Smartwatch Wearing Behavior Analysis: A Longitudinal Study

Studying longitudinal wearing behaviors

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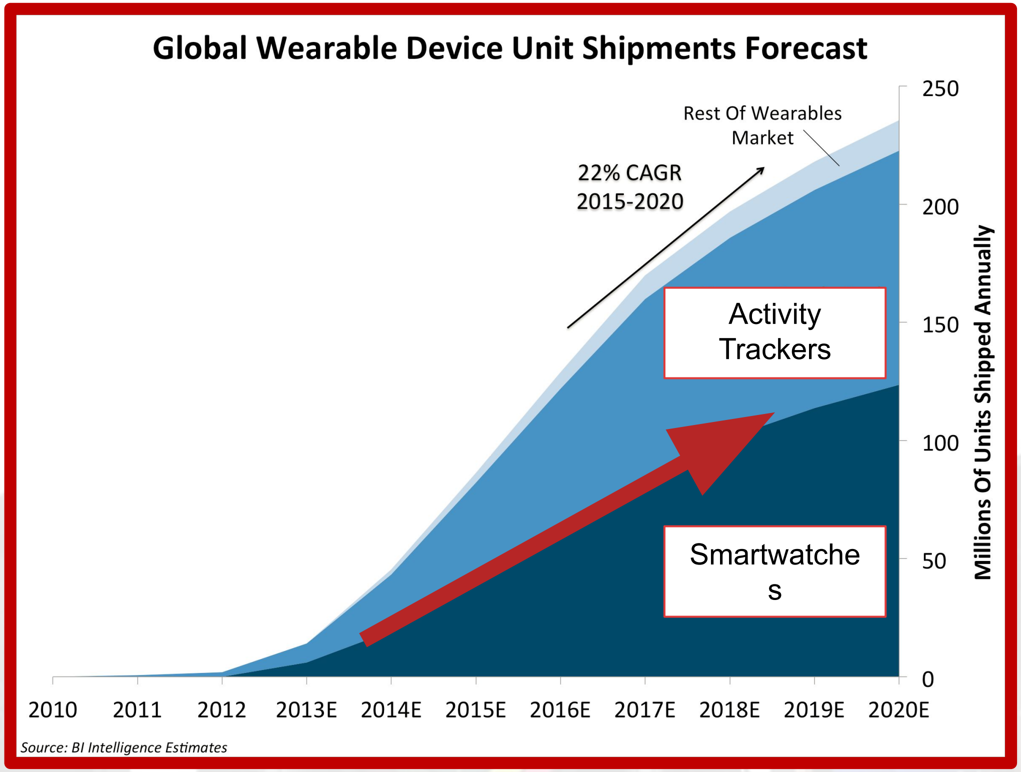
http://blog.wellable.co/2017/01/04/survey-nearly-25-of-americans-own-a-wearable-device


Global Wearable Device Unit Shipments Forecast
Rest Of Wearables Market
22% CAGR 2015-2020
Activity Trackers
Smartwatches
250
200
150
100
50
0
Millions Of Units Shipped Annually
2010
2011
2012
2013E
2014E
2015E
2016E
2017E
2018E
2019E
2020E
Source: BI Intelligence Estimates

Smartwatch Studies

- **Major purposes**: Time & notification checking, activity tracking, calling (Schirra & Bently, CHI’15, Pizza et al., CHI’16)
- **Micro-interaction:** short/frequent interaction as a smartphone companion (38% of sessions lasted less than 5 seconds) (Min et al., ISWC’15)
- **Usefulness**: smartphone ***companion*** with a glancable (second) display (supporting multitasking, and less disruptive for socializing) (Pizza et al., CHI’16)
- **Preferences**: electronics vs. fashion accessories? Shape, color, brand matter (Lyons, ISWC’15; Jung et al., 2016)

Motivations

Prior studies uncovered important aspects of smartwatch usage.
But there is still a lack of **comprehensive study** on
how people wear their smartwatches over time

Goal of this work is to investigate
<u>longitudinal wearing behaviors of smartwatches</u>

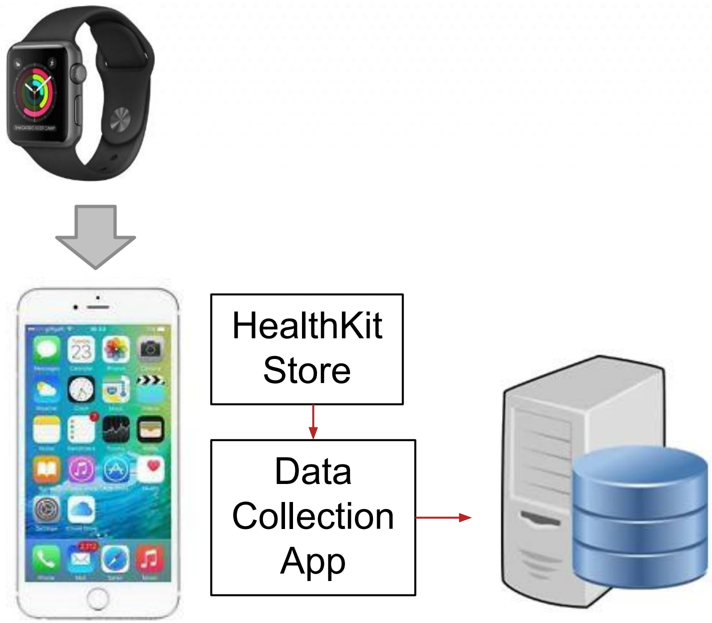
Research Questions

- **Simple questions:**
  - How many hours do people wear?
  - How frequently do people take off their watches?
- **More elaborate question: usage patterns**
  - Are there any diurnal and weekly wearing patterns?
  - Are there any temporal dynamics over time? (persistency)
- **Understanding why:**
  - What are the key reasons of such wearing behavioral patterns?

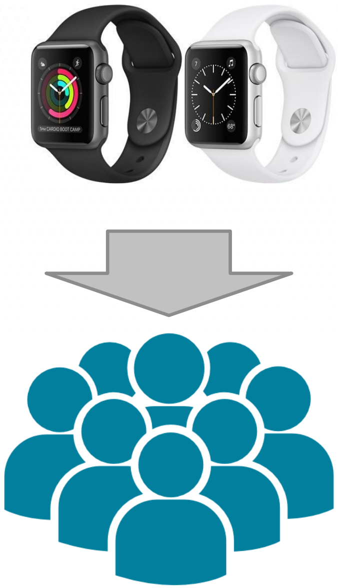
Key Contributions

Longitudinal data collection	Wearing state recognition method	Wearing behavior analytics	Factors affecting wearing behaviors
50 Apple Watch users over 200 days (HR + step counts)	Instant classifier w/ DHMM achieves 97% accuracy	Identified unique diurnal/weekly/temporal patterns	Contextual, but nuanced

Longitudinal Data Collection



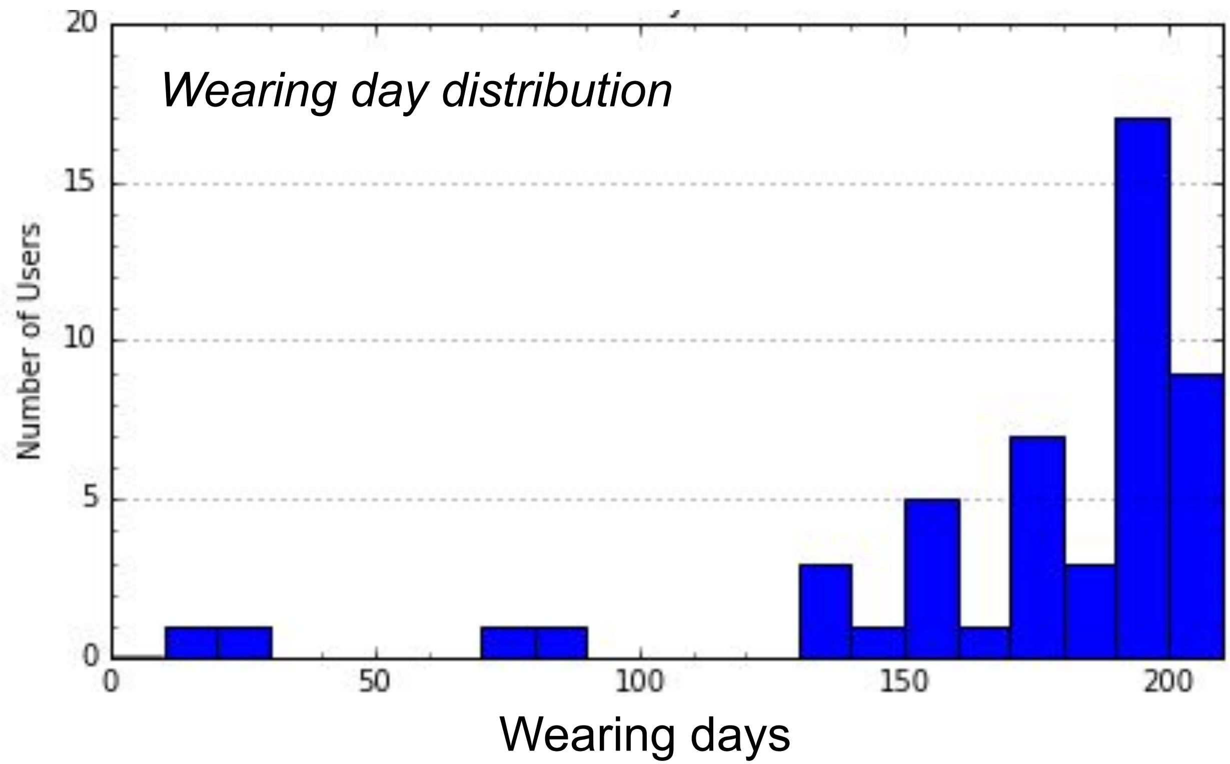
Data Collection SW
(**HR + step count**)



Data collection campaign @ KAIST:
50 people were randomly selected
(36 male, 11 under, 37 grads, 2 staff/faculty)
(giving watches as incentives
for longitudinal data collection)

Longitudinal Data Collection

- 203 days of data collection (Mar 23 – Oct. 16, 2016)
- Only four dropped out (but included in our analysis)



Wearing State Recognition: Why?

- **Challenging to know whether a user wore a watch, by only observing <u>heart rate (HR) and step count data</u>**
  (Apple Watch does not have an API for detecting whether a user is wearing a watch or not)

Sporadic, inaccurate HR sampling w/ mobility

Step count works even not wearing, say in the bags or pockets

Wearing State Recognition: Method

Data Collection (Ground

91%

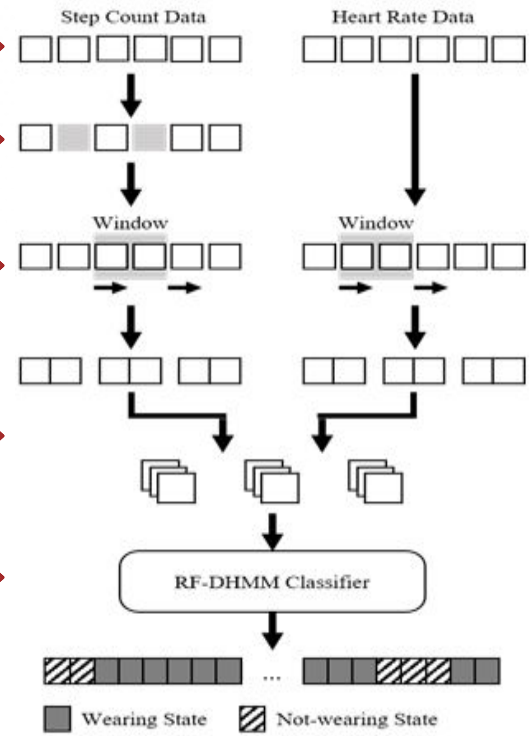
Dataset #1) 6 users performing scripted activities
(Take-off, Charge, Study/work, Walk, Eat, Rest, Sleep, Exercise)

97%

Dataset #2) 4 users for semi-naturalistic wearing data collection for a week

Building a Machine Learning Model

Data
Noise Filtering
Slide Window
Feature Extraction
Random Forest w/ DHMM Correction



Wearing Behaviors

- **Average wearing hours: 10.48 (SD=3.47)**
- **Average take off frequencies: 3.17 (SD=1.11)**

Wearing Behaviors: Diurnal Patterns

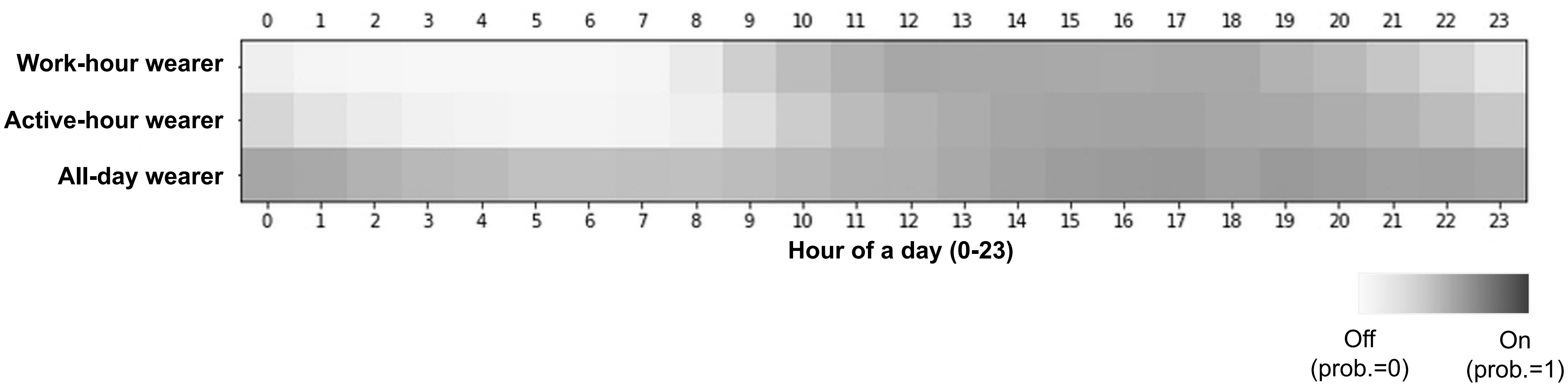
- **Calculated a 24-dimensional vector for each user**
- **Each dimension represents wearing prob. for a given hour of a day during the entire period**

Attribute Number (Time)	0	1	2	…	22	23
Wearing Probability Vector	(0.78,	0.59,	0.68,	…	0.79,	0.64)

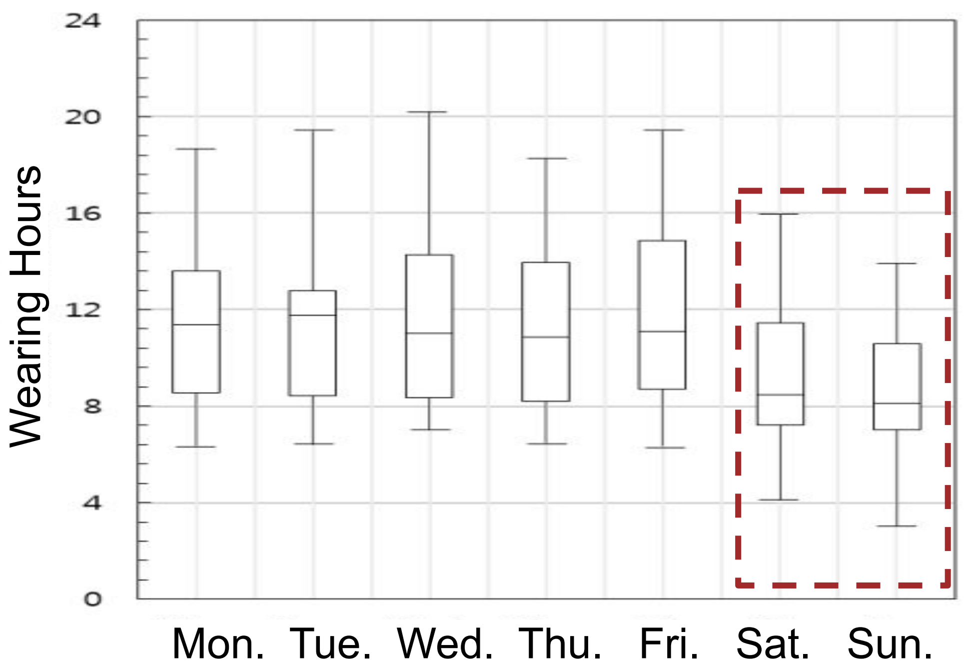
78% chance of wearing

Wearing Behaviors: Diurnal Patterns

- **Spectral clustering results (w/ three clusters):**
  - Work-hour wearers (n=29, 58%)
  - Active-hour wearers (n=15, 30%)
  - All-day wearers (n=6, 12%)



Wearing Behaviors: Weekly Patterns



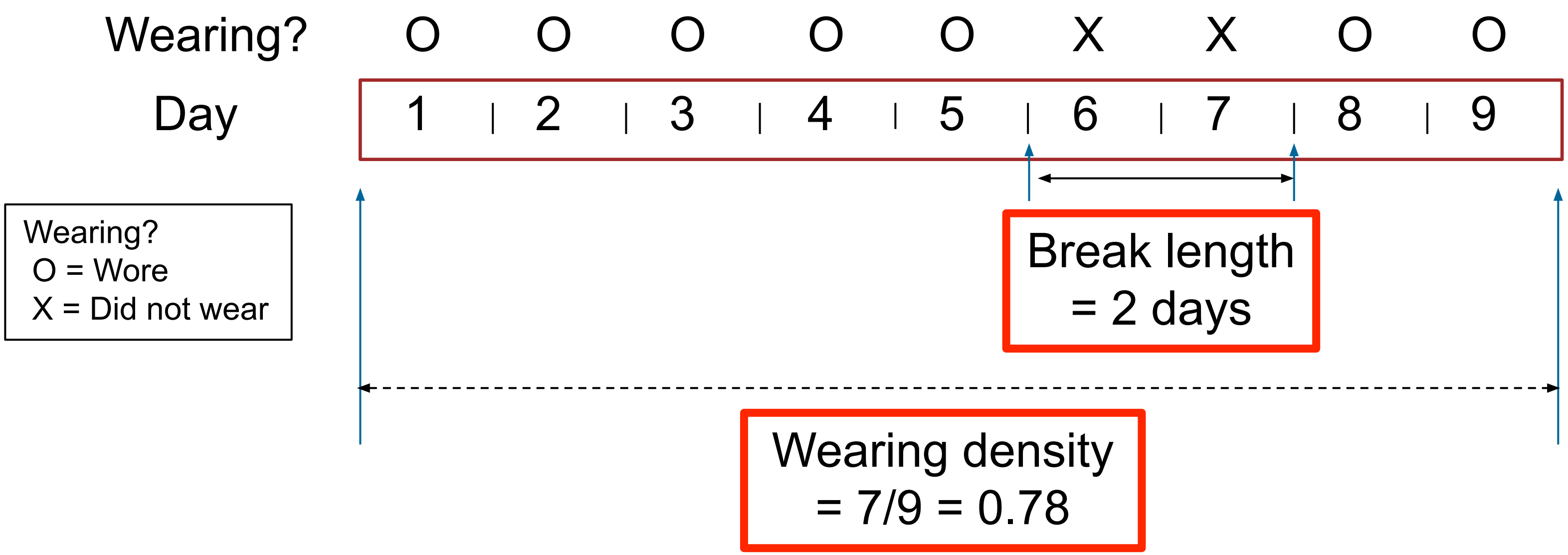
Weekly rhythm exists

Less usage on weekends

(11.92 vs. 8.61, $p<0.05$)

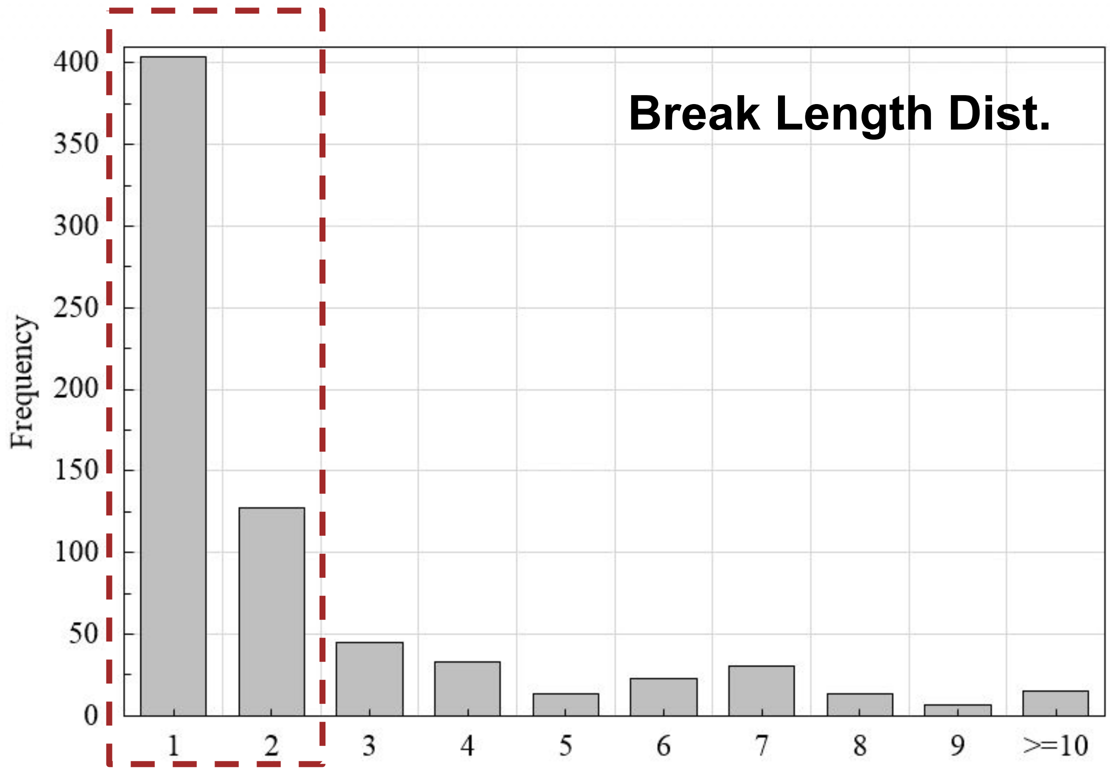
Wearing Behaviors: Temporal Dynamics

- **Break length: # consecutive days of not wearing**
- **Wearing density: # wearing days / total # days**



Wearing Behaviors: Temporal Dynamics

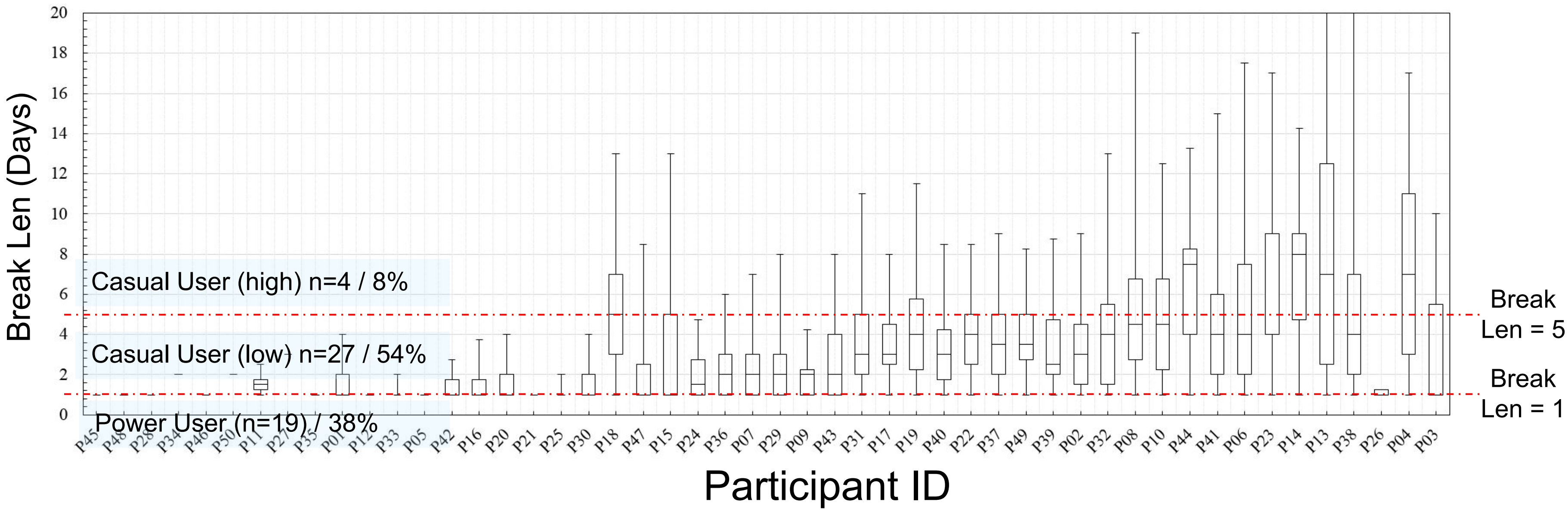
- Very short breaks: mostly 1 or 2 days
- Avg. wearing density = 0.90



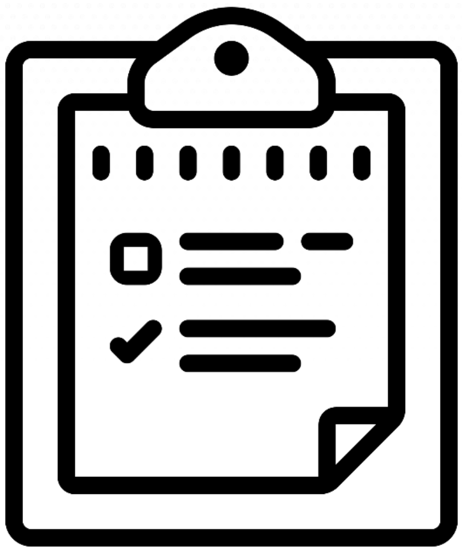
Break length (day): # consecutive days of not wearing

Wearing Behaviors: Temporal Dynamics

- **User groups based on temporal dynamics**
  - Power users: median break len = 1 day (n=19 / 38%)
  - Casual users: median break len > 1 day (n=31 / 62%)
    - High casualness: median break len >5 days (n=4 / 8%)
    - Low casualness: median break len ≤ 5 days (n=27 / 54%)



Understanding Why? Methods



Online survey (n=47)

- Usage purposes and practices
- Reasons for wearing/not-wearing
- Wearing preferences across different contexts (time/place)

Interview (n=20)

- How do you use your watch?
- When do you wear/take off your watch?
- How do you use during …?
- What are positive/negative…?

Understanding Why: Contextual Preference

Time

Time	Wearing Frequency Score
After waking up - Before going to work	2.74 (SD=1.55)
After going to work - Before leaving work	4.43 (SD=1.02)
After leaving work - Before going to bed	2.53 (SD=1.49)
After going to bed - Before waking up	1.38 (SD=0.90)

- **Most likely at work**
- **Least likely in the bed**

Place

Place	Wearing Frequency Score
Home, Dormitory	2.83 (SD=1.47)
Workplace, Classroom	4.57 (SD=0.71)
Restaurant, Café	4.51 (SD=0.72)
Gym, Sports field	3.83 (SD=1.36)

- **Most likely at work/class & restaurant/café**
- **Least likely at home/dorm**

- **Weekly rhythm due to home staying over weekends**

Understanding Why: Contextual & Nuanced

[Major themes of wearing & not wearing]

Wearing	But nuanced	Not Wearing
Being responsive	Constant connectivity stress after work	Wearing discomfort
Multitasking	Distractive	Charging smartwatches
Activity tracking	Lack of supported activities & breakage concern	Breakage concern

Summary

- **Patterned smartwatch wearing behaviors**
  - Diurnal usage: active-hour, work-hour, all-day wearers
  - Weekly rhythm: less usage on the weekends
  - Temporal dynamics: power user vs. casual users (low & high)
- **Higher wearing density as opposed to activity trackers:**
  - Apple Watch: 89% vs. VitaDock Tracker: 67% (Meyer et al., CHI’17)
  - Smartphone companion vs. standalone tracker
- **Wearing behaviors are highly contextual and also nuanced**

Design Implications

- **Supporting contextual and nuanced usage**
  - Dealing with possible distraction and technostress
  - Proactively mediating contextualized wearing (e.g., reminding wearing or taking off)

- **Wear-aware health intervention delivery mechanism**
  - Delivering intervention when users wear their watches
  - Possible to predict wearing behaviors and also, proactively mediate wearing behaviors

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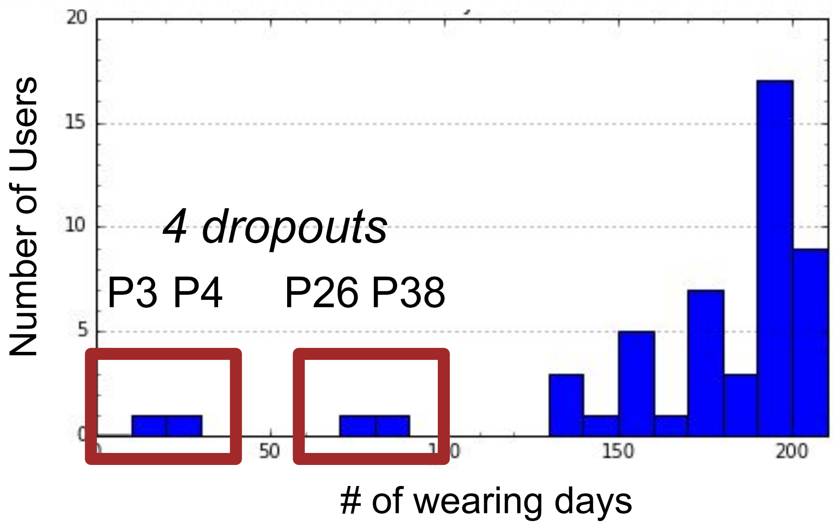
Wearing Behaviors: Dropout Users



P38: All-day wearer,
low casualness, low take off freq

P26: Active-hour wearer,
power user, moderate take-off freq

P4: Active-hour wearer,
high casualness, low take-off freq

P3: Work-hour wearer,
low casualness, moderate take-off freq

Dropouts did not happen gradually,
but these users also show diurnal/weekly/temporal patterns