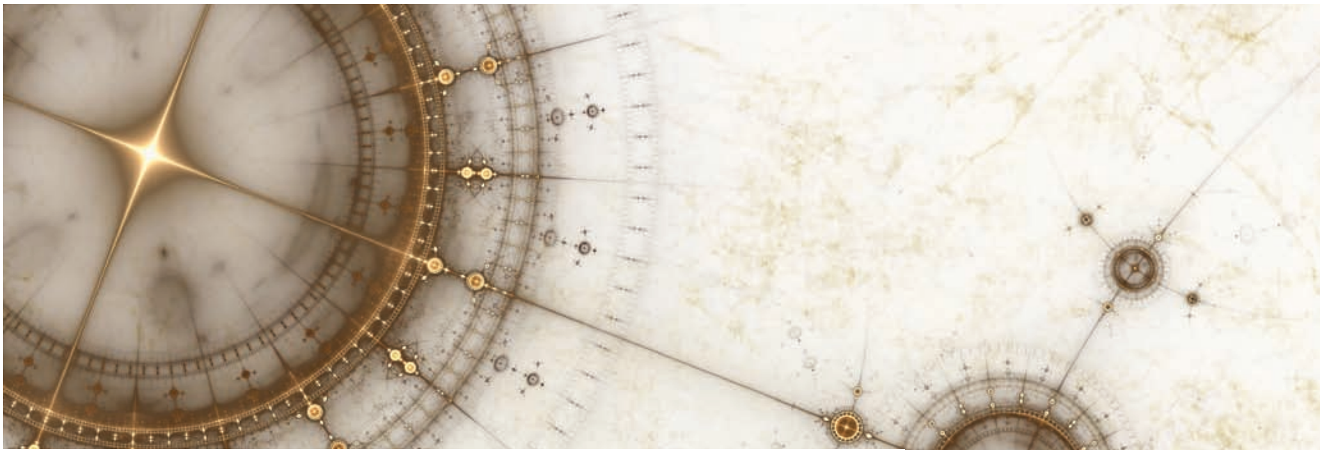


When the Field Was Young

David Alan Grier, George Washington University

The 1970s were a time of great expansion and great disruption in the world of computing—both of which can be seen in the early pages of Computer.

When the IEEE Computer Society (CS) was born on 31 December 1970, *Computer* was a young publication in a young field, and it was the product of a young organization—the Society's predecessor, the IEEE Computer Group. The president of the freshly franchised Society wrote that the time was right for looking back on the accomplishments of the founding IEEE Computer Group before "we start 1971 as the IEEE Computer Society."

The CS was a radical expansion for its parent organization, IEEE, as it accepted "computer professionals who may not be engineers" as members. The new Society assured the IEEE leadership, who were somewhat anxious about the nature of these new professionals, that "suitable professional qualifications will be required of such individuals." At the time, however, these qualifications weren't easily defined. If anything, the CS seemed willing to accept members from a wide variety of backgrounds. As the decade unfolded, CS leadership began to discover the common traits of computer professionals, and the pages of *Computer* began to describe the nature of those traits.

In 1971, computing was about to be radically changed by a new technology, the microprocessor, which was implemented in a large-scale integrated (LSI) circuit. "Microprocessors are 'relatively new,'" wrote Theodore Laliotis in a 1974 issue of *Computer*. "They are the one component with the most far-reaching implications, for future developments in digital systems since the transistor." But the article understated the impact of the microprocessor. Intel announced its first commercial microprocessor, the 4004, in November 1971. Within four years, these chips formed the basis of a desktop computer for hobbyists, the Altair 8800. Three years later, they were used to produce a personal business computer—the Apple II.

While the microprocessor was pushing computing in one direction, software was pushing it another. During the early 1970s, software developers started recognizing that they were unable to produce error-free software.

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They simply didn't have the software engineering tools to help them manage and develop high-quality software. Through much of the early 1970s, software engineers discussed the nature of their field in the pages of *Computer*. These articles discussed the role of standards, managerial procedures, and common components like libraries.

The year 1976 marked the 30th anniversary of the electronic computer, which suggested to a number of *Computer* contributors that the time had come to assess the state of computing. This group included several people who would eventually become editors of CS periodicals or leaders of the Society itself. They met at a workshop in Portland and produced a document they called the Oregon Report. One author explained that it was an "analysis of problems being created for the 1980s by the events of the late 1970s."

Another group member said that the "microcomputer revolution started with the great hope that a standard LSI chip set would become the standard programmable logic element. Those who held this hope thought that the microcomputer was so versatile that it was just 'a small matter of programming' to serve any of a broad range of applications." Woefully, he observed that this "view has proven to be far too limited."

The series of articles on the report—covering topics from LSI chips to software engineering, databases, computer architecture, and education—appeared in the 1978 issues of *Computer*. The articles were less a prediction of the future than an assessment of the state of the field, recognizing that the birth of the CS coincided with a shift in the nature of computing. The professionals who were making the most valuable contributions to the field were those who were trained on mini- and microcomputers. The report also recognized the central role of software and the need to make it reliable: "Software failure can—and does—cause large-scale financial and social loss."

The Oregon Report also considered the problem that had been present since the birth of the CS: the qualifications of a computing professional. The problem, it argued, began with computing education. "In far too many situations, the student is placed in a position of having to choose between a computer science or computer engineering curriculum"—neither of which they saw as a perfect preparation. As a result, the report read, the "student ventures into industry ill-prepared for the challenges" that he or she will meet.

Yet, articles surrounding this report suggested that CS members were starting to understand the qualifications of a computing professional. An article on the new IEEE standard on software quality assurance argued that professional software engineers needed to follow well-designed procedures to avoid errors. Another article on floating-point arithmetic showed that the computing field was becoming less tolerant of diversity. For 30 years, each brand of computer handled floating-point arithmetic in its own way. As the decade drew to a close, *Computer* argued these different forms of floating-point numbers with a single IEEE standard. A final article—and one of the last *Computer* articles of the 1970s—on the game *Zork* showed that computing professionals could be both highly creative and very clever when building systems.

The 1970s were a time of great expansion and great disruption in the world of computing. *Computer*, like the CS itself, had tracked both dynamics of the field and was starting to identify the qualities that the field and its professionals would need to advance.

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ELSEWHERE IN THE CS

EDITOR LEE GARBER
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Computer Highlights Society Magazines

The IEEE Computer Society's 13 peer-reviewed technical magazines cover cutting-edge computing topics including scientific applications, Internet computing, machine intelligence, pervasive computing, security and privacy, digital graphics, cloud computing, and computer history. Here, we highlight recent issues of other Computer Society magazines.

IEEE Software

No consolidated set of software engineering best practices for the Internet of Things (IoT) has yet emerged. Too often, unprepared programmers develop IoT systems in an ad hoc fashion and release them into the marketplace, often without proper testing. *IEEE Software*'s January/February 2017 special issue aims to provide the basis for a set of best practices that will guide the industry through the challenges of **software engineering for the IoT**.

IEEE Internet Computing

Intelligent user interfaces can enable a high-quality, contextually relevant user experience but can also cause privacy-related problems. The authors of "**Privacy Risks in Intelligent User Interfaces**," from *IEEE Internet Computing*'s November/December 2016 issue, review some of the risks and potential mitigation measures.

IEEE Intelligent Systems

Rating prediction is the main form of information processing performed by recommender systems. "Influence of Rating Prediction on Group Recommendation's Accuracy," from *IEEE Intelligent Systems*' November/December 2016 issue, addresses the problem of predicting ratings by analyzing how system accuracy is influenced by the choice of prediction method and by the use of predicted values in cases where there is a shortage of relevant data. The article's authors found that predicting the ratings for individual users instead of for groups yields better results.

Computing in Science & Engineering

As we enter the Internet of Things era, in which lightweight mobile devices become our main online terminals, **transparent computing** presents both opportunities and challenges. *CiSE*'s January/February 2017 special issue highlights this new paradigm.

IEEE Security & Privacy

The authors of "The Outcomes of **Cybersecurity Competitions** and Implications for Underrepresented Populations," from *IEEE S&P*'s November/December 2016 issue, consider how these contests could increase student awareness of cybersecurity careers. The article focuses on gifted students and females, as well as low-income and high-risk groups.

IEEE Cloud Computing

The articles in *IEEE Cloud Computing*'s November/December 2016 special issue on **using the cloud to enhance living environments** discuss several projects designed to achieve that goal, including an Internet of Things architecture, a large-scale service framework, secure and resilient cloud services, and a fog-based emergency system.

IEEE Computer Graphics and Applications

CG&A's January/February 2017 special issue on **water, sky, and the human element** includes articles on a natural interface for underwater robots' remote operation, decision support for a sustainable water-distribution system, the real-time visual tracking of deformable objects in robot-assisted surgery, and a machine-learning-driven sky-illumination model.

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IEEE MultiMedia

The EU is funding work designed to create a framework that will help users without fine motor skills interact naturally with multimedia. As part of this project, the authors of "**Eye-Controlled Interfaces** for Multimedia Interaction," from *IEEE MultiMedia*'s October–December 2016 issue, developed a gaze-based control paradigm. In the article, they address the challenges they faced and present initial project results.

IEEE Annals of the History of Computing

The authors of "The Dawn of Digital Light," from *IEEE Annals*' October–December 2016 issue, say the first digital images—still photos, video games, and computer animations—were made on early computers in the late 1940s and early 1950s. This fresh perspective on digital pictures establishes a different take on the history of early computers and unifies **the history of digital images**.

IEEE pervasive COMPUTING

Initial **drone research** was mostly concerned with improving technical capabilities, such as battery life and flight accuracy. More recent research investigates how drones can support existing application domains and even create new ones. *IEEE Pervasive Computing*'s January–March 2017 special issue discusses this more recent work. In addition, instead of looking at the type of large drones used by the military, the issue focuses on smaller drones that fly at lower altitudes, which could play a more significant role in pervasive applications.

IT Professional

Information and communications technology (ICT) environments have dramatically changed. They now include complex distributed architectures and mission-critical services and applications. However, determining whether these services and applications are correctly coded against attacks and other problems can be difficult. In "**Practical Correctness in ICT Environments**," from *IT Pro*'s November/December 2016 issue, the author examines this concern and presents possible solutions.

IEEE micro

To reach its potential, the Internet of Things must break down the silos that limit applications' interoperability and hinder their manageability. Doing so would enable the building of ultra-large-scale systems. To deal with the resulting complexity, the authors of "Emergent Behaviors in the Internet of Things: The Ultimate Ultra-Large-Scale System," which appears in *IEEE Micro*'s November/December 2016 issue, propose **hierarchical emergent behaviors**.

50 & 25 YEARS AGO

EDITOR **ERICH NEUHOLD**
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MARCH 1967

The Maintainability Factor in System Design (p. 1) "We have been searching for those facets of the physical system implementation which will have the greatest effect on improved system maintenance and the least effect on classical system design factors such as cost, size, speed, etc. Two appear to be dominant. One is the inclusion of a read-only memory (ROM); the other is the use of a molecule (major board) as large as possible given other non-maintainability considerations. [For the ROM:] The regularity of structure and simplicity of construction, coupled with the minimal mutual interaction of its ancillary active components (i.e., drivers and sense amplifiers), make the memory particularly easy to check, test, and diagnose with a minimum of additional diagnostic hardware. [For the major board:] Once replaced with an appropriate spare, the faulty element is diagnosed offline on a special-purpose, computer-controlled device."

Chairman's Letter (p. 2) "The 31 December 1966 membership count for the Computer Group showed 9,701 members in grades other than students; 1,203 students (at the discounted rate of $1); 232 students at the regular rate; and 89 affiliates for a grand total of 11,225. This is the first penetration of the 11,000 level by any Group. Congratulations!"

Criteria for Assessing the Reliability of Total Computer Systems (p. 9) "To achieve a minimum overall cost-of-ownership, studies of many indices of utility and cost must be performed. Calculated tradeoffs such as original cost, spares and logistics costs, maintenance costs, consequences and costs of downtime, maintainability, and reliability figures-of-merit, etc., must be made to achieve the optimum balance between utility and cost."

1967 McDowell Award to J.W. Backus (p. 11) "John W. Backus, IBM Fellow, has been named as recipient of the 1967 W.W. McDowell Award of the IEEE Computer Group, it was announced by the Computer Group Awards Committee. The award, the second in an annual series, will be presented to Mr. Backus at the Spring Joint Computer Conference."

A Workshop on Multiprogramming (p. 12) "One question alone—How much of the implementation is by hardware and how much is by software?—appears to have as many answers as there were people present. … The only agreement reached on the problem of resource allocation is that the problem is difficult and warrants much further study." [*Editor's note: It's interesting to note that a debate occurring 50 years ago about the balance among hardware, firmware, and software support for multiprogramming is still going on today regarding multicore, multithread programming.*]

MARCH 1992

www.computer.org/csdl/mags/co/1992/03/index.html

Computer Society Message (p. 4) "The society has over 100,000 members. It is the largest society of computer professionals in the world, and by far the largest constituent society within the IEEE." [*Editor's note: The Computer Society had 32 technical committees in 1992. This fact, together with the membership numbers in the 1967 Chairman's Letter, shows that the Computer Society has maintained its position in the world of computer professionals.*]

The Usability Engineering Lifecycle (p. 12) "The model presented here is a modified and extended version of Gould and Lewis' 'golden rules': early focus on users, user participation in the design, coordination of the different parts of the user interface, [and] empirical user testing and iterative revision of designs based on the test results. … Usability heuristics [include] use simple and natural dialogue; speak the user's language; minimize user memory load; be consistent; provide feedback; provide clearly marked exits; provide shortcuts; provide good error messages; [and] prevent

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errors. … The top six methods according to rated impact on usability are (1–2) iterative design and task analysis of the user's current task, (3) empirical testing with real users as subjects, (4) participatory design, [and] (5–6) visit to customer location before start of design and field study visits to customers."

SoundWorks: An Object-Oriented Distributed System for Digital Sound (p. 25) "The field of computer-based music encompasses issues in music composition, synthesis, manipulation, and performance. Here we address the manipulation and synthesis of sounds. Our primary goal in this work was to provide standard sound manipulation (or editing) features like splicing, looping, and mixing."

Mediators in the Architecture of Future Information Systems (p. 44) "A mediator is a software module that exploits encoded knowledge about certain sets or subsets of data [for example, from databases] to create information for a higher layer of applications [for example, decision making]. We place the same requirements on a mediation module that we place on any software module: It should be small and simple so that it can be maintained by one expert or, at most, by a small and coherent group of experts."

Taxonomy and Current Issues in Multidatabase Systems (p. 50) "Multidatabases are an important area of current research, as evidenced by the number of projects in both academia and industry. The trade press has also documented the need for user-friendly global information sharing. The next level of computerization will be distributed global systems that can share information from all participating sites. Multidatabases are a key component of this advancing technology. … [Classes within the] taxonomy of global information-sharing systems [are] distributed database, global schema multidatabase, federated database, multidatabase language system, homogeneous multidatabase language system, [and] interoperable systems."

The Stanford DASH Multiprocessor (p. 63) "Directory-based cache coherence gives DASH the ease-of-use of shared-memory architectures while maintaining the scalability of message-passing machines." [*Editor's note: Stanford DASH was the first operational machine to include scalable cache coherence*.]

Boehm Outlines DoD Software Technology Strategy (p. 103) "[Barry] Boehm said this goal means that a typical system or upgrade started in the year 2000 would cost half as much as the same capability would cost using 1992 technology and practices. As director of the Software and Intelligent Systems Technology Office of the Defense Advanced Research Projects Agency, Boehm had a large part in drafting the 400-page Software Technology Strategy report on which he based his speech." C

SPOTLIGHT ON TRANSACTIONS

Persistent Memory

This installment of Computer's series highlighting the work published in IEEE Computer Society journals comes from Computer Architecture Letters.

Daniel J. Sorin, Duke University

Nonvolatile memory (NVM) technologies—particularly storage class memory (SCM)—offer computer architects exciting new opportunities. Unlike more traditional storage such as hard disks or solid-state drives (SSDs), SCM uses a well-known interface that allows architects to read and write at byte-level granularity. SCM can serve in many roles: as a main memory replacement for DRAM, a new level in the memory hierarchy between the main memory (DRAM) and disk (either hard disk or SSD), or an independent memory region that operates in parallel with the DRAM and disk.

But along with persistent memory's opportunities come challenges. How does one synchronize accesses to volatile and nonvolatile memory? How does one provide atomic semantics for groups of accesses? And, paramount for architects, how does one do all of this efficiently and while placing minimal burden on the programmer?

Libei Pu and her colleagues explore such challenges in "Non-Intrusive Persistence with a Backend NVM Controller" (*Computer Architecture Letters*, vol. 15, no. 1, 2016, pp. 29–32). Through a remarkably simple example—a programmer wishes to write to three variables atomically (either all writes succeed or none)—the authors highlight the ordering and atomicity problems that can arise. What if some, but not all, of the writes have propagated to persistent memory when power fails? How does a core find the most recent copy of a piece of data in a complicated memory hierarchy that includes SCM?

Synthesizing the key innovations of various proposed SCM designs, Pu and her colleagues present an elegant solution for a system in which SCM is the main memory replacement. Programmers simply annotate the regions of code they wish to be atomic and their new NVM controller ensures that accesses obtain the most recently written values, even if those writes haven't propagated to the SCM. It isn't yet clear whether an all-hardware or a hybrid hardware–firmware solution for the NVM controller is more appropriate; architects and systems designers will likely debate this and other design decisions in the near future.

This is an exciting time for computer architects, with many new memory technologies emerging after years of being restricted to SRAM for caches, DRAM for memory, and hard disks for storage. One of these technologies' most promising aspects is nonvolatility. Pu and her colleagues' paper nicely illustrates some of the challenges—and possible solutions—for architects seeking to incorporate NVM into their systems.

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Quality-of-Life Technologies

Katarzyna Wac, University of Geneva and University of Copenhagen

Homero Rivas, Stanford University

Maddalena Fiordelli, University of Lugano

As we embrace personal digital health technology applications, computing power is increasingly exploited for its capacity to improve our quality of life (QoL). Beyond wearables that capture and transmit our vitals, QoL technologies present a variety of opportunities for extending the human health span—not just how long we live, but how well we are.

See **www.computer.org/computer-multimedia** for multimedia content related to this article.

Powerful, personalized, and miniaturized computing technologies and their applications have markedly improved our quality of life (QoL). Yet, even as they enhance the understanding of and ability to improve our everyday physical and psychological health, social interactions, environmental conditions, and decision making, the causality between the technologies and individual QoL gains is not straightforward. In addition, as is often the case, these new innovations raise many new social, design, economic, and legal challenges that must be addressed before the emerging QoL-enabled and -driven computing paradigm can become efficient, effective, and widely adopted.

Emerging Internet technologies and computing services are now an indispensable part of our lives, supporting our need for information, communication, and entertainment—anywhere, anytime, and anyhow. We have observed a shift in use of these services and technologies from a passive style to one that is more mobile, interactive, and real-time. These services have significantly improved our capacity to make informed decisions about our everyday activities, which has a particular impact on our physical and psychological health, social interactions, and environment.

Overall, the ways we use and experience these services on a growing scale contribute to our QoL. According to the World Health Organization (WHO), QoL refers to "individual[s'] perception[s] of their position in life in the context of the culture and value systems in which they live and in relation to their goals, expectations, standards, and concerns" (www.who.int/healthinfo/survey/whoqol-qualityoflife/en; 1995). The WHO has also defined an assessment scale called WHOQOL that assesses an individual's QoL across four domains: physical health, psychological health, social relationships, and environment, as well as 24 subdomains (see Table 1).

The QoL subdomains cover both subjective and objective aspects of life. They are collectively exhaustive, mutually nonexclusive, and potentially correlated; for example, there is an influence of noise—an environmental aspect—on an individual's sleep and rest, which is a physical health aspect. Of course, overall health is an aspect of the individual's life that spans all QoL domains.

We define QoL technology research—the focus of this special issue—as fundamental information and communication technologies (ICT) research that leverages methods, models, algorithms, and services. To that end, research enables the identification of a specific individual's QoL needs as well as the design of ICT-based solutions to address a range of challenges, thus improving the individual's QoL across multiple domains. Delivery of QoL technologies to users can be in fixed services, but is increasingly mobile.

However, the effectiveness of ICT relies on heterogeneous technologies and computing services, as well as our understanding of the implications of various decisions made by Internet technologies, service architects, designers, and developers on users' QoL. Although some QoL technologies improve mobility and support the everyday activities of those with disabilities or sensory impairment, the impact of these technologies on the general population is less well known. As a result, research challenges and opportunities continue to be identified and studied, including in this special issue.

AS OUR UNDERSTANDING OF QoL TECHNOLOGIES' IMPACT IMPROVES, THEIR USE WILL LIKELY EXPAND INTO MANY AREAS OF HUMAN ACTIVITY.

IN THIS ISSUE

In "Can Fitness Trackers Help Diabetic and Obese Users Make and Sustain Lifestyle Changes?," Mirana Randriambelonoro, Yu Chen, and Pearl Pu used longitudinal research methods to assess individuals' physical activity levels and whether the use of tracking devices led to sustainable behavior changes. The research presented expands our understanding of how environmental factors influence our level of physical activity—in this case, users' activity levels increase as a result of the device presenting information in a playful manner. The article represents QoL research within the "physical health" domain and the "activities of daily living" and "mobility" subdomains.

In “The Science of Sweet Dreams: Predicting Sleep Efficiency from Wearable Device Data,” Aarti Sathyanarayana, Jaideep Srivastava, and Luis Fernandez-Luque present hardware and software solutions that help generate an accurate sleep-quality assessment. With a wide array of sleep-monitoring applications and devices, our ability to collect data on sleep patterns using wearables is relatively well established. However, the data these technologies accumulate and how best to analyze them is still an area for exploration. The authors describe advanced modeling techniques and examine ways to benefit users in terms of interventions that could improve sleep efficacy through these QoL technologies. These results offer additional opportunities to improve QoL technologies in the “physical health” domain and the “sleep and rest” subdomain.

In “Are They Paying Attention? A Model-Based Method to Identify Individuals’ Mental States,” Tongda Zhang, Renate Fruchter, and Maria Frank describe a Mental Motion State Model that advances our ability to determine an individual’s mental state. The application of the described technique centers on fatigue, cognition, and engagement levels when study subjects are engaged in specific activities. The research falls under the domain area of “psychological health” and the “thinking, learning, memory, and concentration” QoL subdomain.

In “Using Multimodal Wearable Technology to Detect Conflict among Couples,” Adela C. Timmons, Theodora Chaspari, Sohyun C. Han, Laura Perrone, Shrikanth S. Narayanan, and Gayla Margolin present some initial results from a field study that utilizes mobile computing, sensing

BEYOND THE COVER

Guest editor Katarzyna Wac interviews authors Mirana Randriambelonoro, Aarti Sathyanarayana, Renate Fruchter, Adela Timmons, and Theodora Chaspari, whose research is featured in this issue. Listen to the interviews by visiting *Computer*’s multimedia page (www.computer.org/computer-multimedia) or the IEEE Computer Society YouTube channel (www.youtube.com/user/ieeeComputerSociety).

TABLE 1. Quality-of-life domains and subdomains based on the World Health Organization Quality of Life (WHOQOL) report.*

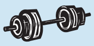
QoL domain	Facets incorporated within QoL domain
Physical health 	Activities of daily living Dependence on medicinal substances and medical aids Energy and fatigue Mobility Pain and discomfort Sleep and rest Work capacity
Psychological health 	Bodily image and appearance Negative feelings Positive feelings Self-esteem Spirituality/religion/personal beliefs Thinking, learning, memory, and concentration
Social relationships 	Personal relationships Social support Sexual activity
Environment 	Financial resources Freedom, physical safety, and security Health and social care: accessibility and quality Home environment Opportunities for acquiring new information and skills Participation in and opportunities for recreation/leisure activities Physical environment (pollution, noise, traffic, and climate) Transport

*Table is reprinted from K. Wac et al., “Quality of Life Technologies: Experiences from the Field and Key Challenges,” *IEEE Internet Computing*, vol. 19, no. 4, 2015, pp. 28–35; doi:10.1109/MIC.2015.52.

technologies, and real-time systems to determine an accurate assessment of individuals' psychological state, specifically in the context of romantic couples and the level of tension or conflict between partners. The authors collected data from wearable physiological sensors as well as individual self-reports on emotional state and reflections on recent interactions with their partners. The analysis of the data identifies some patterns in couples that could reveal opportunities to improve communication or mitigate conflicts. Such technologies contribute to the QoL research in the "social relationships" domain and the "personal relationships" subdomain in particular.

The research methods covered within these articles are nearly all quantitative—focusing on the technical requirements and speed, accuracy, dependability, and computational modeling complexity these QoL technologies offer in terms of reliable and timely individual state assessments. Additionally, Mirana Randriambelonoro and her colleagues describe qualitative methods through focus groups and interviews that enable data collection regarding an individual's perception and user experience while using QoL technologies for behavior change.

The articles in this special issue shed light on diverse challenges and opportunities in QoL technologies research and applications, and they help advance the QoL-driven computing paradigm in terms of improving efficiency, effectiveness, and efficaciousness. As QoL technologies are in their nascent stage, and as our understanding of their impact

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continues to improve, we expect that their use will expand into many areas of everyday human activity.

Thus, to succeed, future QoL technology research requires interdisciplinary efforts to ensure user-centric, holistic applications—including improvements in physical, psychological, social, and environmental aspects. As researchers better address challenges relating to infrastructure; human–computer interaction; ethics; privacy; trust; behavior economics; and the organizational, financial, environmental, and legal facets of developing, deploying, and using these technologies to the maximal benefit of individuals, the potential depth and breadth of QoL technologies' benefit to humanity will be astounding. For that reason, we see QoL technology research as a long-term endeavor, rather than one that is short-term or self-contained. Additionally, as these technologies advance and become widely adopted, our needs and expectations for their use will continue to change. C

Can Fitness Trackers Help Diabetic and Obese Users Make and Sustain Lifestyle Changes?

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Diabetic and obese users given a Fitbit fitness tracker for seven months identified the device's playfulness, practicality, persuasiveness, personalization, and privacy as the top motivators for its use. These results provide insights into designing wearable health monitors that are engaging enough to effect long-term change.

According to a World Health Organization (WHO) report on the global status of noncommunicable diseases in 2010, diabetes and obesity are among the diseases most responsible for worldwide mortality.[1] In response to the epidemic of diabetes in the past few decades, WHO has actively promoted healthy living through exercise and diet, which is less painful than surgical interventions such as gastric bypass surgery and less invasive than prescriptions that can have significant and sometimes dangerous side effects.

However, diet alone—which often involves restricting intake—can lead to a feeling of deprivation. Research on diabetes and obesity has shown that physical activity not only helps prevent diabetes and obesity but also assists in treatment. Combined with a healthy diet, regular physical activity at a certain level can control blood glucose, regulate blood pressure, prevent cardiovascular events, and elevate mood.

Unfortunately, developing ways to engage and motivate people to adopt a healthy behavior has proven more difficult than imagined, even with affordable wearable health trackers and creative companion applications. The sidebar "Empowering Users to Control Their Health" describes research to define device features that users find motivating enough to change their lifestyle.

See **www.computer.org/computer-multimedia** for multimedia content related to this article.

Despite the extensive research on pervasive fitness sensors and applications and how diabetic and obese users can benefit from them, motivational techniques for using this technology remain largely unexplored. Research is focusing instead on aspects such as self-monitoring glucose levels,[2] body weight, and food choices. Little work has been done to investigate how these technologies influence users' behavior and environment or how they can aid users with chronic diseases to change their lifestyle over the long term through solutions such as increased physical activity.

To address this lack of research, we conducted a study over seven months (December 2013 to June 2014) involving 18 individuals ages 36 to 73—all of whom were formally diagnosed with diabetes, obesity, or both. We gave each participant the Fitbit One fitness tracker (www.fitbit.com/us/one) and interviewed them before, during, and after the study to identify what they expected from the tracker, how the tracker influenced their lifestyle, and what was required for the technology to change their long-term health decisions. The seven-month study is an extension of a previous one-month study of behavioral change.[3]

Our second study gave us a deeper understanding of how fitness trackers can motivate diabetic and obese users to engage in more physical activity over the long term. We identified a set of requirements, which we evolved into recommendations for the design of wearable health trackers that aim to effect long-term lifestyle changes in their users' behavior.

STUDY METHODOLOGY

We recruited our 18 users from a primary healthcare center in a large city in Switzerland. Our study was endorsed by the center's ethical committee to protect patient safety and privacy. Users included 12 diabetics, 5 of whom were also obese, and 6 obese and overweight patients. Of the 18 users, 7 were male and 11 were female.

Over the seven months, we held three interviews with each user: an initial hour-long interview before users began wearing the Fitbit One and two half-hour interviews—one a month after device use and one at the end of the study. The interviews were semistructured in that we had prepared topics for questions from a sensor-adoption model,[4] but we also encouraged users to share their expectations for the device and experience with technology in general (first interview) and then to describe their reactions to the tracker and show us how they used it (second and third interviews). At least two researchers were present for each interview: one to interact with the users and the other to observe and take notes.

We chose to use the Fitbit One tracker because it is unobtrusive and users can easily attach it to their clothing. It also collects relatively comprehensive physical activity data, including number of steps, number of stairs, calories burned, and distance traveled in kilometers. In addition, Fitbit awards badges for walking milestones. Users can also manually log their diet, weight, and glucose levels and access all their data from accounts on both the Fitbit website and mobile app. As an incentive to participate in the study, we told users they could quit the study at any time and still keep the device.

Interviews

The goal of the first interview was to understand users' daily life, disease management, and expectations for a fitness tracker. All but two users had smartphones, which they used mainly for calls and texting; seven had experience with pedometers; and two had previously used mobile fitness applications but had stopped employing them because of accuracy or usability problems.

In the two remaining interviews, our focus was on device use. Questions were designed to assess users' experience and their perspectives on the tracker's effectiveness. The last interview was to ascertain if users had continued to employ the tracker and whether it had prompted them to change their lifestyle or environment.

DESPITE THE EXTENSIVE RESEARCH ON PERVASIVE FITNESS SENSORS, MOTIVATIONAL TECHNIQUES FOR USING THEM REMAIN LARGELY UNEXPLORED.

Data analysis

We audio-recorded all interviews (total of 1,963 min), transcribed them into English, and analyzed the resulting 268,931 words according to the grounded-theory approach.

EMPOWERING USERS TO CONTROL THEIR HEALTH

Researchers have extensively studied user needs and research prototypes for wearable devices,[1,2] and they have investigated how users employ their devices and evaluate them.[3] Results show that these devices have tremendous potential to equip diabetic and obese users to manage their own health. Eric Topol's book *The Patient Will See You Now* effectively develops the paradigm of patient empowerment in which patients are no longer followers but the main actors in managing their health.[4] Studies about proactive health management systems that empower chronically ill patients with self-care are on the rise, as many individuals realize noncommunicable diseases like diabetes can be prevented and managed by adopting a healthy lifestyle.

PROACTIVE DECISION MAKING

Many researchers have pointed out the need for patients to actively learn about their diseases and make healthy decisions.[5,6] One ethnographic study attempted to understand current diabetes management practices and identified that helping users to associate glucose levels with their lifestyle is an essential design requirement.[7] In another study, researchers designed the Continuous Health Awareness Program, which lets users log glucose levels and complement them with a report of activities, diet, medication, and emotional states.[5] Another group also extended the value of glucose levels and supplemented it with photographs of users' meals, exercise routines, and events that made them happy or sad, aiming to help diabetics reflect on past actions and make decisions about future ones.[6]

MOTIVATION CHALLENGES

Motivating and engaging users with chronic diseases to actively monitor and change their lifestyle is a promising yet challenging area in patient self-management.[2,5] One study showed the difficultly of introducing exercise habits into some diabetics' sedentary lifestyles, and noted that the participants relapsed in a short time.[6] Another group proposed persuasive technologies to address this issue, but provided no concrete applications or empirical studies.[5] Meanwhile, technologies that help users monitor their lifestyle are on the rise.[7] Researchers have been actively designing technologies that motivate physical activities to prevent obesity,[2] but few studies have evaluated the impact of these technologies on obese and diabetic patients. The study most relevant to our work examined the experience of normal users who had already adopted activity-monitoring devices for a long term (3 to 54 months).[8] However, the study targeted the general population rather than patients.

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After reading all the transcripts, two researchers generated a starting list of codes based on the research questions and the patterns that emerged from the data. The researchers then returned to the data and conducted a systematic axial coding to identify emergent themes. After several coding iterations, the researchers identified and categorized the themes and reached a consensus mediated by a third researcher.

LIFESTYLE EVOLUTION

Overall, users made positive lifestyle changes. By the end of the study, only two users had stopped employing the device. As a result, the data reported for seven months is for 16 users, although we still have interview feedback from the two users who dropped out. For simplicity and anonymity, we labeled users P1 to P18.

Before the study

Most users entered the study physically inactive, yet were aware of the benefits of physical activity in maintaining proper glucose levels and body weight. They reported that they did not perform routine or intense physical exercises on their own, only those that the hospital organized. Half had participated in exercise programs for diabetic and obese patients organized by the hospital, usually in three one-hour sessions weekly that lasted for three months. Users reported that regular training programs had benefits such as making them feel accomplished and more confident. For example, P3 said, "With the monitoring, I had to take a pace and did everything regularly. I liked it, and I think it was fun, but it was just for three months."

Users also liked the program because it was an external motivator to push them to exercise with professional and clinical support. However, none of them continued exercising regularly after the program ended. P5 said, "I want to do more physical exercises, but I am always postponing it. I want everything to be perfect and at a steady pace. I want to do it right."

Some users also reported physical restrictions from their disease and its complications. Three had gastric bypass surgery, which gave rise to many side effects such as nausea, trauma, and slow recovery from anesthesia. Therefore, it seems that the users had not integrated physical exercise into their daily lives and tended to rely on professional support.

Overall, those who prioritized their time sacrificed physical activity to other duties, reporting that their busy lifestyle prevented them from exercising. P4 did not have time because she was too busy with her work: "I often drive because I'm responsible for many associations, and I feel like I'm wasting my time walking. Although it's not far, I still drive because I always carry many files." P18 claimed to be too busy with her family: "When I'm with my husband and my son, I can't exercise even if I want to."

After a month

We noted changes in activity awareness, motivation to participate in activity, and a stronger sense of social connection.

Activity awareness. Users initially reported that monitoring their daily steps and stairs helped them be more aware of their inactivity. P5 said, "I realized I don't have to go through stairs at all in my everyday habits, so I started to take the stairs from the underground parking to the mall." Thirteen participants had chosen opportunities to exercise more each day. In addition to gradually taking the elevator and escalator less often, some had deliberately created opportunities to walk more, parking their car farther away or exiting at a bus stop before their regular one.

Although these actions taken alone might seem trivial, their repetition over time shows the potential to create a more meaningful long-term change. The tracker prompted them to rethink and redefine physical activity in terms of number of steps, which they could easily integrate into their daily routine. P8, for example, was surprised by the number of steps taken while doing his weekly job of monitoring cars in a parking lot.

Motivation. As users felt the benefits of integrating physical activity on their health and wellness, they were more motivated to be active. P10 reported, "As I walk I feel like my glucose level is more stable, my health is better." P18 said, "Instead of just sitting, I do many things as long as I can increase my number of steps. After I send my son to school, I walk in the city. I have lost 1 kg since I started using Fitbit."

Social connection. Wearing the device gave users a sense of pride when showing their tracker to others. They felt they were not only following the technological trends, but were also adopting a healthy behavior in the form of more physical activity. P4 reported, "I showed it to my parents and my children. Now, I'm a cool mom."

Moreover, they were able to influence others by sharing their experience. Some users related their study participation to their diabetic association and asked for financial help to

TABLE 1. Average activity reported from 16 users.

Activity	After 1 month	After 2 to 6 months
No. of steps	7,852.72	9,002.30
No. of stairs	19.23	22.06

TABLE 2. Users' requirements for activity-monitoring technologies.

Requirement	Explanation	No. of users mentioning requirement		
		Before use	After 1 month	After 7 months
Playfulness	Metaphors, fun messages, motivating messages, colors	5	15	10
Pervasiveness and practicality	Ease of integration into daily life, small, lightweight, simple information	11	13	11
Persuasiveness	Notifications, rewards, warnings, comparisons, suggestions	12	10	9
Personalization	Personalized goal, information relevant to disease, recommendations	9	5	5
Privacy	Control over data sharing	3	1	2

distribute it to all the members. Some participants influenced their family, friends, and colleagues to be more physically active. P3 said, "Just by seeing how inactive I am with my number of steps, my colleague who is always with me could relate to it and started to be aware of being too sedentary as well." P2 reported, "When I was with my daughter, I told her to take the stairs and not the elevator."

After seven months

After seven months, the 16 users still wearing the device reported visible health and lifestyle changes. At this point, physical activity was translating to visible results such as weight loss, which reinforced activity awareness, although some users reported losing the device or forgetting to wear it. Social connection also remained.

Activity awareness. Many users became aware of the benefits of physical activity in lasting change. For example, P18 lost an additional 3 kg (on top of her loss of 1 kg at the one-month milestone), and intentionally changed her habits to be consistent with an active lifestyle. This is a significant improvement for obese patients. As one researcher in a separate study noted, "the achievement of weight normalization is often unrealistic and does not have to be the ultimate goal of a weight-reduction strategy. Moderate weight loss can have substantial health benefits."[5]

P13, who was both obese and diabetic, reached an average of 70,000 steps per week, which he had considered challenging in the past. He proudly shared his achievements with his friends when he reached a total distance of 1,000 km of walking. P8 and P16 began participating in a Nordic Track walking program every Monday afternoon and were continuing to do so as of late January 2017.

Table 1 shows the average steps and stairs taken by the remaining 16 users at two points in the study.

Of the two users who stopped wearing the device, one became so busy that he forgot to wear the tracker after the first two weeks. The other user reported being more interested in her average caloric intake and average steps. Once she had that information, she did not want to continue wearing the device.

Social connection. Some participants reported even greater impact on their social circles. P8 got financing through his diabetes association to distribute the device to a larger population. P11, who works as a secretary, also had the opportunity to influence others. Her office was planning to buy a coffee machine because they had to walk a long distance to the cafeteria. After an extended period with the Fitbit tracker, this user realized that she had been too sedentary and began to get up more often to get water. When her coworkers and boss noticed her activity, she explained her need to exercise. Ultimately, a decision was made to refrain from buying the coffee machine and continue walking to the cafeteria. We were surprised by this spreading fitness effect: users altered not only their behavior but also influenced those around them to do the same.

USERS' EXPECTATIONS AND REQUIREMENTS

On the basis of interviews and observations, we identified five requirements that users have for a wearable activity monitor: persuasiveness, pervasiveness and practicality, personalization, playfulness, and privacy. Table 2 summarizes these properties along with the number of participants who mentioned them. Figure 1 shows how often users mentioned each requirement as a percentage of the number of times all requirements were mentioned.

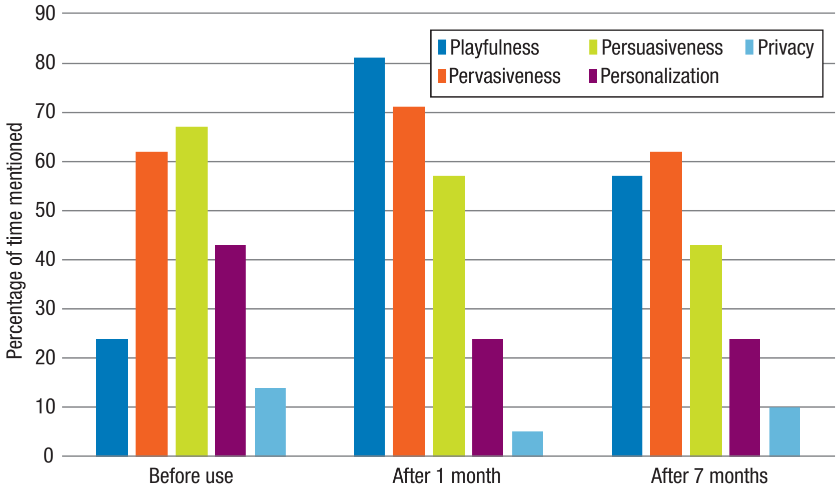

FIGURE 1. User requirements for an activity-monitoring device as a percentage of the time each requirement was mentioned. The graph shows that initially participants did not value playfulness, but it became a motivating factor for continued use and remained second only to pervasiveness, which was consistently high.

Before the study

As Table 2 shows, users most often cited persuasiveness followed by pervasiveness and practicality, and then by personalization. Playfulness and privacy were less desirable overall.

Persuasiveness. Most users (12) wanted a tool that nudges them to exercise. Some complained about applications that only display activity data without analyzing it or providing some user interaction. They expected a coaching function such as persuasion, reminders, rewards, warnings, comparisons with previous days, visualizations, and so on. P10 noted, "It would be nice if it could send me motivating messages from time to time. We need something that stays around and reminds us what we need to do. The problem is that we forget easily."

Pervasiveness and practicality. This requirement was easily the next in demand, with 11 users mentioning that the device should be integrated into their life seamlessly and that information should be easy to understand. Users in their 60s were less curious about new data, preferring that the technology be easy to use and practical.

Information simplicity also influenced users' willingness to adopt the technology. P16 said, "It's good to have some value that we understand easily and not just some meaningless number." Visualization techniques are a possible solution. For example, P18 expected the results to be displayed in figures that are easy to interpret.

Personalization. Nine users expected advice and information related to their disease. As P14 reported, "I want it to give me some practical advice on what I should do with my disease and not just show the numbers."

Because diabetes and obesity represent major risk factors for a number of other chronic diseases like high blood pressure, heart disease, and high blood cholesterol, users also expected the device to give them information such as heart rate and glucose level.

Playfulness. Fewer than a third of the users (five) wanted a wearable device that is fun and entertaining. Some users were motivated by things they like to do, instead of things they have to do. Having a chronic disease already filled their life with constraints and stress, so a device that could lighten that burden would be more desirable. P2 expected some music functions to encourage physical activities, and P6 noted, "It has to be fun and playful. We already have enough problems every day, so it should be entertaining."

Privacy. Three users were concerned about confidentiality, mainly that others could guess their activities unless they controlled data sharing. P7 said, "I am worried that someone may see what I did. I should be able to control who can see my profile and my performance."

After a month

The users' requirements ranking changed drastically a month into the study, with playfulness now being the most important requirement for continued use, followed by pervasiveness and practicality and then persuasiveness. Personalization and privacy continued to be in low demand.

Playfulness. Of the 16 remaining users, all but one considered the fun element the most important motivating property. Of these, 10 users were amused by the device's messages. P4 said, "I love the message on the Fitbit screen. One day when I tried to hang it on my clothes, it said 'Go for a short walk?' and I answered, 'No, I still have to eat.' That made me laugh out loud."

Eleven users liked the flower on the Fitbit screen, which shows at a glance whether the user has been active because it gets taller as the user walks. P4 said, "I look at the screen at least twice per day, in the morning and in the evening, and also when I'm back from a walk. I want to see if the flower is growing."

Some users were entertained by the color coding of activity levels on the Fitbit dashboard. P14 said, "When I reach the daily goal, everything suddenly turns from orange to green; when my performance is bad, everything is red. The color system is really interesting."

Pervasiveness and practicality. After wearing the device for an extended time, 13 users mentioned that Fitbit is pervasive and easy to use and that wearing it and checking steps were convenient. P4 said, "It's handy. In the morning, I fix it to my trousers and at night I check how much I did during the day."

Users also appreciated that the tracker is unobtrusive, being small, light, and easy to wear in a way that is not obvious and potentially embarrassing. They did not perceive wearing the device as a burden. However, the flip side of unobtrusiveness is that the device is easy to misplace. P10 noted, "It is too small. For an old person like me, I forget everything and lose it easily. If we can call it like a phone, it would be easy to locate it. I am frustrated when I cannot find it."

Fitbit helped users integrate physical activities into their daily life rather than having to set aside a chunk of time dedicated to physical activity. P8 reported, "I was checking 29 cars for my association the other day and had three times more steps [than usual]. Before using the sensor, I did not know that this job would lead to so much physical activity."

Users tended to avoid functions like sleep tracking that involved more effort and were less convenient. Most did not want to wear the wristband with the sensor inside while they slept. P4 said, "I just used the sensor to get fitness data. I didn't use the sleep tracking because I didn't understand how to use it." Additionally, even though the Fitbit application provides functions for logging diet, weight, glucose levels, and blood pressure, users rarely used them because of the extra effort required.

Finally, for many users, "ease of use" translated to having a minimal IT background, and even with that assumption, a few of the older users encountered technical problems while using the application. The spouse of P7, who joined the user interview, reported, "We did not know how to use the dashboard on the computer. What we saw was not the same as that on the Fitbit screen. I was frustrated with the computer, and he was frustrated with the Fitbit. We are old and it is difficult." Some participants also encountered various technical problems but managed to use the essential functionality.

FITBIT HELPED USERS INTEGRATE PHYSICAL ACTIVITIES INTO THEIR DAILY LIFE RATHER THAN HAVING TO DEDICATE TIME TO PHYSICAL ACTIVITY.

Persuasiveness. Users appreciated Fitbit's monitoring and features that nudged them to exercise. They also wanted congratulations and rewards when they were doing well by their own standards. P2 shared, "Riding a bicycle for 30 minutes is not easy for me but when I saw that I had been active for 28 minutes, I told myself 'I am almost there, and I won't die if I reach 29.' If there are some sweet messages like that, it can motivate me to stay till the end."

Personalization. Only five users expected the device to adaptively personalize fitness goals for them. Most users expected to start with an achievable goal and then increase it steadily. However, some were overwhelmed by the Fitbit's "demands." P6 said, "I was disappointed because I thought every time I reach 5,000 steps, it will congratulate me. 5,000 was already very difficult, but it asks for 10,000 steps. It is almost discouraging. If the goal is increased little by little based on my performance, I will be more motivated."

Users wanted accurate monitoring and comparisons with past performance. While accuracy and self-comparison are important for healthy individuals as well, such information is particularly valuable for patients to associate with their glucose levels and body weight and learn about health practices by themselves. For example, P9 mentioned that knowing his glucose level while exercising is important so that he can determine if he is in a hypoglycemic state and needs to eat something sweet.

Privacy. Only one participant mentioned privacy, being concerned that insurance companies might obtain her health-related data and adjust her payment on the basis of it.

After the study

According to the transtheoretical model of behavior change,[6] users went through all the phases, from precontemplation—in which they were aware of physical activity's benefits but were not motivated to be more active—to maintenance, in which they are engaged in performing the new behavior over the long-term. Our results are consistent with other researchers who showed that even though goals and practices varied along the study, participants still derived value and motivation from the technology.[7] However, these researchers did not provide concrete insights into how motivation and requirements evolve.

As Table 2 shows, our users' expectations and requirements changed across the seven months. By the end of the study, the top requirement was pervasiveness and practicality followed by playfulness and then persuasiveness. Personalization and privacy remained the least mentioned.

Because the end of the study gave us our final set of insights, we opted to focus on design implications in presenting our seven-month results.

DEVICE DESIGN RECOMMENDATIONS

Before wearing the Fitbit One tracker, users were more concerned about whether such technology could nudge them and provide personalized healthcare information. They also expected the device to be pervasive, practical, and easy to use. However, after wearing it for one month, users became more impressed with its playfulness and fun elements, although they still wanted it to be pervasive and practical to use. Only a few users were initially concerned about privacy, and this lack of concern persisted. This was somewhat surprising, as privacy is typically considered a sensitive topic in clinical data collection.

The shift of focus in user requirements across the study demonstrates the importance of playfulness in engaging new users and the need for pervasiveness and practicality in sustaining that use. On the basis of our findings, we derived four requirement areas with recommendations for wearable health monitor designers: persuasiveness and personalization (which we combined into one area), playfulness, pervasiveness and practicality, and privacy.

ALTHOUGH PREFERENCES FLUCTUATED, USERS GENERALLY WANTED ACCURATE MONITORING ALONG WITH TIMELY PRACTICAL ADVICE AND PLAYFULNESS.

Persuasiveness and personalization

The goal should be to create persuasive techniques that are easy for the user to integrate into daily life. The device should consider the user's preferences and environment and give a timely recommendation based on the user's past behavior. An app that provides information at a glance can reduce the time users spend with the system and thus increase their willingness to use it over a long period.

Personalized information is also important. For users suffering from chronic conditions, a continuous update of health-related parameters is essential. Health parameters should be conveyed and displayed in a way that is easy to understand, for example, not just showing curves and graphics but also including an understandable interpretation in terms of impact on the user's health. To maximize user acceptance, goals and recommendations must be tailored to the user's needs, preferences, and abilities.

Playfulness

Technology should motivate users in an entertaining way, such as by using metaphors adapted to the user's preferences (such as music) to convey information. Users should be able to reflect on their behavior without feeling pressured to reach a performance goal. Another approach is to associate virtual incentives with the user's improvement to foster their extrinsic motivation to exercise more. For example, after a certain amount of walking, users could receive badges or coins that enable them to play music. The more they walk, the more they can enjoy their favorite songs.

With the increasing popularity of virtual reality, another solution might be to immerse users in a virtual world and map their achievement in that world. This could motivate users to perform beyond their daily habits. For example, the user might be an avatar in a game to find hidden images, which can be unlocked only by moving in the physical world—along the lines of *Pokémon Go*.

Pervasiveness and practicality

To keep users motivated to wear the device, it must be pervasive and

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practical to use. Techniques might include notifications that strike a balance between making the device unobtrusive and reminding the user to wear it. The system should be as simple as possible and minimize the need for user input, such as logging into the website or app or entering health information manually. A smartphone's locked screen could display the user's improvement automatically, for example.

Additional usability studies will help designers and engineers find the right balance between the need for unobtrusiveness and the minimum interaction that the system requires. A timely notification in the right context can help users remember the device, application, or health goals they have set. The device might suggest walking instead of driving to an event, for example, or present a social challenge that requires walking if the user is with someone. Finally, both the mode of system interaction and the information displayed must be simple and easy to understand.

Privacy

We believe that our users were less concerned about privacy because they did not understand the privacy risks involved in using the device. In general, any device must incorporate methods to address privacy concerns before the technology is deployed.

Managing the tradeoff between the benefits of using the system and the risks associated with sharing data will lead to fewer concerns about privacy. However, a system that ensures privacy, particularly with regard to health-related data, remains essential in engaging users. Privacy settings should be simple enough for users to easily decide what to share and with whom. For users to freely decide how much privacy they want, they need a straightforward way to modify privacy settings and easily understood information about the possible risks of sharing each data type.

Our longitudinal ethnographic study showed that when sufficiently motivated, diabetic and obese users can change their habits to align with a healthier lifestyle. The healthcare community is already envisioning technology as a driver of behavioral change. A well-designed activity monitor can do much more than record a user's glucose level and weight; through personalization and pervasiveness, it can help users manage their lifestyle to incorporate healthier choices. Our study also showed that users' expectations of the device change with continued use. Thus, in addition to tailoring the device for the user and the user's environment and making it entertaining and easy to use, designers should consider ways that the device can adapt to changing expectations across periods of use.

We recognize that our study has a small and narrowly focused sample size, but our aim was to gain a deeper knowledge of how these technologies are accepted and adopted by chronically ill patients, how technology can help patients engage in a healthier lifestyle, how the device's requirements change over time, and how designers can make the device more efficient.

We plan to follow up on our results in a study with a broader sample size for a longer period to quantitatively investigate the behavior and health changes for individuals with other chronic illnesses. It is also worth exploring how social and living environments affect behavior and how technology can alter those environments to promote desirable behavioral changes. ◼

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The Science of Sweet Dreams: Predicting Sleep Efficiency from Wearable Device Data

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Lack of sleep can erode mental and physical well-being, often exacerbating health problems such as obesity. Wearable devices that capture and analyze sleep quality through predictive methodologies can help patients and medical practitioners make behavioral health decisions that can lead to better sleep and improved health.

With the increased pace of daily living, sleep has become essential to academic and workplace performance. Sleep deprivation can result in catastrophic events for those in professions that require high accuracy and safety levels, such as construction crane operators or school bus drivers, and driving in general can be dangerous with little or no sleep. In the US alone, an estimated 810,000 sleep-related collisions per year result in 1,400 fatalities and cost $16 billion.[1] Studies also confirm that lack of sleep worsens a variety of health problems—from obesity, diabetes, and sleep apnea to Alzheimer's and cancer.[2–4] Other studies show that sleeplessness is becoming more widespread.[5]

In light of these findings, systematic sleep studies have become a high priority. Sleep science is a multidisciplinary research area, with contributions from endocrinology, pulmonology, and public health. Increased knowledge of the importance of sleep is fostering the inclusion of sleep education (also known as sleep hygiene) as part of patient education for diseases such as diabetes.[3] In addition, healthcare providers are developing applications that act as sleep coaches for cancer patients[4] and otherwise healthy people with sleep disorders.[6,7] In all these developments, technology is proving to be a crucial element in sleep health—particularly wearable devices.

Wearables are unique in that they spread sleep awareness beyond clinicians and researchers to include the

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million users who rely on health applications to track their physical activity and sleep. These users often integrate their physical activity and sleep data in mobile health repositories, such as Apple's HealthKit—which can subsequently be integrated into electronic health records (EHRs). Consequently, the study of sleep efficiency is becoming a data science problem.

Traditional sleep analysis based on wearables' data is limited in scale and cannot keep pace with the explosion of wearable use for health monitoring and analysis.[8–11] To address this scale problem, we conducted a study to explore an innovative approach that combines deep learning with an algorithm that automates human activity recognition (HAR) to predict sleep quality from wearables' physical activity data.[12] Because our approach can scale to the wide deployment of sleep data analytics based on wearables, it can serve as the foundation for tools that noninvasively screen for sleep disorders, diagnose their nature, and identify the lifestyle factors affecting a particular disorder.

We conducted a series of experiments to statistically compare our approach with the traditional approach of actigraphy combined with a sleep expert's annotations—the current technique for studying sleep and physical activity patterns from a wearable motion sensor that tracks an individual's activities. Relative to this sleep expert, our approach showed up to a twofold improvement in the area under the curve (a statistical predictor of best model). These results are evidence that our method can greatly enhance (and perhaps even revolutionize) applications that assist patients and medical practitioners in making critical behavioral health decisions.

SLEEP SCIENCE'S EVOLUTION

For centuries, researchers have been exploring the elements of sleep. In *Bioelectromagnetics*, published in 1791, Luigi Galvani explained how electric currents from neurons passed signals to active muscles in frogs. His work relating electricity to the nervous system eventually led to Hans Berger's 1929 report of the first human electroencephalograms (EEGs) for brain study. A decade later, Alfred L. Loomis published a study describing different EEG patterns during sleep, which became the basis for defining sleep stages. Gradually, new signals evolved to characterize other sleep aspects, such as rapid eye movement (REM).

Early sleep studies

The next three decades saw an explosion of sleep knowledge and insights into sleep characteristics, which led to a new era in sleep science and its clinical aspects. In 1960, G.W. Vogel observed that narcolepsy patients have different EEG patterns during sleep as compared to healthy subjects. By the mid-1900s, sleep laboratories began to appear that were dedicated to studying sleep-related disorders such as restless legs syndrome, sleep-obstructive apnea, narcolepsy, and insomnia.

These labs resulted in more systematic sleep studies and the evolution of polysomnography (PSG), a sleep-study methodology that incorporates various sensor to capture brain activity, leg movement, oxygen saturation, breathing frequency, and snoring.[13] Although it is a major diagnostic tool that is considered the gold standard for sleep research, PSG is performed only in sleep laboratories in hospitals. During a PSG test, the patient spends at least one night in the unnatural environment of a sleep laboratory monitored by a clinician and attached to multiple sensors. On one hand, PSG is a high-fidelity test; on the other hand, it is challenging to scale, too expensive for many individuals, does not consider physical activity, which is tightly linked to sleep quality, and does not provide insights into the patient's behaviors in a natural environment or during daily routines. As a result, PSG cannot keep pace with the growing number of sleep disorders, and large segments of the population still suffer from inadequate sleep.

Actigraphy and first wearables

Wearable devices provide the first hope of solving these problems because they can be used to study sleep and physical activity for longer periods and outside the laboratory or hospital. Because a wearable monitors the patient's body continuously, collected signals can be used to determine sleep quality and screen for sleep disorders.

Actigraphy devices, such as the GT3X from ActiGraph (actigraphcorp.com/support/activity-monitors/gt3x), are clinical-grade wearables approved for sleep studies that use inertial sensors to collect physical activity and sleep data. As of mid-January 2017, actigraphy was being used in more than 100 clinical trials registered in the US clinical trials database (www.clinicaltrials.gov). In many applications, actigraphy can be a cheaper and simpler alternative to PSG, and actigraphy devices are already advancing sleep science in areas such as obesity, diabetes, cancer, and mental and public health. Machine learning applied to actigraphy data is widely used to study sleep patterns and characteristics.[8–11]

TABLE 1. Computing areas that can enhance sleep science.

Area	Subcategories	Potential contribution
Electronics, wireless communication, and embedded systems	Pervasive and ubiquitous computing, wireless sensor networks, the Internet of Things (IoT)	Design/development of sensors and actuators to capture contextual information about sleep, including integration of sensors in a body area network and in the IoT
	Biomedical engineering and medical devices	Development of novel medical devices to monitor sleep and aid sleep-disorder treatment
Machine learning and AI	Machine learning, pattern recognition, real-time analysis and event recognition	New insights into sleep that will help disease and disorder diagnosis, prognosis, and treatment
Data storage and curation	Data quality and management (annotation, validation redundancy, and so on)	New techniques for data annotation and for handling duplications
	Security to ensure data privacy, including anonymization in clinical studies	Advanced anonymization techniques and security that can prevent the use of biosignals such as an electrocardiogram (ECG)
	Data interoperability and semantic integration, data fusion	Techniques that enable semantic interoperability and the subsequent integration of sleep data that is currently in various silos, such as electronic health records (EHRs) and fitness companies
Applications and services	Data visualization	Novel visualization techniques that can facilitate the understanding of sleep data sources with complex multidimensional and temporal characteristics
	User modeling and adaptation of applications for consumers and professionals	Data-driven approaches for developing more personalized applications—for example, recommender systems—that support decision making for patients' (such as sleep coaches) and clinicians (such as clinical decision support systems)
	Human factors and human–computer interaction	New insights into the role of human factors, such as usability, in adopting complex health technologies to analyze and treat sleep-related disorders, which typically involve multiple stakeholders and a range of patient behaviors

New wearables, new possibilities

Sleep analytics is no longer restricted to researchers and clinicians, as the pervasiveness of health and wellness applications attests. Millions of people use affordable wearables to track their physical activity and sleep, and companion apps integrate tracked data into mobile health repositories, such as Apple's HealthKit. These repositories enable integration with other medical devices, such as heart-rate monitors, and even with EHRs. Along with the myriad fitness trackers and smart watches that can monitor sleep are context sensors, such as Aura from Withings (www.withings.com/ca/en/products/aura/sleep-sensor-accessory), which includes a sensing mat for sleep monitoring that integrates with the Nest Internet of Things platform (nest.com) to automatically adjust room temperature for optimal sleep quality.

The Apple Watch has an instrument suite to collect data on various bodily functions, including tri-axial movement and heart rate. The watch seamlessly syncs with iOS devices, enabling a variety of applications to use the collected data. With appropriate permissions, Apple's HealthKit API allows queries to the collected data as well as its use in new applications.

Other smart-device manufacturers, such as Samsung, have created wearable platforms based on their respective OSs, and specialized wearables companies like Fitbit have developed their own platforms.

COMPUTING CHALLENGES

The importance of data for health research has become mainstream in recent years, and sleep science is no exception. The National Institutes of Health (NIH) created the National Sleep Research Resource,[14,15] a portal aimed at integrating heterogeneous data sources for clinical sleep research (www.sleepdata.org). The portal, part of the well-known Big Data to Knowledge (BD2K) initiative, contains a wide variety of datasets for sleep research.

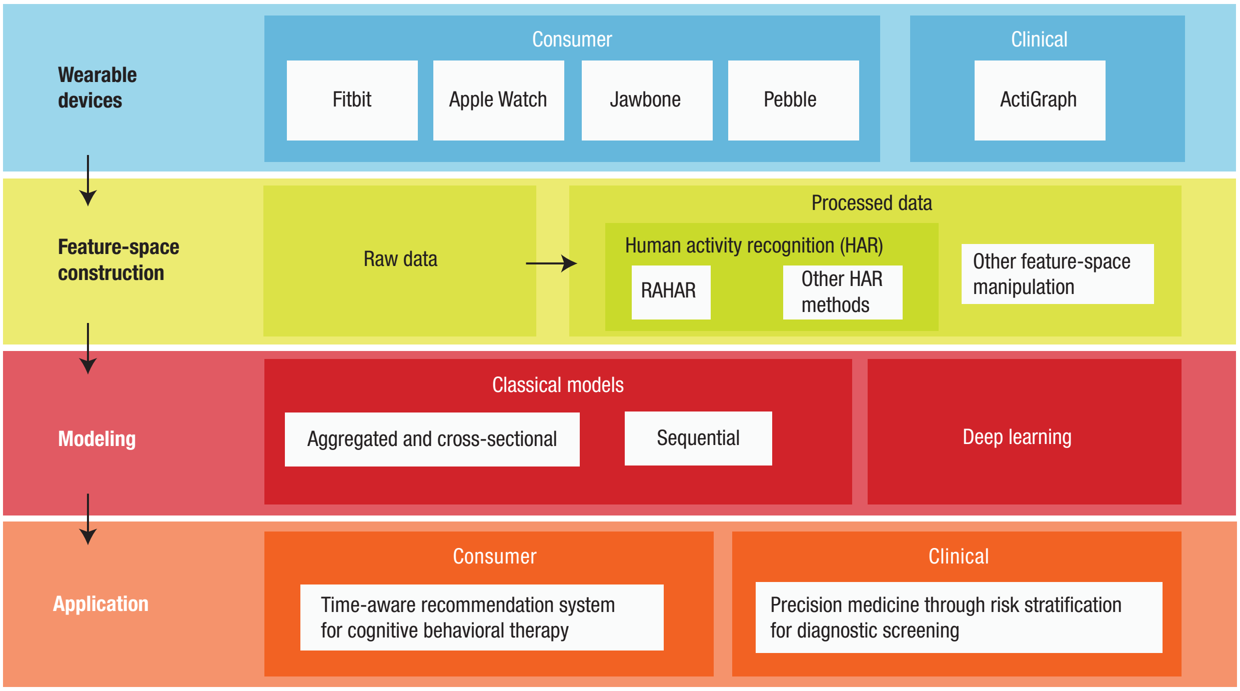

FIGURE 1. Proposed flow for capturing and analyzing data from wearables to enhance sleep efficiency. Data from wearables is processed using algorithms for human activity recognition (HAR), which can be fed to classical models such as aggregated and sequential techniques or to deep-learning models. These models then serve as the foundation for consumer and clinical applications. RAHAR: Robust Automated Human Activity Recognition algorithm.

As consumer health, wellness, and fitness data combines with EHRs, integration is becoming more problematic. The demand to fuse information from multiple wearable sensors, such as an accelerometer and heart-rate monitor, requires new algorithms. Research is still far from producing fully integrated smart analytics for heterogeneous sleep-related data sources, but as Table 1 shows, computer science can further sleep medicine in multiple ways, particularly in addressing big data analytics, predictive modeling, and activity recognition.

Big data analysis

Correlating wearable-sensed human activity with sleep patterns can provide insights to clinicians and individuals for the early diagnosis of sleep problems, which in turn can help identify which behaviors directly influence an individual's sleep quality. In addition to the analysis of actigraphy data in studying sleep characteristics, the development of sensors and pervasive computing solutions enable sleep diagnostics in the home.[16]

As Figure 1 shows, wearables can be clinical or consumer devices. Clinical devices are validated through clinical trials in which a ground truth has been established. These devices are used for research studies and clinical evaluation. Consumer devices have popular appeal and target a wider audience. These devices encourage self-monitoring and empower their users to make behavioral changes to improve their fitness and quality of life.

Both device types generate volumes of data in real time and at a high velocity. For example, a GT3X wearable generates 16 Mbytes of data each day for one individual. Analyzing this data to build descriptive and predictive models and provide actionable knowledge for practitioners and users is a big data challenge.

The data consists of features from multiple sensors collected over an extended period. Depending on the analytical goal and thus model type, data can be presented in either its raw form or with preprocessing. Raw data generally has a small number of features (triaxial accelerometers, for example, have three coordinates, gyroscopes have three rotational velocities, and so on) collected at thousands or more points in time. The result is a time series of $n \times m$ dimensions, where n is small and m is significantly larger. Moreover, because the accelerometers or gyroscopes track every movement with equal weight, raw data is noisy.

Deep-learning models can effectively handle raw data characteristics, but classical aggregated models (such as linear or logistic regression, support vector machines, and random forest), sequential models (such as sequential pattern mining), and decision trees also require feature construction to assist in data interpretation. HAR summarizes the behavior of individuals over the time series into clean interpretable features. Our algorithm, Robust Automated Human Activity

Recognition (RAHAR), is a scalable method for extracting knowledge from wearable activity sensors.[12]

Predictive modeling

Predicting sleep quality is important for behavior modification. While an automated version of actigraphy enables interpretation of sleep quality from data collected while the user wore the device to sleep, it would not enable the user to adjust his or her behavior to ensure improved sleep quality. A cognitive behavioral therapy system or application that not only monitors physical activity but also provides recommended behaviors can empower users to improve their quality of life. Moreover, many users do not like to wear devices while they sleep.

Clinicians looking to screen their patients for sleep disorders need a high-fidelity prediction model (such as a deep-learning model) to provide insight before exacerbation.[17] Additionally, using RAHAR in combination with sequential pattern mining could help sleep researchers identify behavioral patterns that lead to good or poor sleep. For users who wear their device regularly, data can be collected for weeks or months, thus allowing for personalized pattern identification and precise sleep treatment.

Human activity recognition

Because human movement is a key feature in recognizing activity, many HAR applications construct a feature space from raw triaxial accelerometer data by labeling portions of a person's physical-activity time series. Depending on the application area, the activity labels can be activity type (sitting, walking, jumping, running, and so on) or exertion level (sedentary, light, moderate, vigorous, and so on). Multiple activity types might require the same exertion level; conversely, the same activity type might occur at different exertion levels.

Categorizing raw accelerometer output in this way abridges the feature space, which removes noise and summarizes output. It also rebalances data dimensions and can thus improve predictive model quality. Activity categories can either be aggregated as percentages over a time segment or be interpreted as an event sequence.

Current HAR methods have been tested primarily on simulated rather than natural behavior, with most methods using data collected from sensors attached to an individual in a laboratory. The participant is instructed to complete a series of preassigned activities, and the algorithms scan through the raw sensor data, attempting to identify and label these activities. The algorithms require a high level of supervision, do not generalize well to natural daily behavior, and focus on event type rather than exertion level.

The latter drawback is troublesome because exertion is of particular interest in sleep science research, which seeks to more fully understand the relationship between physical activity levels and sleep. Researchers have established that physical activity and sleep influence the production of many physiological processes, such as hormone production, and thus the relationship can influence important health aspects, such as metabolism and the immune system. In teenagers, for example, sleep deprivation is high, which can increase obesity and reduce academic performance.

Scalability and expense are also concerns. In sleep studies, a specialist typically performs HAR on a single individual with the aid of software such as ActiLife—a process that is impractical and inefficient for large-scale clinical trials. The Precision Medicine Initiative announced by the Obama administration in 2015 was designed to collect genetic, environmental, and behavioral data from more than a million individuals.[18] Manually annotating wearable data from a cohort this size would be impractical and subject to human error and bias.

RAHAR: AUTOMATING ACTIVITY RECOGNITION

Our motivation for developing RAHAR was to reduce the bottlenecks of analyzing wearable data and automate the process of identifying and labeling activity periods based on an individual's exertion levels. The resulting HAR data segments can then be used to build predictive models.

Figure 2 shows RAHAR's process for translating raw accelerometer data from actigraphy sensors into output suitable for modeling. Because RAHAR does not require a sleep specialist's supervision, it can be built into mobile applications for self-monitoring.

Sleep-period annotation

RAHAR begins by detecting the sleep period from the HAR time series, which it identifies by scanning for periods of no accelerometer movement. A sleep period is 15 continuous minutes of no movement; an awake period is 30 minutes of continuous movement. In our sleep experiments, each dataset contained a continuous time series (that is, we told participants not to remove the device), so we used recorded sleep-period evaluation as the ground truth for predicting sleep quality. Our evaluation method for predicting sleep quality based on physical activity is based

FIGURE 2. Steps in the RAHAR algorithm. From wearables' raw sensor data, RAHAR detects periods of low activity and uses a state machine to annotate sleep periods, essentially dividing activity time into segments. It then identifies the point during wakefulness at which an individual changes activity-exertion levels during wakefulness. The last step is to label activities. RAHAR output is suitable for a variety of models, from classical prediction to machine learning.

on sleep science definitions and gold standards.[19]

Time-series segmentation

RAHAR segments the time series at the endpoints of all sleep periods, so each segment contains a period of awake time, followed by a sleep period. It then evaluates both the awake and sleep periods to predict sleep quality.

Change-point detection

In this phase, RAHAR identifies changes between activity-exertion levels within the awake period. To personalize activity segmentation according to the individual's unique behavior (as opposed to generalizing over all participants), RAHAR uses hierarchical divisive estimation,[20] in which each change point is the basis for dividing each of the multiple awake periods into subintervals. Each subinterval corresponds to a physical exertion level.

Its ability to identify behavior changes specific to an individual makes RAHAR robust to diverse populations. For example, the raw accelerometer output of a physically fit 18-year-old woman and an overweight 70-year-old man might be the same, but the physical exertion levels would not be interpreted as equal.

Activity classification

RAHAR determines each subinterval's activity classification by calculating the statistical mode of labels determined by cutpoints[21] over each data point in a change-point interval. By automating activity labeling, RAHAR eliminates the need for cumbersome annotation by sleep experts, enabling the widespread evaluation required in large clinical trials.

Many metrics are suitable for quantifying sleep quality, such as *sleep duration*, the time between falling asleep and waking up; *wake after sleep onset* (WASO), the time spent awake during the sleep period; and *latency*, the time between trying to sleep and actually falling asleep. However, sleep efficiency—the ratio of sleep duration minus WASO to sleep duration minus latency—is most the effective sleep-quality benchmark[22] because it involves all three metrics.

Output

RAHAR output can be used as the feature space for classical models, such as logistic regression, that aim to predict sleep quality when activity data within the sleep period is not available. Many wearable devices (including the Apple Watch) require overnight charging, which precludes the direct tracking of sleep behavior. Moreover, machine-learning applications require sleep-quality prediction to provide real-time feedback that can change a user's behavior to optimize sleep.

PREDICTIVE SLEEP EXPERIMENTS

To evaluate RAHAR, we conducted a series of experiments to assess its use with traditional machine-learning algorithms and to explore the potential of deep learning in sleep-quality prediction. The health and behavioral dataset we used is small enough that additional runtime for training is negligible. Thus, all our results are in terms of predictive performance.

Our experimental dataset consisted of data collected in a one-week observational trial involving 92 male and female adolescents from ages 10 to 17. The trial, conducted by Weill Cornell Medical College in Qatar, employed the GT3X, which uses a triaxial accelerometer to collect data on physical activity and sleep features from inertial sensors. The dataset was the seven-day vertical-axis time series extracted from the accelerometer.

Generalizing our results from this dataset might be problematic, as sleep quality changes across regions and ages. Although our data had a high ratio of teenagers with poor sleep to those with good sleep, that ratio might be different in other countries.

Usefulness in feature construction

In one of our experiments, the goal was to evaluate RAHAR as a tool for constructing features that can be useful for models that attempt to predict sleep quality.[12] Table 2 shows the results of RAHAR in predicting sleep quality versus the traditional approach of using a sleep expert plus ActiLife software (SE+AL). We evaluated the usefulness of activity labeling in SE+AL and RAHAR as input to five models: adaptive boosting, random forest, support vector machines (SVM), and logistic regression. Each model returned a binary classification through a likelihood score for belonging to the positive class—the class

TABLE 2. Results for two statistical methods when using a sleep expert plus ActiLife software (SE+AL) and the Robust Automated Human Activity Recognition (RAHAR) algorithm as input for models that predict sleep efficiency.

	AUC–ROC*		F1 score		Sensitivity		Specificity	
Model	**SE+AL**	**RAHAR**	**SE+AL**	**RAHAR**	**SE+AL**	**RAHAR**	**SE+AL**	**RAHAR**
Adaptive boosting	0.7489	0.8132	0.5574	0.6885	0.5484	0.5526	0.7759	0.9333
Random forest	0.8115	0.8746	0.6885	0.7500	0.6774	0.6316	0.8448	0.9333
Support vector machines	0.7497	0.7895	0.3721	0.7077	0.2581	0.6053	0.9310	0.8667
Logistic regression	0.5884	0.8649	—	0.6875	—	0.5789	—	0.8667

*AUC–ROC: area under the curve–receiver operating characteristic (measure of best model). Dashes in metrics for logistic regression denote cases in which results produced uniform classification predictions.

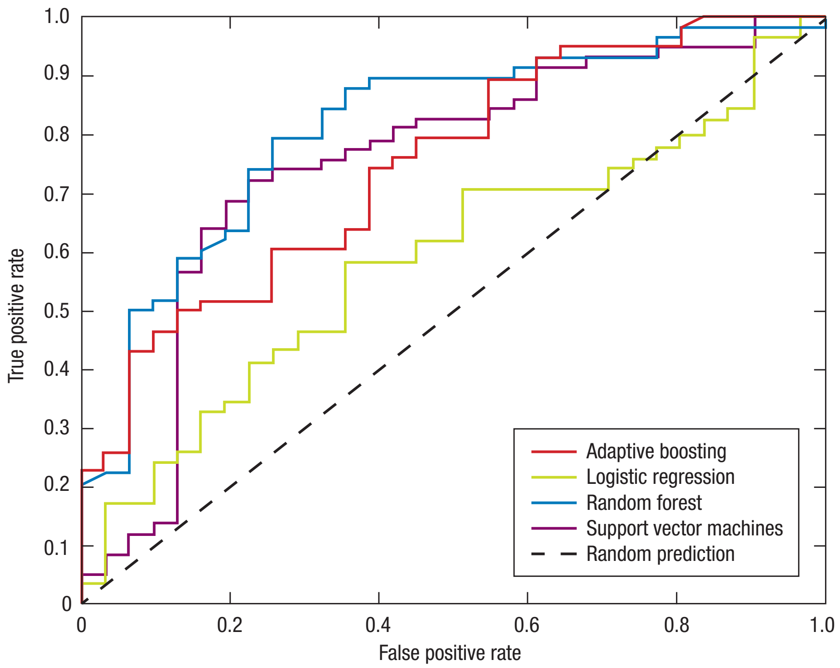

FIGURE 3. ROC curves for predicting sleep efficiency using a sleep expert plus ActiLife software (SE+AL), which represents the traditional method of gauging sleep quality. Although this method is accurate, it is hard to scale to large clinical trials or mass deployment.

that represented good sleep quality. The threshold was 0.5. Figures 3 and 4 show the curves of false and true positives for SE+AL and RAHAR for each of these models.

Identifying sleep problems

Deep learning can be important in sleep science, primarily for first-pass screening of potential sleep problems, which can be confirmed by alternative analytics and a clinical encounter with a health professional. Deep-learning models have the best predictive power for estimating sleep quality based on an individual's behavior. These high-fidelity black-box models can interpret raw accelerometer data without RAHAR or any preprocessing, reducing overall workflow. However, these models contain hidden layers and thus are not transparent about the predictive process or any justification for the output.

In our experiment to explore deep learning, we used the feature-construction experiment dataset and applied deep-learning methods.[23] To train our model to decrease overfitting, we randomly partitioned the dataset: 70 percent for training and 15 percent each for testing and validation.

Table 3 shows results from feeding raw accelerometer data using logistic regression as a baseline into four deep-learning models: multilevel perceptron, convolutional neural network, simple recurrent neural network (RNN), and long short-term memory (LSTM) RNN. We also included a time-batched version of LSTM to read the input time series in batches rather than individual epochs. This allows the model to incorporate long-time dependencies in the data without a vanishing gradient.[23]

When the model must be explainable, standard analytic models are more suitable for analysis than deep-learning models. These algorithms can predict the expected sleep quality of individuals based on their physical activity and provide insight into the contributing factors. This insight

TABLE 3. Using deep learning to predict sleep efficiency.

Model	AUC-ROC	F1 score	Precision	Recall	Accuracy
Logistic regression (baseline)	0.6463	0.8193	0.7083	0.9714	0.7231
Multilevel perceptron	0.9449	0.9118	0.9394	0.8857	0.8929
Convolutional neural network	0.9456	0.9444	0.9189	0.9714	0.9286
Simple recurrent neural network (RNN)	0.7143	0.7711	0.6667	0.9143	0.6607
Long short-term memory (LSTM) RNN	0.8531	0.8500	0.7556	0.9714	0.7857
Time-batched LSTM*	0.9714	0.9211	0.8537	1.0000	0.8929

*Reads the input time series in batches, allowing the model to incorporate long-time dependencies in the data without a vanishing gradient.

can be leveraged to make recommendations for behavioral modification with the goal of improving quality of life. In diagnostic screening, however, explanation is not as critical as classification accuracy, which makes deep learning an excellent screening tool to identify sleep behaviors.

The expanding field of sleep science is a multidisciplinary research area focused on understanding sleep in human health. As sleep science progresses, we can start to understand the link between sleep and many health conditions such as obesity and cancer. In many ways, these advancements have been relying on the process of engineering and computer science as increasing amounts of data is being captured from new technologies.

Our analysis, which involved collaborating with practicing sleep scientists in a clinical setting, ensured that our results were realistic and that they could significantly impact healthcare practices. Future research will be required to integrate our work in systems for helping professionals and patients with decision making, including algorithmic performance, human factors and usability, development of pervasive and persuasive applications for behavioral change, and generalization of our models in other populations.

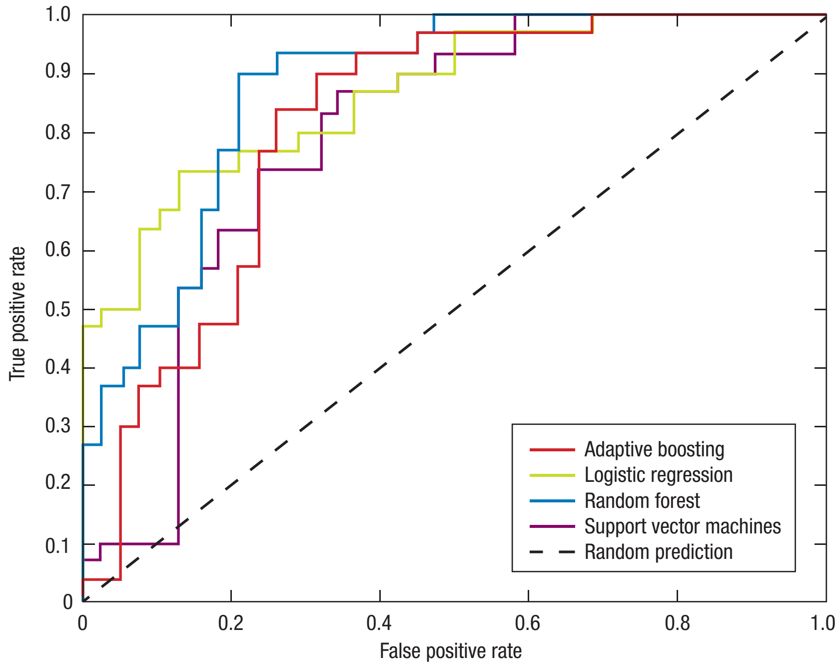

FIGURE 4. ROC curves for predicting sleep efficiency using RAHAR. Accuracy remains high, and automated activity labeling prevents human error and bias in the volumes of data that wearables generate for a large population.

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Are They Paying Attention? A Model-Based Method to Identify Individuals' Mental States

Tongda Zhang, Renate Fruchter, and Maria Frank, Stanford University

In a global economy, online meeting participants often have different backgrounds, making it difficult to know their mental and physical states. The Mental Motion State Model, trained by applying the Gaussian mixture model to electroencephalogram data, can indicate degrees of engagement and fatigue levels, providing a feedback channel for self-regulation.

Projects in an increasingly complex distributed work environment with 24/7 schedules often require online meetings that cross time zones, cultures, disciplines, technologies, and task-execution styles.[1] During these meetings, participants are often unaware of others' engagement and fatigue levels and frequently power through the event without realizing that people might be tuning out or working on something else. One way to address this inefficiency is to implement a feedback channel that makes all the participants' emotional, mental, and physical states transparent. As the meeting progresses, participants can self-regulate to adjust the meeting's flow and pace.[2]

Although this idea might seem a distant reality, recent studies have shown that integrating bioelectrical signals with cognition and behavioral understanding opens opportunities to infer people's emotions and mental and physical states.[3] Commercial sensor technologies already detect and monitor a range of bioelectrical signals, such as electrocardiography (ECG), electroencephalography (EEG), Galvanic skin response (GSR), and heart-rate variability (HRV). Researchers have explored how to use EEG band frequencies or the ratios between

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them to detect and measure attention, meditation, alertness, and mental workload,[3–6] typically through controlled experiments that demonstrate how these EEG signals can be used to measure people's cognitive states and task engagement.[3]

However, detecting and labeling mental states is difficult, even when using manual labeling and video coding, as most mental states are not directly observable. That is, it can be obvious what people are doing, but much harder to gauge what they are thinking or their cognitive workload. Moreover, labeled datasets of mental states are in short supply, so most studies use direct measures or basic statistical values, such as the mean or median of an EEG band's power spectral density (PSD). To explore relative mental states, most studies compare PSD values in different activities session by session.

As part of ongoing efforts to validate the idea that EEG bands can be used to indicate mental workload, we conducted a study that became the basis for developing the Mental Motion State Model (MMSM). The model uses a novel unsupervised learning algorithm[6] based on the Gaussian mixture model to capture the transitions, or *motions*, between mental states. Relative to raw EEG signals, these transitions provide a more meaningful way to distinguish engagement during project activities.

To evaluate the model, we collected two EEG datasets from participants in a graduate-level global teamwork course at Stanford University involving partners worldwide.[1] One dataset consisted of unlabeled EEG signals collected during two-hour weekly project meetings; the other consisted of signals labeled with five activities considered typical in most projects: work, listen, collaborate, multitask, and relax. These activities are based on two decades of global teamwork studies in the Project-Based Learning Laboratory at Stanford.[1] We then trained the MMSM by applying our learning algorithm to the unlabeled data and validated the trained model using the labeled dataset. Finally, as an illustration of the model's effectiveness, we combined the trained MMSM and EEG data from a randomly chosen individual and demonstrated the feasibility of discovering the subject's different mental states and the transitions between them.

We view the MMSM as a first step toward interpreting mental states from EEG data. It can become the basis for a mechanism that will accurately measure participants' engagement and fatigue levels during communication, such as online meetings, which participants can use as feedback to help them better manage the event.

EEG DATA

We collected EEG data from 10 male and 10 female graduate students taking a global teamwork course at Stanford.[1] For data collection, each student wore a Neurosky Mindwave headset, which has a dry sensor system that provides the PSD value of each EEG band directly.[7,8] The wearable headsets, which are used in many consumer applications of EEG technology, did not change the way the students participated in theiractivities.

Data collection

We collected unlabeled recordings from the students during their weekly two-hour online project team meetings, which took place over four regions with different time zones: Central Europe, Caribbean, Midwest US, and West Coast US. The projects lasted four months, giving us recordings for an extended period. For the labeled dataset, we asked students to participate in the five activities during a controlled setting in which we asked them to focus on each of the five activities for 10 minutes at a time, with the aim of emulating project teamwork tasks.[1] The five activities had specific requirements:

- *Work*. Participants worked on a homework assignment with directives such as type, model, sketch, diagram, or data search.
- *Listen*. Participants selected and listened to a TED talk from a given list.
- *Multitask*. Every two minutes, participants had to switch performing multiple tasks simultaneously, such as listening to a TED talk, checking email, taking calls, interacting with Facebook friends, or conducting some other chosen activity.
- *Collaborate*. Groups of three participants each were part of a collaborative exercise in which they used a web-conferencing tool to share a sketching application. To keep all participants constantly engaged, a signal was given every few seconds, at which time the participant controlling the digital pen had to give it to the next person in the group to add to the sketch.
- *Relax*. Participants were asked to find a comfortable position, close their eyes, and listen to a guided meditation designed to bring them to a relaxed state.

For the labeled EEG recordings, we used a coding schema that represented the five activities.

TABLE 1. Power spectral density (PSD) values for five electroencephalography (EEG) bands across five activities in our study.

PSD value	Work	Listen	Multitask	Collaborate	Relax
mean(δ)	406,024	405,066	376,958	554,594	218,457
median(δ)	132,525	120,316	122,405	287,753	30,336
mean(θ)	99,278	97,819	101,539	130,228	67,092
median(θ)	39,308	36,690	40,799	54,449	23,388
mean(α)	54,757	45,097	53,149	63,932	59,311
median(α)	26,367	23,449	26,493	31,533	41,037
mean(β)	37,429	29,028	38,761	51,105	25,010
median(β)	21,109	18,541	22,060	25,836	17,450
mean(γ)	19,600	14,555	252,711	31,733	10,108
median(γ)	10,649	9,489	126,605	18,354	6,251

Dataset characteristics

We processed and cleaned the artifacts of labeled and unlabeled EEG recordings for the 20 participants and discarded any incomplete datasets. We ended up with complete datasets of labeled and unlabeled records for 13 participants: 7 male and 6 female. In total, we had 2 million second-by-second EEG unlabeled records (approximately 60 hours) from the weekly project meetings and more than 50,000 second-by-second labeled EEG records (approximately 14 hours).

The EEG data includes the PSD values of the classically defined EEG band frequencies—delta, theta, alpha, beta, and gamma—collected continuously for 1-second intervals. Each line in the EEG record includes a time stamp and eight EEG PSDs: delta, theta, low-alpha, high-alpha, low-beta, high-beta, low-gamma, and mid-gamma. The PSD values have no units; they are meaningful only as quantities relative to each other and themselves.

Table 1 shows the basic statistical values we calculated including the mean value and the median value of the PSD time series in terms of the EEG band frequencies: delta, theta, alpha, beta, and gamma (δ, θ, α, β, and γ).

Data interpretation

Although studies exploring the correlation of mental states with EEG bands differ in how they define EEG bands' boundaries, they are generally consistent in how they assign hertz to mental state. For example, delta (0.1 Hz to approximately 3 Hz) represents deep sleep that is not rapid eye movement (REM) sleep; theta (4 Hz to approximately 7 Hz) represents creative, recall, imagery, and switching thoughts; alpha (8 Hz to approximately 12 Hz) represents a relaxed but not drowsy state; and gamma (30 Hz to approximately 100 Hz) represents higher mental activity, thinking, and an integrated thought process.

Relax activity. We found that statistical values for the relax activity differed from those for all the other activities in that it was characterized by a low value in the delta, theta, beta, and gamma bands and a high value in the alpha band. Unlike the other four activities, relax requires participants to remain in a mental state with the highest relaxation and lowest attention levels. The other four activities have less distinguishable characteristics.

Mental workload. Mental workload is of particular interest because it is a measure of the cognitive processing level, which relates to thinking, interacting, and other activities during a meeting. Research has shown that EEG signal oscillations from the frontal

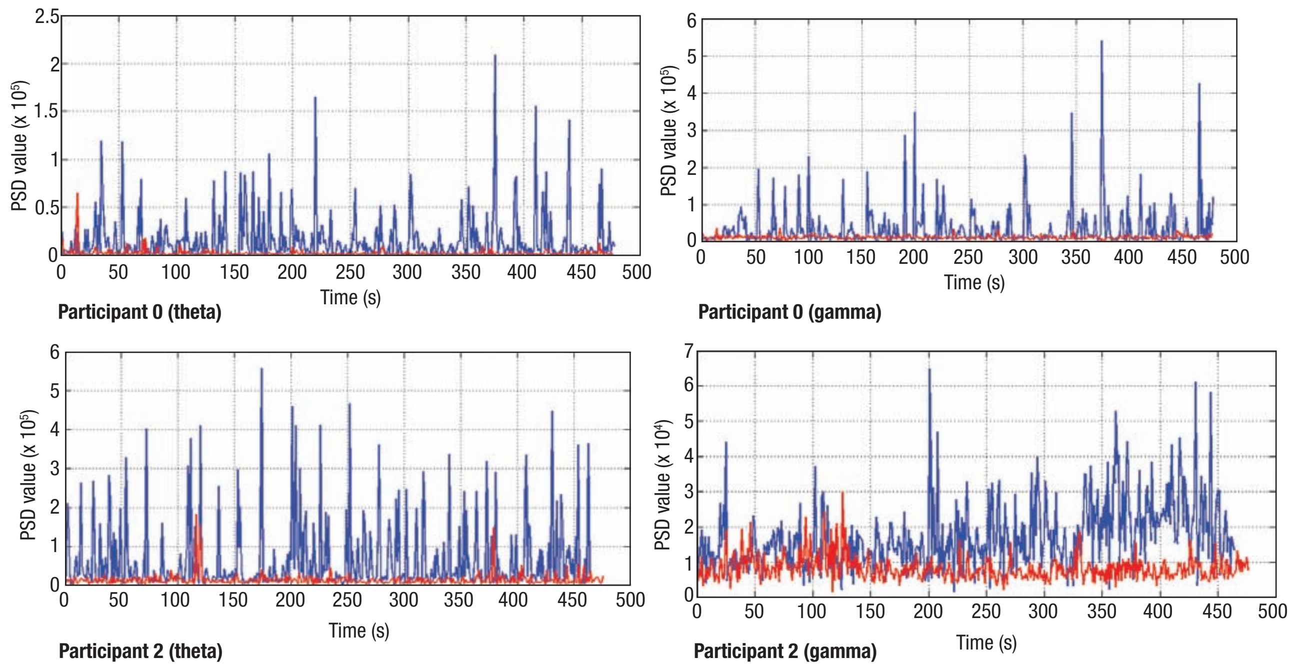

FIGURE 1. Power spectral density (PSD) values in the theta and gamma electroencephalography (EEG) bands for two randomly selected participants, which indicate mental workload. The values are taken for 500 seconds during the work (blue lines) and relax (red lines) activities. The curves show much higher values during the work activity, although the oscillation curves are slightly different for each participant, indicating that mental workload fluctuates during work activity.

theta and lateral gamma are strongly correlated to mental workload.[3,9–11] For that reason, we further investigated the role of theta and gamma EEG bands in indicating mental workload.

Figure 1 illustrates the changes in PSD of the theta and gamma bands over time for two randomly chosen participants during both work and relax activities.

Results were similar for the listen, multitask, and collaborate activities, during which mental workload also did not remain consistently high. The implication is that when participants worked, they seemed to interleave heavy mental workload states with a lighter "recovery" state. This finding—that people tend to alternate between several mental workload states with different mental workload levels—motivated us to develop the MMSM.

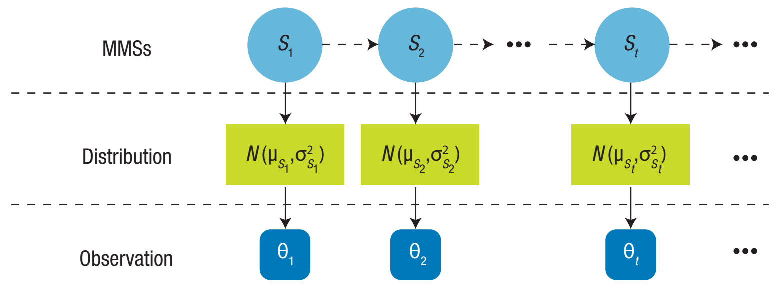

FIGURE 2. Layers in the Mental Motion State Model (MMSM). The top layer is a time-indexed series of possible mental motion states (MMSs); the distribution layer describes the distribution the lower layer followed; and the observation layer is a sample EEG signal sequence generated from the distributions in the middle layer.

CAPTURING MENTAL STATE TRANSITIONS

We created the MMSM because analyzing raw EEG signals, as we did in Figure 1, does not sufficiently distinguish activities. The MMSM, in contrast, captures the transitions between mental states, each of which has a different mental workload.

The model's underlying assumption is that an individual's mental state defines the observed EEG signal. A mental motion state (MMS) is a stable level of cognitive and thinking intensity. As Figure 2 shows, the MMSM has three layers: MMS, distribution, and observation.[6]

The MMS layer is a time-indexed MMS sequence $\{s_1, s_2, \ldots, s_t, \ldots\}$, where $s_i \in$ {possible MMSs} and $i = 1, 2, \ldots, t, \ldots$ is the time index. For each MMS s_i, we assume there is a corresponding Gaussian distribution

$$N(\mu_{s_i}, \sigma^2_{s_i})$$

that generates the actual EEG signal θ_i we observed. Given the MMS sequence $\{s_1, s_2, \ldots, s_t, \ldots\}$ in the MMS layer, the distribution layer is the corresponding

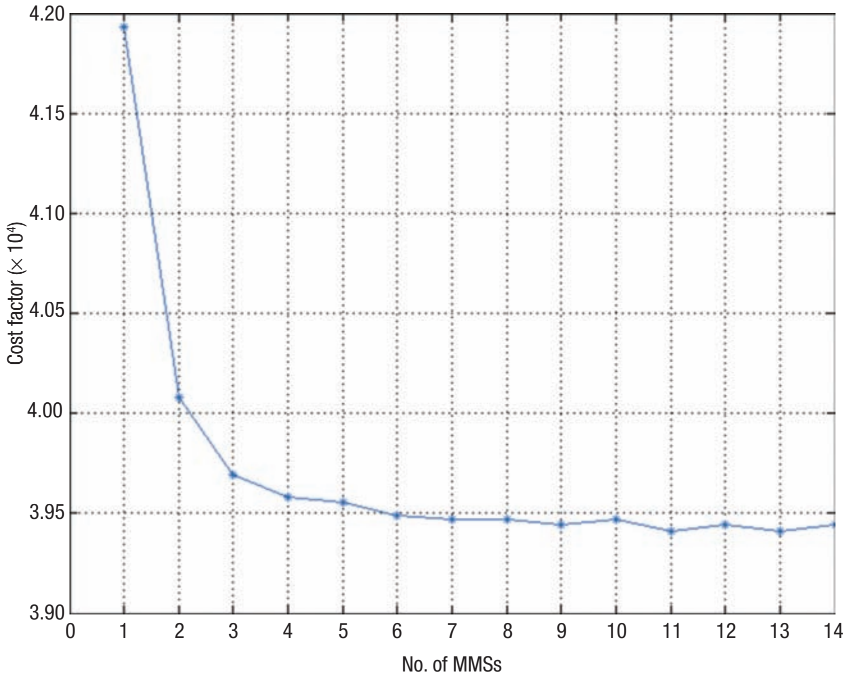

FIGURE 3. Determining model fit. Cost value drops dramatically at the beginning but remains almost unchanged after six MMSs. Although a model with more MMSs has a lower cost and thus a better fit with the data, more MMSs can mean a less understandable model.

time-indexed EEG signal distribution sequence

$$\{N(\mu_{s_1},\sigma^2_{s_1}),N(\mu_{s_2},\sigma^2_{s_2}),\ldots,N(\mu_{s_t},\sigma^2_{s_t}),\ldots\}.$$

The observation layer is an EEG signal sample sequence generated from the corresponding distributions in the distribution layer. The signals are those obtained through the Mindwave headset. For simplicity, we considered the observed second-by-second PSD value of each EEG signal band as a 1D data stream, so the corresponding distributions are 1D Gaussian distributions. For the 2D case, Gaussian distributions are 2D distributions—the MMSM is essentially modeling the process in which a person constantly switches between different MMSs.

Learning algorithm

According to our MMSM definition, the parameters that can describe a MMSM are

$$\{K,N(\mu_1,\sigma_1^2),N(\mu_2,\sigma_2^2),\ldots,N(\mu_K,\sigma_K^2)\},$$

where K is the number of all possible MMSs that people have and $\{N(\mu_1,\sigma_1^2),N(\mu_2,\sigma_2^2),\ldots,N(\mu_K,\sigma_K^2)\}$ is the set of means and variances of the K corresponding distributions for each MMS.

Initially, the only available data is the observed EEG signals time sequence $\{\theta_1, \theta_2, \ldots, \theta_t, \ldots\}$, which is captured in the MMSM's observation layer. To train the

$$\{K,N(\mu_1,\sigma_1^2),N(\mu_2,\sigma_2^2),\ldots,N(\mu_K,\sigma_K^2)\}$$

model parameter, we used a learning algorithm based on the Gaussian mixture model.

We assume that the MMSM parameters

$$\{K,N(\mu_1,\sigma_1^2),N(\mu_2,\sigma_2^2),\ldots,N(\mu_K,\sigma_K^2)\}$$

are already known and that the MMSM's sampling processes generate EEG signals from a certain distribution at different time points that are independent from each other. Given observed EEG data θ_t at time point t, the probability calculated by the Gaussian mixture model for data point θ_t can be expressed as

$$P(\theta_t) = \sum_{k=1}^{K}\lambda_k \cdot P(\theta_t \mid \text{state} = k)$$
$$= \sum_{k=1}^{K}\lambda_k \cdot N(\theta_t \mid \mu_k,\sigma_k)$$
$$= \sum_{k=1}^{K}\lambda_k \cdot \frac{1}{\sqrt{2\pi\sigma_k}}\exp\left(-\frac{(\theta_t-\mu_k)^2}{2\sigma_k^2}\right) \quad (1),$$

where λ_k is the prior probability of the kth MMS, and μ_k and σ_t^2 are the mean and variance of the distribution of the kth MMS.

Assuming n EEG signal points $\{\theta_1, \theta_2, \ldots, \theta_n\}$, we used maximum-likelihood estimation to estimate the model's parameter set

$$\chi = \{(\mu_1,\sigma_1^2),(\mu_2,\sigma_2^2),\ldots,(\mu_K,\sigma_K^2)\}.$$

The objective function is

$$\max_{\chi}\sum_{t=1}^{n}\log\left(P(\theta_t)\right),$$

where the Gaussian mixture model's $P(\theta_t)$ is given by Equation 1. The complete expression for the log-likelihood function is

$$\max_{\chi}\sum_{t=1}^{n}\log\left(\sum_{k=1}^{K}\lambda_k \cdot \frac{1}{\sqrt{2\pi\sigma_k}}\exp\left(-\frac{(\theta_t-\mu_k)^2}{2\sigma_k^2}\right)\right) \quad (2).$$

We used the expectation maximization (EM) technique to find the estimated parameters $\hat{x}$ of the optimization problem in Equation 2. EM is an iterative process that goes through each expectation step (E-step) and maximization step (M-step) repetitively.[12] The E-step uses the current estimated mean and variance parameters to estimate the probability that each data

TABLE 2. Training results with the 1D Mental Motion State Model given as the mean for each mental motion state (MMS).

Distribution parameters	MMS 1	MMS 2	MMS 3
$\hat{\mu}$	0.2105×10^5	0.6938×10^5	2.1776×10^5
$\hat{\sigma}$	9.6735×10^5	3.2484×10^4	1.1661×10^5

point belongs to each MMS. The M-step updates the mean and variance of each MMS's distribution on the basis of probabilities calculated in the E-step. The EM learning process for n observed data points $\{\theta_1, \theta_2, \ldots, \theta_n\}$ and K number of MMSs can be expressed as E-step:

$$\varpi_{tk} = \frac{\lambda_k \cdot \frac{1}{\sqrt{2\pi\sigma_k}} \exp\left(-\frac{(\theta_t - \mu_k)^2}{2\sigma_k^2}\right)}{\sum_{j=1}^{K} \lambda_j \cdot \frac{1}{\sqrt{2\pi\sigma_j}} \exp\left(-\frac{(\theta_t - \mu_j)^2}{2\sigma_j^2}\right)} \quad (3).$$

M-step:

$$\xi_k = \sum_{t=1}^{n} \varpi_{tk}$$
$$\mu_k = \frac{1}{\xi_k} \sum_{t=1}^{n} \varpi_{tk}\theta_t$$
$$\sigma_k^2 = \frac{1}{\xi_k} \sum_{t=1}^{n} \varpi_{tk}(\theta_t - \mu_k)^2$$
$$\lambda_k = \frac{1}{n} \sum_{t=1}^{n} \varpi_{tk} \quad (4),$$

where ϖ_{tk} (t=1, 2, …, n; k = 1, 2, …, K) is the estimated probability that data point θ_t belongs to kth MMS; ξ_k (k = 1, 2, …, K) is the normalization term for the kth MMS.

Model training

The training results of both the 1D and 2D MMSM show that the model accurately represents the actual data. The 1D MMSM has PSD values for the theta band only (the gamma band only will produce similar results), and the 2D MMSM has PSD values for the theta and gamma bands together.

1D model. For the 1D MMSM, we used only the theta band's PSD signal; using gamma band only will generate a similar result. Applying the EM process in Equations 3 and 4, we can estimate the MMSM's parameters

$$\chi = \{(\mu_1, \sigma_1^2), (\mu_2, \sigma_2^2), \ldots, (\mu_K, \sigma_K^2)\}$$

with a given number of MMS K. However, K is also one of the unknown parameters that must be estimated. Consequently, we removed K from the objective function by substituting variable K with 1, 2, …, 14. Because we observed that cost does not decrease appreciably after six MMSs, we chose 14 (a large number) to test our observation.

Figure 3 shows that the cost value drops dramatically at the beginning and remains almost unchanged after this initial decrease. That is, the more complex the model is, the better that model fits with the data. However, a more complex model also means the EEG data will be interpreted with more MMSs, making it harder to understand. Therefore, there is a tradeoff between model complexity (the number of MMSs chosen) and how the model fits the dataset.

On the basis of the Akaike and Baysian information criteria, we determined that three MMSs were optimal. We used $\hat{K} = 3$ as the estimate of total MMSs and applied the EM process in Equations 3 and 4 to determine the remaining model parameters

$$\chi = \{(\mu_1, \sigma_1^2), (\mu_2, \sigma_2^2), \ldots, (\mu_3, \sigma_3^2)\}.$$

Table 2 shows the training results.

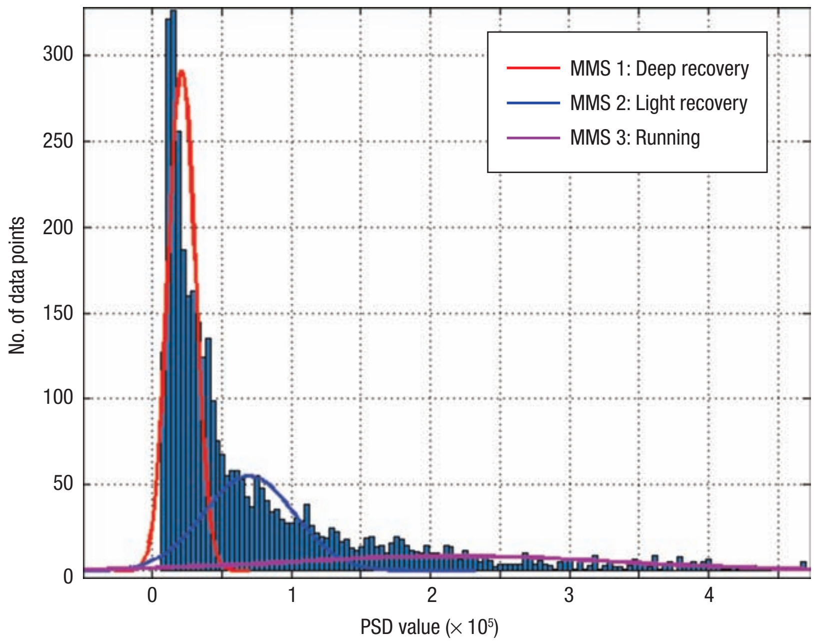

FIGURE 4. How the 1D MMSM (EEG theta band only) compares with a histogram of the actual data (blue bars). The curves for the three MMSs show that the trained MMSM has a good fit with the data.

TABLE 3. Results of 2D MMSM training.

Distribution parameters	MMS 1	MMS 2	MMS 3
$\hat{\mu}^{(\theta)}$	0.2609×10^5	0.6708×10^5	2.1776×10^5
$\hat{\mu}^{(\gamma)}$	0.6665×10^4	1.4801×10^4	3.6212×10^4
$\hat{\Sigma}$	$\begin{bmatrix} 1.383 & -0.098 \\ -0.098 & 0.082 \end{bmatrix} \times 10^8$	$\begin{bmatrix} 1.221 & 0.017 \\ 0.017 & 0.049 \end{bmatrix} \times 10^9$	$\begin{bmatrix} 1.414 & 0.145 \\ 0.145 & 0.074 \end{bmatrix} \times 10^{10}$

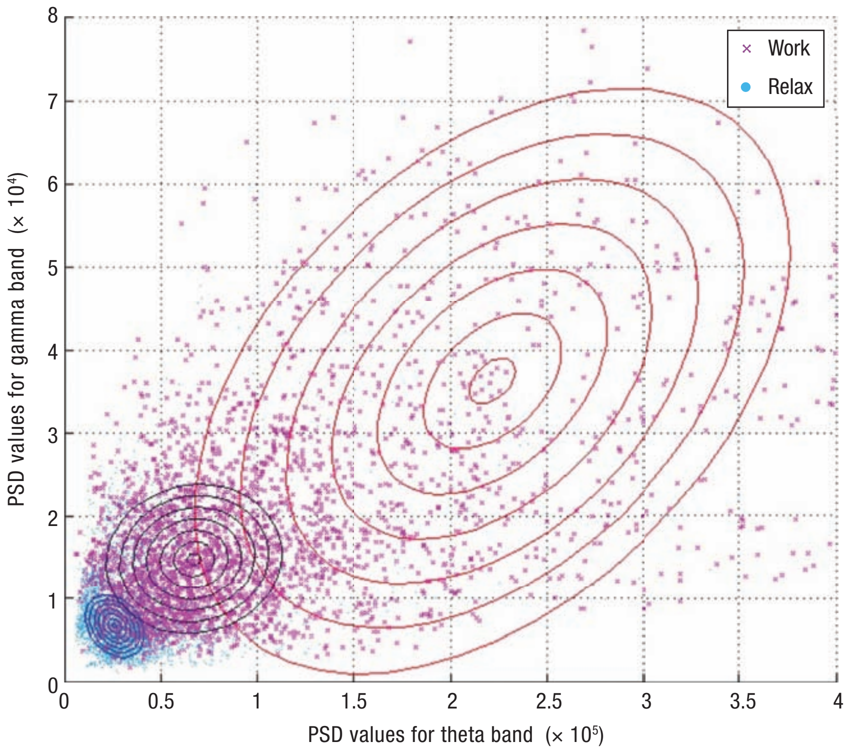

FIGURE 5. How the 2D MMSM fits with a 2D scatter plot of PSD values (for gamma and theta in the work and relax activities). The three MMSs (spirals) fit well with the data. MMS 1 (blue spiral) is the deep recovery state, which fits with the concentration of relaxation data points. MMS 2 (black spiral) is the light recovery state and fits data that shows a transition (mix of work and relax data points) from relaxation to heavy work in MMS 3 (orange spiral), which is the running state.

Because the mean value of each MMS's distribution reflects the individual's average mental workload, we labeled the three MMSs in terms of workload using a running analogy:

- *Deep recovery* (MMS 1) has a relatively low mental workload; participants are assumed to be relaxing.
- *Light recovery* (MMS 2) has a medium mental workload. Participants are assumed to be generally thinking, processing information, or conducting simple tasks.
- *Running* (MMS 3) has a heavy mental workload. Participants are assumed to be conducting a difficult or high-level cognitive task.

Figure 4 shows how the trained 1D MMSM fits with the actual dataset—the histogram of PSD signals in the theta band. Consequently, the training result is satisfactory.

2D model. We used a similar training process for the 2D MMSM, in which the observation layer includes the PSD signals of both the theta and gamma bands from the work and relax activities. The model parameter set becomes $\{K, (\mu_1, \Sigma_1), (\mu_2, \Sigma_2), \ldots, (\mu_K, \Sigma_K)\}$, where

$$\left(\mu_i^{(\theta)}, \mu_i^{(\gamma)}\right)\left(i = 1,2,\cdots,K\right)$$

is the mean vector (theta and gamma bands) of the ith MMS; and Σ_i ($i = 1, 2, \ldots, K$) is the covariance matrix of the corresponding 2D MMSM's Gaussian distribution. As in the 1D MMSM (see Figure 3), the 2D MMSM curve of cost versus number of MMSs has a dramatic drop in cost at the beginning and remains almost unchanged after the initial decrease. Similarly, after applying the Akaike or Bayesian information criterion, we identified $\hat{K} = 3$ as the optimal number of estimated MMSs, and we calculated the remaining parameters $\{(\mu_1, \Sigma_1), (\mu_2, \Sigma_2), (\mu_3, \Sigma_3)\}$. Table 3 shows the training results.

Figure 5 shows the comparison of a 2D scatter plot of PSD values from both theta and gamma bands with the trained 2D MMSM. Like the 1D MMSM, the 2D MMSM fits well with the actual data.

Sample application

To illustrate the MMSM's effectiveness, we randomly chose a participant from the activity-labeled data and translated the corresponding EEG raw data collected from the five activities into five MMS transition sequences. Figure 6 shows the three MMSs and the second-by-second state transitions of the five activities.

Visualizing the EEG data as MMS transitions provides insights into when individuals were in a state characterized by relaxation or deep thinking. Predictably, in the relax activity, the participant spent more time in deep recovery, relative to the other four activities. But for the work, multitask, and collaborate activities, Figure 6 reveals interesting mental patterns. For example, the work activity was focused on familiar homework tasks, so the participant entered the running state only sporadically. In multitasking, however, the participant must exert more cognitive effort to organize tasks, which the MMSM analysis and visualization support: the multitask activity is characterized by initially large running segments that likely reflect the cognitive overload in processing significant amounts of diverse information feeds.

In the collaborate activity, the MMSM analysis shows that the participant sporadically interleaved the three MMSs, following the cognitively demanding running state with microrecovery moments. This behavior is desirable because it incorporates the mental recovery that keeps thinking processes sharp for longer periods.

However, the interleaving of the three MMSs was not the result of explicit and systematic participant behavior, which we believe can lead to higher task performance. As a next step, we plan to further investigate the MMSM data analysis results with the meeting recordings to look for a correlation between MMSs interleaving and task performance. Such a correlation would let us formalize recommendations for increasing global learners' and knowledge workers' performance.

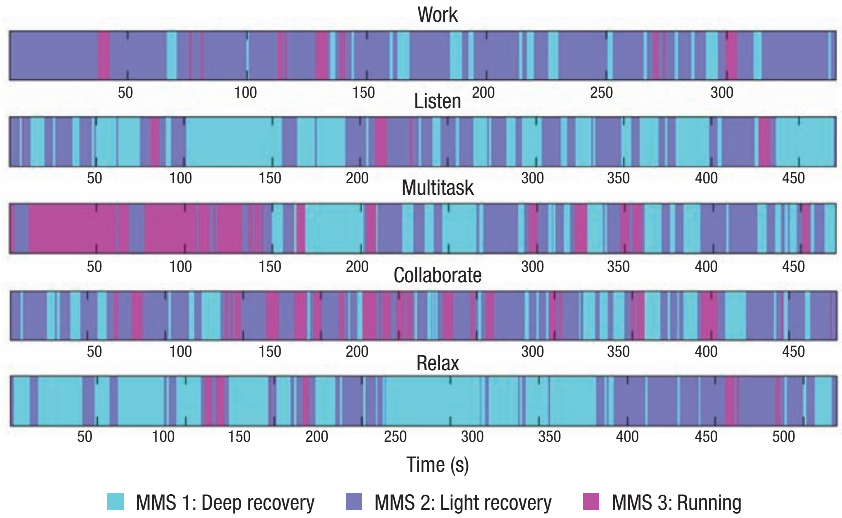

FIGURE 6. Interpreting activity transition states. Visualizing data in terms of transition states reveals interesting mental patterns. For example, this participant spent more time in the deep recovery state during the relax activity than in any of the other four activities and had a surprising amount of light recovery time during the work activity.

Model validation

To validate the MMSM, we used the labeled EEG dataset as the ground-truth test set and the unlabeled data as the training set. Our validation results showed that the three MMSs we defined (deep recovery, light recovery, and running) are consistent with both the activity labels in the ground-truth test set and our observations during data collection. For example, relax data represents data captured while participants were in deep recovery, and work data was collected while participants were working and processing information—that is, when they were switching between the light recovery and running states. An example is document editing, in which people tend to think for a bit, type for a bit, and then resume thinking; they do not type constantly.[6]

Therefore, if our assumption is right, we should be able to identify the deep recovery MMS only in the data labeled "relax" and the light recovery and running MMSs in the data labeled "work." To determine if this was the case, we used the learning algorithm to train a 1D MMSM from the relax data (with one MMS) and from the work data (with two MMSs). The results of the two training models gave us the same three MMSs: deep recovery, light recovery, and running. Thus, the model trained on the unlabeled dataset is consistent with the actual activity labeling (relax and work), verifying that it is useful in improving the degree of distinction among activities.

We also used Weitzman's overlapping coefficient—widely regarded as the measure of distributions' agreement or similarity—to compare each pair of the three distribution parameter sets (the three MMSs). Our results showed that the overlapping coefficients of the distributions of the three mental states learned from the test set and the training set are 0.721, 0.944, and 0.993. They are all higher than 0.7, which indicates that results were highly consistent.

Finally, considering the label of the five activities as ground truth, we used the degree of distinction as a metric to compare the MMSM with the raw mental workload indicator signals on the ability to distinguish those five different activities. Our results show that the proposed MMSM can greatly increase the degree of distinction between activities compared to approaches using only raw EEG mental workload indicators such as the theta and gamma PSD values. This result shows that the MMSM can reveal more details about participants' activities relative to using the predefined EEG frequency bands directly.[6]

Globalization has affected the way people collaborate in corporate and academic projects, which greatly influences the quality of online meetings. Understanding meeting participants' mental and physical states helps build an awareness of engagement style and fatigue level and can lead to self-regulated meetings.

Fluctuations of the theta and gamma bands hinder the understanding and interpretation of individuals' mental activities when using raw EEG signals. The MMSM describes these fluctuations in a more meaningful way as transitions between MMSs, allowing greater distinction among activities than is possible with just EEG indicators, such as the PSD values of EEG theta and gamma bands. The MMSM's unique learning algorithm provides detailed information about mental processes for individuals to self-regulate their degree of engagement, activity pace, and workload balance. This regulation could lead to better task performance and a higher overall quality of life.

The MMSM can serve as the foundation for interesting research, such as integrating additional EEG bands as other mental property indicators and automating the activity-labeling algorithm. As a next step, we plan to integrate MMSM data analysis results with other sensor data analysis indicators such as heart rate and body motion. We also plan to use the MMSM as an intermediate signal-processing level with state transitions becoming part of the data for analyzing higher-level mental processes, such as problem solving, cost benefit analysis, negotiation, conflict resolution, and decision making.

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Using Multimodal Wearable Technology to Detect Conflict among Couples

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By monitoring human behavior unobtrusively, mobile sensing technologies have the potential to improve our daily lives. Initial results from a field study demonstrate that such passive technologies can detect a complex psychological state in an uncontrolled, real-life environment.

Mobile, real-time, multimodal monitoring of people in real-life settings represents a new computing trend with important implications for both our physical and mental health. From physical activity to physiological arousal to language use, we can monitor a vast number of variables on an ongoing basis. By collecting data via multiple channels over long periods of time, we can obtain an unprecedented amount of information about ourselves and our lives. For example, we can test data streams to determine how day-to-day events impact our emotions, behaviors, and physical well-being across time as well as how these factors are interconnected.

Wearable technologies can also be interactive, so information obtained from such data (such as increasing levels of vocal pitch indicative of emotional arousal) could trigger messages that prompt interventions aimed at behavioral change and improved psychological functioning (for example, a text message prompting a guided meditation exercise). Such systems could be used alone or integrated with standard clinical interventions to increase their effectiveness and maximize therapeutic gains.

Although the applications of such mobile sensing systems are exciting, they also present many challenges. Specifically, monitoring human behavior in uncontrolled settings is wrought with difficulty; researchers must synchronize signals across devices, integrate multiple platforms, securely and efficiently store large amounts of data, and process and analyze that data. They must also minimize the burden and intrusiveness of these monitoring systems so that they are not overly disruptive to daily life and people are willing to wear them.

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Although devices and procedures for collecting big data have proliferated in recent years, the infrastructure for processing and interpreting such data has lagged behind, creating a bottleneck between the collection of data and its application to real-world uses. For example, developing algorithms that can detect events of interest in real time is a major hurdle because data collected in everyday settings can be noisy, introducing errors to modeling schemes. Beyond these practical concerns, researchers must keep in mind privacy and ethical considerations and work to maximize the data's security and reduce the risk of psychological harm to system users.

The University of Southern California (USC) Couple Mobile Sensing Project (homedata.github.io) is an interdisciplinary collaboration between engineers and psychologists that uses ambulatory computing technologies to study interpersonal relationships, with the eventual goal of developing interventions to improve couple functioning. Here, we report the initial results from a field application involving the use of wearable technology to detect psychological states. In our study, young-adult couples wore biosensors measuring their electrodermal and electrocardiographic activity, physical activity, and body temperature and carried smartphones that collected audio recordings and GPS coordinates for one day. The couples also completed phone surveys each hour to report on their ongoing moods and if they experienced conflict. Classification experiments using binary decision trees resulted in unweighted accuracies as high as 86.8 percent when we combined the features from all sensor modalities. The procedures described in this article could be extended to develop interactive, real-time interventions to decrease conflict and prompt alternative behavior, improving couples' relationship functioning and quality of life.

USING WEARABLE TECHNOLOGY TO DETECT PSYCHOLOGICAL STATES

Being able to identify, monitor, and alter our emotional states in real time is an important next step toward developing more effective interventions for improving quality of life. For example, engaging in daily positive activities has been linked to improved well-being.[1] In addition to emotional states, the quality of our relationships plays a central role in our mental and physical health. Interpersonal conflicts, such as arguments with coworkers, greatly impact our daily moods.[2] Romantic relationships in particular play a central role in individuals' quality of life; high levels of relationship conflict, in particular divorce, are linked to increased risk of psychological problems.[3]

WEARABLE TECHNOLOGY CAN BE USED TO MONITOR PROBLEMATIC RELATIONSHIP DYNAMICS IN REAL LIFE.

Current therapies aiming to improve relationship functioning typically alter couples' interaction patterns and communication processes. These interventions are usually administered during therapy sessions, with the expectation that any gains made in the session will translate into behavioral change outside of the therapy room. However, in their home lives, couples often find themselves pulled into arguments that escalate, become entrenched over time, and are hard to exit.

One method to address this problem is to use wearable technology to monitor problematic relationship dynamics in real life. Mapping these patterns across time could provide data on what variables predict conflict and what factors are associated with conflict resolution. Results from these data could eventually be used to detect conflict and send behavior prompts to alter maladaptive relationship processes as they occur at home.

See the "Previous Research on Detecting Psychological States" sidebar for other work in this area.

Features of conflict

A large body of laboratory research has examined how distressed and nondistressed couples differ in terms of how they interact, respond physiologically, and speak to each other during conflict. For example, heightened electrocardiographic (ECG) activity and electrodermal activity (EDA) during problem-solving discussions are linked to decreased marital satisfaction.[4]

Relatedly, covariation in physiological responses over time, or *synchrony*,

PREVIOUS RESEARCH ON DETECTING PSYCHOLOGICAL STATES

Numerous studies have attempted to use machine-learning techniques to automatically detect conflict in spoken conversations, but most of these human-activity recognition attempts have been in controlled settings.[1,2] Applying these methods in real-life, uncontrolled environments is difficult for several reasons. First, many events of interest, such as conflict, have low base rates, meaning there is less information available for building the classification schemes. Second, signals recorded in such environments tend to be noisy, creating additional challenges for recovering and representing the inherent information. Third, fluctuations in variables (such as electrodermal activity) can reflect other processes (including exercise and anxiety) in addition to the event of interest, making it difficult to differentiate across events.

Some research has attempted to detect behaviors in daily life, but such projects usually focus on directly observable behaviors, such as whether people are talking,[3] that are easier to identify than more subjective experiences, like whether conflict is occurring. Moreover, different people can exhibit a range of behavioral, emotional, and physiological reactions in response to conflict, making it difficult to create one system that works well for all individuals. Although detecting psychological states in uncontrolled environments is difficult, developing this ability could have many important applications.

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has been associated with both attachment style (that is, how secure versus anxious people feel in their interpersonal relationships) and marital satisfaction.[5,6] Exactly what partners say to each other when they are angry is also important; studies have shown that even subtle aspects of language, such as the pronouns we use, are related to important relationship processes. That is, second-person singular pronoun use (such as "you" and "you'd") during problem-solving discussions is thought to reflect higher levels of blaming (for example, "You didn't do the dishes"), whereas first-person singular pronoun use (such as "I" and "I'll") is thought to reflect better communication skills (for example, "I felt frustrated when I saw the dishes in the sink").[7] It is also possible that couples in more distressed relationships use more negative emotion words (such as "sad") and certainty words (for example, "You *always* criticize me").

Beyond what couples say to each other, the tone of speech might be an important indicator of relationship functioning. Thus, we can use acoustic measures such as vocal intensity (or loudness) and fundamental frequency (or pitch, F0) to obtain additional data on couples' communication patterns.[8]

Prototype model

Using mobile computing technology, our field study collected self-reports of mood and the quality of interactions (MQI) between partners, EDA, ECG activity, synchrony scores, language use, acoustic quality, and other relevant data (such as whether partners were together or communicating remotely) to detect conflict in young-adult dating couples in their daily lives. We conducted classification experiments with binary decision trees to retroactively detect the number of hours of couple conflict.

To assess our approach's usefulness, our study addressed four interrelated research questions that generated four tasks:

- *Question 1*: Are theoretically driven features related to conflict episodes in daily life? *Task 1*: We conducted individual experiments for theoretically driven features, including self-reported MQI, EDA, ECG activity, synchrony scores, personal pronoun use, negative emotion words, certainty words, F0, and vocal intensity.
- *Question 2*: Are unimodal feature groups related to conflict episodes in daily life? *Task 2*: We combined the features into unimodal groups to determine the classification accuracy of different categories of variables.
- *Question 3*: Are multimodal feature combinations related to conflict episodes in daily life? *Task 3*: We combined the feature groups into multimodal indices to examine the performance of multiple sensor modalities.
- *Question 4*: How do multimodal feature combinations compare with the couples' self-report data? *Task 4*: We statistically compared the classification accuracy of our multimodal indices to the couples' self-reported MQI to ascertain the potential of these methods to identify naturally occurring conflict episodes beyond what participants themselves reported, hour by hour.

Our objective here is to present preliminary data and demonstrate our classification system's potential utility for detecting complex psychological states in uncontrolled settings. Although this study collected data on dating couples, these methods could be used to study other types of relationships, such as friendships or relationships between parents and children.

RESEARCH METHODOLOGY

The participants in our study consisted of young-adult dating couples from the Couple Mobile Sensing Project, with a median age of 22.45 years and a standard deviation (SD) of 1.60 years. The couples were recruited from the greater Los Angeles area and had been in a relationship for an average of 25.2 months (SD = 20.7). Participants were ethnically and racially diverse, with 28.9 percent identifying as Hispanic, 31.6 percent Caucasian, 13.2 percent African-American, 5.3 percent Asian, and 21.1 percent multiracial.

Out of 34 couples who provided data, 19 reported experiencing at least one conflict episode and thus were included in the classification experiments.

All study procedures were approved by the USC Institutional Review Board.

Measures

All dating partners were outfitted with two ambulatory physiological monitors that collected EDA and ECG data for one day during waking hours. They also received a smartphone that alerted them to complete hourly self-reports on their general mood states and the quality of their interactions. The self-report options, which were designed to assess general emotional states relevant to couple interactions, included feeling stressed, happy, sad, nervous, angry, and close to one's partner. Responses ranged from 0 (not at all) to 100 (extremely).

Additionally, each phone continuously collected GPS coordinates, as well as 3-minute audio recordings every 12 minutes from 10:00 a.m. until the couples went to bed.

Physiological indices. We collected physiological measures continuously for one day, starting at 10:00 a.m. and ending at bedtime. EDA, activity count, and body temperature were recorded with a Q-sensor, which was attached to the inside of the wrist using a band. ECG signals were collected with an Actiwave, which was worn on the chest under the clothing. ECG measures included the interbeat interval (IBI) and heart rate variability (HRV), and EDA features consisted of the skin conductance level (SCL) and the frequency of skin conductance responses (SCRs). Estimates of synchrony, or covariation in EDA signals between romantic partners, were obtained using joint-sparse representation techniques with appropriately designed EDA-specific dictionaries.[6]

We used computer algorithms to detect artifacts, which were then visually inspected and revised. All scores were averaged across each hour to obtain one estimate of each measure per hour-long period.

Language and acoustic feature extraction. A microphone embedded in each partner's smartphone recorded audio during the study period. The audio clips were 3 minutes long and collected once every 12 minutes, resulting in 6 minutes of audio per 12 minutes per pair (male and female within a couple). This resulted in a reasonable tradeoff between the size of the audio data available for storage and processing and the amount of acquired information. For privacy considerations, participants were instructed to mute their microphones when in the presence of anyone not in the study.

We transcribed and processed audio recordings using Linguistic Inquiry and Word Count (LIWC) software.[9] For our theoretically driven features (task 1), we used preset dictionaries representing personal pronouns (such as "I" and "we"), certainty words (such as "always" and "must"), and negative emotion words (such as "tension" and "mad"). To test unimodal combinations of features, we used four preset LIWC categories, including linguistic factors (25 features including personal pronouns, word count, and verbs), psychological constructs (32 features such as words relating to emotions and thoughts), personal concern categories (seven features such as work, home, and money), and paralinguistic variables (three features such as assents and fillers).

Voice-activity detection (VAD) was used to automatically chunk continuous audio streams into segments of speech or nonspeech. We used speaker clustering and gender identification to automatically assign a gender to each speech segment. We then extracted vocally encoded indices of arousal (F0 and intensity). To map the low-level acoustic descriptors onto a vector of fixed dimensionality—independent of the audio clip duration—we further computed the mean, SD, maximum value, and first-order coefficient of the linear regression curve over each speech segment, resulting in eight features. All acoustic and language features were calculated separately by partner and averaged per hour.

> **OUR STUDY RESULTS SHOW THAT DATA COLLECTED VIA MOBILE COMPUTING ARE VALID INDICATORS OF INTERPERSONAL FUNCTIONING IN DAILY LIFE.**

Context and interaction indices. In addition to our vocal, language, self-reported, and physiological variables, we assessed numerous other factors that are potentially relevant for identifying conflict episodes. The contextual variables included whether participants consumed caffeine, alcohol, tobacco, or other drugs; whether they were driving; whether they exercised; body temperature; and physical activity level. The interactional variables involved the GPS-based distance between partners and information related to whether the dating partners were together, interacting face to face, or communicating via phone call or text messaging and if they were with other people.

The data for the contextual and interactional feature groups were collected via various mechanisms, including physiological sensors, smartphones, self-reports based on the hourly surveys, and interview data.

Conflict. We identified the hours in which conflicts occurred using the self-report phone surveys. For each hour, participants reported whether they "expressed annoyance or irritation" toward their dating partner using a dichotomous yes/no response option. Because determining what constitutes a conflict is subjective, we elected to use a discrete behavioral indicator (that is, whether the person said something out of irritation) as our ground-truth criterion for determining if conflict behavior occurred within a given hour. This resulted in 53 hours of conflict behavior and 182 hours of no conflict behavior for females and 39 hours of conflict behavior and 206 hours of no conflict behavior for males.

Conflict classification system

The goal of the classification task was to retroactively distinguish between instances of conflict behavior and no conflict behavior, as reported by the participants. The analysis windows constituted nonoverlapping hourly instances starting at 10:00 a.m. and ending at bedtime.

To classify conflict, we used a binary decision tree because of its efficiency and self-explanatory structure. We employed a leave-one-couple-out cross-validation setup for all classification experiments. For tasks 2 and 3, feature transformation was performed through a deep autoassociative neural network, also called an *autoencoder*, with three layers in a fully unsupervised way. The autoencoder's bottleneck features at the middle layer consisted of the input of a binary tree for the final decision (Y = conflict and N = no conflict). Unimodal classification followed a similar scheme, under which the autoencoder transformed only the within-modality features.

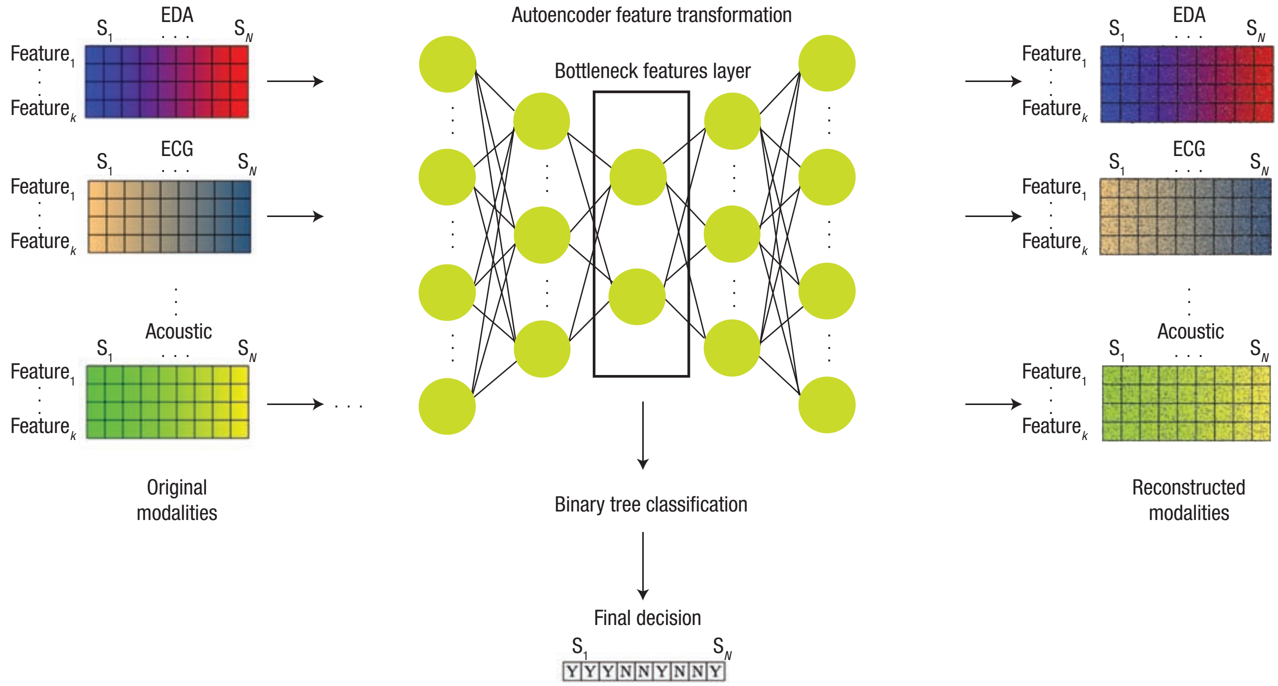

FIGURE 1. Schematic representation of the final classification system. Multimodal classification (task 3) between conflict and non-conflict samples (S_1 ... S_N) used combinations of features from each modality: self-reported mood and quality of interactions (MQI), electrodermal activity (EDA), electrocardiogram (ECG) activity, EDA synchrony measures, language, and acoustic information.

Figure 1 presents a schematic representation of the classification system as it applies to our dataset.

Further details regarding the system, a list of the entire feature set, complete results from all our experiments, and confusion matrices (that is, tables showing the performance of the classification model) are available online at homedata.github.io/statistical-methodology.html.

RESULTS

Our study results showed that several of our theoretically driven features (such as self-reported levels of anger, HRV, negative emotion words used, and mean audio intensity) were associated with conflict at levels significantly higher than chance, with an unweighted accuracy (UA) reaching up to 69.2 percent for anger and 62.3 percent for expressed negative emotion (task 1). This initial set of results is in line with laboratory research linking physiology and language use to couples' relationship functioning.[4–8] When testing unimodal feature groups (task 2), the levels of accuracy reached up to 66.1 and 72.1 percent for the female and male partners, respectively. Combinations of modalities based on EDA, ECG activity, synchrony scores, language used, acoustic data, self-reports, and context and interaction resulted in UAs up to 79.6 percent (sensitivity = 73.5 percent and specificity = 85.7 percent) for females and 86.8 percent (sensitivity = 82.1 percent and specificity = 91.5 percent) for males. Using all features except self-reports, the UA reached up to 79.3 percent. These findings generally indicate that it is possible to detect a complex, psychological state with reasonable accuracy using multimodal data obtained in uncontrolled, real-life settings.

Because we aim to eventually detect conflict using passive technologies only—that is, without requiring couples to complete self-report surveys—we compared the UAs based only on self-reported MQI to combinations incorporating passive technologies (task 4). These results showed several setups where multimodal feature groups with and without self-reported MQI data significantly exceeded the UA achieved from MQI alone. This indicates that the passive technologies added predictability to our modeling schemes.

Figure 2 shows receiver operating characteristic (ROC) curves for several feature combinations. The results showed that the area under the curve (AUC) for our multimodal indices reached up to 0.79 for females and 0.76 for males.

DISCUSSION

The results we report here provide a proof of concept that the data collected via mobile computing methods are valid indicators of interpersonal functioning in daily life. Consistent with laboratory-based research, we found statistically significant above-chance associations between conflict behavior and several theoretically driven, individually tested data features. We also obtained significant associations between conflict and both unimodal and multimodal feature groups with and without self-reported MQI included. In fact, our best-performing combinations of data features in

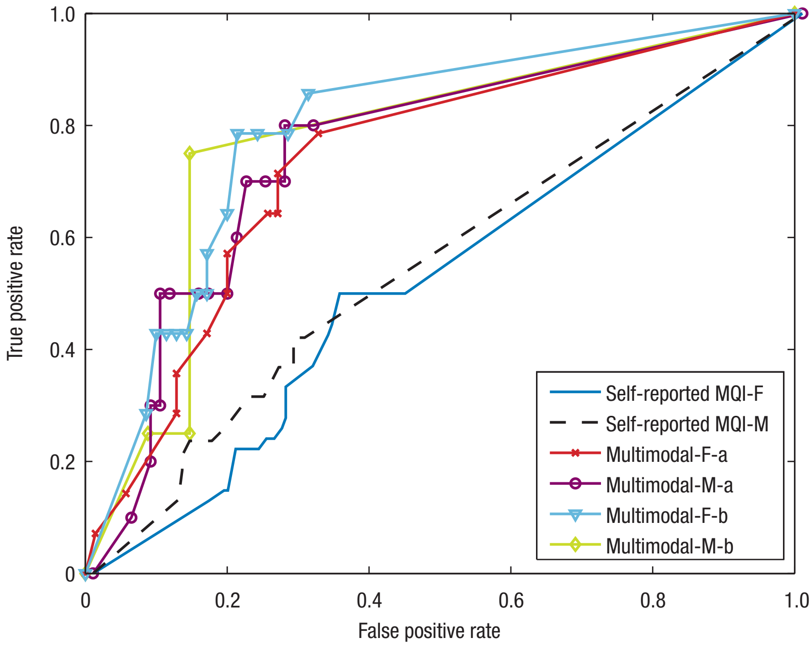

FIGURE 2. Receiver operating characteristic (ROC) curves for self-reported mood and quality of interaction (such as stressed, happy, sad, nervous, angry, and close) and multimodal feature groups. Multimodal-F-a = female EDA, psychological, personal, interaction, context; Multimodal-F-b = female self-reported MQI, EDA, psychological, personal, acoustic, interaction, context; Multimodal-M-a = male ECG activity, psychological, acoustic, interaction, context; Multimodal-M-b = male self-reported MQI, EDA synchrony, paralinguistic, personal, acoustic, interaction, context.

several cases reached or exceeded the UA levels obtained via self-reported MQI alone.

To our knowledge, the prototype model developed for this study is the first to use machine-learning classification to identify episodes of conflict behavior in daily life using multimodal, passive computing technologies. Our study extends the literature by presenting an initial case study indicating that it is possible to detect complex psychological states using data collected in an uncontrolled environment.

Implications

Couples communicate using complex, cross-person interactional sequences where emotional, physiological, and behavioral states are shared via vocal cues and body language. Multimodal feature detection can provide a comprehensive assessment of these interactional sequences by monitoring the way couples react physiologically, what they say to each other, and how they say it. Couples in distressed relationships can become locked into maladaptive patterns that escalate quickly and are hard to exit once triggered. Detecting and monitoring these sequences as they occur in real time could make it possible to interrupt, alter, or even prevent conflict behaviors.

Thus, although preliminary, our data are an important first step toward using mobile computing methods to improve relationship functioning. The proposed algorithms could be used to identify events or experiences that precede conflict and send prompts that would decrease the likelihood that such events will spill over to affect relationship functioning. Such interventions would move beyond the realm of human-activity recognition to also include the principles of personal informatics, which help people to engage in self-reflection and self-monitoring to increase self-knowledge and improve functioning. For example, a husband who is criticized by his boss at work might experience a spike in stress levels, which could be reflected in his tone of voice, the content of his speech, and his physiological arousal. Based on this individual's pattern of arousal, our system would predict that he is at increased risk for having an argument with his spouse upon returning home that evening. A text message could be sent to prompt him to engage in a meditation exercise, guided by a computer program, that decreases his stress level. When this individual returns home, he might find that his children are arguing and that his wife is in an irritable mood. Although such situations often spark conflict between spouses, the husband might feel emotionally restored following the meditation exercise and thus be able to provide support to his wife and avoid feeling irritable himself, thereby preventing conflict.

A second option is to design prompts that are sent after a conflict episode to help individuals calm down, recover, or initiate positive contact with their partners. For example, a couple living together for the first time might get in an argument about household chores. After the argument is over, a text message could prompt each partner to independently engage in a progressive muscle relaxation exercise to calm down. Once they are in a relaxed state, the program could send a series of prompts that encourage self-reflection and increase insight about the argument—for example, what can I do to communicate more positively with my partner? What do I wish I had done differently?

In addition to detecting conflict episodes, amplifying positive moods or the frequency of positive interactions could be valuable. Potential behavioral prompts could include exercises that build upon the positive aspects of a relationship, such as complimenting or doing something nice for one's partner. Employing these methods in people's daily lives could increase the efficacy of standard therapy techniques and improve both individual and relationship functioning. Because the quality of our relationships with others plays a central role in our emotional functioning, mobile technologies thus provide an exciting approach to promoting well-being.

Limitations

Although the results from our classification experiments suggest that these methods hold promise, our findings should be interpreted in light of several limitations. Our system's classification accuracy, while moderately good given the task's inherent complexity, will need to be improved before our method can be employed widely. In our best-performing models, we missed 18 percent of conflict episodes and falsely identified 9 percent of cases as conflict. Classification systems that miss large numbers of conflict episodes will be limited in their ability to influence people's behaviors. At the same time, falsely identifying conflict would force people to respond to unnecessary behavior prompts, which could annoy them or cause them to discontinue use.

In our current model, classification accuracy is inhibited by several factors.

First, we relied on self-reports of conflict. Future projects could use audio recordings as an alternative, perhaps more accurate, way to identify periods of conflict.

Second, conflict and how it is experienced and expressed is highly variable across couples, with people showing different characteristic patterns in physiology or vocal tone. For example, some couples yell loudly during conflict, whereas others withdraw and become silent. One method for addressing this issue could be to train the models on individual couples during an initial trial period. By tailoring our modeling schemes, we might be able to capture response patterns specific to each person and thereby improve our classification scores.

Third, we collapsed our data into hour-long time intervals, which likely caused us to lose important information about when conflict actually started and stopped. Many conflict episodes do not last for an entire hour, and physiological responding within an hour-long period could reflect various activities besides conflict. Using a smaller time interval would likely increase accuracy.

Fourth, outside of the synchrony scores, we did not take into account the joint effects of male and female responses. Considering these together (such as male and female vocal pitch increasing at the same time) could improve our results.

OUR MODELING SCHEME COULD BE USED TO CREATE INTERVENTIONS TO IMPROVE COUPLES' FUNCTIONING AND QUALITY OF LIFE MORE GENERALLY.

Future directions

Future research should examine the classification accuracy of multiple classifiers. We chose a decision tree for classification because of its running-time efficiency and intuitive nature, but different classifiers could provide additional benefits. With future iterations of these procedures, classification accuracies will likely improve, increasing the usefulness of these methods for influencing behavior in the real world. Still, the occasional false positive, which would prompt couples to engage in relaxation or other self-reflective activities, would most likely not be harmful, as long as the frequency of such events is minimal.

In addition to increasing our classification accuracy, several practical considerations for developing these methods deserve note. In the current study, we retroactively detected conflict, but interventions aimed at improving couple functioning would need to detect these episodes as they occur. In particular, such monitoring with audio data might be difficult because software must be capable of transcribing language, processing word counts, and extracting acoustic patterns in real time. We also manually transcribed the audio recordings, which could have resulted in less error than automated transcription techniques. We expect that methods for ongoing monitoring of physiology and behavior will continue to be developed and become more sophisticated over time.

There are also numerous ways that these methods could, albeit

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inadvertently, negatively impact the quality of life of the people using them. Answering surveys at regular intervals could be disruptive and annoying for participants, and wearing physiological sensors could be uncomfortable and even embarrassing. Future work should aim to make use of passive sensing technologies rather than rely on self-reported data. Many of our multimodal indices using only passive technologies performed well, suggesting it is possible to develop monitoring technologies that do not require active participation. In a similar vein, developing sensors that are smaller, more stylish, and less obtrusive will be important for increasing couples' willingness to use the technology. Integrating these methods with trendy devices such as smartwatches or smart clothes will be an important component in encouraging the use of these methods.

Once highly accurate classification systems have been developed, future research will need to concentrate on designing interventions and testing them in real-world settings. While our intention is that these methodologies will improve the quality of life of the individuals using them, it is possible that there will be unforeseen negative consequences or other barriers to utilization, so several iterations of interventions will need to be developed and tested to ensure their efficacy.

Beyond these recommendations, it is important that researchers take steps to keep data secure and minimize the risk of harmful privacy breaches. Care should also be taken to assess if couples are appropriate for the intervention and if there are any risks to safety—for example, individuals with suicidal ideation or violent couples would require interventions more appropriate to their needs.

Although preliminary, the proposed modeling scheme could eventually be used to create interventions that provide feedback and behavioral prompts to improve couple functioning and quality of life more generally. Ultimately, our method could be expanded to other types of relationships (such as parent–child) and to other types of behaviors (such as increasing positive interactions). Future iterations of this model will aim to improve upon the classification accuracy and incorporate ongoing, interactive monitoring to detect and predict conflict as it occurs in real time.

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RESEARCH FEATURE

Applications and Challenges of Wearable Visual Lifeloggers

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Advances in the manufacturing of miniaturized low-power embedded systems are paving the way for ultra-lightweight wearable cameras that can visually log the minute details of people's daily lives. This survey highlights the possible applications of wearable cameras, from industrial to personal, and outlines the main challenges in realizing their full potential.

Digital cameras are embedded in many consumer gadgets, such as smartphones, tablets, laptops, and even smart watches. Recent advances in camera and display technologies coupled with miniaturization trends have paved the way for a new category of compact wearable visual lifeloggers (WVLs) that can continuously record high-quality pictures and videos from the first-person perspective. Example devices include eyeglasses-based WVLs such as Epson and VUZIX smart glasses and Google Glass; mounted WVLs such as the GoPro, Narrative Clip, Autographer, and Microsoft SenseCam; and recently introduced wearables with flying capabilities such as Nixie. Several of these devices also feature communication capabilities based on Bluetooth or Wi-Fi interfaces, embedded sensors that support natural human interactions via gesture and voice commands, and screens for displaying information. The hands-free nature of WVL interaction combined with the ease of uploading and viewing data has made collecting and sharing pictures and videos easier than ever before.

The new generation of WVLs can support a plethora of new applications far beyond what can be achieved with conventional cameras and even smartphones. For example, people with visual, auditory, physical, or mental impairments can use a WVL as an assistive and rehabilitative tool.[1]

We present a survey of the WVL application landscape, highlighting how current state-of-the-art approaches are attempting to address the challenges that are likely to arise as WVLs become more pervasive, such as energy constraints, privacy issues, social restrictions, and legal uncertainties.

HISTORY OF WEARABLE VISUAL LIFELOGGERS

The first documented use of a wearable camera dates back to 1968, when Ivan Sutherland designed a head-mounted

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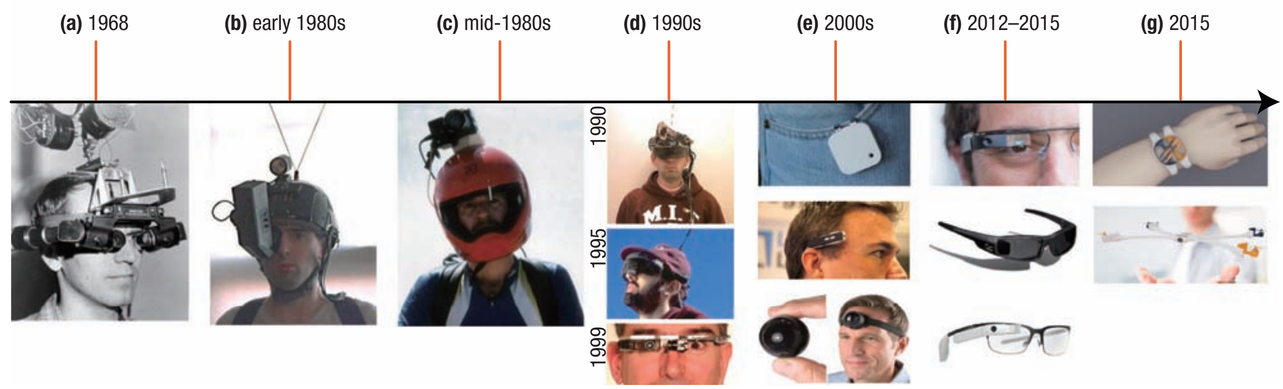

FIGURE 1. The evolution of wearable visual lifeloggers (WVLs): (a) the first wearable camera in 1968, (b) the first portable wearable camera in 1981, (c) the first helmet-based video camera in 1987, (d) wireless cameras and webcams in the 1990s, (e) miniaturized wearable cameras in the 2000s, (f) eyeglasses-based cameras developed between 2012 and 2015, and (g) next-generation wearable cameras.

display that showed the wearer a virtual world superimposed on the real world (see Figure 1a).[2] The system was primitive in terms of both user interface and realism. For example, the virtual environment consisted of wireframe rooms, and the wearer was tethered to a workstation that was powered by an AC outlet. In 1977, C.C. Collins developed another early wearable system that used a head-mounted camera to convert images into a 10-inch square tactile grid on a vest to assist people with visual impairments.

In the 1980s, there were several attempts to build more general-purpose wearable systems. The first truly wearable camera was invented by Steve Mann in 1981.[3] Mann's device was a backpack-mounted computer that controlled photographic equipment (see Figure 1b). Unlike Sutherland's camera, this device did not require any infrastructure and was powered by a DC battery, making it more portable. In 1987, using a VHS cassette and a consumer-grade camcorder, mountain bike enthusiast Mark Schulze created a helmet camera by rigging a video camera to a portable video recorder (see Figure 1c). The helmet camera was heavy and awkward, but it was the first to offer the ability to create first-person video of this exciting sport.

The rapid emergence of portable computing in the early 1990s resulted in several efforts to create a new generation of wearable cameras. For example, Thad Starner and his team at the MIT Media Lab developed wearable computers that attempted to detect faces or recognize American Sign Language in real time.[4] As part of the MIT Digital Eye Project (DEP), Steve Mann developed the first wearable wireless webcam in December 1994. Mann's webcam transmitted images from a head-mounted analog camera to an SGI base station via amateur TV frequencies over a point-to-point connection. The images were processed by the base station and viewed on a display in near real time. Built in 1999, his final design is similar to today's eyeglasses-based cameras (see Figure 1d). The DARPA Lifelog Project was another milestone; this project aimed to use technology to capture everything a person sees, says, and hears, but it was officially canceled in 2004 after privacy concerns emerged.

Rapid developments in the manufacturing of small and mobile smartphones in the late 1990s and early 2000s forced wearable cameras to take a backseat. A 2015 study in the US showed that 67 percent of smartphone users use their phones to share pictures and videos or to produce commentary about events happening in their community, and 35 percent of this user population does so repeatedly.[5]

Nevertheless, recent advances in digital camera technology and miniaturization have rekindled interest in wearable cameras, as lighter and higher-resolution versions can now be attached to users directly, such as on clothing or on the head (see Figure 1e). This next generation of wearable camera devices is promoting an entirely new mode of photography in which the camera discretely or continuously captures large quantities of opportunistic images with minimal interactions with the user. This mode of operation—a concept known as *lifelogging* or *visual lifelogging*—is widely available to consumers through devices such as the Narrative Clip, Autographer, Microsoft SenseCam, and GoPro.

An important development in WVLs occurred in 2012 when Google introduced its first prototype of the Project Glass, now known as Google Glass (see Figure 1f). Google Glass can record and display information in a hands-free format. It can communicate with the Internet and interact with the wearer through natural-language voice commands. Since then, other companies have also developed eyeglasses-based cameras, such as VUZIX, Epson, Lumus, OrCam, Recon, and Pivothead.

Some interesting developments point to wearable camera technology's possible future evolution. A recent prototype called Nixie is a wearable camera in the form of a wristwatch that can fly off the wrist and transform itself into a remote-controlled quadcopter. After capturing images of the wearer, Nixie returns to the wrist (see Figure 1g).

This brief history shows that WVLs have come a long way since their inception. Due to their increasing ubiquity, we expect these devices to create a new era of sophisticated visual-sensing applications.

WHAT IS A WVL?

A WVL is a wearable device that includes a camera to capture a picture or video with or without a flash. Such devices typically include a mount mechanism that can be fixed (such as Google Glass) or attached wherever the user desires (such as Narrative Clip). They might also include an on-board memory to save the recorded data, an export interface such as a USB port to transfer data to a computer, a battery and charging interface, and a small keyboard or touchpad to control the device.

WVL elements

These devices can include additional facilities such as a wireless interface (Wi-Fi or Bluetooth), a microphone (for audio interaction and recording) and speaker, a small screen to display content, and other components such as a waterproof cover or autonomous flying hardware. In addition, WVLs might even be equipped with sensors such as an accelerometer to determine the device's orientation; a gyroscope to track its rotation, which can be used to increase the accuracy of the orientation detected by the accelerometer; and a magnetometer for navigation purposes.

Figure 2a shows the typical components of a WVL, and Figure 2b illustrates the arrangement of these hardware components in Google Glass. The recently developed WVLs also have an operating system for programming the device—mainly Android, Android Wear, Linux, Tizen, or iOS.

Working principles of lifelogging

Usually, there are six main steps in lifelogging:

1. *Setting*: The user defines the desired settings for the life logger (such as the picture and video resolution and the frequency of capture). The privacy policies can also be specified in this step.
2. *Capture*: The physical camera captures the raw pixels.
3. *Store*: The captured pictures are stored in the device's local memory and optionally also transferred to an external storage device.
4. *Process*: The stored pictures can be processed locally on the device or externally on a host machine for image optimization or privacy purposes, either manually or automatically. The recorded data can also be labeled, annotated, and sequenced for better access in the future.
5. *Access*: Various applications have different permissions for access to the processed information.
6. *Publish*: The processed pictures and videos can be published on social networks or any other location.

Recent wearable devices are able to take photos at very high frequencies. For example, Narrative Clip can capture up to 120 images/hour, and Autographer can collect up to 360 images/hour. This means that a few thousand photos can be collected over the course of a single day. Other devices such as Google Glass and VUZIX can continuously capture videos as well.

APPLICATIONS

WVLs' ability to continuously monitor and record the environment have made them appealing in a range of applications, including medical, industrial, military, education, environmental, and personal. WVLs can be also used in augmented reality (AR) systems in which the user sees the real world, with virtual objects superimposed on the real environment.[6]

Health

We can categorize the proposed WVL applications in the health domain into four main groups:

- early disease detection via continuous data collection on the patient's lifestyle;
- assistance and rehabilitation of visual, auditory, physical, or mental impairments such as autism or cognitive decline;
- surgical applications such as the real-time recording of surgeries; and
- education and training purposes.

In the first group, WVLs can provide insights into lifestyle behaviors, enabling doctors to correctly diagnose an illness rather than rely solely on patient self-reporting, which is often prone to substantial errors associated with recall, comprehension, and social desirability bias.[1] In addition, WVLs and their associated software analysis tools can be used to enhance dietary assessment techniques and to measure patients' sedentary behavior, physical activities, and nutrition-related behaviors. As an example, B.P Clarkson developed and evaluated computational methods to extract patients' life patterns from wearable sensor data that were collected over 100 days.[7]

In the second group, WVLs have been used alone or as part of a solution to assist or rehabilitate patients. For example, researchers have proposed several WVL-based solutions that help the visually impaired navigate and avoid obstacles and even find a particular object in the surrounding environment.[8] Moreover, the visually impaired can use a WVL as a text-reading tool. In addition, some studies have used WVLs to improve autobiographical memory in patients with limbic encephalitis or episodic memory impairment, as a companion tool to improve social-emotional learning in autistic individuals, and as a rehabilitation tool for children with anterograde amnesia.[1] Another medical application of WVLs is monitoring the effectiveness of such rehabilitation measures.

In the third group, researchers have used WVLs for surgical purposes such as remote electrocardiogram interpretation and real-time recording of surgeries for training, documentation, and monitoring purposes.[9,10] Recording via the WVLs has three advantages over traditional capturing methods, such as using camcorders or fixed cameras in the operating rooms. First,

FIGURE 2. Typical WVL hardware. (a) The main hardware components for a WVL include camera, memory, export port, audio player/recorder, touchpad, battery and charger, and screen. (b) This example illustrates how these components are arranged in Google Glass.

WVLs do not require an assistant to shoot the video or control the camera's location. In addition, the surgeon has complete control over what is being recorded rather than relying on a third party to make decisions. Second, because the recordings are made from the surgeon's viewpoint, they offer the most unrestricted view of the procedure, which can provide the most detail and unique insights for training purposes. Researchers have also specifically investigated the feasibility of deploying Google Glass in a forensics setting (see Figure 3a[9]).

We discuss the fourth group, the potential health education and training uses of WVLs in the next section, along with other educational applications.

Education and training

WVLs can potentially be used for many education and training purposes.[11] For example, students could use WVLs to record lectures and whiteboard content. In addition, an eyeglasses-based camera such as Google Glass, which is a kind of a microcomputer, can be used to create an integrated simulation-based

(a) (b)

FIGURE 3. Using WVLs for medical and industrial purposes. (a) A forensic pathologist can take a picture of a heart using Google Glass. The resulting heart image is thus captured from the pathologist's unrestricted viewpoint. (b) A mechanic wearing a WVL can see an augmented reality overlay as he repairs a device. (Courtesy of VUZIX.)

training system that lets teachers and students share information. Moreover, eyeglasses-based cameras can help educators and students search, take pictures, record videos, answer questions, and translate their voices to different languages. A WVL can also scan and detect text within pictures, which can be useful for both automatic translation and augmenting visual impairments.

Eyeglasses-based WVLs are also promising for medical education and training purposes (the fourth group from the last section). A recent study showed that wearable technology improved education and thereby patient outcomes in a cardiology fellowship program.[11] In that study, a mock trainee wearing Google Glass performed several activities. The live video stream from the trainee's glasses was transmitted via Wi-Fi or Bluetooth to a smartphone, tablet, or personal computer that allows the supervisor to see the trainee's observations.

Industrial and business purposes

The service industry has already felt the impact of wearable technology from its use of WVLs to free up workers' hands. For example, service technicians can receive real-time information about a job over WVL displays while carrying out a service, which can increase accuracy and performance. AR-enabled WVLs such as Atheerglass can also be implemented to visually help technicians identify and repair problems through a live collaborative operation (see Figure 3b[12]). WVLs can also be used to document procedures undertaken by technicians for training and verification purposes.[12] In one example, CSIRO in Australia developed a WVL-based application, Guardian Mentor Remote (GMR), which remotely connects technicians with aviation experts around the world to provide guidance and reduce aircraft downtime and maintenance costs. The GMR prototype has been tested by Boeing and Aviation Australia and will be commercialized in the near future.

Some studies have suggested that WVLs could be used in the logistics and transportation business. For example, in big warehouses, an operator wearing an eyeglasses-based camera can efficiently pick or stack items, based on a plan displayed on the device's screen, which saves both physical space and time. The same technique can be used for freight loading and drop-off.

WVLs can be also used to estimate the number of visitors to large exhibitions. For example, a head-mounted camera has been used to approximate the number of attendees at exhibitions. Many industries could also use WVLs for online customer service feedback. For example, a camera-clad passenger flying an airline can visually document and report customer service issues, such as unclean toilets, rude staff, delayed departures, or other inappropriate conditions.

Police and military applications

Wearable cameras can help to maintain clear visibility during police operations and thereby increase accountability. Small cameras can be clipped onto officers' uniforms to record their interactions with the public. The recorded video can thereby be used to verify the wearers' behavior and performance.

In a military setting, WVLs can assist with real-time monitoring and battlefield mapping as well as help improve soldiers' postaction reports. Soldiers might leave out vital observations and experiences in their after-mission reports that could be valuable in planning future operations. Thus, DARPA has explored using soldier-worn sensors and recorders to help improve soldiers' recall and reporting capabilities. Moreover, army intelligence agents can employ WVLs to gather visual data from the battlefield, which they can use to create combat plans and maps. For example, WVLs can help create a digital battlefield using information technology to intelligently command and control a battle.

Finally, advanced WVLs capable of showing data, playing audio, and offering wireless communication can help realize digital battlefields (DBFs),[13] which enable infantrymen to digitally distribute orders, maps, and intelligence. Such DBFs might also allow command to remotely monitor the physical activity and health conditions of soldiers as well as to improve the situational awareness of ground troops. Moreover, AR techniques can be employed to identify and tag potential foes. This data then can be shared with all troops connected to the network.

Real-time disaster mapping

Wearable camera–based systems can be used for real-time monitoring and mapping of disaster areas.[14] MIT researchers have developed a device that consists of a camera, a laser scanner, and a number of sensors that wirelessly transmit data that can be used for real-time mapping in such scenarios. The laser scanner computes the distance between the wearer and a nearby physical structure, and the camera captures a photo every few meters as the subject walks, feeding the information to a remote station. Several important features, including a location's color pattern, and contours can be extracted using special software.

Location recognition

In general, user-mounted sensors such as microphones, accelerometers, and cameras can provide location detection as an alternative to traditional approaches, such as GPS and RF-based methods. For example, researchers have used a mathematical framework that benefits from the spatial relationships between places to estimate location from a sequence of images captured by multiple wearable cameras.[15] The images recorded via WVLs can be also used to reliably recognize places. In addition, an image-sequence–matching technique can be used to recognize the locations of previously visited places.

Activity recognition

Human activity recognition is a key component for many applications such as indoor positioning, surveillance systems, and patient-monitoring systems. It is also important for various systems that involve interactions between people and electronic devices, such as socially enabled robots and human–computer interfaces. Wearable cameras can facilitate human-activity recognition in such scenarios.[16] For example, researchers have developed a method that can recognize the user's activity by analyzing the picture captured by a front-facing camera embedded in eyeglasses.[17]

Journalism

The possibility of live streaming from a versatile, portable, head-mounted camera can potentially change and even disrupt journalistic reporting, as anyone who is witnessing an important event can easily record and publish the news from the heart of the incident. Moreover, in traditional news gathering, the reporter records events using text, images, or audio and sends the data back to the news center after some simple editing. WVLs can help reporters to complete this series of tasks when gathering news, such as acquiring photos, audio, and video and uploading the data, which the news center can then access.[17]

Because they are often connected to the Internet, WVLs can also act as mobile TV stations and be used to report live news and record interviews. Courses that focus on the media applications of WVLs is being offered at several universities, including the University of Southern California (www.glassjournalism.io/2014/12/02/launching-glass-journalism).

Personal applications and tourism

The ability to continuously capture high-quality pictures without using one's hands has made WVLs an interesting appendage for people wishing to record important personal events or scenes, such as a baby's first steps or first words. These are instantaneous and fleeting moments that might not be possible to capture with a regular camera. Wearable cameras not only free a user's hands for more important tasks, but also free a user's gaze. That is, the user does not need to stare at a screen or through a lens. To automatically record interesting moments, a WVL-based framework called inSense has been developed jointly by MIT and ETH Zurich that can perform real-time context recognition and predict the moment of interest to trigger the camera and capture a scene.[18]

In a travel setting, WVLs can provide tourists with information about the places they are visiting. For example, researchers have developed a WVL-based solution to assist visitors during an outdoor tour of a cultural site. It exploits computer-vision techniques to accurately localize the user and provide information about a scene.[19]

CHALLENGES OF USING WEARABLE CAMERAS

Although there is clearly tremendous potential for WVLs in many application domains, several key challenges still exist that must be addressed before this technology can see wide adoption. These challenges can be broadly categorized into two main groups: technical issues (such as power constraints, poor camera operation in low-light areas, automatic labeling and analysis of the captured data, and incorrect camera positioning[20]) and nontechnical challenges (such as privacy issues, social restrictions, and legal uncertainties). For the purposes of this discussion, we focus on two main challenges from each category: battery limitations and data labeling and analysis for technical issues, and privacy issues and legal uncertainties for nontechnical issues.

Battery power limitations

Because they must be comfortably worn by individuals, wearable cameras are necessarily small. As a result, there is limited space for all the electronics and the battery in a device. The small battery size imposes unique constraints on WVLs. With an average power consumption of 1 W for capturing high-resolution pictures (20 frames/min) and 2 W for video (30 frames/s), we have found that the available WVLs in the market, on average, can continuously capture images or video for up to 10 and 2 hours, respectively. Simultaneous use of other device functions such as communication, audio, display, and sensors further decreases the battery life.

Thus, wearable solutions currently on the market can last for a reasonable period on a single battery charge if the device is only used for capturing images at a moderate rate. However, capturing videos severely limits the operations on a single charge. Moreover, other actions such as transferring images or videos over a communication interface and operating the LCD display can significantly reduce the lifespan.

Many applications outlined in the previous sections typically impose a greater than normal load on the wearable devices. Therefore, the current crop of wearable devices might not offer sufficient battery life for most of those applications. However, development trends in more efficient rechargeable batteries suggest that battery lifetimes will significantly increase in the near future.

Automatic data analysis

To efficiently and easily access recorded data, it needs to be broken down into sequences and annotated or tagged to enable users to search and locate relevant scenes/events. Nevertheless, automatic data sequencing and annotation is challenging because the contextual information for each picture (such as the location or a keyword) needs to be constantly extracted and recorded while the main data is captured. This in turn will run down a WVL's battery quickly.

Some solutions have been developed to address this issue. For example, using machine-learning techniques on a host device, researchers have proposed a privacy preservation framework for WVLs that can automatically detect the context (ambient environment and user activity) for each recorded picture with 95 percent accuracy.[21] This contextual metadata is used later to detect and prevent disclosing possible sensitive subjects within each picture.

Privacy issues

Visual imagery is extremely rich in content and thus is particularly sensitive to privacy concerns. Although all the items captured by WVLs (such as pictures, videos, and voices) might not violate privacy requirements, some sensitive information such as people's pictures, objects (credit cards, for example), and private locations (bedrooms and bathrooms) could be disclosed.

Several researchers have investigated these privacy concerns and proposed solutions to address them. Table 1 summarizes the most important efforts in protecting a bystander's privacy.[22] In most research, the proposed frameworks let users declare their desired privacy rules by communicating with the WVLs using an interface such as a mobile phone or by wearing a tag or specific cloth or color. Then, the subject of the desired policy is identified using facial-recognition techniques and is deleted or blurred as needed. This could occur during the capture, access, or publish phases.

In other works, hardware-based solutions have been proposed that prevent a camera from recording images or videos in restricted areas. In addition, as outlined in Table 2, many attempts have also been made to efficiently detect sensitive objects and places, and different mechanisms have been proposed to protect them from unauthorized disclosure.

Social issues and legal uncertainties

Although many privacy-aware solutions have already been developed

TABLE 1. Proposed approaches to protect people from unwanted disclosure.

Title	Short description
FaceBlock	Allows a user's mobile device to share privacy policies with nearby wearable visual lifeloggers (WVLs) using a P2P communication channel (Bluetooth). Unauthorized pictures are then blurred.
Visor	A hardware-based solution that prevents unauthorized face image revelation by adding invisible noise signals to images.
Personal Picture Policy Framework (P3F)	Enables users to express their picture privacy policies to WVLs in a machine-readable format and (to some extent) automatically enforce it.
Respectful Camera	Allows people to remain anonymous by wearing colored markers such as a hat or vest.
Offline tags	Similar to Respectful Camera and P3F, lets people declare their privacy preferences by using some symbols, such as stickers or badges.
Privacy.Tag	Uses a QR code to express privacy and shares protocols that prevent the publication of unauthorized face images.
Negative Face Blurring	Maintains a policy database containing the faces of people who agree to be disclosed, and blurs all other captured faces.
Courteous Glasses	Uses low-fidelity sensors such as far-infrared devices along with the usual wearable camera to detect people's faces in order to respect their privacy concerns.
SensorSift	Proposes a framework to balance sensor data privacy and the performance/utility of automated face recognition.
DARKLY	Protects a user's pictures from perceptual applications.

TABLE 2. Proposed approaches to protect locations and objects in restricted areas.

Title	Short description
PlaceAvoider	Allows WVL owners to blacklist sensitive spaces (such as bathrooms and bedrooms).
Public Restroom Detection	Actively probes the environment by playing a 0.1-second sine wave sweep sound and then detecting the place by analyzing the impulse response.
World-Driven Access Control	Proposes an extensible framework that imposes an access control mechanism for continuous monitoring of video, audio, or other sensor data.
Screen Avoider	Presents a framework that aims to detect and protect computer screens from all captured images.
MarkIt	Proposes a framework that lets users specify and enforce fine-grained access control over captured videos to protect sensitive objects.
Blindspot	Proposes a system that can actively seek and detect cameras in the environment and prevent them from capturing by emitting a strong localized light beam at each detected camera.

to avoid disclosure of unauthorized information (Table 1) and items (Table 2),[22] people are still skeptical about being exposed to WVLs because there is no way to ensure that camera wearers will abide by privacy rules. Moreover, because WVLs can potentially violate the confidentiality of people's activities, they might be considered disturbing devices. In some cases, people have even been assaulted for wearing cameras in bars or other public places.

On the other hand, camera holders might be legally required to report evidence of criminal activity to authorities, potentially without consent. For example, failing to report evidence of child or elder abuse is a criminal offence in some jurisdictions. These consequences might also make people uncomfortable and unwilling to use WVLs.

In addition, there are currently no specific statutes or laws in many countries that directly regulate the intrusion of WVLs on personal privacy rights.[23] Laws on video surveillance and privacy rights can be considered a good starting point to force WVL holders to respect people's privacy.[23] Clear legislation and appropriate implementation of the existing legal framework[24] that explicitly declares the WVL holder's obligations and bystander's rights is still a necessity.

A new generation of wearable devices such as Google Glass will soon make first-person cameras nearly ubiquitous, capturing vast numbers of images without deliberate human action. There are many interesting opportunities to utilize these devices in a variety of applications ranging from healthcare to education. Nevertheless, widespread adoption will require that some key challenges, such as privacy concerns, energy limitations, automatic data annotation and analysis, social issues, and legal uncertainties, be addressed.

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Standards for the Enterprise IT Profession

Chuck Walrad, Davenport Consulting

Standards ensure that the enterprise IT profession, like other recognized professions, is based on a core set of well-understood activities and their corresponding requisite competencies.

In an increasingly digital and connected world, technology has become so pervasive in our work and personal lives that it now has the potential to cause great disruption and harm. We rely on technology to make our lives easier, but when it fails, it can mean pandemonium for airlines or screeching and braking in the financial world, for example. Thus, although an enterprise might rely on technology, those who depend on this technology can't necessarily trust it to perform to the level that the enterprise needs.

As engineers, we've developed professionally. We have high standards. We shun "slapping things together" and "hacking" (despite the ways that term is overused in the media). As Justice Sandra Day O'Connor of the US Supreme Court once said, "To me, the essence of professionalism is a commitment to develop one's skills to the fullest and to apply [them] responsibly to the problems at hand. Professionalism requires adherence to the highest ethical standards of conduct and a willingness to subordinate narrow self-interest in pursuit of the more fundamental goal of public service."[1]

The essential elements of professionalism are

- competence;
- personal integrity, responsibility, and accountability; and
- public obligation.

Very often, organizations promote the idea that professionalism is conferred by certification. This alone isn't sufficient, if it depends merely on passing a test. Having some staff certified in the use of specific vendors' tools or languages or methods isn't enough to claim a

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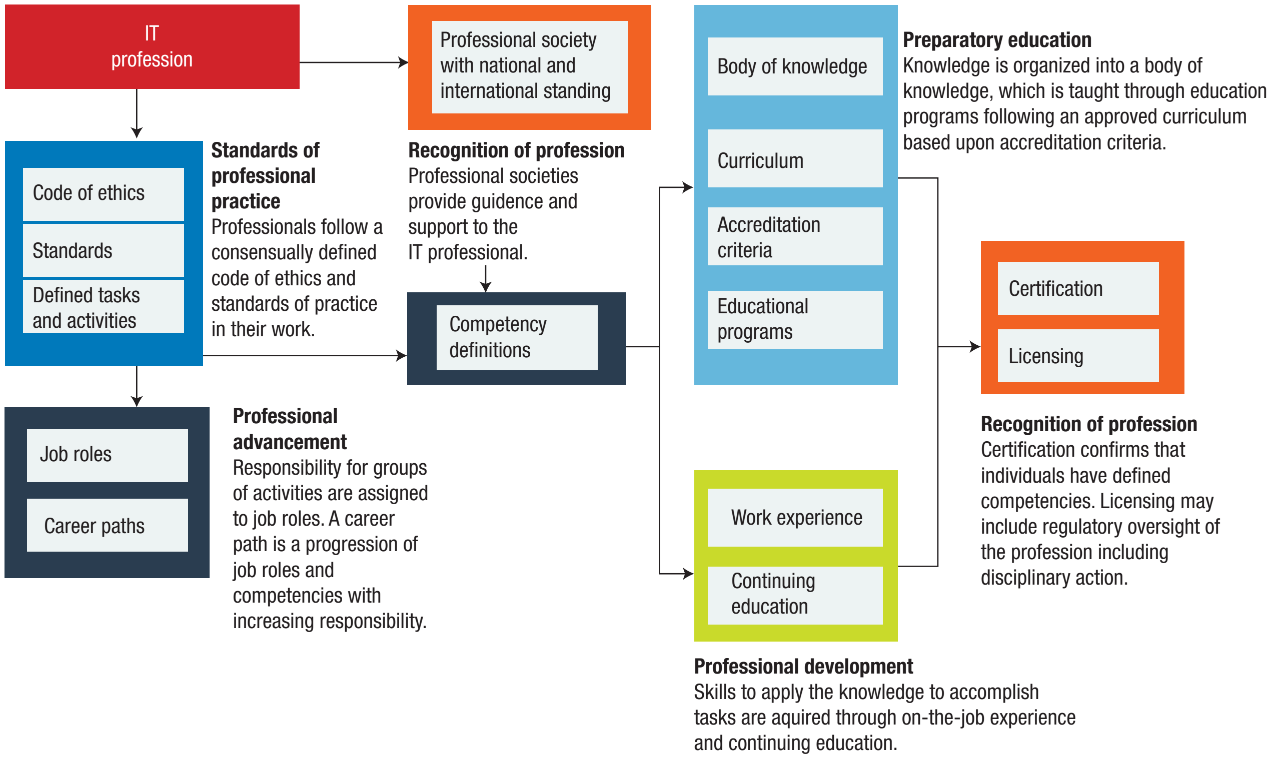

Figure 1. The IEEE Computer Society's Professional Activities Board enterprise IT (EIT) professionalism model. The model shows that the EIT profession, like other recognized professions, is based on the establishment of a core set of well-understood activities and their corresponding requisite competencies (such that, for example, roles and responsibilities can be commonly recognized and career paths designed), along with establishment of a supporting body of knowledge and corresponding university curricula (and their accreditation) and continuing professional development. These provide the common basis for meaningful external validation via certification and, in some cases (such as life-critical systems), licensing.

professional organization. For a certification to be useful to employers looking to hire well-qualified staff members, it needs to be based on well-accepted standards and principles of professional practice, not just knowledge of particular tools.

ENTERPRISE IT COMMUNITY EFFORTS

For several years now, countries around the world have been pressing for the certification of enterprise IT (EIT) professionals; such certification could also apply to entire EIT organizations. In the UK, the EU, Canada, and Japan, for example, certification is seen as a necessary part of recognizing EIT organization workers' professional status. Similarly, the IEEE Computer Society's Professional and Educational Activities Board includes certification as an element of its EIT professionalism model (see Figure 1). In addition to the area's body of knowledge, its standards and code of ethics form part of the complete model of the profession that EIT workers at all levels should learn from and that certification should be based on.

The Computer Society has contributed to the advancement of EIT professionals by developing technology standards (essential technologies such as IEEE 802); practice standards such as those widely used for requirements engineering, testing, and architecture (also adopted jointly by the International Organization for Standardization [ISO] and the International Electrotechnical Commission [IEC]); and internationally recognized guides to the bodies of knowledge in software engineering (SWEBOK; www.computer.org/swebok), enterprise IT (EITBOK; eitbokwiki.org), and systems engineering (SEBOK; sebokwiki.org/wiki, with INCOSE).

The Computer Society also participates in ISO and IEC efforts to develop standards for the entire EIT

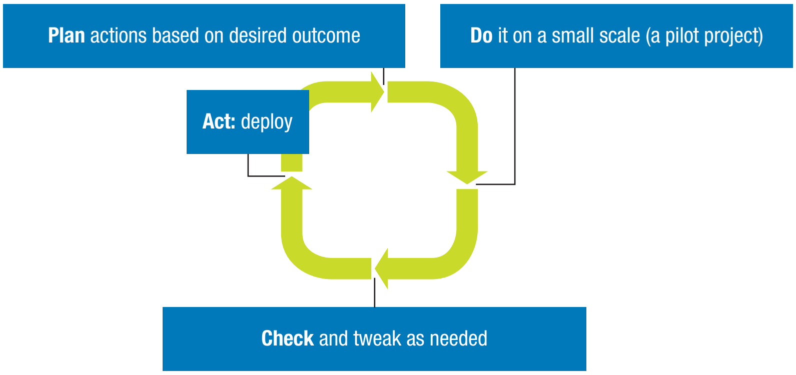

Figure 2. Plan, do, check, and act (PDCA). Originally known as the Deming cycle, the PDCA cycle is a continuous improvement model to reduce risk when introducing change and to support continuous improvement and learning.

community. The primary ISO entity that develops standards for EIT is Joint Technical Committee 1 (JTC 1; the IT committee) comprising ISO and the IEC, established in 2013. Whereas several entities focus on standards about workings within EIT, Subcommittee 40 (JTC 1/SC 40) addresses processes for governing EIT to ensure that it's meeting the organization's goals. The subcommittee is responsible for the areas of IT service management and governance, with a focus on auditing, digital forensics, governance, risk management, outsourcing, service operations, and service maintenance. However, having been formed relatively recently, the bulk of SC 40's work so far has gone into three areas:

- enterprise IT governance—the ISO/IEC 38500 series;
- business process outsourcing—the ISO/IEC 30105 series; and
- enterprise IT service management—the ISO/IEC 20000 series.

ENTERPRISE IT GOVERNANCE: THE 38500 SERIES

In a 2014 interview, John Sheridan, the first chair of JTC 1/SC 40, explained that "IT governance is what the board of an organization might be doing, and not necessarily what is being done by the IT managers or IT specialists. IT governance looks to ensure that the decisions about IT within an organization are being made in the right way, and that those decisions are actually supporting the vision that the board has for the organization."[2]

The 38500 series includes high-level standards that educate governing boards by providing a framework for good corporate governance of the EIT organization. It does so by identifying six principles that should guide decision making in an organization's EIT operations:

- The governing board should accept responsibility for decisions regarding both the demand and supply of EIT capabilities.
- The business strategy must account for the current EIT capabilities; strategic planning should address ongoing and future needs.
- Acquisitions related to EIT capabilities should be made on the basis of examined business needs, appropriately balancing short- and long-term costs and benefits.
- EIT performance should be assessed to determine whether it's fit for its purpose of supporting the larger organization's needs for service and quality levels.
- Good EIT governance ensures its compliance with legislation, regulations, and policies.
- Governance in the EIT organization must demonstrate respect for the human needs of its staff.

The governing board is responsible for directing, monitoring, and evaluating the organization it governs.

BUSINESS PROCESS OUTSOURCING: THE 30105 SERIES

This series of standards is designed for those who provide outsourced IT-enabled services to other organizations. Their consultation can also help customers understand what to expect and what to require when contracting outside services so that both the customer and the provider achieve expected business results. The focus is on the business processes of outsourcing, not the technical processes.

The series provides process reference and assessment models, a process measurement framework, and an organizational maturity model.

The process reference model addresses the entire lifecycle of an outsourced arrangement:

- strategic planning and direction setting,
- contracting,
- transitioning into outsourcing performance,
- management monitoring and evaluation,
- management of customer and supplier relationships,
- solution development,
- service delivery, and
- transitioning from the outsourcing agreement.

SERVICE MANAGEMENT: THE 20000 SERIES

Most EIT professionals are aware of the Information Technology Infrastructure

Library. ITIL and ISO/IEC 20000 have many similarities, but they're not the same. For instance, ITIL is a proprietary best-practice framework supported by many vendors; ISO/IEC 20000, on the other hand, is an international standard and isn't proprietary—anyone can buy and apply the standard.

ITIL certification is directed at individuals employed in EIT, while the ISO/IEC standard is aimed at IT service providers who implement and maintain service management systems. ITIL provides guidelines for practitioners, whereas ISO/IEC defines many process requirements against which service providers can be assessed. Despite their differences, there have been efforts to greater align the two. In fact, many organizations first implemented ITIL and then went on to ISO/IEC 20000 certification.

Like the other standards groups discussed earlier, the ISO/IEC 20000 series is designed to establish a beneficial relationship between an enterprise and its EIT. It's based on the plan–do–check–act methodology, or PDCA cycle, originally known as the Deming cycle—a continuous improvement model of four repeated steps to reduce risk when introducing change as well as to support continuous improvement and learning (see Figure 2).

As you might have noticed, the PDCA cycle is also the foundation of good governance. Good governance at the highest level provides strategic direction and a high-level plan, directs its rollout, monitors and evaluates performance, and makes tweaks as necessary along the way. In this aspect, JTC 1/SC 40's portfolio of projects and standards can be seen as providing a coherent framework for how enterprise management can work effectively with EIT and outsource service providers to their mutual benefit—resulting in a positive environment in which EIT professionals can apply their considerable individual skills to advancing EIT capabilities to benefit the enterprise. C

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You Never Forget Your First Project

Scooter Willis, Avera Cancer Institute

New editor Scooter Willis reflects on his journey to becoming an electrical engineer and how we can promote the work of students who've found their passion.

I clearly remember the day I realized I wanted to be an electrical engineer and, more importantly, the project that convinced me. The summer before my senior year in high school, I attended a math and science camp at Florida State University. That particular day, each student was handed a box of wires, microchips, a breadboard, and a wiring diagram—but no instructions, detail, theory, or even hint about what we were being asked to make. I spent a couple of hours getting the breadboard to match the picture, and then connected the power. Three 7-segment displays lit up and the breadboard started counting. That was the moment I knew I'd found my life's work.

See **www.computer.org/computer-multimedia** for multimedia content related to this article.

I located my instructor straightaway, informing him that I had a Kaypro II computer that I wanted to use to control a robot. (With no battery and weighing 27 lbs., the Kaypro II—released in 1982 and based on the Z80 microprocessor and CP/M—was one of the first portable computers.) He explained that I could use the parallel port and a 2N222 transistor to control a relay that turned the motor on and off, and then showed me how to wire a double-pole, double-throw relay to run the motor in forward and reverse. In the span of three hours, my life had changed—all because I'd built a clock and someone had shown me how to turn a motor on and off with a parallel port.

THE JOURNEY BEGINS

Upon returning to school in the fall, I decided to design a robotic control system for my science fair project. Back then, the library didn't have books on building robots and I needed help. So the school administrator picked up the phone directory, looked up "robotics," and dialed the number for Sally-Corp, a local company specializing in museum and theme

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park animatronics. SallyCorp's head engineer agreed to answer my many questions. What's more, he offered me a job programming Z80 assembly language and laying out circuit boards for their animatronic editing system.

In 1984, programming in assembly language was standard for embedded systems, and circuit boards were taped to vellum on a light board. I didn't mind the assembly language programming but thought the circuit board layout process could be improved. Using one of my school's new IBM PCs, which ran MS-DOS, I wrote a paint program that let me place circles and lines on the screen and print out photo-etched circuit boards on a laser transparency.

I couldn't believe how much I'd learned in just six months of mentorship, and eagerly anticipated the engineering classes I'd take in college. Little did I know that the typical path to an engineering degree would fail to meet my expectations.

THE TYPICAL COLLEGE EXPERIENCE

In the fall of 1985, I enrolled at the University of Florida. Enrollment involved a drop/add process in which I—and 35,000 other students—walked around the gym in search of open course sections. I then filled in each section's circle on a Scantron sheet and lined up to have the sheet scanned in for approval by the mainframe. Some classes required a signature, and thus, a trip to that department; other classes had long lists of prerequisites. As a freshman, I couldn't take Circuits 1 or Digital Computer Architecture until I'd been accepted into the Department of Electrical Engineering.

Two years later and with all the prerequisite courses completed, I was fully admitted to the department. I signed up for what I expected to be interesting classes, only to discover that they focused on book work and theory.

SUBMIT YOUR PROJECT

I want to hear about interesting student-led design projects in computer science and engineering. If you'd like to see your project featured in this column, please email willishf@gmail.com.

I wouldn't get to make anything or work on a project until I was in graduate school—another three years away.

At this point, my goal became to finish school quickly and find a job in which I would actually get to build things. The situation's irony had hit home: you could graduate with a bachelor's degree in electrical engineering and not know how to solder. You definitely wouldn't know that when you solder, you should breathe out to avoid inhaling the fumes. Furthermore, my classmates didn't share the same passion for wiring circuit boards and writing code nor did they experience the pure excitement that came from creating a solution to a problem.

Similar challenges exist in computer science: you can graduate without appreciating the importance of writing unit tests or, at a minimum, having a strong opinion about the best integrated development environment (IDE) or the use of tabs versus spaces. (For those not familiar with the tabs-versus-spaces argument, this YouTube video puts it into humorous perspective: goo.gl/pFYufX.)

LIFE AFTER COLLEGE

As chief technology officer of numerous start-ups, I did my share of interviews. A standard question I posed to potential hires was, What's your favorite editor? The only wrong answer was Microsoft Word, because they'd obviously misunderstood the question. If they said NetBeans, my personal favorite, then their odds of getting the job increased. If they answered Emacs or vi, I knew I'd found a programmer with strong Linux skills who could also do system administration work. (For details on the editor war, see en.wikipedia.org/wiki/Editor_war.) Having a favorite editor or IDE signified experience and was a stronger indicator of success than an outstanding grade-point average.

Sadly, getting an engineering job straight out of college at a company willing to invest in job-specific training is no longer the norm. Start-ups are looking for hires with specific skills that can be put to use the first day on the job.

OUR FUTURE: THE NEXT GENERATION OF STUDENTS

During my formative years—the early 80s—I worked on my bike and built forts and skateboard ramps. Playing video games involved a trip to the mall with a pocket full of quarters. In contrast, today's typical first-grader has a room full of Legos and has mastered complex video games, having spent countless hours watching YouTube videos to learn the tricks. The next generation of students—having been exposed early in life to technology and problem solving—wants to tackle new challenges but is less interested in being told how. Our educational institutions have been slow to change and embrace these students' true potential.

I've seen firsthand the effect of technology competitions on young people's lives. For 20 years, I've been a mentor in FIRST robotics (www.firstinspires.org), which holds robotics competitions for 400,000 K–12 students worldwide. For example, in the FIRST LEGO League, teams build a Lego EV3 robot with a range of sensors and LabVIEW block programming. FIRST Tech Challenge teams use an Android-based robotics control system—which includes an augmented reality software development kit that uses the phone's camera and object recognition—to track a robot's position and field orientation. And FIRST Robotics Competition teams have six weeks to build a robot that then competes in tournaments. VEX Robotics offers a similar competitive robotics program with 10,000 teams worldwide (www.roboticseducation.org). The Science Olympiad hosts 7,300 middle- and high-school teams at 33 different events, 9 of which focus on building or programming (www.soinc.org). These programs all start with a common goal: to get middle- and high-school students hooked on the thrill of competition by presenting them with a challenge and specifications that define the problem. After high school, there are fewer such STEM-related competitions available.

As this column's new editor, I see an opportunity to promote the work of students who've found their passion. More importantly, I hope to raise awareness about college-level engineering competitions—and increase the number of electrical engineering graduates who know how to solder and computer science graduates who have a favorite editor. C

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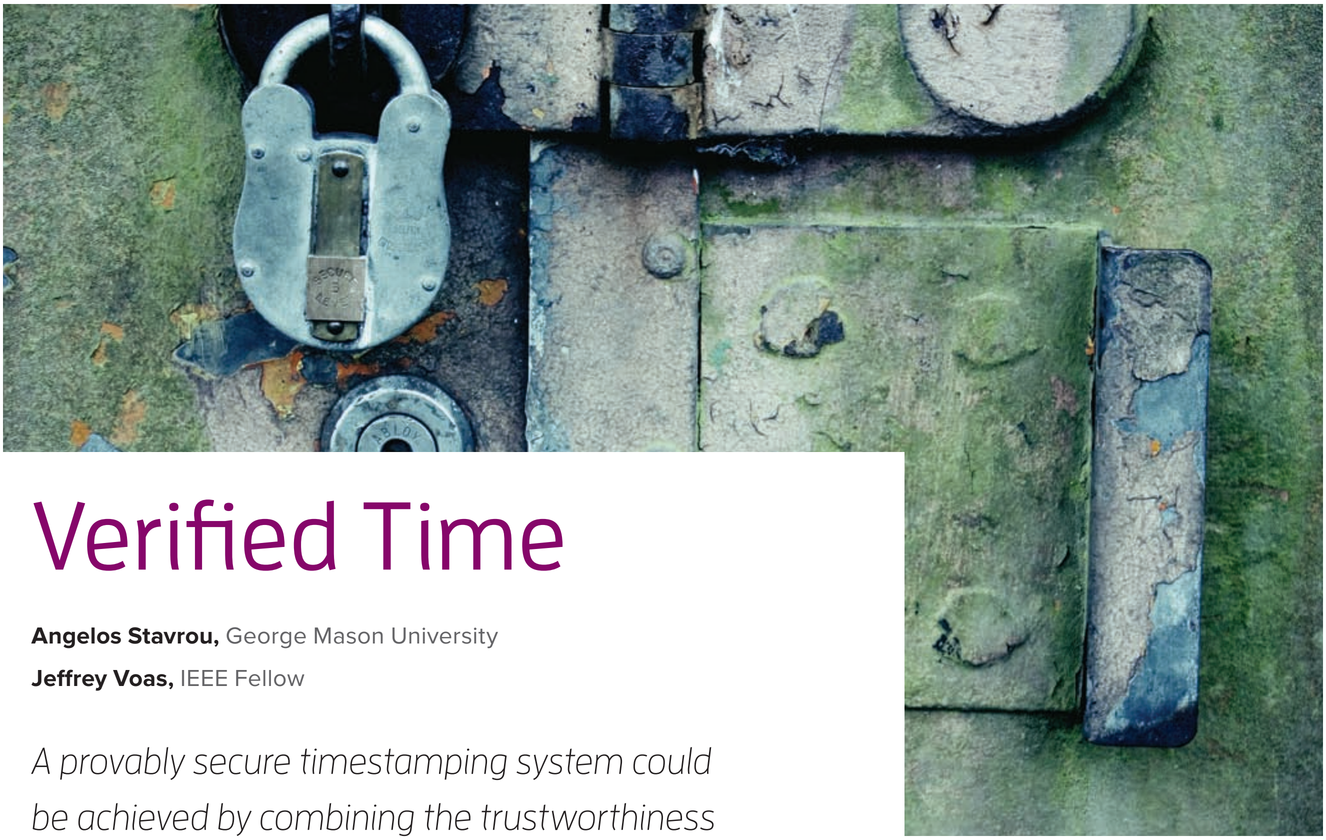

Verified Time

Angelos Stavrou, George Mason University

Jeffrey Voas, IEEE Fellow

A provably secure timestamping system could be achieved by combining the trustworthiness and accuracy that comes from having a set of trusted centralized timestamping authorities with the open, decentralized nature of blockchain protocols.

In *Thank You for Being Late*, Thomas Friedman states that we are moving into an "age of accelerations" that will transform "almost every aspect of modern life."[1] Examples of this transformation are everywhere. Consider a basic one: computing power's exponential increase has led to dizzying improvements in performance that, in turn, have enabled faster transaction speeds. Tasks that previously took milliseconds now take microseconds.

The Internet of Things (IoT) fosters acceleration—in the form of large-scale sensing, big data generation, and unprecedented parallel computing—by interconnecting a seemingly limitless number of devices, sensors, and other objects. However, trusted timing mechanisms must coordinate events in networks of things (NoTs) to make NoTs practical. For example, a global timing mechanism is necessary to synchronize dataflows and workflows in most NoTs because of the things' potential geographic distribution.[2,3] In addition, malicious owners of specific objects could deliberately modify NoT efficiency by tampering with the times data is allowed to flow to and from NoT computations.[2] This clearly violates a central goal of net neutrality: to prohibit certain ISPs from deliberately slowing down or speeding up data uploads.

NEED FOR TRUSTED TIMESTAMPS

Businesses and governments have long sought the ability to link provably secure, publicly verifiable trusted timestamps to activities and transactions as evidence.[4] Numerous use cases rely on such evidence, ranging from validating the time of creation and modification of a document to creating patents to financial accounting. "Establishing the time when a digital signature was generated is often a critical consideration," notes Elaine Barker in NIST Special Publication 800-102. "With the

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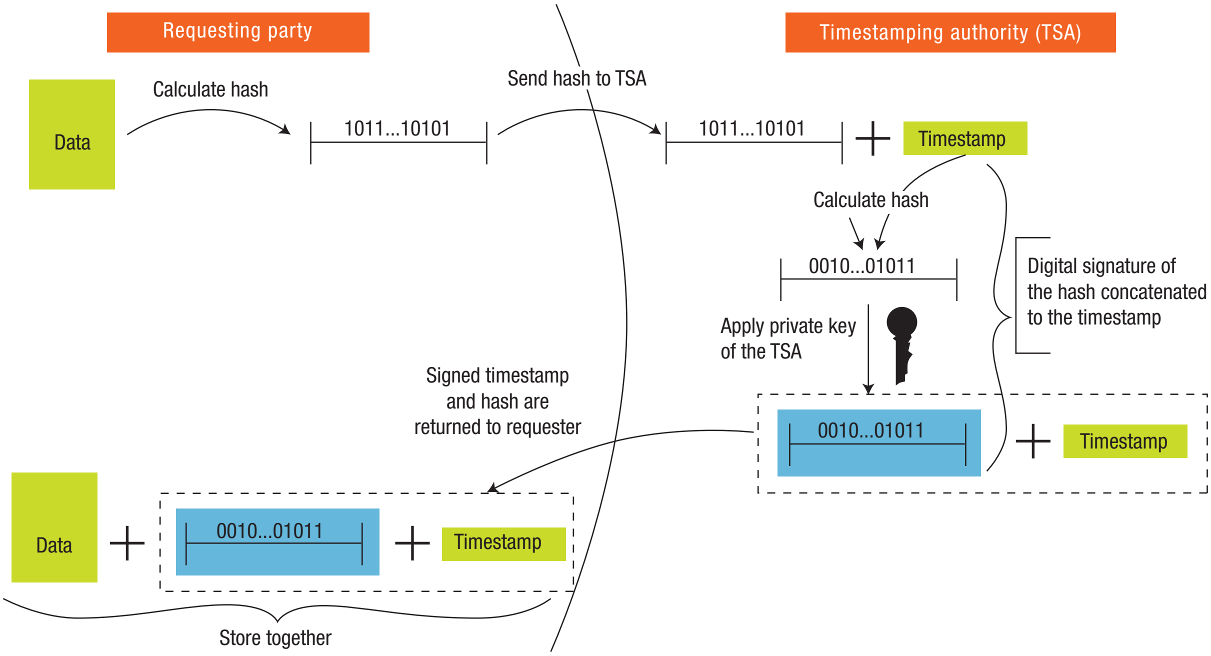

Figure 1. Trusted timestamping process in which timestamps for individual transactions are issued by a timestamping authority (TSA). If the TSA becomes compromised, so does the trustworthiness of the signed data. (Source: Adapted from an SVG diagram by Tsuruya of an original figure by Bart Van den Bosch; commons.wikimedia.org/wiki/File:Checking_timestamp.svg.)

appropriate use of digital signature-based timestamps from a Trusted Timestamp Authority (TTA) and/or verifier-supplied data that is included in the signed message, the signatory can provide some level of assurance about the time that the message was signed."[4] Beyond legal and financial accounting considerations, research by the EU Agency for Network and Information Security (ENISA) shows that trusted timestamps make services significantly more efficient and cost-effective.[5,6]

For geographically distributed systems lacking global governance such as the IoT and blockchain databases, trusted guarantees of the times events occur are especially important because markets operate on a first-come, first-serve basis, and trusted timestamps can serve as a fair basis for precisely determining where and when transactions originated.

TIMESTAMPING SECURITY RISKS

Unfortunately, current protocols rely on a central TTA or *timestamping authority* (TSA) to issue timestamps, as Figure 1 shows. This provides security for individual transactions but raises reliability concerns because the integrity of the timestamping process is inevitably bound to that of the TSA.[7] If the TSA is compromised, all of the issued timestamps can become invalid, compromising the trustworthiness of the signed data.

A December 2013 survey by ENISA of 51 TSAs across 20 EU member states revealed five major security risks to timestamping services.[5,6] Table 1 lists the risk, impact, probability, and deviation values (on a scale of 0 to 100) of each risk, and Figure 2 graphically depicts the impact and probability values. TSAs rank loss or compromise of a service's signature creation date as the scenario having the biggest impact, compromise of the main time source as having the highest risk, and unavailability of the main time source as the most probable. Moreover, dependency on a single TSA raises concerns in the research and business communities about potential abuse of that service by its administrative authority, which could be either a government or private entity.

BLOCKCHAIN TECHNOLOGY

Can we do better? Is there a secure mechanism available that can prevent timestamping services from being secretly subverted while also allowing multiple TSAs to offer services without any geographic or other boundaries? We believe the answer is yes, and that the solution lies in recent advances in digital cryptocurrency systems.

The past few years have seen widespread adoption of bitcoin, a

TABLE 1. Timestamping security risks.*

Risk type	Risk value	Impact value	Probability value	Deviation value
Loss or compromise of service's signature creation data	38	100	22	59
Loss or alteration of evidence in chain of trust	37	51	39	68
Compromise of the main time source	58	51	47	98
Loss of accuracy of the main time source	47	37	60	94
Unavailability of the main time source	52	37	63	100

*All values are on a scale of 0 (minimum) to 100 (maximum).

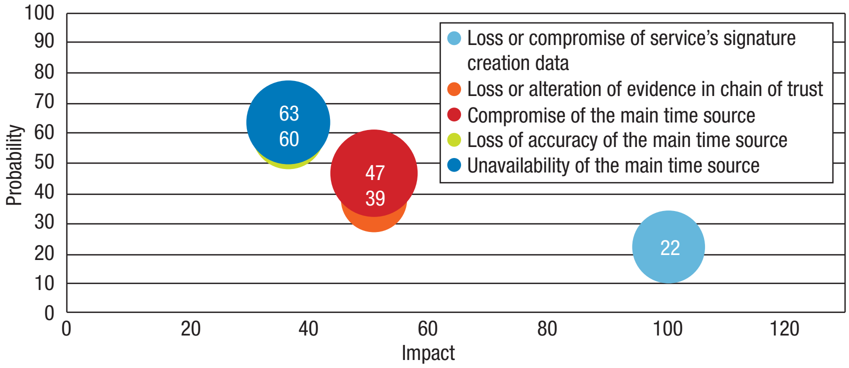

Figure 2. Graphic depiction of the probability and impact values of the five timestamping security risks listed in Table I.

digital cryptocurrency and payment system that relies upon a decentralized peer-to-peer network with thousands of distributed nodes.[8] Any computing device connected to the network with the appropriate software can participate in the system. As Figure 3 shows, bitcoin transactions occur directly between users, without a central administrator, and are recorded in a *blockchain*—a ledger of publicly verifiable digital signatures shared among all nodes. Many believe that blockchain technology is what makes bitcoin and other bitcoin-inspired virtual currencies so successful.

Researchers have suggested harnessing the bitcoin blockchain to make timestamping services more secure.[9,10] One application of such a service for timestamping, Proof of Existence (proofofexistence.com), was introduced in 2012.

Using blockchain protocols has the advantage of empowering multiple parties to validate timestamps[11] but is computationally expensive and requires numerous network interactions. Moreover, there's no direct incentive for mutually trusted independent parties to cooperate, which has limited adoption of decentralized timestamping approaches.

Furthermore, relying solely on bitcoin or any other public blockchain scheme to maintain timestamps has clear security risks: any such system can be subverted when the majority of the participating nodes (CPUs in the case of bitcoin) are subverted. Thus, a blockchain ledger won't be provably secure, rendering the timestamps unreliable for many use cases.

Any blockchain protocol can verify a digital signature but not necessarily the timestamp used by the signature or reported by the generating entity. A public ledger can offer proof of existence based on when the timestamp was received by the rest of the network nodes and the timestamps of the previous and next transactions, but all of that information depends on the public ledger shared among the nodes and their corresponding uncertified and potentially conflicting timestamps.

AN INTEGRATED APPROACH

We believe that a provably secure timestamping system could be achieved by combining the trustworthiness and accuracy that come from having a set of trusted centralized timestamping authorities with the open, decentralized nature of blockchain protocols. Specifically, one or more public or private TSAs that offer trusted timestamping services would embed their timestamping data inside a publicly maintained blockchain ledger such as bitcoin.

These TSAs would issue digital signatures for timestamps as they receive them and publish them in the next block using the previous block hash as part of their certificate-issuing process for the data. Thus, instead of signing a hash value of the data, they'll sign a concatenation of the hash of the data and the previous blockchain hash. Both the hash of the blockchain block used and the certificate are returned to the customer for proof of timestamping.

Because the produced TSA timestamping becomes "part" of the public ledger, there would be publicly available proof of knowledge of timestamped transactions if any TSAs were compromised. Having their transactions as part of a public ledger would also let TSAs detect a certificate compromise or leak by looking for nonauthorized transactions in the public ledger.

A side benefit of having TSAs validate timestamps in a blockchain protocol is that historical transactions stored in the blockchain are also protected: even if the majority of the blockchain nodes get subverted, they can't modify past transactions because they'll be "chained" with timestamping data that can be independently verified. TSAs that detect an invalid block created by attackers who refuse to provide a trusted timestamp for that block can alert the rest of the network to the inconsistency, thereby acting as sentinels for blockchain integrity.

Existing TSAs can still issue trusted timestamps for transactions, but all the data hashes are concatenated and their corresponding signatures will become part of the blockchain ledger and merged with other timestamped transactions coming from other TSAs. Binding timestamps to other transactions and their timestamps provides security in case of certificate loss or misuse. Should this occur, the time of the last valid transaction is made public, all future transactions become invalid for that certificate inside the blockchain, and a new certificate is issued.

An alternative implementation is to have TSAs form their own trusted blockchain without tethering their data to bitcoin or some other widely used digital currency system. To comply with industry best practices as well as regulatory requirements,[12,13] the TSAs would become accountable for their timestamping signatures through an auditable public ledger. However, this implementation comes with a tradeoff: although it retains more control of pertinent timestamping data, there's also higher probability of subversion given that TSAs and regulatory auditors might be the only blockchain participants due to the lack of incentive for other parties to participate.

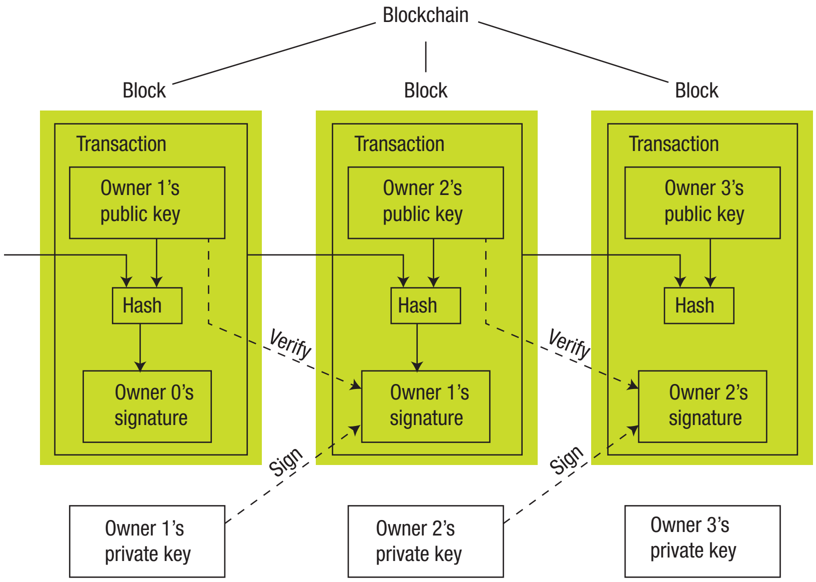

Figure 3. Bitcoin blockchain. Transactions occur directly between users, without a central administrator, and are recorded in a chain of publicly verifiable digital signatures shared among all nodes. (Source: Adapted from an original figure by S. Nakamoto in "Bitcoin: A Peer-to-Peer Electronic Cash System," Oct. 2008; bitcoin.org/bitcoin.pdf.)

Tethering TSA transactions to existing blockchain protocols has two important side benefits. First, it will make applications that rely on trusted, real-world time more reliable and secure by preventing attackers who might overpower the network from altering historical blocks. Second, the use of trusted timestamps by multiple TSAs can give rise to blockchain designs that use proof of knowledge instead of traditional proof of work or of storage. This can be used to slow down aggressive nodes that try to overwhelm computational or network capacity.

Currently, trusted timestamping processes are specified in Internet Engineering Task Force (IETF) RFC 3161, *Internet X.509 Public Key Infrastructure Time-Stamp Protocol*,[7] and the American National Standards Institute (ANSI) X9.95 standard for trusted timestamps,[14] which expands on RFC 3161 by adding data-level security requirements to ensure data integrity. The newer ANSI X9.95 standard is used by financial institutions and regulatory bodies to create trustworthy timestamps that can't be altered without detection. However, both specifications describe processes that require a central TSA to issue timestamps and ensure their validity.

The ultimate aim will be to extend NIST Special Publication 800-102 to cover those use cases where a TSA can participate in blockchain architectures by providing on-demand or periodic verifiable information or by including hashes inside blocks that can be further signed and disseminated by the blockchain participants. From a practical standpoint, this could be implemented using a network service leveraging the ANSI X9.95 standard for trusted timestamps but still remain compatible with the widely used RFC 3161 for older servers.

As more things become interconnected in the IoT, there's a growing need for provably secure timestamps to establish transaction precedence whenever race conditions or tampering with past events are possible. Integrating time-stamping services with blockchain technology provides a novel means to accomplish this by combining the reliability of recognized TSAs with the openness and flexibility of a decentralized public ledger. Verifying time at increasingly smaller time scales is a challenge that might require distributed synchronization of multiple TSAs.

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On the Problem of (Cyber) Attribution

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Is the recent report from the three-letter agencies on the alleged Russian hack of the Democratic National Committee evidence-based attribution or attributibabble?

Attribution is one of those topics that few understand well, but everyone ought to study. It gets at the heart of human cognition—or, perhaps more accurately, what goes wrong with human cognitive processes. Fritz Heider, the father of attribution theory, used it to account for the way humans reconcile perceptions and observations in their quest for understanding.[1] A characteristic of human attribution is fundamental attribution error, whereby perceivers read more into a context than they take from it. Put another way, humans tend to be cognitive misers in that they search for the simplest explanation of events consistent with their disposition, biases, and world view. Nowhere has this been more evident than in the political Rumspringa of the current US president.

Attribution theory has been a staple of modern social psychology since Heider's seminal book. To be sure, there are refinements on the work.[2] But, so far as I know, the refinements don't detract from the theoretical foundation. That said, the public and media have yet to fully appreciate attribution theory and sibling psychological phenomena—a critical flaw in this era of "fake news." Is a feature of human nature to bring cognitive biases to a description of, and inferences from, perceptions? Attitudes and judgments have these biases baked into them. Failing to appreciate this simple fact allows all sundry forms of popular nonsense to remain unchallenged. Such is the case with cyberattribution.

TECHNICAL CHALLENGES

Any forensics examiner worthy of the name would begin an investigation with the assumption that any adversary is every bit the examiner's equal in terms of proficiency. While this assumption might not hold true, it guides the examiner to first look for hardest evidence, rather than the easiest conclusion to reach. If the adversary lacks the examiner's skills, perhaps the investigation takes a bit longer. However, the most troublesome and fruitless investigations spring from a trail of missed clues. Such is the case with much of the cyberattribution proffered by government agencies and reported in the commercial media in response to the alleged recent hack of the Democratic National Committee (DNC) by Russia. We'll return to this topic below.

By way of background, let's profile a typical state-sponsored cyberadversary. State sponsors have the most resources, and in all likelihood hire those with the strongest skillsets. We might include military cyberwarfare

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units like North Korea's Unit 110, China's People's Liberation Army Unit 61398, Israel's Unit 8200, the UK's Government Communications Headquarters (GCHQ), the US National Security Agency, and so forth. It goes without saying that the Russians have similar agencies. In fact, all developed countries have operational cyberwarfare programs, under different auspices and of varying capabilities and budgets. In addition, we must include a coterie of government-financed private security companies (aka "pure plays") for each of these agencies, not to mention a network of individual freelance hackers who also hire out their services.

Such cybermercenaries are well known and their activities well documented, thanks to whistleblowers like Edward Snowden and investigative journalists like James Bamford[3,4] and Tim Shorrock.[5] Corporate players include Stratfor, HBGary/ManTech International, Gamma Group, the Equation Group, Cellebrite, and HackingTeam, to name but a few. The point to bear in mind is that in addition to their own internal apparatuses, state sponsors of cybercrimes, cyberterrorism, and cybersurveillance have a wide variety of private cybermercenary support at their disposal as well. In addition, there's a multimillion-dollar grayware market for malware.[6,7] US intelligence agencies even have a secret procedure to oversee the acquisition and retention of such malware called the Vulnerability Equities Process.[8] But whether the source of the attack is a government agency, corporate cybermercenaries, or independent agents, the source is likely to be highly skilled.

For example, in the case of the FBI decryption of the San Bernardino terrorists' iPhone, the technical expertise needed to circumvent the device's encryption has been attributed to both Cellebrite[9] and freelancers.[10] It's worth noting that state sponsors have nearly endless cyberweapon resources, especially those intelligence agencies connected with the STONEGHOST network made up of the English-speaking Five Eyes countries (the US, the UK, Canada, Australia, and New Zealand).

Attribution theory is relevant to cyberattribution. It's commonly politically motivated. Anup Ghosh, CEO of Invincea, refers to this activity as a blame game. "Nonetheless, many private firms and security researchers are quick to reach a conclusion on who is behind an attack based on code and infrastructure re-use, as well as the tactics, techniques, and protocols (TTPs) they have previously ascribed to bad actors with cute names. The methods typically would not pass a court of law's evidentiary standards, but are good enough for Twitter."[11] His point is well-taken. Politicians and the power elite find it very convenient to engage in this blame game as they seek to discredit adversaries, avoid responsibility for insecure practices and inept leadership, influence politics and elections, and exploit attribution biases in support of cherished big government programs. In the words of singer-songwriter Bruce Hornsby, "That's just the way it is."

So whenever a politician, pundit, or executive tries to attribute something to one group or another, our first inclination should always be to look for signs of attribution bias, cognitive bias, cultural bias, cognitive dissonance, and so forth. Our first principle should be cui bono: What agendas are hidden? Whose interests are being represented or defended? What's the motivation behind the statement? Where are the incentives behind the leak or reportage? How many of the claims have been substantiated by independent investigators? However, these are cerebral questions that require thorough study, unlike viewing footage of police shootings and surfing the web for cats that look like Hitler. That's the reason we see more of the latter from commercial media.

Humans tend to be cognitive misers in that they search for the simplest explanation of events consistent with their disposition, biases, and world view.

FAITH-BASED ATTRIBUTION

Faith-based attribution is a term used by security specialist Jeffrey Carr to denote nonscientific analysis that leads to untestable attribution to a security incident. Carr sums this up nicely in a recent article:[12]

> *It's important to know that the process of attributing an attack by a cybersecurity company has nothing to do with the scientific method. Claims of attribution aren't testable or repeatable because the hypothesis is never proven right or wrong. Neither are claims of attribution admissible in any criminal case, so those who make the claim don't have to abide by any rules of evidence (i.e., hearsay, relevance, admissibility).*

As Carr points out, no one holds the private security contractor who makes such claims accountable if they are subsequently proven false because the notion of evidentiary proof is anathema in this domain. If it's possible, government accountability is even less likely because of secrecy claims and security policies. Further, governments have an effective bully pulpit from which to spawn memes.

Such was the case with the 2014 Sony hack when FBI Director James Comey leveraged familiar "trust me" and "if you only knew what I know" claims to advance a variety of accusational frameworks. This reaffirmed that truth is a moving target for government agencies when it comes to preferred narratives.[13] If this sounds like modern politics to you, it's not coincidental. The same sleight-of-hand tactics are used by political operatives. As we saw in the last election cycle, some politicians are quite comfortable making false claims knowing full well that they'll neither be critically examined nor held up to even a minimal evidentiary standard. We call this political deception. In cyberspace, the same phenomenon is called evidence-free accusation or faith-based attribution. The term faith-based may also be used to describe novice cybersecurity practices as well,[14] and should probably be extended to all political narratives.

But the general phenomena is far more generic than these examples suggest. Long before Comey took on the role of the FBI's chief misattributionist, the controlling elite perfected the art of placing blame for political, economic, or social advantage at the feet of their adversaries. That's how the names of Saddam Hussein, Fidel Castro, and Kim Jong-il entered the popular lexicon. Every empire needs bête noirs to keep the public's adrenaline running high.

SENSITIVE SOURCES AND METHODS INDEED

The fanfare surrounding the 6 January 2017 report from the Office of the Director of National Intelligence (ODNI) on the recent hack of the DNC[15] seems to be inversely related to the reader's understanding of computing networks. To borrow a phrase from Columbia journalism professor Nicholas Lemann, this report was a "golden-brown wobbly soufflé of speculation." There was no evidence produced, no data revealed, no forensics mentioned—just 13 pages of undocumented opinion by the same folks who claimed that the Soviets were four years away from building an atomic bomb the eve before they detonated one, the USSR would never place missiles in Cuba, China wouldn't get involved in the Korean War, North Vietnam attacked US forces in the Gulf of Tonkin, and Saddam Hussein had weapons of mass destruction, and who failed to foresee both the Iranian revolution and the Soviet Union's collapse. I have no idea whether Vladimir Putin and his cyber hit squad was behind the DNC hack. And based on the report under review, it's an open question whether the security agencies do either. Intelligence services hide behind the mantra that they can't disclose sensitive sources and methods, real or imagined. For want of a better term, we'll call this fantasy intelligence.

Intelligence services hide behind the mantra that they can't disclose sensitive sources and methods, real or imagined. For want of a better term, we'll call this fantasy intelligence.

Let's consider for a moment what these "sensitive sources and methods" might be. Here are a sampling of known knowns to digital forensics experts. First, suspected malware file hashes can be matched against any number of detection programs to identify usual suspects (www.virustotal.com is a good starting point). These programs for the most part use public databases. There's nothing sensitive about this information. Second, any malware can be statically reverse-engineered by de-compilation or disassembly and searched for string signatures that betray anomalies or exploits. Again, no news here. Further, runtime debuggers can be used to dynamically determine linkages and runtime dependencies associated with suspected malware. File headers might reveal compile dates, mnemonics used, file sizes, version numbers, and so forth that provide circumstantial clues to program authors and sources. Of course, state-sponsored cyberunits have the best tools known for these purposes—but even the best tools don't provide prosecutable evidence. The operative point is that there's nothing "sensitive" about any of these information-gathering tools and tactics. They're well known and used worldwide by computer forensicists. The likelihood is that if all of these methods were disclosed to the public, no "sensitive" information would be revealed if only personally identifiable information were redacted.

On the network side, state actors routinely sniff all network traffic they can get their hands on—including, as the disclosures concerning the NSA's bulk data collection programs revealed, information about private citizens not suspected of any crimes and without benefit of court order. So let's assume that the US intelligence agencies have captured all network traffic to and from their suspects and have analyzed them down to the packet level. What would that reveal? If the adversaries are worth their money, very little. It's likely that Russian cybercapability is in a league with our own. Such being the case, the IP addresses, MAC addresses, and ISPs involved in the traffic are very unlikely to be traceable back to Putin, Russia, or the hackers themselves. If the perpetrators are "A Team" hackers, the traffic is more likely to trace back to a daycare center in Milan.

Professional hackers don't leave digital fingerprints on the computer and network resources they use. Script kiddies might, but not professionals. Again, any such information released by the US government is unlikely to disclose anything "sensitive," because all security experts already know these agencies' capabilities, and the "perps" we must assume are every bit the equal of the cybersleuths seeking to out them. Of course, both sides occasionally make mistakes. But a mistake so large as to identify the president of a sovereign nation as involved in hacking another sovereign state is exceedingly improbable. Consider that no forensics traced Stuxnet back to the second Bush administration. Plausible deniability is the matron to every controversial or unpopular big government initiative. As Carr has pointed out, the tangible facts in the DNC breach were distorted by press reports into Disney-like caricatures.[16]

Security experts David Clark and Susan Landau[17] provide an overview of the attribution problem from a defensive perspective. They accurately sum up the problem: "Attribution is central to deterrence … and the Internet was not designed with deterrence in mind." A more technical description is supplied by David Wheeler and Gregory Larsen.[18] Taken together, these papers are notable for the absence of detailed strategies to provide justiciable, evidence-based cyberattribution. There's a reason for that: there is none. The most we have is informed opinion. And the intelligence agencies that offered such opinions concerning the recent alleged "Russian Activities and Intentions in Recent US Elections" assesment[15] have an exceedingly spotty reputation when it comes to such reports' accuracy.[19,20]

The recent survey of attribution challenges by Earl Boebert[21] is to be recommended in this regard. As Boebert observes, the Internet infrastructure itself works against attribution. Network address translation, the Dynamic Host Configuration Protocol, the triviality of spoofing IP and MAC addresses, the lack of source authentication in DNS registration, proxy servers, encryption, anonymizing services, and the like all work against justiciable cyberforensic attribution

THAT LEAVES US WITH HUMINT

This is where Fancy Bear and Cozy Bear meet Guccifer 2.0.[22,23] Are the claims about Russian hacking groups' involvement in the DNC breach by Guccifer 2.0, a Russian misinformation specialist, legitimate or meant to deflect criticism? Is he really Romanian? I have no idea, but that misses the central point. There's no way to build confidence in any of this reporting without the ability to follow the incentives—and that's the data that the three-letter agencies are guarding so zealously. I would be remiss if I failed to mention that it was certainly timely that just when the three-letter forefingers were poised to point, Guccifer 2.0 was overcome with grandiloquence. Do the intelligence agencies have the goods on someone? It's impossible to tell from this side of the veil of government secrecy. That's by design.[24]

In any case, state-sponsored cyberwarriors certainly have the technical capacity to identify adversaries biometrically. As I mentioned above, modern intelligence agencies have enormous resources to draw upon, including various cyberweapons merchants and others who provide a cornucopia of communication and media interdiction tools, rootkits, remote session hijacking tools, worms, viruses, zero-day exploits, and sundry other tools to spy on cyberadversaries in situ. That said, the other side has comparable access to such tools and are aware that these tools can be used against them. Rooting a journalists' computer is very different from rooting the computer of a highly skilled security specialist in the employ of a state sponsor. This is very much a case of cyber cat and mouse where neither has the predictably clear advantage. Could Western intelligence agencies root computers of state adversaries? Sure, but it's not very likely unless the target has a rookie asleep at the console.

It's interesting to note that an equally wobbly soufflé of speculation about alleged Trump/Putin ties was offered to the DNC in 2016 by an unnamed paid source.[25] This report, recently made public, has much the same character as the ODNI report: no verifiable claims and no ground-truth data mentioned. While these claims seem vague on the surface, on deep analysis they're seen to be nothing more than attributibabble. This is the stuff of which dimestore novels are made.

> Plausible deniability is the matron to every controversial or unpopular big government initiative.

As Carr points out, there are disincentives to criticizing the received view of anything.[26] The choice of reflection over simple absorption of a received view is intellectually demanding, time-consuming, unlikely to be profitable, and will win few friends among the controlling elite. However, it's precisely this unpopular and unprofitable "truth to power" approach that will yield the truth. The choice intellectuals have before them is between investing in the search for truth or living in the world of alt-facts. The latter is the substance of George Orwell's and Aldous Huxley's dystopia.

I would be remiss if I failed to direct attention to the real problem of the

DNC hack: the content of the emails. A more shameful display of partisan myopia and disregard for democratic principles is difficult to imagine. ■

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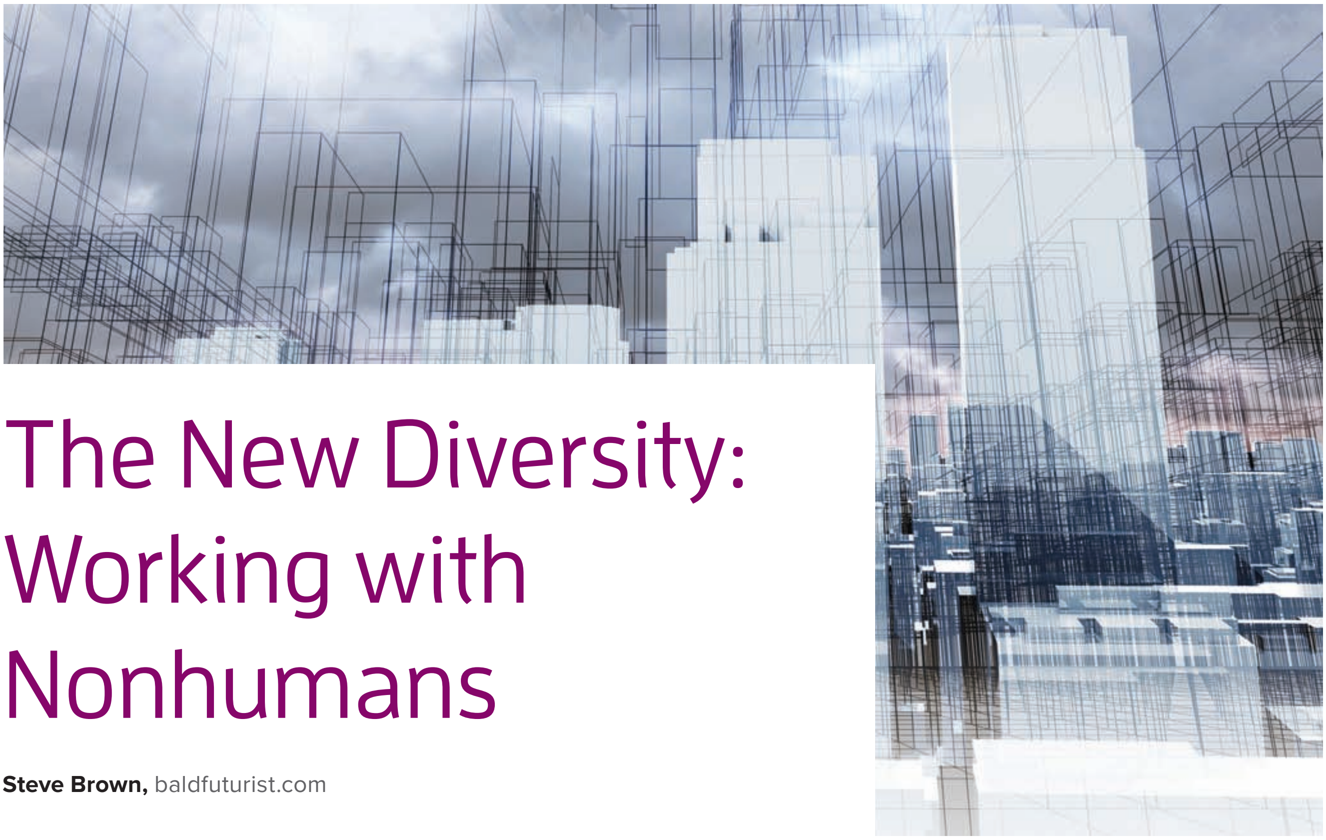

The New Diversity: Working with Nonhumans

Steve Brown, baldfuturist.com

In the workplace of the future, people will need to be comfortable working alongside digital intelligence, and businesses will need to find the optimal pairing of humans and machines.

FROM THE EDITOR

Futurist Steve Brown envisions a future in which humans and robots will work side by side—and no business will go unaffected. –*Brian David Johnson*

An employee's most important skill is the ability to work well with others. Soon, this will extend to include the ability to work alongside autonomous machines and algorithms. Welcome to the new diversity.

Diversity and inclusion remain key to business success and social justice. Savvy companies understand that making their workplaces more inclusive yields benefits that go way beyond government requirements—increased diversity helps organizations maintain their market relevance and boost their speed of innovation. But despite efforts, many industries still lack workplace diversity in terms of gender, race, age, and sexual orientation. And to this list we must now add another dimension: nonhumans. The future's most effective teams will include not only more women, people of color, LGBTQ individuals, and people of all ages, but also robots and algorithms.

YOU ARE YOUR NETWORK

Prior to the Industrial Revolution, your value as a worker was mostly related to physical ability: your strength, stamina, and dexterity. With the coming of the Information Age, what you knew and how well you created and processed information became increasingly important.

We now live in the Network Age, in which knowledge is being commoditized. Your value relates less to what you know and more to who you know, the strength of your relationships, and how well you can leverage your personal network to get things

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done. That network will soon include nonhumans.

In many fields, human judgment—based on decades of experience—is being replaced by learning algorithms that make better-quality decisions than humans can. Consider the "merchant princes" in apparel companies who use their "gut feelings" to determine next year's clothing lines and decide how to display and market merchandise. Predictive analytics will soon make this role obsolete.

As a result of such commoditization of knowledge and experience, your ability to collaborate on a team becomes more important to an organization than the knowledge rattling around in your head. That's not to say that knowledge no longer matters; physical attributes such as stamina remain relevant. But your ability to network, and put that network to work for you, will be your most vital skill. Thus, in today's Network Age, knowing how to collaborate to find the information you need to get something done is what matters. And in many cases, algorithms will provide much of that information.

THE NEW WORK TEAM: HUMAN AND DIGITAL INTELLIGENCE

To be successful in the workplace of the future, we'll all need to be comfortable working alongside digital intelligence. This includes both autonomous machines and algorithms, respectively the physical and nonphysical instantiations of digital intelligence.

Smart managers will resist the temptation to simply replace humans with robots and algorithms as technology advances. This temptation is strong in some sectors of US industry, as bean counters worry about the $15 minimum wage. But companies risk stripping out the humanity from their operations, and thus their brand, if they blindly take this approach. Every brand has a human element at its foundation.

Leaders should step back and consider ways to optimize their labor force by forging partnerships between humans and machines (or between humans and algorithms). As in any diverse team, humans and machines each have different strengths and weaknesses.

ROBOTS VERSUS HUMANS VERSUS ALGORITHMS

Machines have many advantages over humans. Robots are much stronger and have endurance and speed on their side. Algorithms, analytics, and AI not only operate at incredible speed, but they can spot complex patterns in vast seas of data that humans just can't see.

But don't panic. Humans still excel in areas where machines will remain weak for the foreseeable future; creativity, dexterity, and adaptability are fine examples. Another, empathy, is a vital skill for all aspects of customer service. We are of high value just by virtue of our humanity. After all, nobody wants a machine to tell them they have stage-3 liver cancer.

Machines and algorithms will succeed at repetitive tasks (even very complex ones) that are learned by analyzing huge datasets and that have measurable outcomes. For example, radiologists are highly trained and highly skilled. But if you show a deep-learning algorithm enough computed tomography scans and X-rays of potential tumors and then tell it which ones portray positive results and which ones have negative results, the algorithm can be a very effective radiologist. The diagnostic component of other jobs such as doctors and mechanics will go the same way. Algorithms will first show up as assistants, working alongside the human experts. Once the humans' accuracy is outstripped by the machine, the humans will be free to take on tasks that machines can't do, like spending time face-to-face with patients.

AUGMENTING HUMAN CAPABILITIES

In these future workplaces, managers will need to design their teams so that tasks are intelligently split between humans and nonhumans. Managers will need to decide which tasks are best handled by humans and which by robots, and what role algorithms, analytics, and AI should play in helping humans perform their jobs better.

The robots are coming. That's no longer in doubt. Analytics and AI will transform every sector of industry for the better. And so every business will need to find the optimal pairing of human and machine—and we'll all need to learn to work with, and for, nonhumans. **C**

In future workplaces, managers will need to design their teams so that tasks are intelligently split between humans and nonhumans.

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CALL AND CALENDAR

CALLS FOR ARTICLES FOR IEEE CS PUBLICATIONS

IT Professional plans a November/December 2017 special issue on graph databases.

The management and analysis of huge volumes of unstructured data, connected through pervasive and diverse cross-links, increasingly permeates most applications. The traditional relational database management system faces limitations in dealing with such data and with agile processes. Nonrelational (NoSQL) databases can accommodate mountains of unstructured data, offer greater design and implementation flexibility, and support less stable processes.

Graph databases, which are specialized NoSQL databases, bring a novel dimension to traditional data management. Equipped with new capabilities, graph databases are attracting considerable interest among researchers and industry.

This special issue will explore several aspects of emerging graph databases, outline their applications and devel-opment, and discuss recent advances, research insights, novel applications, practical experiences, challenges, and prospects.

Articles are due **1 April 2017**. Visit www.computer.org/it-professional/2016/11/15/graph-databases-call-for-papers to view the complete call for papers.

IEEE Transactions on Emerging Topics in Computing (TETC) plans the following special section for its June 2018 issue, with articles due **1 June 2017**:

Cybersecurity threats and defense advances: Visit www.computer.org/cms/Computer.org/transactions/cfps/cfp_tetcsi_cstda.pdf to view the complete call for papers.

IEEE Transactions on Emerging Topics in Computing (TETC) plans the following special sections for its June 2018 issue, with articles due **1 September 2017**:

Advanced command, control, and on-board data processing for space avionic systems: Visit www.computer.org/cms/Computer.org/transactions/cfps/cfp_tetcsi_avionics.pdf to view the complete call for papers.

Green computing in the Internet of Things: Visit www.computer.org/cms/Computer.org/transactions/cfps/cfp_tetcsi_gciot.pdf to view the complete call for papers.

eGovernment development and applications: Visit www.computer.org/cms/Computer.org/transactions/cfps/cfp_tetcsi_siegda.pdf to view the complete call for papers.

IEEE Transactions on Emerging Topics in Computing (TETC) plans the following special section for its March 2019 issue, with articles due **1 March 2018**:

Design of reversible computing systems: Visit www.computer.org/cms/Computer.org/transactions/cfps/cfp_tetcsi_drcs.pdf to view the complete call for papers.

SUBMISSION INSTRUCTIONS

The Call and Calendar section lists conferences, symposia, and workshops that the IEEE Computer Society sponsors or cooperates in presenting.

Visit www.computer.org/conferences for instructions on how to submit conference or call listings as well as a more complete listing of upcoming computing-related conferences.

APRIL 2017

4–7 April: IC2E 2017, IEEE Int'l Conf. Cloud Eng., Vancouver, Canada; conferences.computer.org/IC2E/2017

10–12 April: ICRC 2017, 1st IEEE Int'l Conf. Robotic Computing, Taichung, Taiwan; icrc.asia.edu.tw

18–21 April: IoTDI 2017, 2nd IEEE Int'l Conf. Internet-of-Things Design and Implementation, Pittsburgh; conferences.computer.org/IoTDI

19–21 April: BigMM 2017, 3rd IEEE Int'l Conf. Multimedia Big Data, Laguna Hills, California; bigmm.eecs.uci.edu

MAY 2017

12–14 May: ICCP 2017, IEEE Int'l Conf. Computational Photography, Stanford, California; iccp2017.stanford.edu

20–28 May: ICSE 2017, 39th Int'l Conf. Software Eng., Buenos Aires, Argentina; icse2017.gatech.edu

COMPSAC 2017

The 41st IEEE International Conference on Computers, Software, and Applications (COMPSAC 2017) is sponsored by the IEEE Computer Society.

COMPSAC is the IEEE Computer Society's signature conference on computers, software, and applications. It targets attendees in academia, industry, and government.

COMPSAC 2017 will provide a forum for in-depth presentations and discussions of the technical challenges, successes, and failures of moving from traditional person-centered and person-directed activities and services to those based on autonomous systems.

Topics will include autonomous computing, wearable computing, the Internet of Things, social networking, cross-domain data fusion, privacy and surveillance, security, cloud computing, big data, physiological computing, and self-aware and self-expressive systems.

COMPSAC 2017 will take place 4–8 July 2017 in Turin, Italy. Visit www.computer.org/web/compsac2017 for complete conference information.

SEEKING PAPERS ON SOFTWARE ENGINEERING

Computing in Science & Engineering seeks submissions on scientific-software engineering. The magazine seeks to provide a venue for the publication of significant work in the field, recognizing that the development of scientific software differs significantly from that of other software. Learn more at www.computer.org/cms/Computer.org/ComputingNow/docs/2016-software-engineering-track.pdf.

26–28 May: BigDataSecurity 2017, 3rd IEEE Int'l Conf. Big Data Security on Cloud, Beijing; bigdata-security.org/bj2017/datasec

JUNE 2017

26-28 June: SNPD 2017, 18th IEEE/ACIS Int'l Conf. Software Eng., Artificial Intelligence, Networking and Parallel/Distributed Computing, Kanazawa, Japan; www.acisinternational.org/snpd2017

SEEKING PAPERS ON COMPUTATIONAL SOCIAL SYSTEMS

IEEE Transactions on Computational Social Systems welcomes submissions on topics such as modeling, simulation, analysis, and the understanding of social systems from the quantitative and/or computational perspective. Learn more at www.ieeesmc.org/publications/transactions-on-computational-social-systems/call-for-papers-and-special-issues.

EVENTS IN 2017

APRIL 2017

4–7 .... IC2E 2017
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26–28 .... BigDataSecurity 2017

JUNE 2017

26–28 .... SNPD 2017
26–28 .... CSCloud 2017
26–29 .... DSN 2017

JULY 2017

4–8 .... COMPSAC 2017
17–21 .... ICAC 2017
21–26 .... CVPR 2017
26–28 .... ICCI*CC 2017

26–28 June: CSCloud 2017, 4th IEEE Int'l Conf. Cyber Security and Cloud Computing, New York; 2017.csclouds.org

26–29 June: DSN 2017, 47th IEEE/IFIP Int'l Conf. Dependable Systems and Networks, Denver; dsn2017.github.io

JULY 2017

4–8 July: COMPSAC 2017, 41st IEEE Int'l Conf. Computers, Software, and Applications, Turin, Italy; www.computer.org/web/compsac2017

17–21 July: ICAC 2017, 14th IEEE Int'l Conf. Autonomic Computing, Columbus, Ohio; icac2017.ece.ohio-state.edu

21–26 July: CVPR 2017, 2017 IEEE Conf. Computer Vision and Pattern Recognition, Honolulu; cvpr2017.thecvf.com

26–28 July: ICCI*CC 2017, 16th IEEE Int'l Conf. Cognitive Informatics and Cognitive Computing, Oxford, UK; www.ucalgary.ca/icci_cc/iccicc-17

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Digital Trade

David Alan Grier, George Washington University

The Internet has become central to every economy on the planet.

For a summer in the early 1990s, I served as the backup site for the North American Free Trade Agreement (NAFTA) between Canada, Mexico, and the US. Every night, one of the negotiators would give me a floppy disk containing the most recent version of the treaty, and I would return the disk from the day before. The negotiation took place on neutral ground, in the meeting rooms of a local hotel. No one had given much thought about how to protect their work. They had no central file server, no backup service, and no cloud-based storage. The legal staff felt that one copy needed to be kept offsite and concluded that I was the most trustworthy person to keep that copy—or so I would like to think.

Free trade agreements, though controversial, are one of the foundations of the global economy. They are, after all, products of negotiations. Few parties are able to leave a negotiation without feeling that everyone else at the table got a better deal than they did. In addition, free trade agreements are deeply connected to information technology. This is evidenced by the 1865 International Telegraph Convention, which allowed European telegraph services to collaborate and pass messages across borders.

Eighty years later, in the same month that the US Army revealed the electronic computing machine called the ENIAC, the victorious powers of World War II announced a General Agreement on Tariffs and Trade (GATT), which would become the World Trade Organization (WTO). Without computers to collect and process data, GATT would have been difficult to enforce. Without GATT, the computer industry would have expanded much more slowly.

When GATT became the WTO in 1995, the organization announced a new trade agreement for digital technologies: the Information Trade Agreement (ITA). Initially, the ITA was accepted by 29 countries that agreed to give one another the lowest possible tariffs on telecommunications and computing equipment. Currently, 81 countries are signatories to the ITA. These signatories recently agreed to further reductions to tariffs for computing and information products and services. The first cuts began in July 2016.

However, negotiations are never complete: economies change and force countries to reposition their industries, and technologies change and create products that can't easily fit into the old agreement. NATFA was completed before the rise of the commercial Internet. It covers Internet services in a haphazard way, and the three parties have been reluctant to renegotiate the agreement to include Internet services. Once negotiations are opened for one sector, parties quickly find themselves discussing the terms of the entire agreement. Yet, the Internet has become central to every economy on the planet. NAFTA needs to handle it in a more sophisticated way.

In thinking about the Internet as a trade platform, we need to consider a variety of issues that were viewed as unimportant two decades ago, including the free flow of data, protection of source code, security and privacy, data localization, and digital customs. The Trans-Pacific Partnership (TPP) dealt with these issues in a fairly effective way (a summary of the digital trade provisions can be found at ustr.gov/sites/default/files/Digital-2-Dozen-Final.pdf). In January 2017, the Trump administration withdrew from the TPP negotiations, arguing that it isn't in America's interest to pursue the agreement. However, digital technology will continue to advance, and digital trade needs to be guided by clear and current trade agreements. We could probably improve the ITA. We almost certainly need to bring NAFTA up to date. When we do, I don't expect to be the backup site. Not this time.

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