



Mobile Health Technology: From Daily Care and Pandemics to their Energy Consumption and Environmental Impact

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Abstract

Mobile health technology is a rapidly growing field with numerous promises to make substantial impact in our lives. To open this special issue, which brings to you many exciting research results in mobile health technology, we discuss two important aspects of this technology. One is how they can be integrated in our daily lives as important care devices, especially during periods such as the more and more frequent pandemics around the world. Having discussed their advantages, we calculate their estimated footprint in the energy consumption and dioxide carbon they produce globally. With that we raise awareness and invite researchers to work on reducing their energy consumption to ensure that they maintain a low footprint even if their numbers explodes in the near future. We finish this article with a brief teaser of the papers published in this special issue and wish you a good read.

Keywords Mobile health technology · Wearables · Footprint · Energy consumption · Pandemics · Early warning score

1 Introduction

Recent advances in the mobile technology, and particularly wearable healthcare devices, have led to unprecedented access to physiological data. Mobile health technologies are used in many applications, such as well-being and sport activities [1–3], physical health [4–8], and mental health [8–11]. These advanced devices provide access to a vast amount of data, which can revolutionize our understanding of human health and the healthcare system.

The COVID-19 pandemic locked us all in and captured our attention. Now, we appreciate the importance and hardship of healthcare personnel more than ever. They provide care to COVID-19 patients knowing that they are extremely exposed. Most healthcare facilities are understaffed (at least for coping with such a pandemic, if not always) and the personnel are all exhausted of the extra hours of hard work. This exhaustion may lead to a moment of absentmindedness and a small but fatal mistake. The pandemic highlighted the importance of reducing their burden beyond the potential economic savings that mobile health technologies can bring to healthcare facilities.

Another characteristics of this pandemic is the recommendations of self-isolation, even if (and especially if) one is certain that they have contracted it. That is, naturally, until the point that the symptoms are not too grave for homecare and one is not in absolute need of professional care at a healthcare facility. However, an important question here is how to recognize that “point”? The critical point upon which one is in such conditions that requires professional care and referring to healthcare facilities. In Section 2, we discuss Early Warning Score (EWS) system as a solution and how it can be rendered feasible at home and in isolation too.

In Section 3, we discuss another side of the coin, namely the footprint of the mobile health technology. We estimate the overall energy consumption of all wearable healthcare devices world-wide and its impact on environment. In

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particular, what would it take to compensate for their carbon footprint. Even though this footprint at the moment may not be a major issue globally, given the exponential growth in the mobile health technology sector, they can soon constitute a significant portion of our footprints. Therefore, it is important to be mindful of their footprint and while we work on designing better and more ubiquitous wearable devices, keep an eye on their energy consumption and take steps in decreasing their power consumption.

In Section 4, we briefly review the exciting research papers that are published in this special issue edition before concluding in Section 5. We would like to thank you for your time and attention and hope that you will enjoy reading this special issue. We are grateful to the authors of the many exciting articles published in this special issue and the editorial staff at MONET, without whose contributions this special issue would not come to existence. Thank you.

2 Daily care and pandemics

Studies in the 80's showed that a certain biological measures are good indicators of potentially life-threatening health deteriorations. They realized that by assigning a score to out-of-range values of these metrics and summing them up, majority of cases, where patients were sent to Intensive Care Unit (ICU) or lost their lives could be predicted up to twenty four hours in advance [12]. This led to various -slightly different- scoring systems, called Early Warning Score (EWS), which have been in use since then to enable an agile preventive measure against such severe health deteriorations. To this end, a healthcare professional (usually nurses) go to hospitalized patients on regular intervals to manually measure these metrics. These metrics are heart rate, respiratory rate, systolic blood pressure, core body temperature, oxygen saturation level, and level of consciousness. The higher the EWS, the more at risk the subject is, and sooner they should be subject to more intensive care [13].

Here, there are a few things that are not optimal currently. First, this takes a lot of time and energy from the healthcare personnel. In times such as the COVID pandemic, when healthcare facilities are severely understaffed (and way more than usual), this issue is more critical than ever. More importantly, this exposes the highly on-demand healthcare personnel to a high risk, since they have to come in contact with COVID patients, or anybody else with a highly contagious diseases. Moreover, these measurements are not continuous, which means some precious hours may be lost between each two checkups. Trying to reduce the health risk for the patients by more frequent checkups means a larger

burden on the time and energy of healthcare personnel and higher exposure to risk. Last but not least, a point which affects COVID-19 patients significantly, this procedure is not and often cannot be conducted at home by the patients themselves. Whereas it is desired to do so, for many patients like those who are in self-isolation due to COVID-19, or were recently released from hospitals, pandemic times or not. The solution, as you may guess, is trying to perform this automatically and using wearable devices.

Assessing EWS using wearable devices has its own challenges too. One of the most important challenges is the reliability of measurements [6, 14]. Whereas nobody wants a missed alarm, too many false alarms also have unwanted repercussions; the cost it imposes on healthcare system to have a closer look on the health status of the patients and potential drop in sensitivity and reaction to the raised alarms are two of these repercussions. Causing unnecessary extra stress and psychological burden for patients and their family is another. However, these procedures are highly error prone due to the uncontrolled conditions of use, and many non-idealities such as noise and movement artifacts [15, 16]. Therefore, it is crucial to identify [16, 17] of such problems and addressing them [4–6, 14, 15]. Another challenge is the number of sensors and devices required to measure all these parameters. Currently, the state-of-the-art in research is using a portable device and four or five sensory devices [15]. Even though the portable device can be a regular cellphone, as you can imagine, wearing so many sensors -especially continuously and for a longer time- is not very comfortable and in many setups not feasible.

Some of these devices, such as the ones for blood pressure measurement, even in their digital form are not made for continuous measurements. Some others, such as the ones used for direct respiratory rate measurements are extremely cumbersome to wear for a long time and may interrupt some daily activities since they involve a mouthpiece. Therefore, there has been several efforts in trying to measure respiratory rate indirectly [18–21]. However, they often have a very large measurement error (in the range of actual respiration rate at rest) unless in very controlled conditions that are not very realistic in practice. To tackle this challenge, we proposed a frequency analysis technique which outperformed previous methods [6]. More importantly, it managed to reduce the average error -despite movement artifacts- to a mere 3 breaths per minute, which is an acceptable error margin for the purpose of EWS assessment.

Being able to measure respiratory rate using smart-watches allows for future development of applications that detect irregularities and disruptions of the respiratory system. A crucial symptom, which its early detection using

a smartwatch, an everyday object, can save lives of many affected by COVID-19, without requiring expensive and hard to use medical devices.

In a further attempt to reduce the number and cost of necessary sensors for measuring EWS and enabling a continuous monitoring of this parameter, we proposed [7]. In [7], we showed that using the same smartwatch as before, the blood pressure can be estimated using a single Photoplethysmogram (PPG) signal from the smart watch. The simple initial algorithm that we have proposed has an acceptable accuracy of around 10%, which is an acceptable error range for EWS. Therefore, using a single PPG signal of a smart watch, three of the five biosignals necessary for EWS can be measured. A smartwatch, such as Empatica [22], which provides a temperature sensor can further increase this ratio to four out of five. Hence, with a complementary finger-tip wearable sensor for measuring oxygen saturation, all above parameters can be measured by in-home patients themselves and in a continuous fashion. However, there is still room for improvement. Integrating oxygen saturation measurement into a wrist-worn device, which is a reasonably feasible feat, can further facilitate EWS measurement by completely improving any inconvenience and intrusion that a finger-worn device may introduce to daily activities of individuals.

3 Energy consumption and environmental aspects

Although wearable electronics consume a negligible power by themselves, given their large number and exponential growth, together they have a considerable effect on the energy consumption world-wide. Cisco reports that 19% of approximately 12.5 billion connect Internet of Things (IoT) devices in 2022 are health related. That is, 2.37 billion devices [23]. From these devices, 1.1 billion are estimated to be wearables [24] ($n_{total} = 1.1 \times 10^9$). These devices had a large range of variations in terms of their power consumption. An Electroencephalogram (EEG) sensor can have an average power consumption as low as 2mW [25] and a smartwatch as high as 310mW [26]. Therefore, let us assume their average to be a representative number for the average power consumption of wearable devices, i.e., $P_w = 156\text{mW}$. They usually use Bluetooth to connect to a hub, e.g., a cellphone, to show their outputs or connect to the internet to send their data to necessary databases. We take the energy consumption of such a hub to be the 500mW reported in [27] for Bluetooth connection (and excluding any calculations and execution of any applications on the phone), i.e., $P_h = 500\text{mW}$. Therefore, we can estimate the average power associated with using a wearable healthcare

device to be

$$P_{avg} = P_w + P_h = 156 + 500 = 656 \times 10^{-3}. \quad (1)$$

Using the average power consumption associated to using a wearable healthcare system and their total number, we can now estimate their overall power consumption in 2022 to be

$$P_{tot} = n_{total} \times P_{avg} \\ = (1.1 \times 10^9) \times (656 \times 10^{-3}) = 721.6 \times 10^6 \quad (2)$$

or 727MW. If we assume one hour for charging the devices and 23 hours usage otherwise, we have

$$E_{tot} = 727 \times 23 = 16721\text{MWh}, \quad (3)$$

or 1.67GWh. To better understand the meaning of such a number let us consider the following.

Assuming a 12 hours daylight and a typical photo-voltaic panel from [28], we can calculate that wearable healthcare devices in 2022 consume an energy equal to what **17.4 million solar panels** would produce.

Using [29] as a reference, we calculate that the footprint of these devices in 2022 is equal to 1942 tons of CO₂. According to [30], this implies that to compensate for the effect wearable healthcare devices in 2022, we need about **11.34 million conifer trees**. If we were to absorb the produce CO₂ with plain field grass only, we would need an area equivalent to Morocco or Iraq.

We note that above numbers and calculations regard only 2022. With the expected exponential growth in the number of these devices their effect on energy sector and environment will grow exponentially too. Therefore, it is mandatory to slow down this growth by designing wearable healthcare devices that consumer less power. The work presented in [25, 31] are two examples of such an approach at hardware and software level.

4 An overview of accepted articles

This special issue features many exciting research results that help in improving mobile health technology.

“Confidence-enhanced early warning score based on fuzzy logic” focuses on improving the EWS assessment, which we presented and discussed at length in Section 2, and the reliability of the diagnosis. One of the aspects in this work is to consider that the patients health changes gradually and continuously. Hence, using fuzzy functions and logics when assessing changes in the health status of the subject can filter out many false alarms that would have been otherwise caused due to non-idealities of wearable systems and the condition in which they are used.

“Detection and removal of motion artifacts in PPG signals” takes a different approach in improving the reliability of diagnosis using wearable devices, namely how to detect and remove motion artifacts. This includes methods that take advantage of accelerometers integrated in many wearable devices but also methods which do not use accelerometer data.

“A Self-Aware Epilepsy Monitoring System for Real-Time Epileptic Seizure Detection” proposes a self-adaptive system that monitors itself and adapts its behavior to improve the real-time seizure detection in epileptic patients.

“A Novel Edge Analytics Assisted Motor Movement Recognition Framework Using Multi-Stage Convo-GRU Model” shows an application scenario for the validation of an edge analytics assisted deep learning based motor movement recognition framework; this allows for analyzing the scale of physical activity of the patient using wearable devices, and giving them real-time suggestions.

“Wearable Vibrotactile System as an Assistive Technology Solution” presents a device which uses vibrations for delivering customizable tactile patterns to be used for relaying feedback information through the skin, by means of frequency and amplitude modulation.

“Supervised Recovery of Shoulder Muscular Skeletal Disorders Through a Wearable-Enabled Digital Application” presents the Shoulder Physiotherapy digital application. This is an application with a rehabilitation protocol for the treatment of shoulder impingement syndrome; the application allows for a patient-centered physiotherapy program and remote monitoring of the therapy and its progress. As an IoT device enables the rehabilitation to be executed both in clinic and at home.

5 Conclusions

In this paper, we briefly discussed the role and importance of mobile health technology in daily care, especially during pandemics. We then calculated their estimated footprint in terms of energy consumption and environmental effects world-wide and emphasized the role they may play in the future, which demands for low power designs that can keep their effect contained. The energy they consume is currently equal to the energy produced by more than 17 million solar panels and we need more than 11 million conifer trees to absorb the CO₂ they produce. Given the exponential growth in their number, every bit of energy saved in each device will be substantially multiplied. Finally, we provided a brief

overview of the papers that are published in this special issue.

Acknowledgments We sincerely hope the reader finds this special issue useful and that it will inspire further research in this very important area of Mobile Health. We would like to thank all authors who submitted articles to this special issue. Special thanks go to the reviewers for their time and diligence during the review process and the editorial staff of the journal for offering us the opportunity to edit this special issue.

References

- Perego P, Rahmani AM, Taherinejad N (2018) Wireless mobile communication and healthcare. Lecture Notes of the Institute for Computer Sciences. Social Informatics and Telecommunications Engineering. Springer International Publishing, Berlin
- Yin H, Akmandor AO, Mosenia A, Jha NK (2018) Smart healthcare. Foundations and Trends® in Electronic Design Automation 12(4):401–466
- Perego P, Taherinejad N, Caon M (2021) Wearables in Healthcare. Lecture notes of the institute for computer sciences, social informatics and telecommunications engineering book series (LNICST), vol 376. Springer International Publishing, Berlin
- Götzinger M., Taherinejad N, Rahmani AM, Liljeberg P, Jantsch A, Tenhunen H (2016) Enhancing the early warning score system using data confidence. In: International conference on wireless mobile communication and healthcare. Springer, pp 91–99
- Anzanpour A, Azimi I, Götzinger M, Rahmani AM, TaheriNejad N, Liljeberg P, Jantsch A, Dutt N (2017) Self-awareness in remote health monitoring systems using wearable electronics. In: Proceedings of Design and Test Europe Conference (DATE). Lausanne, Switzerland
- Pollreisz D, TaheriNejad N (2020) Reliable respiratory rate extraction using PPG. In: 11Th IEEE latin american symposium on circuits and systems – LASCAS. San José, Costa Rica, pp 1–4
- TaheriNejad N, Rahmati Y (Dec 2020) Blood pressure estimation using a single ppg signal. In: 2Nd EAI international conference on wearables in healthcare (healthwear 2020), pp 1–9
- Freismuth D, TaheriNejad N (2022) On the treatment and diagnosis of attention deficit hyperactivity disorder with eeg assistance. Electronics Journal, 1–18
- TaheriNejad N, Pollreisz D (2016) Assessment of physiological signals during happiness, sadness, pain or anger. In: 6Th mobihealth
- TaheriNejad N, Jantsch A, Pollreisz D (2016) Comprehensive observation and its role in self-awareness; an emotion recognition system example. In: The federated conference on computer science and information systems (FedCSIS)
- Pollreisz D, TaheriNejad N (2017) A simple algorithm for emotion recognition, using physiological signals of a smart watch. In: 2017 39Th annual international conference of the IEEE engineering in medicine and biology society (EMBC), pp 2353–2356
- McGaughey J, Alderdice F, Fowler R, Kapila A, Mayhew A, Moutray M (2007) Outreach and early warning systems (ews) for the prevention of intensive care admission and death of critically ill adult patients on general hospital wards. The Cochrane Library
- Morgan et al (1997) An early warning scoring system for detecting developing critical illness. Clin Intensive Care 8(2):100
- Götzinger M, Azanpour A, Azimi I, Taherinejad N, Rahmani AM (2017) Enhancing the self-aware early warning score system through fuzzified data reliability assessment. In: International

- conference on wireless mobile communication and healthcare. Springer
15. Götzinger M, Anzanpour A, Azimi I, TaheriNejad N, Jantsch A, Rahmani A, Liljeberg P (2019) Confidence-enhanced early warning score based on fuzzy logic. In: ACM/Springer Mobile Networks and Applications, pp 1–18
 16. Pollreisz D, TaheriNejad N (2019) Detection and removal of motion artifacts in PPG signals. In: ACM/Springer Mobile Networks and Applications, pp 1–10
 17. TaheriNejad N (2019) Wearable medical devices: Challenges and self-aware solutions. In: IEEE Life sciences, vol 2, pp 5–6
 18. Schaefer A, Kratky KW (2008) Estimation of breathing rate from respiratory sinus arrhythmia: Comparison of various methods. *Ann Biomed Eng* 36:03
 19. Shah SA (2012) Vital sign monitoring and data fusion for paediatric triage. Phd Thesis. Oxford university, UK
 20. Pollreisz D, TaheriNejad N (2020) Efficient respiratory rate extraction on smartwatch. In: 42Nd annual international conferences of the IEEE engineering in medicine and biology society in conjunction with the 43rd annual conference of the canadian medical and biological engineering society EMBC. Montreal, Canada, pp 1–4
 21. Huang N, Zhou M, Bian D, Mehta P, Shah M, Rajput KS, Selvaraj N (2021) Novel continuous respiratory rate monitoring using an armband wearable sensor. In: 2021 43Rd annual international conference of the IEEE engineering in medicine biology society (EMBC), pp 7470–7475
 22. Empatica smart watch (2019–2022) <https://support.empatica.com/hc/en-us/categories/200023126-E4-wristband>, Accessed: 2022-03-07
 23. CISCO (2022) Cisco annual internet report (2018–2023) white paper. <https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.html>, Accessed: 2022-03-07
 24. Laricchia F (2022) Connected wearable devices worldwide 2016-2022. <https://www.statista.com/statistics/487291/global-connected-wearable-devices/>, Accessed: 2022-03-07
 25. Hafshejani EH, TaheriNejad N, Rabbani R, Azizi Z, Mohin S, Fotowat-Ahmady A, Mirabbasi S (2021) Self-aware data processing for power saving in resource-constrained iot cyber-physical systems. *IEEE Sensors J*, 1–12
 26. Liu X, Chen T, Qian F, Guo Z, Lin FX, Wang X, Chen K (2017) Characterizing smartwatch usage in the wild. In: Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services, MobiSys, vol 17. Association for Computing Machinery, New York, pp 385–398
 27. Carroll A, Heiser G (2010) An analysis of power consumption in a smartphone. In: Proceedings of the 2010 USENIX Conference on USENIX Annual Technical Conference, USENIXATC'10, vol 21. USENIX Association, USA
 28. Muoka PI, Haque ME, Gargoom A, Negnevitsky M (2013) Modeling, simulation and hardware implementation of a pv power plant in a distributed energy generation system. In: 2013 IEEE PES Innovative smart grid technologies conference (ISGT), pp 1–6
 29. Malmudin J, Lundén D (2018) The energy and carbon footprint of the global ict and e&m sectors 2010–2015. *Sustainability*, 10(9)
 30. Chung C-Y, Chung P-L et al (2011) Assessment of carbon dioxide reduction efficiency using the regional carbon neutral model—a case study in university campus, taiwan. *Low Carbon Econ* 2:159–164
 31. Hadizadeh E, Elmi M, TaheriNejad N, Fotowat A, Mirabbasi S (2020) A low-power signal-dependent sampling technique: Analysis, implementation, and application. *IEEE Transactions on Circuits and Systems I: Regular Papers*, 1–14

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