Cell Reports Medicine

CellPress
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Spotlight

Reducing chronic disease may just be a walk in the park

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https://doi.org/10.1016/j.xcrm.2022.100874

Wearable technology allows the collection of real-world granular data at scales that would be impossible using traditional collection methods. Master et al. demonstrate the power of this technology to estimate the risk of disease based on daily step counts.[1]

Fitness trackers such as Fitbit and smartwatches have provided researchers an avenue to study disease. This wearable technology allows individuals to track metrics such as heart rate, step count, and sleep activity in a near-continuous fashion. These devices are easily accessible to the average consumer; in fact, approximately 30% of US adults own and regularly use such a device.[2] The widespread adoption and ease of data collection has provided researchers with a wealth of information. However, relating this information to diseases has been challenging. Electronic medical record data is rarely integrated with wearable technology because of privacy concerns, system interoperability, and storage limitations.[3] Research has thus typically been constrained to the study of individual diagnoses of interest over short periods of time.

The *All of Us* Research Program (AoURP) is an effort by the National Institutes of Health to collect and study health data from a diverse group of at least one million participants.[4] Participants included in this program can share their electronic health record data and their personal Fitbit device data. Large scale databases, such as the AoURP, that connect medical record data with longitudinal wearable data provide an opportunity to find risk factors and predictors of disease.

Until now, studies that looked at the association between step counts and disease were limited to cardiovascular disease, diabetes, and all-cause mortality. Furthermore, these studies typically relied on self-reported data or data collected from a wearable device over only several days. Using the AoURP database, Master et al. were able to analyze the effects of daily step counts on 1,711 diagnostic codes using 5.9 million person-days of wearable data.

The researchers included 6,042 subjects from the AoURP database, with each participant having a median of 4 years of Fitbit data.[1] Looking at nearly two thousand diagnostic codes, the authors found which diagnostic codes had the largest significant association with daily step count. These diagnoses include sleep apnea, obesity, type two diabetes, hypertension, gastroesophageal reflux disease (GERD), and major depressive disorder.

The longitudinal nature of both the medical record data and the wearable data allowed the researchers to build statistical models for each disease. These models calculate the risk of receiving a diagnosis based on the daily step count compared to the average participant. The models showed a clear inverse relationship between daily step counts and the incidence of obesity, sleep apnea, GERD, and major depressive disorder. That is, the higher someone's daily step count, the less likely they would go on to receive one of these diagnoses. For example, the risk of receiving an obesity diagnosis with 14,000 steps is approximately 50% of that compared to someone with 8,000 daily steps. Not all diagnoses, however, showed such a decline with increasing step counts. Reducing the risk of developing hypertension and diabetes showed diminishing returns with increasing daily step counts. In fact, beyond eight or nine thousand daily steps there was no further risk reduction.

While the results of this study demonstrate the power of wearable data collection, there are several important limitations that readers of such exploratory database research should keep in mind. These analyses are association based and often do not incorporate clinical background information that could identify effect confounders, moderators, and mediators. For example, obesity causes increased fat deposition in the upper respiratory tract that narrows the airway, leading to obstructive sleep apnea.[5] Furthermore, increased fat depositions in obesity contribute to the insulin resistance that causes type II diabetes.[6] Therefore, it could be that increasing step counts reduces the risk of obesity, which then mediates the reduction in sleep apnea and diabetes risk presented in this study. Readers should also understand that diagnostic codes in electronic medical records are primarily used for billing specific problems addressed during a clinic visit or a hospital encounter. These codes may not accurately reflect all of an individual's current medical comorbidities and may also include historic diagnoses that the patient has since recovered from.

Large initiates such as AoURP are ushering in a way to study disease through crowd-sourced real-world wearable data. Master et al. have demonstrated the utility of using wearable devices to both inform risk and develop potential targeted treatments, such as increasing daily steps, to

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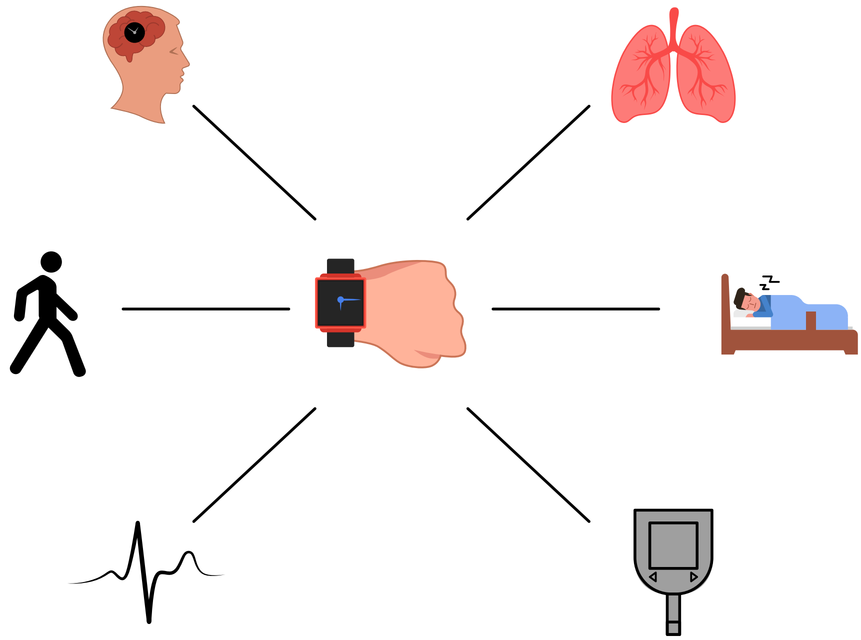

Figure 1. Tracking health with wearables
Wearable devices can measure a myriad of metrics, including circadian phase, step count, heart rate, glucose level, sleep stage, and respiratory rate.

reduce the risk of disease. With this paradigm shift away from the standard laboratory setting, researchers from all areas of medicine are working to build metrics from wearable data to study their domains of interest. Respiratory rate,[7] circadian rhythm,[8] and sleep variability[9] are a few of the many indicators that are currently being studied and extracted from wearable devices (Figure 1).

Daily step count is one of the simplest wearable metrics, yet Master et al. has shown its utility in combination with the AoURP initiative. As further metrics are developed, more accurate and personalized predictors of disease will appear. For example, wearable devices have shown utility in predicting COVID-19 infections.[10] Standard medical diagnosis and intervention may soon extend beyond the medical office to your wrist.

DECLARATION OF INTERESTS

D.B.F. is the CSO of Arcascope. Both he and the University of Michigan own equity in Arcascope.

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