Data Driving Diagnostics

Luka Vukovic
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In the last decade, wearable health devices like fitness trackers (Fitbits, Vivosmarts), continuous glucometers[1] and many others have revolutionized the personal health tracking and lifestyle market. Monitors for heart rate, heart rate variability, sleep quality, glucose, dietary intake, hydration, and in some cases basic EKGs[2] and VO2[3] max tests have become trendy but have also created a tidal wave of data. The streamed information from these devices can map your real-time physiological status while also capturing trends in your past history; however, these devices only address the present and the past.

Where things get interesting is when these devices become connected to digitized health-care records. Once this occurs, medical professionals, data scientists, and perhaps even patients can have the means to accurately predict the future of their trending health based on the stronger links between personalized medicine and vast inbound epidemiological data.

Raghupathi *et al.* (2014) write on predictive healthcare in personalized medicine, allowing it to be used to advise clinicians risk of surgery (or surgery prognosis) based on a patient's current condition, medical history, and drug prescriptions. Will the patient recover promptly or does the surgery risk being fatal? The historical health data wearable devices provide can help to answer this question. This data can also be applied to help organizations like governments better select target interventions that seek to reduce obesity and smoking for massive cohorts. In essence, wearable device data can be used to improve both personalized medicine and larger population health outcomes.

The case of the Intensive Care Unit (ICU) proves even more interesting. There are numerous data holes that need filling as illustrated by Sanchez-Pinto, Luo, and Churpek (2018) in their figure 1, and wearable devices and monitors faller under a particularly important category; physiology. Due to three qualities of the ICU; the diversity of unique interventions, the

[1]Continuous glucometers are devices used for continuously measuring blood-glucose concentrations.
[2]EKG or the electrocardiogram is a measure of the electrical activity coming from the heart muscles.
[3]VO_2 max test is a measure of the maximum rate of oxygen consumption during an exercise test of increasing intensity.

uncertainty of many patient cases, and the difficulty in studying these cases; high-quality data supporting specific ICU interventions remains scarce (Vincent, 2006). As such, many of these interventions remain unproven, potentially increasing patient risk (Celi *et al.*, 2013). With these devices however, clinicians can transition from using patient-reported qualitative observations to more quantitative observations on someone's lifestyle history to improve clinical decision making.

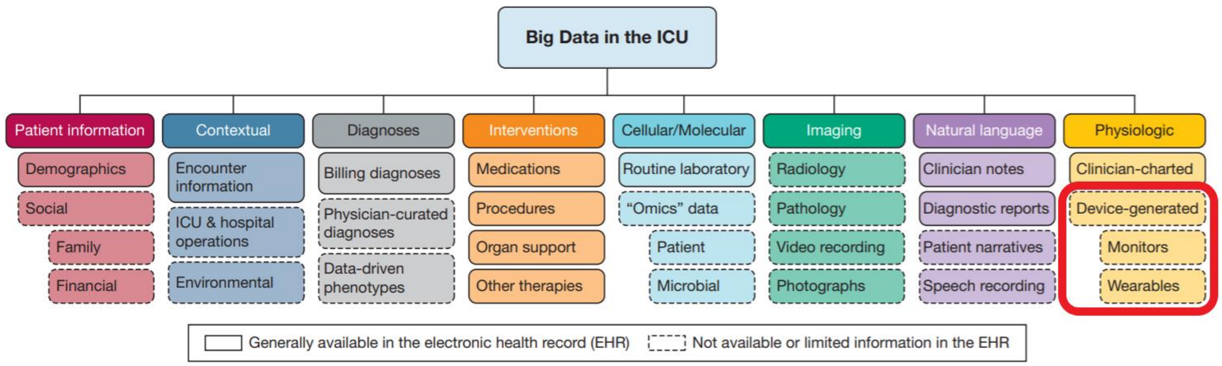

Figure 1 – *Some of the major sources of big data in the ICU. The term "omics" refers to the data derived from modern molecular techniques (eg, genomics, transcriptomics, proteomics, metabolomics, microbiomics). EHR = electronic health record.*

Despite monitors and wearable devices being potentially useful in emergency and diagnostic contexts, their data likely comes with far lower quality than might be accepted by clinical standards. So, before increasing our reliance on these common devices in uncommon medical settings, we need to ask if the sheer volume of all users can help to justify the significance of epidemiological correlates coming from less accurate information. If these technologies continue to improve, the answer to this question will likely trend towards yes.

So, the ability to identify risk factors from lifestyle behaviours exists today, but to interpret this information in the context of your own body becomes the next growing quest. The point being, that wearable device data can help us diagnose and predict health outcomes far before someone succumbs to them, and if we can identify the roots of a disease earlier, it becomes easier to treat. Even if all this predictive power were to play a larger role in diagnostics, there still needs to be a discussion on the legal context. Who should have access to this information; trained medical professionals or the general public? Can false predictions lead to self-fulfilling prophecies, hurting people more than helping them? With this field at our fingertips, how would you use all this information?

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Citations

Celi, L., Mark, R., Stone, D., Montgomery, R., & Celi, L. (2013). “Big data” in the intensive care unit. Closing the data loop. *American Journal of Respiratory and Critical Care Medicine*, *187*(11), 1157–1160. https://doi.org/10.1164/rccm.201212-2311ED

Raghupathi, W., Raghupathi, V., & Raghupathi, W. (2014). Big data analytics in healthcare: promise and potential. *Health Information Science and Systems*, *2*(1), 3–3. https://doi.org/10.1186/2047-2501-2-3

Sanchez-Pinto, L., Luo, Y., & Churpek, M. (2018). Big Data and Data Science in Critical Care. *Chest*, *154*(5), 1239–1248. https://doi.org/10.1016/j.chest.2018.04.037

Vincent, J. (2006). Is the Current Management of Severe Sepsis and Septic Shock Really Evidence Based? (Policy Forum). *PLoS Medicine*, *3*(9), e346.https://doi.org/10.1371/journal.pmed.0030346