Research Challenges of Emerging Technologies Supporting Life-Long Health and Wellbeing

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ABSTRACT

In this article, we identify and discuss challenges imposed on technological research by emerging developments in health and wellbeing. We see an increasing importance of digital health literacy, the convergence of medicine and daily life, a shift from individual health to community care, a growth of personalized medicine, and the impact of internet of things on health. These developments mean challenges for technical research, such as the need, but also difficulties of interdisciplinarity, or the need to translate personal health data into medical information. Today's research approaches are not always best suited to deal with the challenges, e.g. of conducting real long term intervention studies, or taking into account regulatory issues. We propose a joint campaign by HCI, AI, UX and machine learning researchers, engineers, clinicians, regulatory bodies and all other interested parties in these subjects.

CCS CONCEPTS

Applied computing → Life and medical sciences → **Consumer health**;
Social and professional topics → Professional topics → Computing and business → **Socio-technical systems**

KEYWORDS

Emerging technologies, health, wellbeing, personalized medicine, digital health literacy, interdisciplinary research, data, social media, regulations and standards

ACM Reference format:

J. Meyer, P. Eslambolchilar. 2017. Research Challenges of Emerging Technologies Supporting Life-Long Health and Wellbeing. In *MMHealth'17: The 2nd International Workshop on Multimedia for Personal Health and Health Care Proceedings Mountain View, CA, USA, October 2017 (MMHealth'17)*, 8 pages.
https://doi.org/10.1145/3132635.3132639

MMHealth'17, October 23–27, 2017, Mountain View, CA, USA

ACM 978-1-4503-5504-9/17/10…$15.00
https://doi.org/10.1145/3132635.3132639

1 INTRODUCTION

In the last years, as citizens of a digital world, we have seen an overwhelming development in the field of personal health and wellbeing. New sensors, miniaturization, the ubiquity of smart phones, networking and the internet of things, to name just a few, have given us a plethora of new applications and systems that promise to support and improve personal health, wellbeing and fitness. New devices are emerging regularly, addressing i.a. physical activity, endurance sports and resistance training, sleep monitoring, mindfulness practice, posture monitoring, weight management, breathing techniques, cardiac health status and numerous more. Activity tracking alone is a million-dollar market, with 22.5 million devices shipped in Q2/2016 alone [32]. On the other hand, there is still a considerable uncertainty in whether these types of applications are primarily for personal entertainment, or whether they can be of actual practical use. Behavior change interventions face considerable challenges such as early abandonment [18], the lack of sustainable changes [40], or negative effects of tracking [21]. And medical professionals often are reluctant to use personally collected health data, e.g. due to lack of trust in the data, or due to the inability to deal with the heterogeneous and non-standard data brought by their patients [22,35].

Personal health monitoring enables a long-term observation of parameters of health, covering not just weeks or months, but years and decades. The opportunities arising from this fact are discussed in research articles since a couple of years already (e.g. [41,11]). In [42] authors identified five use cases for data from long term self-monitoring: (1) supporting health behavior, (2) improved health understanding, (3) identification of trends and relations, (4) making informed decisions, and (5) storing data for future use. Other researchers addressing long-term use of tracking point into similar directions [33,27].

In this article, we identify and discuss "emerging concepts" i.e. "what will be the future in healthcare and wellbeing" as well as some "emerging challenges" i.e. "what needs to be done" by research communities and relevant interested parties to address those challenges. We also present possible future developments of personal health and discuss opportunities and challenges that computer science, HCI, multimedia research, engineering, health services, regulatory organizations are facing. The presentation is not meant to be complete, but rather to address some selected points, to stimulate discussion.

2 Emerging concepts in health and wellbeing

In this article, we observe some developments in health and wellbeing, often induced by technological developments that may change users' and patients' way of dealing with health and wellbeing. We subsequently describe some of these developments that may have an impact on technology-oriented research.

2.1 From doctor-centric health to health literacy and to digital health literacy

In many countries, the general practitioners are understood to be the "masters of health". If something was wrong with one's health one would go to the doctor to have it treated. However, there is a world-wide movement in healthcare and the public health systems to increase health literacy and change this traditional healthcare, impacted by, i.a. the economic pressure on the health systems worldwide, and supported by increased access to the Internet and public medical information [9, 19]. On the one hand patients, their families and their communities are empowered to be active and equal partners in co-producing health; on the other hand improved understanding of reasons for behavior related diseases increases the number of choices and decisions for the individual. There are increasing pressures on the individuals to care for and promote their health and wellbeing, and on patients to be able to observe, understand and manage their symptoms and make decisions [16]. This is tremendously difficult because health is complex and requires both, motivation and skills that many people don't have. Traditional measures to increase health literacy include public initiatives such as awareness campaigns or the distribution of information material [39].

Additionally, with abundance of health and wellbeing apps on smartphones, activity trackers and smartwatches equipped with activity tracking sensors and apps and, online health and wellbeing information new skillsets, called digital health literacy, are required [61]. Wearable devices and apps capture potentially useful and clinically impactful data if and only if patients find apps and devices usable and their data comprehensible [14]. Moreover, tailoring the digital health information to the individual's information needs in each health situation will reduce the information overload and confusion [1].

2.2 Medicine and daily life are converging

The traditional view on the world of medical devices is: A device used for medical purposes such as diagnosis or therapy must be approved by a regulatory body, e.g. the American FDA or the national bodies implementing the European Medical Device Directive. And any device that is not approved must not be used in a medical context. However, this view is more and more being blurred.

With miniaturization, mobilization and cost efficiency of e.g. heart rate chest belts, generally sold with a heart rate watch (e.g. Garmin or ActiHeart), one may identify a heart rate failure although this is not the primary purpose of the device. In other words, portable ECGs are the core of heart rate monitoring that is used in millions of sports watches for measuring heart rate and heart rate variability. And, it may only be a matter of time before some consumer devices are available that are able to monitor an ECG in more detail and may well be used to identify potential heart diseases. Therefore, such devices that are not official medical devices and are in a slow transition from lifestyle to diagnosis may be moved to a medical use.

Moreover, the technology enables to move devices from the lab to the home, reducing costs by several orders of magnitude. For example, sleep assessment used to require a sleep lab that is extremely costly to use. With low-cost home devices, it is now possible to move some core aspects of sleep assessment into the daily live [34]. For example, a sleep sensor may identify changing health conditions by measuring the changes in breathing rate.

While precision and reliability are still far below gold standard, such systems nevertheless enable an objective monitoring of a key aspect of personal health that previously was impossible to observe in the long-term [34].

Although today's devices are often focusing on – in the broadest sense - cardiovascular health and fitness, in the future patients and users will also be able to monitor other key aspects of health such as mental or skeletomuscular health, addressing major disease burdens relating to e.g. depression or back pain [55]. There are already first solutions available such as the "Spire" [56] device aiming to increase "awareness" by monitoring the breathing rate, or the "Sensoria smart sock" [54] that uses pressure sensors to identify a potential harmful running technique.

2.3 Social Media in Healthcare: from individual health to community care

Internet-based patient communities who use social media [6], Wiki [36], or other purposefully designed online communities [46] are rapidly on the rise. Such platforms bring thousands of patients with variety of health conditions together. For example, PatientsLikeMe [46] has more than 400,000 members. These figures indicate that people are interested in using data-sharing social platforms for healthcare to communicate with other people who have common needs and learn more about themselves [36]. Moreover, people join such platforms to find clinical trials that suit them and share their symptoms or the outcomes of their treatments with other users such as patients, researchers, pharmaceutical companies and other non-profit organizations. Some of these online communities are equipped with apps which collect the data from patients on-the-go. Those apps facilitate personalized and location-based information collection and data sharing at a massive scale [36, 6]. Soon such apps will be able to match patients with other patients nearby for further community support. Some other online platforms use social media for health warnings and disease outbreaks; such platforms as HealthMap and Sickweather encourage users to contribute information about their own or others' illnesses to

generate geolocation data that can warn people when there is an infectious disease outbreak in their area [37].

Social Media in Healthcare could be an empowering tool for patients and their carers in terms of educating the individuals on health matters, digital homecare devices and apps and in general, smooth transition from doctor–lead medicine to digital health literacy (see section 2.1).

2.4 Internet of Things

There are different interpretations of "big data" in each subject area [49,52]. Raghupathi and Raghupathi [49] identify four Vs of data for "big data" in healthcare: (1) velocity (speed of generation of data), (2) variety, (3) volume, and (4) veracity (conformity and accuracy of data). Internet of Things (IoT) - an inter-network of devices and objects with embedded sensors, software, electronics, actuators and network connectivity which enable these objects to communicate with each other and provide an additional layer of information for users or patients [4] - on the other hand, enables apps and tracking devices and smart watches to gather and share information directly with each other or with the cloud [17]. Therefore, data collection, sharing and analyses are happening much faster than traditional methods i.e. pen and paper and these provide a wide range of possibilities from early intervention of a disease to predicting one's risk of illness.

The cost to sequence the human genome rapidly decreasing with the development of high-throughput sequencing technology [8]. Moreover, there are many home test kits available for a variety of blood, saliva, urine and other markers, for example variety of blood measurement kits are offered by Finger Prick Home KITS [25], Thirva [58] and, Walk In Lab [62]. With IoT and availability of apps and devices numerous information could be collected about lifestyle, wellbeing, living and working environment and so on. These all promise a huge potential for delivering PM in near distant future.

2.5 Personalized Medicine

Melanie Swan defines personalized medicine (PM) as using an individual's specific biological characteristics genetic, blood and other biomarker, environmental, lifestyle and other data to tailor therapies to that person, including drugs, drug dosage and other remedies [57]. She later defines consumer PM as the further step of individuals collecting and synthesizing their own data and using it to proactively manage their health [57].

Moreover, IoT provides an excellent opportunity to collect large amounts of data by accessing patient records and other health informatics and social media content. This opportunity is viewed as having great potential for producing new knowledge about illness and disease and contributing to preventive medicine and health promotion [7, 63]. For example, Barrett et al. [7] argue that 'collective health' can be improved with a 'data-driven approach', allowing for the identification of 'personalized risk factors' and with the supposed 'precision prevention' approach that large data sets will offer to health promotion efforts [7].

In the following sections, we will identify and discuss some of challenges research communities face in the context of emerging technologies for long-term health and wellbeing. These challenges have been classified to (1) challenges related to emerging technologies and doing research with rapidly changing technologies, (2) patient collected health data becoming medical data and, (3) challenges current research approaches face with emerging technologies. The aim is provoking thoughts and ideas on "what needs to be done" by research communities to address such challenges.

3 Challenges for technological research

3.1 The need for and the challenges of interdisciplinary

Developing technical solutions for health clearly requires a thorough understanding of health and medicine. However, while in "traditional" eHealth systems where health services and information delivered or enhanced through the Internet and related technologies [23], the evolving role of technology in personalized medicine is a different one. It is not enough to adopt technical work to medical requirements; rather the medical and the technological world need to converge truly and collaborate interdisciplinarily for best results [53].

The HCI community cannot conduct research with patients and other users of healthcare services as easily as other user groups in the real context due to ethical conduct, risk mitigation and patient safety at the least. Singh et al. argue that in interdisciplinary research between HCI and health, the HCI community has much to learn from clinical and health service research community [53]. However, who has ever worked in an interdisciplinary project will have experienced that interdisciplinary work is difficult and takes a lot of time, due to, i.a. the lack of a common language to discuss research, varying research approaches, and different publication traditions. Moreover, such research is demanding in "adhering to mutually acceptable conceptual frameworks" [53]. This may mean to adopt a transdisciplinary mindset—folding, meshing, and extrapolating different concepts, values, concerns, and findings [51]. Although Rogers and Marshall [51] admit that this is a challenging process, they have a positive view on the outcome and encourage HCI researchers to adopt transdisciplinary theories.

The transdisciplinary research method requires a trustworthy collaboration between data analysts and computer scientists who can crunch (and visualize) deep medical/healthcare data to find potential insights, and subject-matter experts such as physicians and healthcare providers, who ultimately apply those findings in patients' treatment plans. In other words, how to get physicians on board along with HCI, AI, and UX researchers to disrupt healthcare ecosystems?

On the other hand, the results and outcomes of interdisciplinary research are much broader validated and much broader accepted than those of single-disciplinary work. The broadness of the results, however, also implies that – with the same effort - less

depth per discipline can be achieved. The broadness of the methods and/or results can also affect the publication venues. There are few conferences and journals that accept such broad methods and results coming from multiple disciplines. Moreover, research panels who assess the quality of papers for Research Excellence Frameworks (REF) or Research Assessment Exercises (RAE) in Higher Education Institutes in countries such as UK, regard such published work as low quality in terms of depth and knowledge in single disciplines. This diminishes the hard work gone into such research. Therefore, the research community needs to balance the interdisciplinarity with the technology-oriented research. And funding bodies and research quality assessment panels need to appreciate the value of interdisciplinary research and not regard them as "second-class" or "lower-class" research or publications.

3.2 Personalized medicine needs more than digital health literacy

Personalized medicine (PM) with an average digital health literacy could still be challenging; patients may risk misinterpreting the information and experiencing confusion on parsing loosely-tied and conflicting research findings, for example [57]. The confusion is caused by carefully conducted therapeutic intervention reports which are based on Randomized Controlled Trials (RCTs) and published by media in lay man's language (e.g. newspapers, news websites, public science magazines and websites). RCTs are the gold standard for health and wellbeing interventions to be accepted into the standard of care and therefore be adopted by Public Health and Health services [45]. RCTs are designed to establish the best treatment or intervention for the "average patient and or public" and ignore the outliers; PM focuses on the outliers identified after RCTs conducted [10]. Such outliers may benefit from using biomarkers, lifestyle, environmental and other data collected via IoT and sharing them with pharmaceutical companies for tailed-made treatments. Therefore, RCTs and PM complement each other [28]. And to benefit outliers to understand their symptoms better, comprehend treatments beyond RCT outcomes and collect the data in the context, the research community requires expertise from many disciplines e.g. clinicians, HCI researchers, computer scientists, data scientists, and engineers.

3.3 Different expectations in the technical vs medical world

Although RCTs represent a "gold standard" for assessing an intervention or an emerging therapy and/or tool, they run in a limited time scale (i.e. shorter than a patient's life). Therefore it is not possible to capture all relevant benefits and harms [15]. Moreover, RCTs that lock down interventions are ill suited for the rapidly changing field of digital behavior interventions [43, 47]. While RCTs will continue to have value, several methods have been proposed that could complement RCTs. For example, methods that allow for iteration and learning during a trial [44], adaptive designs, regression discontinuity designs, A/B testing, open-source platforms [20, 43], N-of-1 studies, and other research methods that yield insights in a shorter time frame or in ways that reflect the granular nature of the intervention effects [44].

Although these new methods look promising in theory, there are some inherent challenges to demonstrate that they are effective [47]. Patrick et al. [47] and Hekler et al. [31] suggest looking beyond both agile methods applied in HCI and RCTs in clinical domains and use "*adapting methods from the engineering community in which development and evaluation occur in parallel, synergistically and iteratively until the solution has been optimized, a process called agile science.*" (p.820) Agile science relies on the development of three "knowledge products:" (1) modules, which represent mechanisms that support behavior change, (2) computational models, which are used to predict how modules, individuals, and context might interact with novel users and context, and (3) personalization algorithms which translate the modules and computational models into dynamic decisions rules to support individuals in changing their behavior [31].

Agile science is in its fancy and there is no evidence to show its effectiveness in emerging technologies adopted in life-long health and wellbeing; however Patrick et al. [47] believe with "given appropriate standards of measurement and ontologies, and an increasingly powerful knowledge base, agile techniques can be used to iteratively improve system inputs and processes to achieve desired health outcomes for individuals and populations." (p.821)

3.4 Providing medical information from personal data

As discussed before health and wellbeing have complex natures and there is not the one factor or variable to observe and study for a certain period to understand one's state of health and wellbeing. There have been numerous debates on effectiveness of health trackers either as devices or apps. For example, Finkelstein et al [26] tracked 800 people from Singapore aged 21 to 65 to see whether using such devices improved their health. Finkelstein et al reported that cash incentives helped increase exercise levels at 6 months, but not enough to benefit health, and 90% of participants stopped using the devices once incentives stopped. Such studies beg the question: How could logging number of steps via pedometer-like apps and devices create a fair view on one's health? For example, the 10,000-steps recommendation is not backed up by scientific evidence yet and researchers argue that any amount of activity beyond what individuals are currently doing is likely to benefit their health [60]. Factors such as diet, nutrition, sleep, living environment, family history of illnesses, and drinking and smoking habits are as important as activity to create a fair picture of health. Therefore, relying on one device or app, which delivers one dimensional data to identify one's state of health and wellbeing is a short-sighted view in the design and the care.

Additionally, manufacturers and app designers introduce different versions of physical activity tracking (PA) devices with different specifications. Even one manufacturer, for example, Garmin produces a few tracking watches with different

specifications. Mobile apps (running solely on the phone) or smart watches however, rely on the built-in sensors on the phone or the watch to log data automatically. These sensors vary in accuracy from one manufacturer to another. To create an IoT for healthcare to conduct cohort studies or deliver personalized medicine, it is crucial to think of ways to translate the semi-structured, non-standardized, untargeted personal health data into a uniform structure that is medically reasonable and or meaningful by medical standards [12].

A study conducted by the "Research 2 Guidance" [50] health research group in 2016 reveals that the number of mobile Health apps that are available on the major app stores in 2016 is around 259,000 apps with a total download rate reaching 3.2B in addition to the growth of sales of health and fitness tracking devices. Bakker et al. [5], Boulos et al. [12] and Piwek et al. [48] list concerns about health apps and consumer health wearables (e.g. PA trackers) such as concerns on safety, reliability, contents and security. Bakker et al. also argue that RCTs are required to validate future mental health apps and the principles upon which they are designed.

To translate personal data into standardized and established medical formats such as IHE, CDA and more importantly to trust data produced by trackers and apps as accurate and reliable as data produced by medical devices, the clock is ticking for some form of app and device regulatory control or certification to be put in place [12, 48].

Ideally, the research community and clinical arena would benefit significantly from personal data being converted to medical data. However, it is unlikely that the personal data will ever be as precise as medical data. Moreover, the data will be acceptable and compressible in more medical terms e.g. CDA by clinicians. Could such medical "languages" be extended to include for example, an estimation of data error captured in personal data?

3.5 Challenges in today's research approaches

3.5.1 Technical challenges in long term studies

Health and care technological landscape changes rapidly: (1) firmware running on Google Android phones and watches gets updated every few weeks and this throws a spanner in the wheel of keeping the native Android apps running smoothly, (2) Apps have a short life (maximum 6 months in Apps Stores) due to novelty factors wearing off, competitive app market and cost of maintenance and, (3) devices and watches are upgraded every few months. On the other hand, consumers lose interest in apps and tracking devices quickly for several reasons explored by, e.g. Asimakopoulos et al. [3] and Harrison et al. [30]. Therefore technologist, UX designers and computer scientists are interested to find ways to design technologies that have a longer life span than a few months. They use agile methods to design such devices and or apps and test and evaluate them in the wild for few weeks or months depending on their budget [13, 51, 64]. The overall focus of such studies is around improving the experience of consumers wearing or using devices and apps so people can wear or use them for longer and keep tuning their behavior. Ongoing use is a great business model for the device manufacturers. For example, if someone likes Fitbit products, they have to buy a new Fitbit every few years for the rest of their lives as the devices fail over time or the new products are more aesthetically appealing than the one they already own.

The rapidly changing technologies and ongoing use of multiple apps and devices affect type, accuracy, storage, privacy and security of data collected over time significantly. Noting these down, questions arise on collecting life-long data for cohort studies and personalized medicine (and even RCTs running for longer than a year). In the next section, we explore methods and approaches for short term studies but for longer term applications.

3.5.2 Regulatory issues

As discussed in section 3.4, the need for regulation of medical devices is undoubtedly reasonable and unquestionable. In February 2013 Happtique, a US mobile health solutions company, aimed at integrating mobile health into patient care and daily life. 'Happtique Health App Certification Program' (HACP), was a voluntary app certification scheme that captured operability, privacy, security (collectively referred to as the 'Technical Standards') and content ('Content Standards'). The HACP however was solely focused on apps targeting the US market. HACP was suspended in December 2013 due to security issues the company revealed about two apps it had previously certified. In February 2015, FDA [24] updated their guidance on mobile medical application (MMA) to reduce potential risks to public health posed by certain MMAs (p.6). They also argue that

"*Mobile apps that transform the mobile platform into a regulated medical device by using attachments, display screens, or sensors or by including functionalities similar to those of currently regulated medical devices. Mobile apps that use attachments, display screens, sensors or other such similar components to transform a mobile platform into a regulated medical device are required to comply with the device classification associated with the transformed platform*" (p.14).

These regulations are not limited to the US. For example, the National Health Service (NHS) in the UK adopts a similar method to regulate health apps [38].

Apple in 2015 announced a development of an open-source software framework for "ResearchKit" [2] to create iOS apps and to use its wearables for medical research. This is a significant step forward to standardize procedures for regulating iOS apps alongside its wearables as Apple make a move towards personalized medicine.

However, as the research community and the consumer market witness a convergence of medical and lifestyle devices, these regulations become challenging. These relate to the final application: A person's use of a lifestyle and wellbeing oriented application or device may slowly transit to a medical use.

- Must the regulatory bodies "forbid" these devices to do medical diagnoses, just because it's not their main purpose? Wouldn't this waste extremely valuable information?
- Does this mean that the initial application must already be medically certified? This would incur increased costs and reduce flexibility.
- Or does this mean that the user must identify the turning point and switch devices? Not very likely that the user is able to identify this point and willing to invest the money and effort. Or is the switch point initiated by user's general practitioner?

Regulation also impacts research. As HCI researchers and UX designers develop new health related interventions and applications,

- Are they restricted to using certified devices only?
- Do systems need to be certified to conduct studies? This would incur a level of complexity, effort and cost that would paralyze most of the research.
- How can designers and researchers balance the required safety of medical regulations for critical applications with the required dynamic of technology research? It makes sense, however, for patients involved in cohort studies and personalized medicine research that the devices and apps are fully certified.

The regulatory issues are not limited to development of devices and apps. They are extended to data ownership and intellectual properties as well. Michie et al. [43] argue that with more digital medium becoming available for data collection, the data ownership is becoming a gray area. Although, the collected data are valuable resources for research communities, patients and public are not fully aware of such potentials and may have reservations about data sharing [43]. This could be addressed via digital health literacy.

Additionally, almost all research involved with population health and wellbeing needs to go through restrictive ethical approval which could take months and a huge amount of paperwork to fill in. More importantly, the consent needs to be sought from patients and participants prior to any study and the consent must assure those participants that their data will be anonymized (no one individual will be identified via collected data) and will be used for research purposes only. While the ethical procedure and the resulting safe-guarding mechanisms are important to protect the patients, they also make it nearly impossible to share valuable and painstakingly difficult health and wellbeing data collected amongst research communities. Repeating such long and costly studies in multiple institutes is impossible. But with restricted access to anonymized patient data in place in many Western countries, how can higher education academic institutes access rich medical and personal data to conduct meaningful research and deliver findings in health and wellbeing? It is time for regulations on anonymized data sharing to change.

3.6 Challenges in technology oriented research

Consumers fall in and out of love with apps and devices constantly. Some people are curious and conscious of their health and wellbeing, some would like to push their body limits and reach milestones in their fitness and exercise, and some are curious about the technology itself. Such people may use apps and devices for extended periods of time.

Most apps and devices have dashboards that are not transferable across platforms or to other apps and devices. One way to address this issue would be moving towards web-based applications and making APIs or modules for trackers available to be imported to dashboards on several platforms.

It is important to note that long term health data is not limited to devices and apps; there is much more diverse health data out there from various disciplines (e.g. electronic health records, physician's notes, genomics, etc., but also everyday data such as social interaction, location etc) to facilitate meaningful analysis of rich and diverse health data.Apps and devices provide users with immediate feedback on, for example, step count, calories burned, stairs climbed, distance travelled, active vs. passive time, sleep cycle and length, heart rate, stress level and many to name [3]. The feedback is available via the device screen or the companion app. The feedback is generally based on simple descriptive statistics—for example, average weekly heart rate and level of activity [48].

With more standardized and established data formats such as IHE, CDA, open-source software frameworks to develop apps and standards for mobile medical applications and devices the research community is one step closer to delivering life-long interventions. On the other hand, the IoT would be able to gather more coherent, dense and expansive data from people, everyday spaces and objects people interact. With such data, intelligent and personalized explanatory feedback would be required more than before [48]. Topol et al. [59] suggest using Google Now, Apple Siri and Microsoft Cortana to provide more accessible and intelligent feedback and create virtual health assistants.

4 CONCLUSIONS

Emerging technologies promoting personal health technologies undoubtedly have the potential to contribute to the revolution in healthcare that the research community is currently witnessing. Such technologies provide insights into one's health over time that so far have been difficult to achieve. However, the more the research community is moving from research in the labs or RCTs into practical applications in the real world and personalized medicine, the more challenges arise. In this article, we identified some developments in health and wellbeing induced by emerging technologies. Then we discussed emerging technologies in healthcare and wellbeing and the challenges they impose on technology-oriented research. While difficult, it is comforting and reassuring that not one single discipline can address those challenges; HCI researchers, data scientists, AI and machine learning experts, engineers, UX designers, public health

researchers, clinicians and many to name, need to come together, leave the differences in each discipline behind and brainstorm. It is exciting to see that such movements have already started around the globe to bring multiple disciplines into one room, for example the Dagstuhl seminar on life-long behavior change in 2015 [11], multiple institute funded international workshop in London in 2015 [43], the first series of GetAMoveOn symposium in London 2017 [29] and many others.

On the other hand, researchers, clinicians and regulatory bodies demand for more uniform and standardized data formats, data types, data storage, privacy and security policies and so on. This is particularly important as technologies change rapidly in the consumer market and ongoing use of multiple apps and devices impacts the factors mentioned above significantly.

As bigger manufacturers of health tracking devices join the open-source software frameworks force, the more likely smaller manufacturers will follow the standard procedures for regulating apps and wearable. This combined with FDA and European Medical Device Directive recognizing the importance of mobile medical devices and introducing recommendations and guidelines, again, the society would be significant steps forward to more coherent and comprehensive health data. However, the convergence of medical and lifestyle data adds new challenges to these regulations from person's use of lifestyle and wellbeing apps to research; who, when and where must follow the regulations, for example.

Sharing valuable and hard-earned health and wellbeing data which are severely anonymized amongst research is still very difficult if not impossible. More needs to be done to show the potentials of health data to public and institutions involved in collecting data to facilitate sharing of such data for research purposes.

And last but not the least, by embracing the IoT, standardized and established data formats, open-source software frameworks, apps and mobile medical applications and devices connected to the IoT, and multimedia data (from images to sound and from numbers to graphs) we are opening the door to supporting life-long health and wellbeing era. This is not just about delivering digital health interventions; this is about learning about one's health and wellbeing and caring for oneself, family members and the bigger community.

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