Wearable Device Data: Signal or Noise?

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Karl A. Poterack, MD, FAMIA
Medical Director, Applied Clinical Informatics, Mayo Clinic
Conflict of Interest

Karl A. Poterack, MD, FAMIA

Has no real or apparent conflicts of interest to report.

Agenda

• Objectives
• Background and Present state
  – Devices/Data
  – Accuracy
  – “Quantified Self”
• Challenges and Barriers
  – Technical
  – Legal/Regulatory
  – Structural
• Solutions
• “Chicken and egg” problem
• Summary and Future

Learning Objectives

• After participating in this activity, the learner will be able to:
  • Identify the types of physiologic data that can be captured, now and in the near future, by wearable physiologic monitoring devices
  • Recognize the considerations in obtaining, curating, storing and retrieving data from wearable physiologic monitoring devices
  • Explain the considerations involved in ensuring data provenance and providing artifact detection when acquiring and managing data from wearable physiologic monitoring devices
  • Analyze the changes that will be required in both clinician outlook and health care delivery in order to make use of the data from wearable devices to improve outcomes at both individual and population levels
• >400 different devices from >100 brands.
• >100 million sold worldwide/yr., inc. >18%/year.
• >50% Americans use
• Fitbit, Xiaomi, Apple, Garmin, Samsung
• Vendors are collecting the data
  – >75 trillion steps, >3 billion nights sleep by Fitbit alone
• Very little wearable device data utilized clinically
• Can this data improve outcomes????
Wearable devices

- Typically wrist watch/band
- Sensors
  - Pedometers, accelerometers, gyroscopes, magnetometers, barometers, altimeters, GPS, photoplethysmogaphers (HR)
- Data
  - Steps, energy, sleep, heart rate, blood pressure, oxygen saturation, glucose, weight, BMI

How is wearable data “different”

• Device not under health system’s control
• Not “medical grade” (technical, regulatory, etc)
• “Continuous” rather than intermittent
• Novel measurements (steps, etc)
HR Accuracy

• “variable accuracy among wrist-worn HR monitors; none achieved the accuracy of a chest strap–based monitor…accuracy … was best at rest and diminished with exercise.”

• “There were very good correlations with the criterion during walking (L: r=0.97; R: r=0.97), but good (L: r=0.93; R: r=0.92) and poor/good (L: r=0.81; R: r=0.86) correlations during jogging and running.”
Fitbit resting HR data

Fitbit’s 100+ Billion Hours of Resting Heart Rate User Data Reveals Resting Heart Rate Decreases After Age 40

*Fitbit analysis of millions of global users also shows U.S. and Singapore have highest resting heart rate*
A sleeper issue

Bedtime and wakeup times for Australian Jawbone users:

<table>
<thead>
<tr>
<th>City</th>
<th>Average bed time</th>
<th>Average wake time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adelaide</td>
<td>11:09 pm</td>
<td>7:04 am</td>
</tr>
<tr>
<td>Brisbane</td>
<td>10:43 pm</td>
<td>6:33 am</td>
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<td>Canberra</td>
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<tr>
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<tr>
<td>Newcastle</td>
<td>10:51 pm</td>
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<tr>
<td>Perth</td>
<td>10:53 pm</td>
<td>6:44 am</td>
</tr>
<tr>
<td>Sydney</td>
<td>11:07 pm</td>
<td>6:55 am</td>
</tr>
<tr>
<td>World average</td>
<td>11:35 pm</td>
<td>7:13 am</td>
</tr>
</tbody>
</table>

Source: Jawbone.
Daily habits: Average number of daily steps for Australian Jawbone users

Jawbone's user data suggests Australians walk further each day than the rest of the world.

<table>
<thead>
<tr>
<th>Location</th>
<th>Steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>World average</td>
<td>7,781</td>
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<tr>
<td>Adelaide</td>
<td>8,579</td>
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<tr>
<td>Brisbane</td>
<td>8,245</td>
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<td>Canberra</td>
<td>9,348</td>
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<td>Fremantle</td>
<td>8,595</td>
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<td>Melbourne</td>
<td>8,791</td>
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<td>Newcastle</td>
<td>8,428</td>
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<tr>
<td>Perth</td>
<td>8,482</td>
</tr>
<tr>
<td>Sydney</td>
<td>8,539</td>
</tr>
</tbody>
</table>

(Graphic: Business Wire)
Quantified Self Movement

• “incorporate technology into data acquisition on aspects of a person's daily life” (Wikipedia)
• “life logging”
• Everything from detailed records of dietary intake to spreadsheets of multiple activity tracker variables
• Wired magazine article 2007
• quantifiedself.com
• qsinsitute.com
Health Care Paradigm vs. QS

- Evidence based vs. case report
- Population level vs. individual level
- Acknowledge the anecdote
- Precision medicine
What does this data mean?

• Accuracy
• Relevance

• Your doctor doesn’t know what to do with your daily steps, or daily heart rate changes
Challenges and Barriers

• Technical
  – Devices not under the health care system’s continuous control
  – Integration into an existing architecture
  – Developing scalable solutions to gathering, storing and curating vast amounts of data
  – Data provenance
  – Artifact rejection - what constitutes artifact?
  – Security (NIST)

• Legal /Regulatory/Privacy
  – HIPAA, etc

• Structural
  – Integrating this continuously obtained data into existing pathophysiologic models
  – Determining how this data may improve health/change outcomes
Not our device

• WHO IS WEARING THE DEVICE??
• Quality control
• Not “Medical grade”
  – standards
  – interfaces
“Obtaining, curating, storing and retrieving data”

• Sheer volume
• Integration with EHR
• Interoperability between EHRs
• Where stored? Who responsible? Who “owns”?  
• “Outside labs” analogy
Data provenance

• Where does the data come from?
• How is the data obtained?
• Format? Sampling interval?
• Fitbit HR ≠ Apple HR
Artifact rejection

- Arm movement example
- Vendor’s internal work
- Machine learning vs. human rejection
Clinician blood pressure documentation of stable intensive care patients: an intelligent archiving agent has a higher association with future hypotension

Caleb W. Hug, Ph.D.,
Dept. of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge, MA

Gari D. Clifford, Ph.D., and
Institute of Biomedical Engineering, University of Oxford, UK; Harvard-MIT Health Sciences and Technology, Massachusetts Institute of Technology, Cambridge, MA

Andrew T. Reisner, M.D.
Department of Emergency Medicine, Massachusetts General Hospital, Boston, MA; Harvard-MIT Health Sciences and Technology, Massachusetts Institute of Technology, Cambridge, MA
Results

• “During periods of hemodynamic stability in an ICU patient population, clinician documented BP values were inferior to an intelligent automated archiving method, as early indicators of hemodynamic instability.”

• “Human oversight may not be necessary for creating a valid archive of vital signs data within an electronic medical record.”
SECURING
TELEHEALTH
REMOTE PATIENT
MONITORING
ECOSYSTEM

Cybersecurity for the Healthcare Sector

Andrea Arbelaez
National Cybersecurity Center of Excellence
National Institute of Standards and Technology

Ronnie Daldos
Kevin Littlefield
Sue Wang
David Weitzel
The MITRE Corporation

DRAFT
November 2018
hitncceo@nist.gov
“Heatmap” for social athlete’s app reveals secret bases, secret places

Data map inadvertently reveals movements of people in dangerous and sensitive places.
Fitbit Extends Corporate Wellness Offering with HIPAA Compliant Capabilities

*Fitbit’s HIPAA compliance safeguards support new business and deeper integration opportunities with corporate customers.*

September 16, 2015 09:00 AM Eastern Daylight Time

SAN FRANCISCO—(BUSINESS WIRE)—Fitbit, Inc., the leader in the connected health and fitness market, today announced that it supports HIPAA compliance, enabling Fitbit Wellness to more effectively integrate with HIPAA-covered entities, including corporate wellness partners, health plans and self-insured employers. The U.S. Health Insurance Portability and Accountability Act (HIPAA) is the primary U.S. law governing the security and privacy of personal health information used by health insurance plans and other covered entities.
Overcoming Challenges

• Technical are “easier”
• Legal/Regulatory are “easier”
• Structural are “harder” (i.e. evidence, best practice, change management)
Structural challenges require paradigm shift

• Previous collection of physiologic data has been limited to patients' intermittent physical interactions with the healthcare system

• Our models of the implications and predictive value is predicated on this

• What do “we” (the health care system) do with wearable data and what does it mean? How can it be used to improve health?
Signal vs. Noise

• An accuracy and artifact question
  – Is the data “real”?
• Also a usefulness question
  – Is the data meaningful?
Review

Using wearable technology to predict health outcomes: a literature review

Jason P. Burnham,¹ Chenyang Lu,² Lauren H. Yaeger,³ Thomas C. Bailey,¹ and Marin H. Kollef⁴

¹Department of Internal Medicine, Division of Infectious Diseases Washington University School of Medicine, St. Louis, Missouri, USA, ²Department of Computer Science & Engineering, Washington University in St. Louis, Missouri, USA, ³Bernard Becker Medical Library, Washington University in St. Louis, Missouri, USA and ⁴Department of Internal Medicine, Division of Pulmonary and Critical Care Medicine, Washington University School of Medicine, St. Louis, Missouri, USA

Corresponding Author: Jason P. Burnham, MD, Division of Infectious Diseases, Washington University School of Medicine, 4523 Clayton Avenue, Campus Box 8051, St. Louis, MO 63110, USA (burnham@wustl.edu)

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Literature review

• Objective: To review and analyze the literature to determine whether wearable technologies can predict health outcomes.

• Results: Eight unique studies were directly related to the research question, and all were of at least moderate quality. Studies developed models for readmission and mortality. In each of the eight studies, data obtained from wearable technology were predictive of or significantly associated with the tracked outcome.
Literature review results

• 168 studies
• 8 studies (mortality and readmission)
• 17,285 patients
  – 16,760 in 2 of the studies
• 4 studies used steps to predict mortality
• 5 studies used steps to predict readmissions
• 1 study of 25 patients
  – 89 features of Fitbit data
  – Predicted readmission with 88.3% accuracy
“Chicken and Egg" or “Bootstrapping” problem:

• The utility of wearable physiologic monitor data in improving outcomes can't really be determined until large amounts of data are collected and use cases are thereby identified.

• BUT large amounts of data can't be collected until the infrastructure is put into place to do so.

• AND FURTHER the resources to put that infrastructure in place may not be allocated until use cases are known ...
A solution?

• Vendors have the device data…..
• Health Care Systems have the patient outcome data
• Partnerships between device vendors and Health Systems to link device data with clinical outcomes
• Could identify potential use cases for utilizing this data to improve clinical outcomes.
Summary and Future

• Tremendous volume of potentially useful physiologic data
• The signal to noise ratio is unclear
  – what data is accurate and what is artifact
  – what are the clinical outcome implications of such data.
• Existing infrastructures do not facilitate the easy integration of patients’ wearable device data into the medical record.
• Technical challenges can be overcome; they require scalable solutions.
• The systemic and attitudinal barriers to utilizing this data need to be addressed as well.
• The "chicken and egg" or "bootstrapping" problem described above will need to be solved, perhaps by opportunities to link vendor data with outcomes contained in health system EHRs.
References


Questions

• poterack.karl@mayo.edu

• Please complete online session evaluation!