CHI 2025

DataSentry : Building Missing Data Management System for In-the-Wild Mobile Sensor Data Collection through Multi-Year Iterative Design Approach

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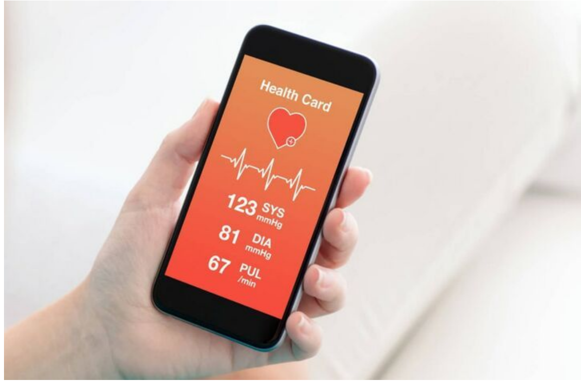
Mobile Data Collection: The Foundation of Mobile Sensing Studies



Diagnosing health conditions [1]

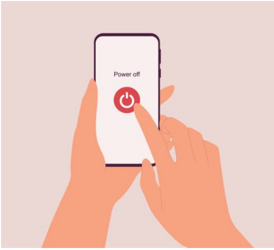
Predicting productivity [2]

Analyzing social interactions [3]

[1] The Perceived Utility of Smartphone and Wearable Sensor Data in Digital Self-tracking Technologies for Mental Health, CHI '23: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems
[2] Understanding Personal Productivity: How Knowledge Workers Define, Evaluate, and Reflect on Their Productivity, CHI '19: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems
[3] Social Sensing: Assessing Social Functioning of Patients Living with Schizophrenia using Mobile Phone Sensing, CHI '20: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems

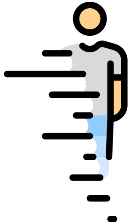
Missing Data Issues in Mobile Data Collection

Participant behaviors [1]



Powering-off

No self-reports

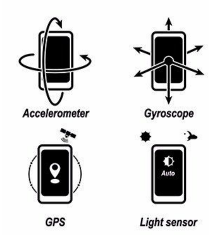


Dropout

System-related issues [2]

Network

Server



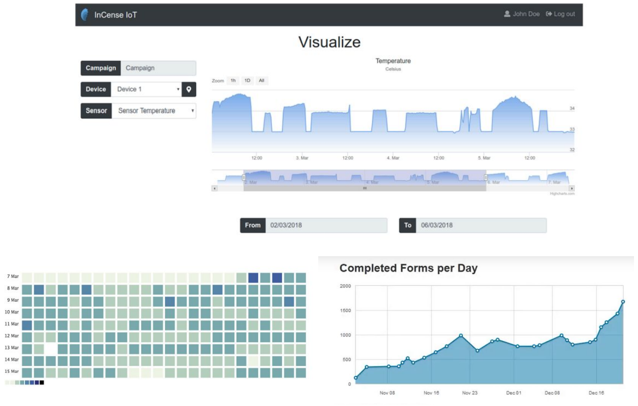
Sensors

Sensor Logging

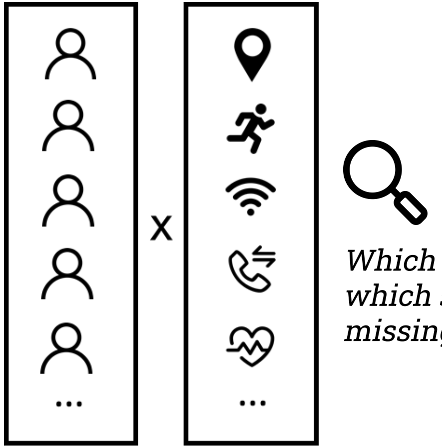
[1] Xuhai Xu, Jennifer Mankoff, and Anind K Dey. 2021. Understanding practices and needs of researchers in human state modeling by passive mobile sensing. CCF Transactions on Pervasive Computing and Interaction 3 (2021), 344–366.
[2] Jennifer Healey, Lama Nachman, Sushmita Subramanian, Junaith Shahabdeen, and Margaret Morris. 2010. Out of the lab and into the fray: Towards modeling emotion in everyday life. In Pervasive Computing: 8th International Conference, Pervasive 2010, Helsinki, Finland, May 17-20, 2010. Proceedings 8. Springer, 156– 173

Challenges in Missing Data Management

Holistic understanding of missing data across many people and sensors



Inspecting **individual** sensor streams or aggregated metrics of **a specific sensor**

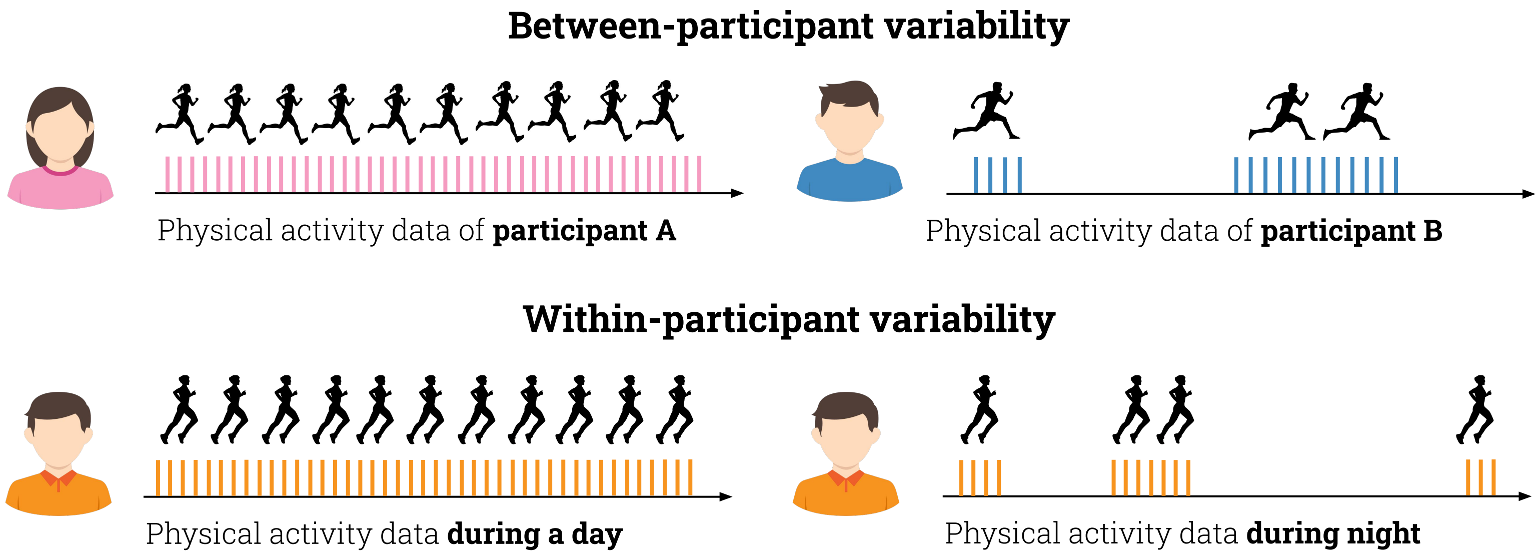


Which participants, which sensors have missing data?

Lack of holistic understanding of missing data **across many people and sensors**

Challenges in Missing Data Management

Needs for considering between- and within-participant variability

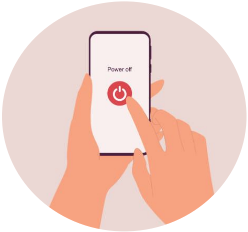


Challenges in Missing Data Management

Difficulty in diagnosing root causes of missing data

Difficult to diagnose…

Participant's common behavior patterns?



Powering off smartphones?

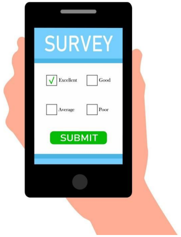
Network or data sync issues?

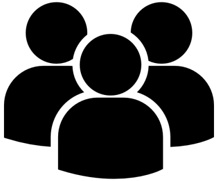
Challenges in Missing Data Management

Communication burden of researchers in addressing the issues

Data collection researcher

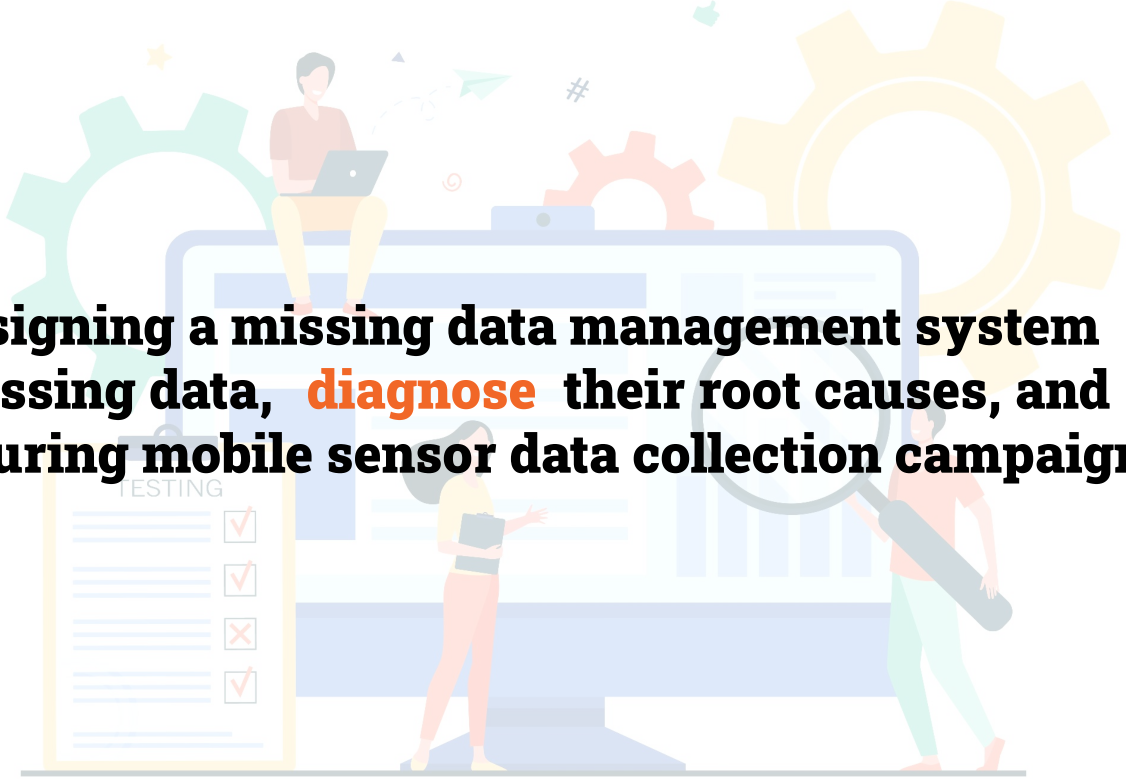
Managing participants for quality data collection





Data collection participants

“Designing a missing data management system to **detect** missing data, **diagnose** their root causes, and **address** them during mobile sensor data collection campaign”



Formative Study

Interviewing **seven**
mobile sensing researchers

Design Requirement 1
Overviewing missing data across many people and sensors

Design Requirement 2
Identifying long missing data in event-based sensing

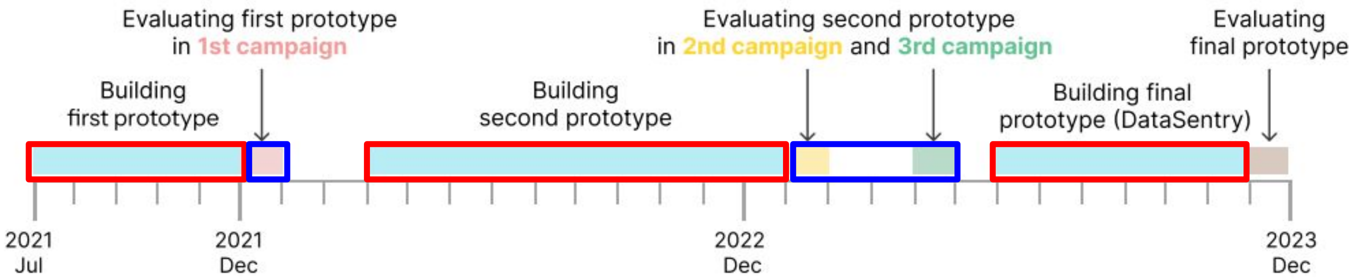
Design Requirement 3
Diagnosing missing data causes

"...it would be helpful to display whether data from each sensor and each person was collected."

"If there's only a small number of rows, it seem like an issue with the sensor. However, it could be because the user didn't move..."

"If I can check multiple data items at a glance, then I can determine why the data was not collected..."

Iterative Design Process



First campaign

Data Collection

17 kinds of mobile sensor data
5 kinds of self-report ESM

Participants

116 participants
(43 women; age: M = 23.5, STD = 3.5)

Researchers

2 researchers
(1 women; age: M = 28.5, STD = 2.2)

Second campaign

Data Collection

19 kinds of mobile sensor data
4 kinds of self-report ESM

Participants

20 participants
(7 women; age: M = 24.8, STD = 2.7)

Researchers

2 researchers
(2 women; age: M = 26.0, STD = 1.4)

Third campaign

Data Collection

5 kinds of mobile sensor data
2 kinds of self-report ESM

Participants

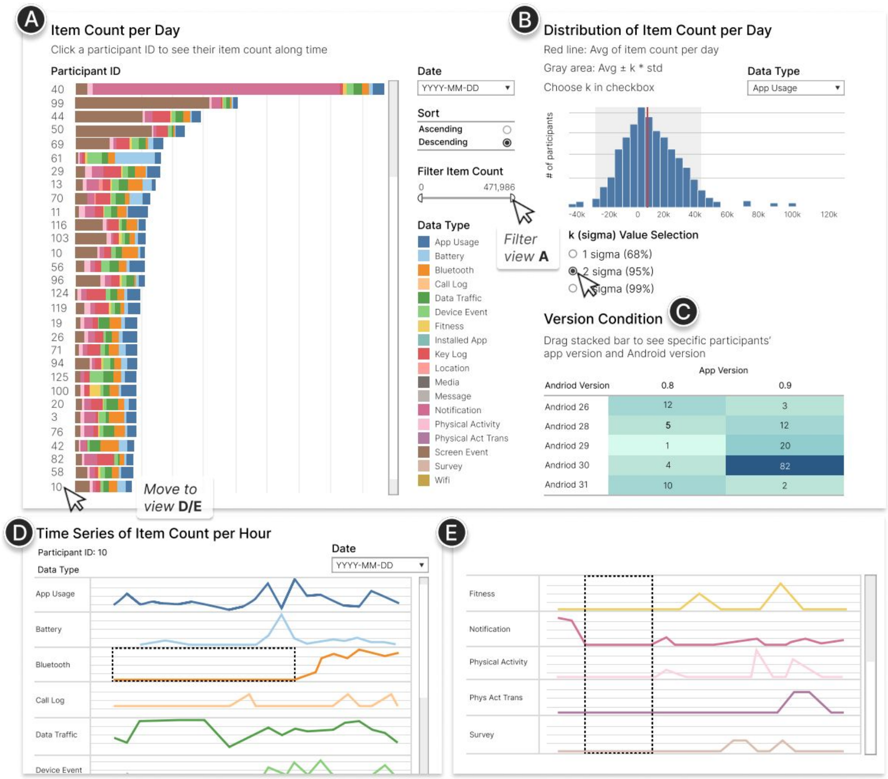
24 participants
(9 women; age: M = 21.3, STD = 2.1)

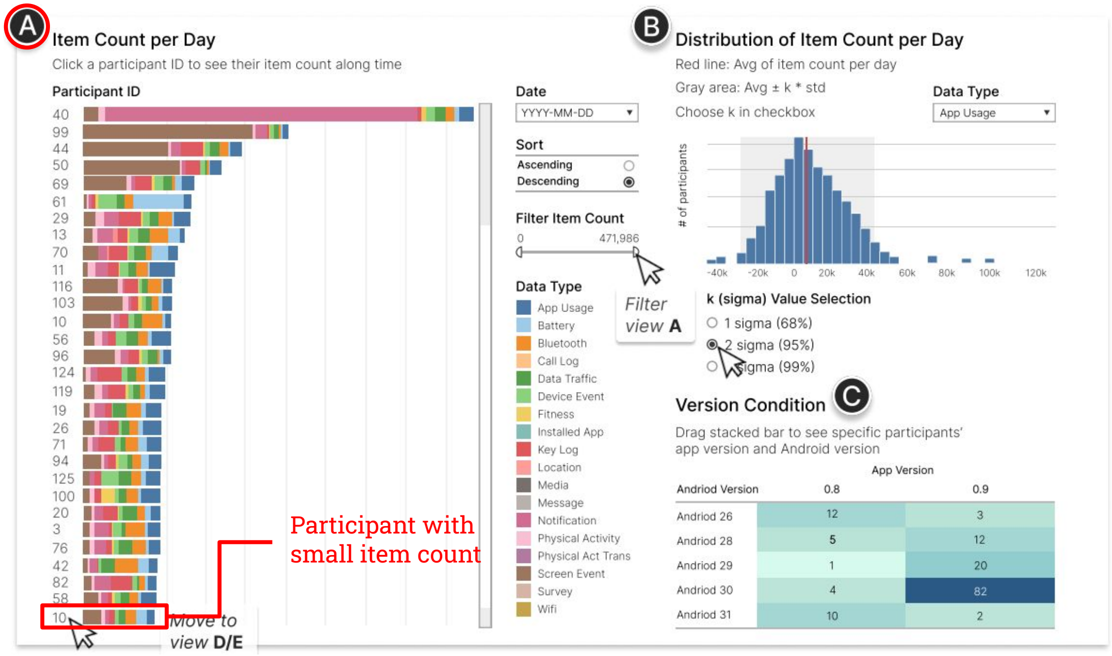
Researchers

1 researcher
(1 man; age = 33)

First Design Iteration

Reflecting three design requirements in formative study

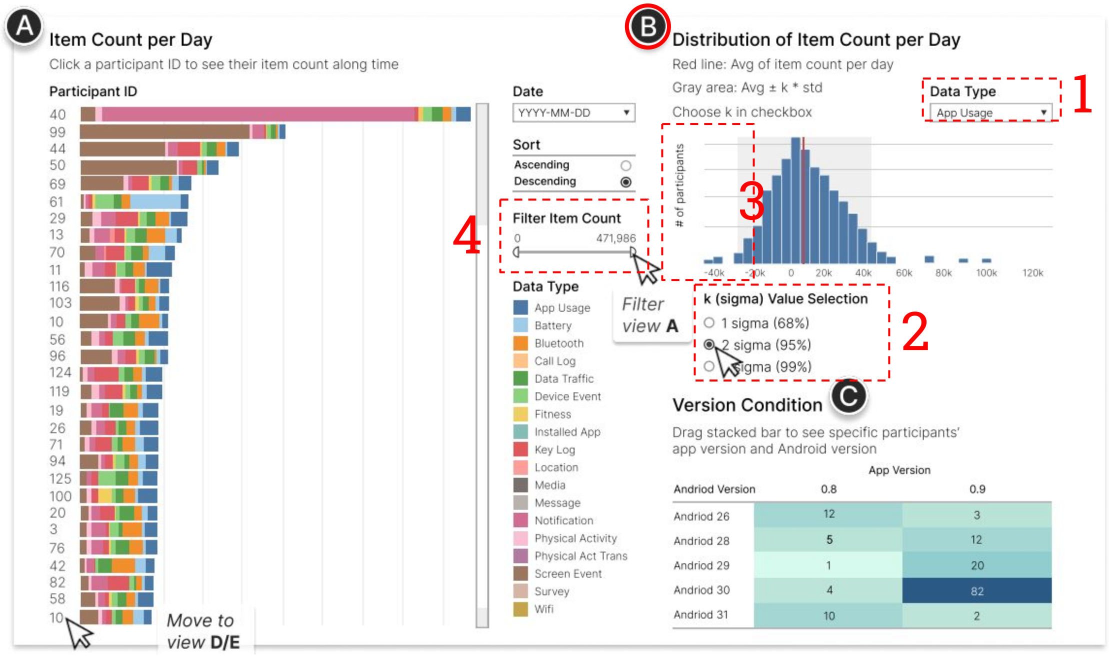




Overview of missing data across people and sensors

(Design Requirement 1)

- Calculating **daily item count** for each sensor and participant
- Visualizing the metric as **stacked bars**



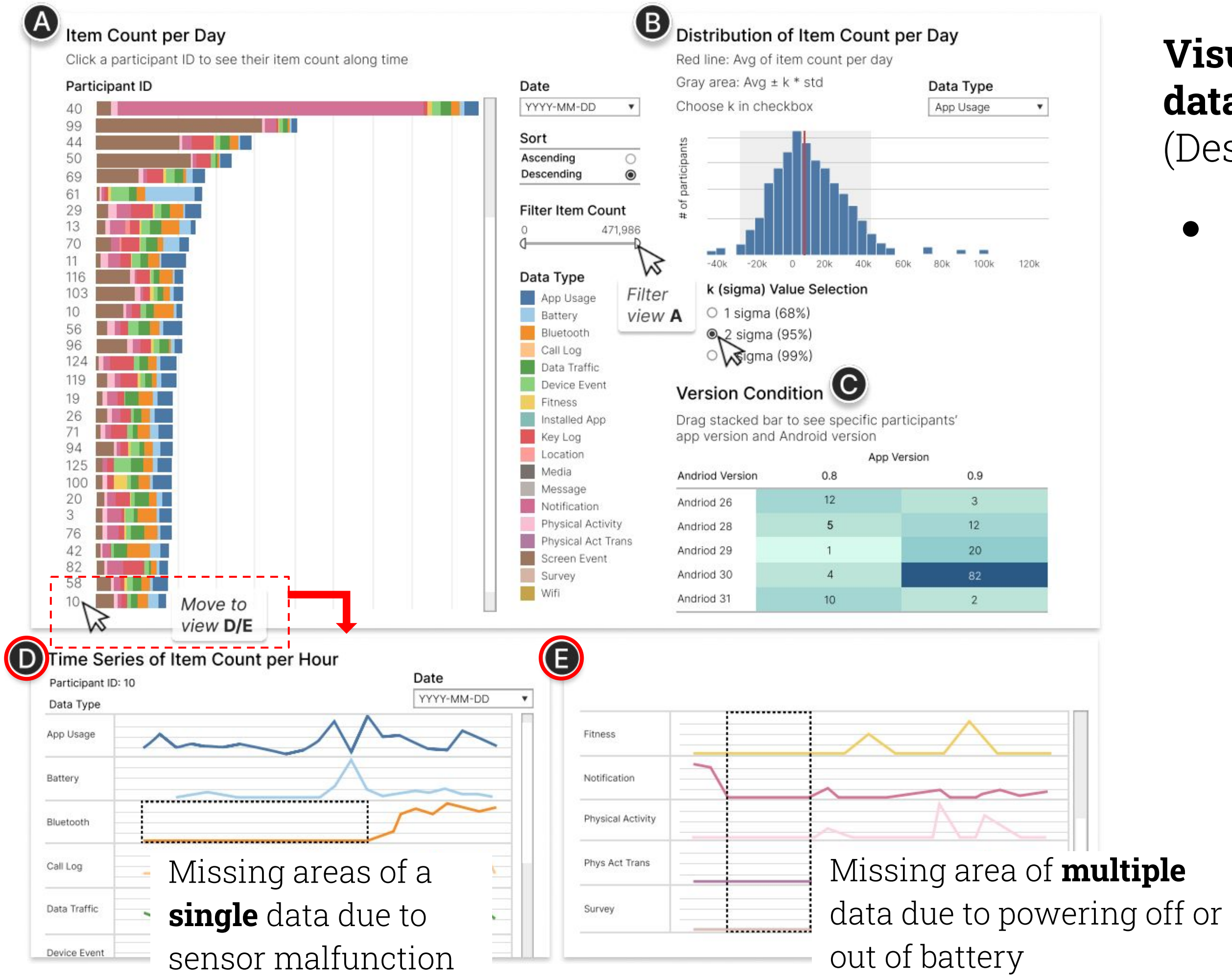
Data-driven guidelines using statistical quality control

(Design Requirement 2)

- Providing guidelines to determine which item count might indicate missing data in **event-based sensing**
- The concept of **control charts**
  → Outlier metric as values outside $[\mu - k\sigma, \mu + k\sigma]$

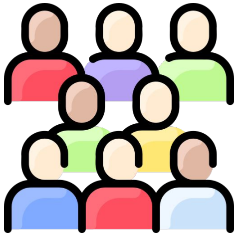
Visual exploration for missing data diagnosis
(Design Requirement 3)

- Inspecting **temporal trend** of item counts in hourly level



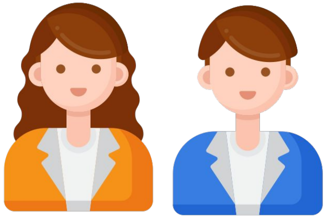
Field deployment

First data collection campaign



116 data collection participants

17 mobile sensor data
5 self-report ESM

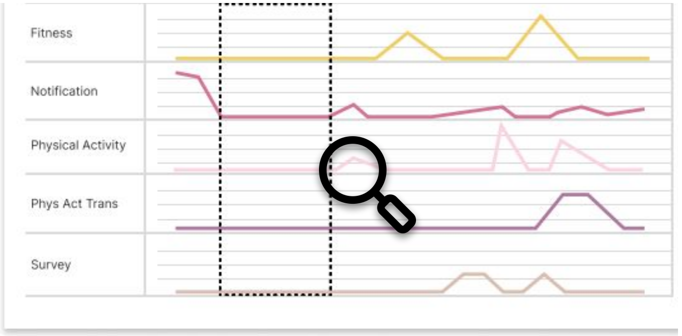


2 managing researchers

Design Insight from Field Deployment

Design Insight 1

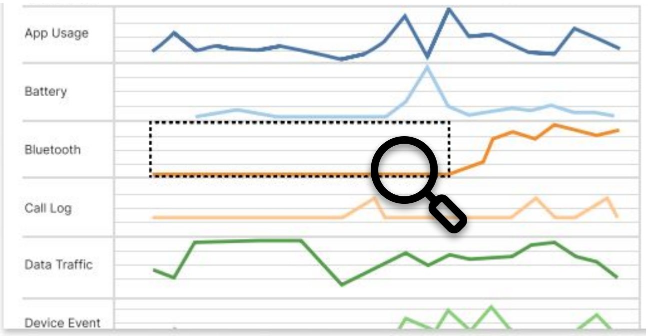
Needs for reviewing
raw sensor data

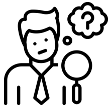


*Difficult to pinpoint **exactly when** the data was missing...*

Design Insight 2

Needs for diagnosing the causes of unexpected
missing data by observing multiple sensor streams



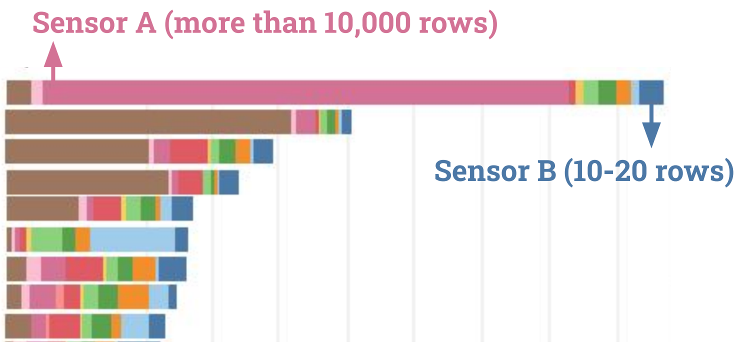


Typical sensing pattern?
Sensor issues?
How about other participants' data?

Usability Issues from Field Deployment

Usability Issue 1

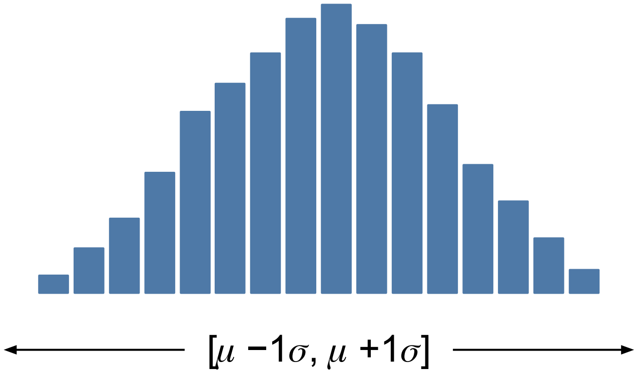
Difficulty of inspecting stacked bars



Wide variation in the scale of count metrics across different sensors

Usability Issue 2

Ineffectiveness of a statistical quality control method



Distribution was usually within $[\mu - 1\sigma, \mu + 1\sigma]$
→ Difficult to find outlying participants

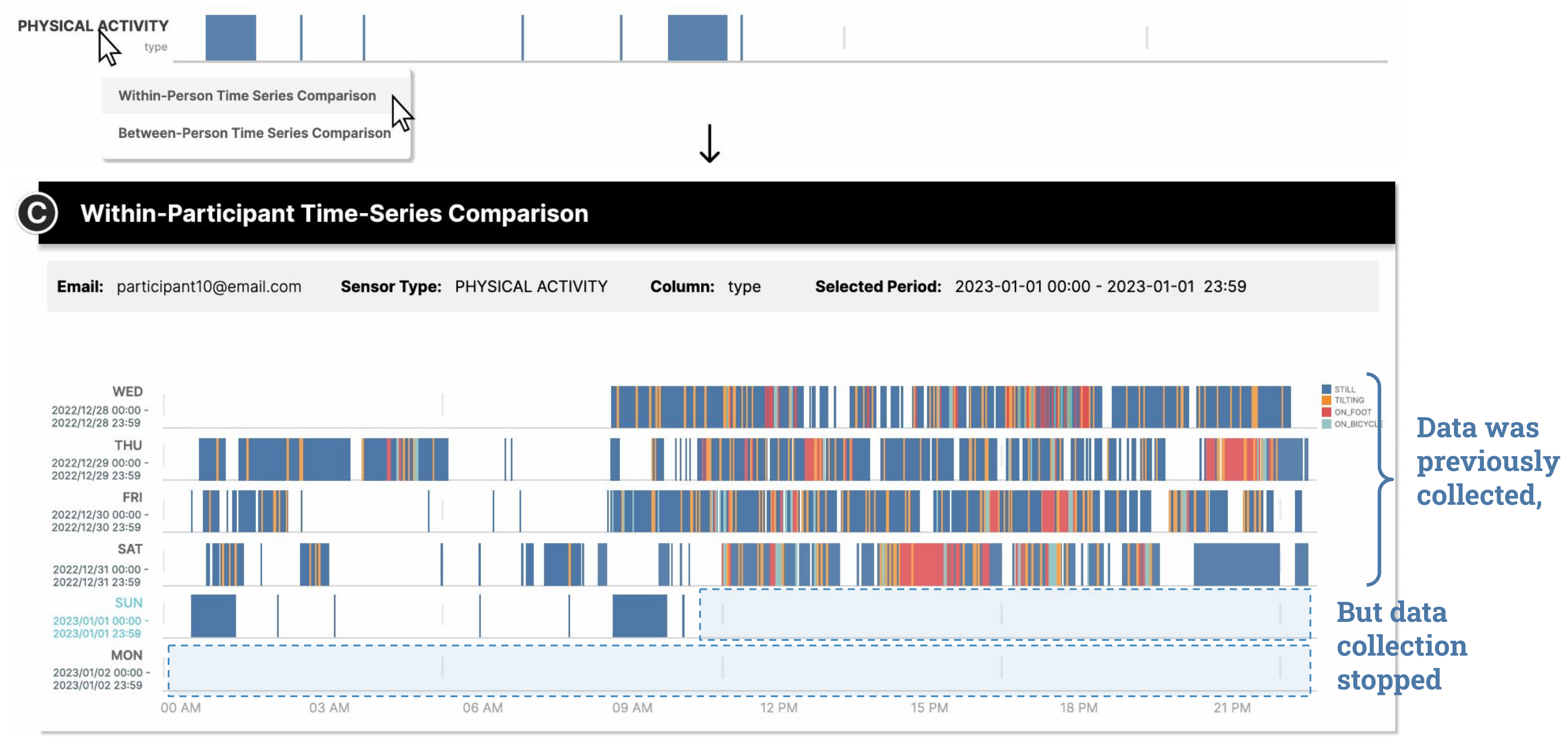
Second Design Iteration

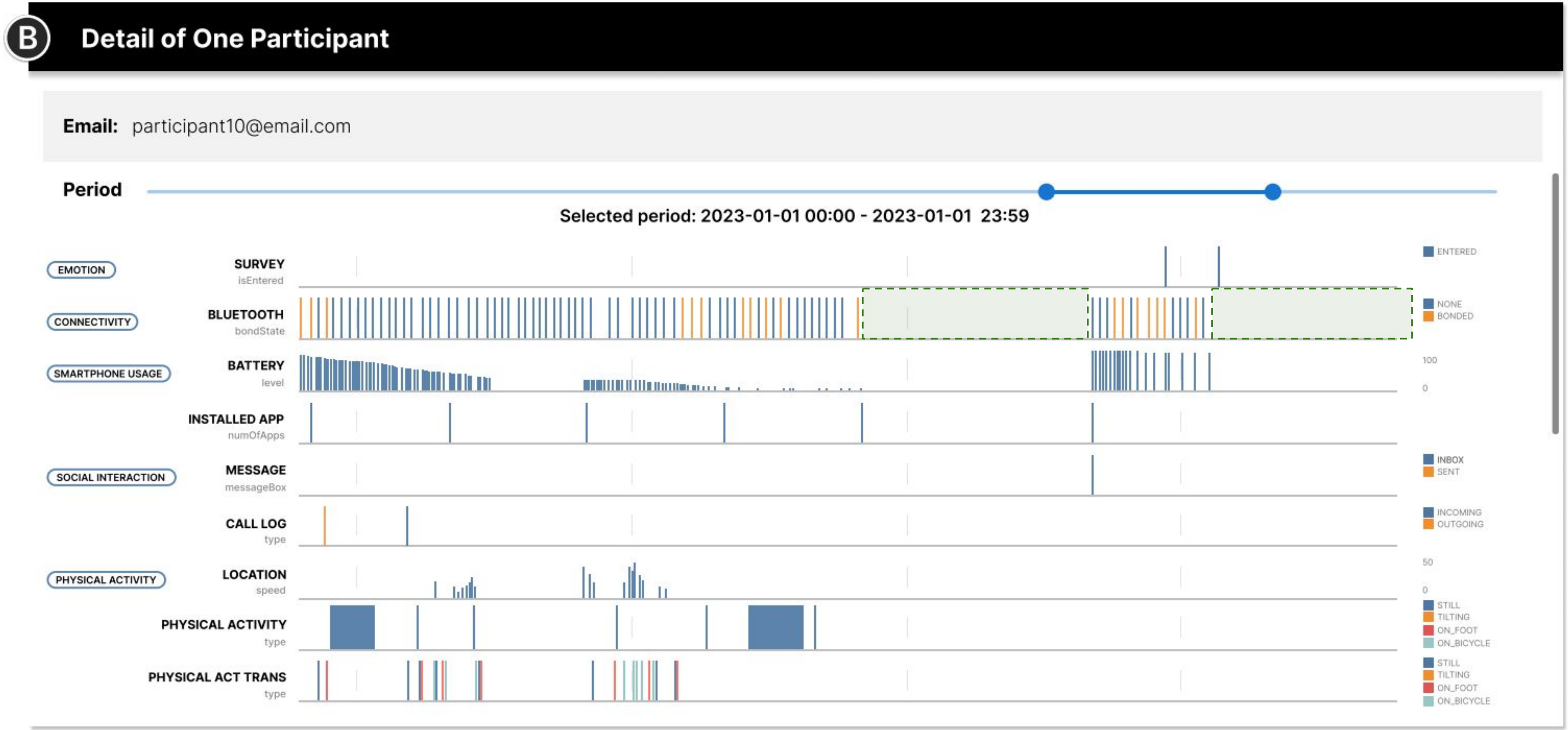
Reflecting design insights and usability issues from first design iteration

Overview of missing data across many people and sensors

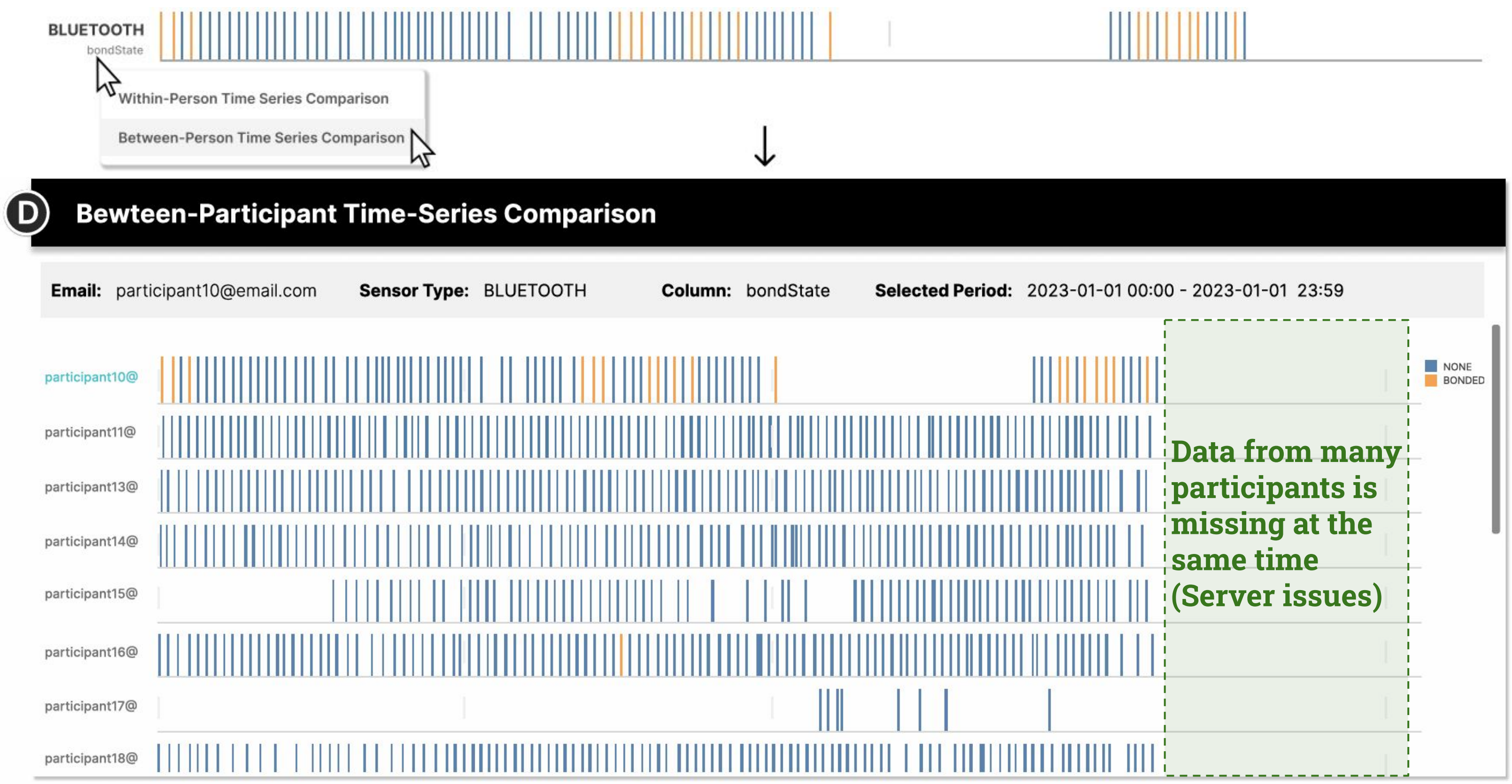
Missing data diagnosis via one participant's multiple sensor streams

Missing data diagnosis using within-participant comparison



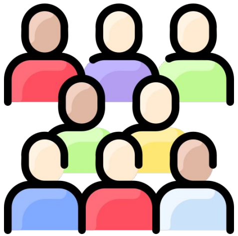

B
Detail of One Participant
Email: participant10@email.com
Period
Selected period: 2023-01-01 00:00 - 2023-01-01 23:59
EMOTION
SURVEY
isEntered
ENTERED
CONNECTIVITY
BLUETOOTH
bondState
NONE
BONDED
SMARTPHONE USAGE
BATTERY
level
100
0
INSTALLED APP
numOfApps
SOCIAL INTERACTION
MESSAGE
messageBox
INBOX
SENT
CALL LOG
type
INCOMING
OUTGOING
PHYSICAL ACTIVITY
LOCATION
speed
50
0
PHYSICAL ACTIVITY
type
STILL
TILTING
ON_FOOT
ON_BICYCLE
PHYSICAL ACT TRANS
type
STILL
TILTING
ON_FOOT
ON_BICYCLE

Missing data diagnosis using between-participant comparison



Field Deployment

Second and third data collection campaigns



Second campaign	20 data collection participants	19 mobile sensor data 4 self-report ESM	2 managing researchers	1 month
Third campaign	24 data collection participants	5 mobile sensor data 2 self-report ESM	1 managing researcher	1 month

Design Insight from Field Deployment

Design insight 1

Needs for streamlined detection of long missing periods

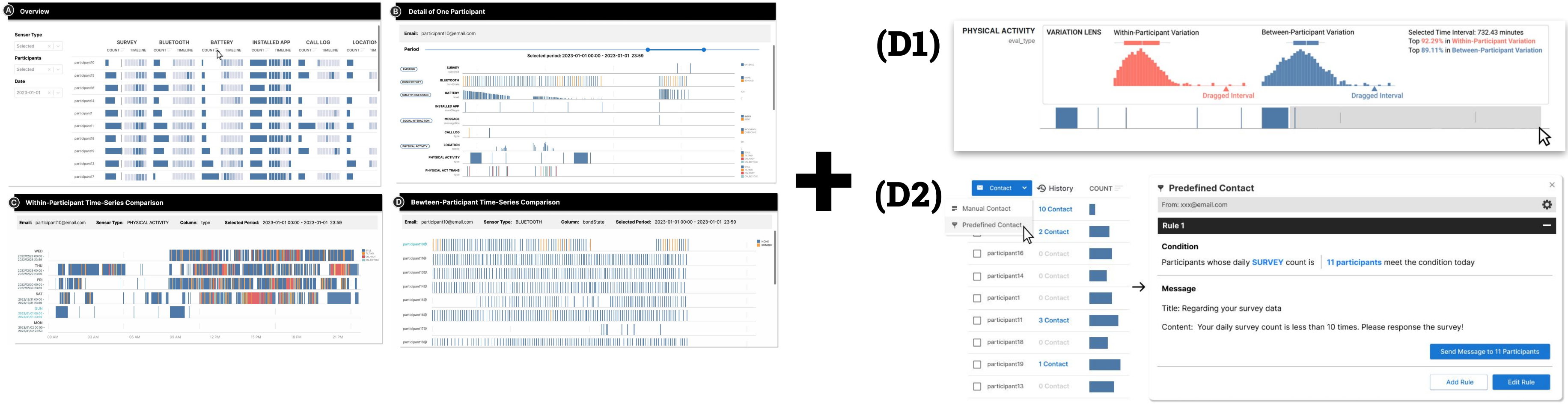
Need to diagnose long missing period by switching several pages repetitively

Design insight 2

Needs for lowering the burden of communication with participants

Third Design Iteration

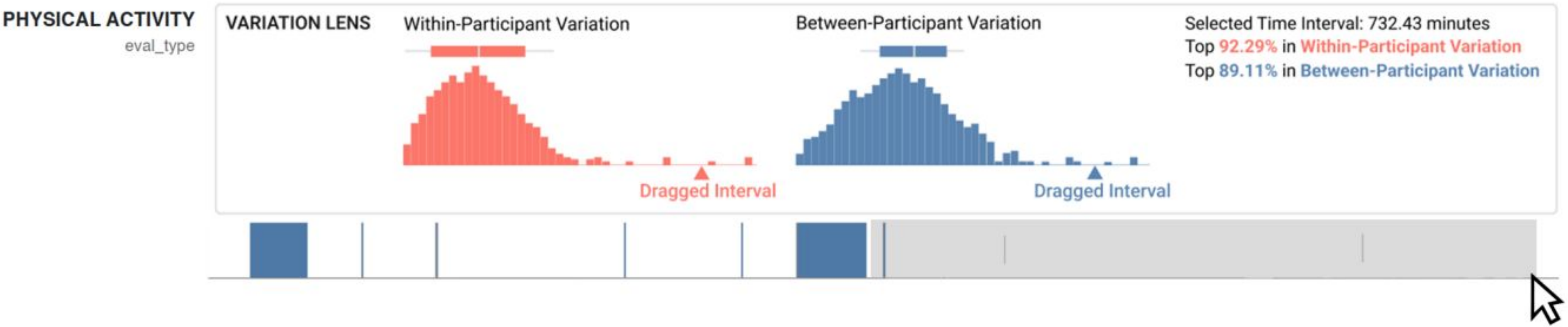
Adding **two main features** reflecting design insights from second design iteration



Within- and Between- Participants Variation Lens

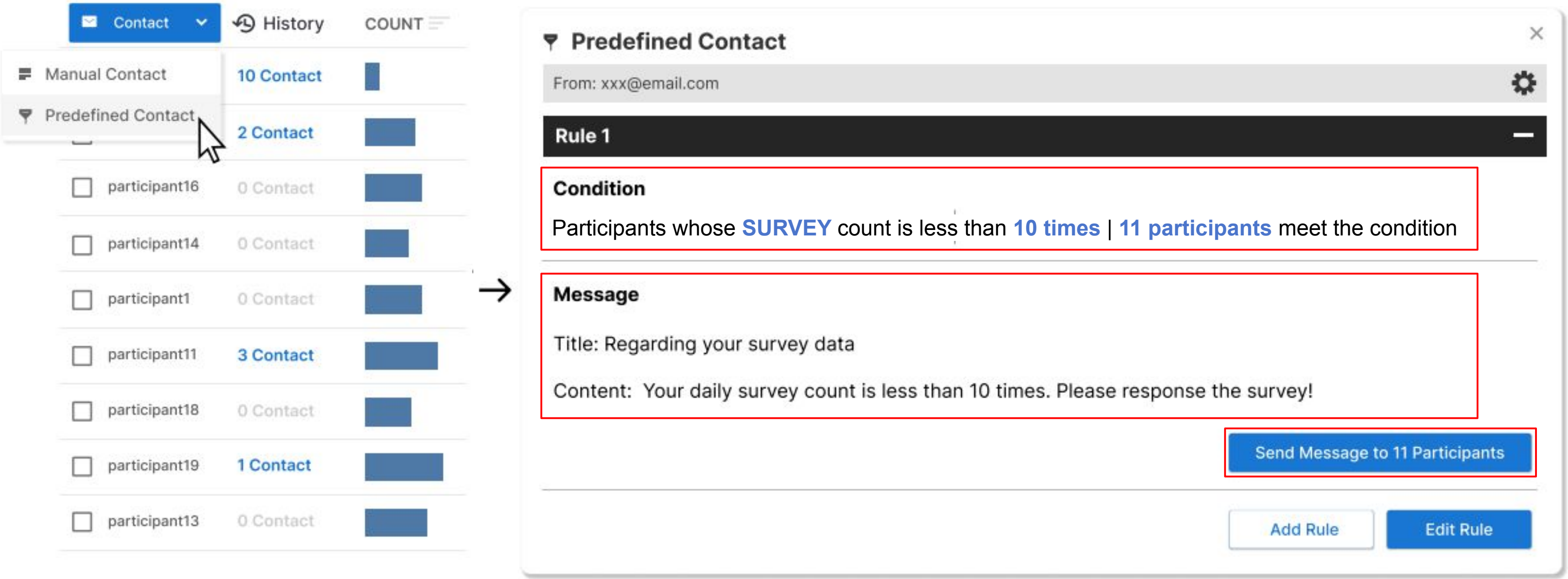
Reflecting Design insight 1

How the selected time interval compares in terms of the distribution of time intervals
1) **Within** the participant's data
2) **Between** participants' data



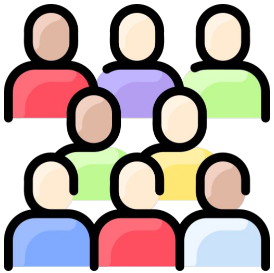
Rule-Based Contact Feature

Reflecting Design insight 2



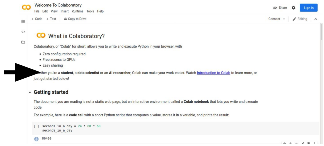
Final Evaluation

Goal 1. To evaluate DataSentry by researchers from various research groups
Goal 2. To observe how user experiences differ depending on whether within- and between-person comparisons are supported



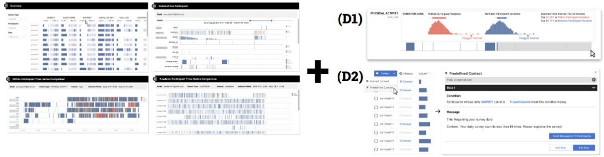
26 researchers from
11 different groups
(Academia and industry)

1. Python plotting
(Google Colab)



2. DataSentry Basic version
(excluding within- and between-participant comparison features)

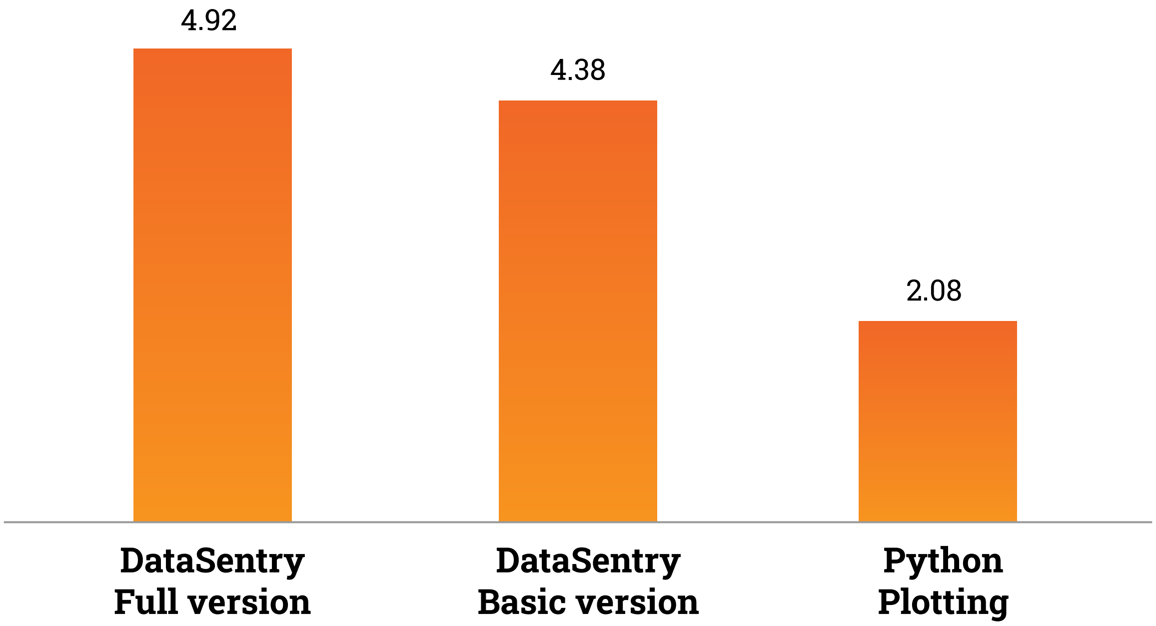
3. DataSentry Full version
(including all features)



Within-subject,
in-lab user study

Final Evaluation

PSSUQ (Post-study system usability questionnaire) score (7-point Likert scale)



Final Evaluation

Helpful in managing missing data, specifically…

Overviewing missing data and **diligence** of participants

"…Keeping track of participant ***diligence*** *has always been a key part of our data collection efforts."*

Detection and diagnosis by **within/between-participant variability**

"By brushing over the empty periods, I could tell if the missing data was an issue, ***both within and between participants****."*

Streamlining **communication** via rule-based supports

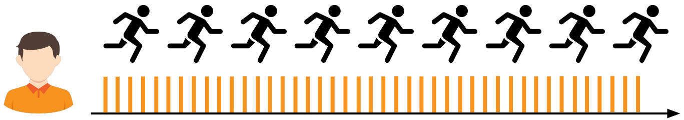
"I appreciated the ability to ***set rules and contact*** *relevant participants…"*

Discussion

Design implication 1

The critical role of understanding within- and between-participant variability to detect and diagnose missing data issues

Detecting and diagnosing missing data considering within- and between-person sensing routines



Frequent logging along
a participant's commuting path

Sparse logging on weekend mornings
between participants

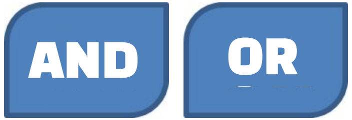
Discussion

Design implication 2

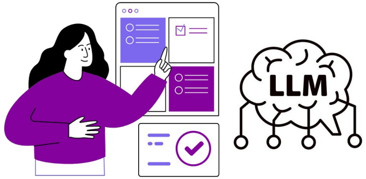
Researchers wanted to define diverse rules related to missing data and communicate with participants based on these rules

Enhancing the expressiveness of missing data management rules

Semantically meaningful predicates



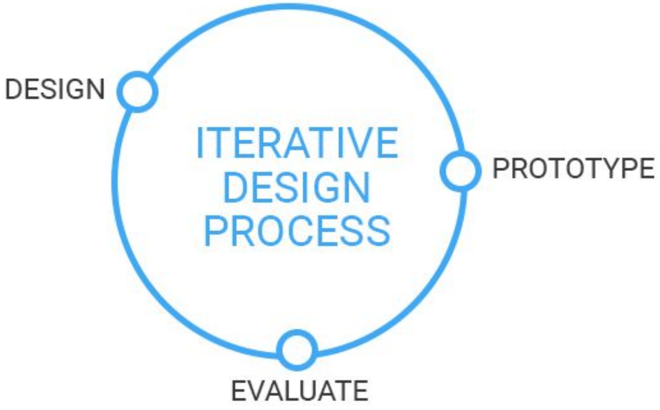
AND/OR conditions



LLM-based rule automation and communications

Discussion

Lessons learned through multi-year, iterative design process



"The in-the-wild deployment and iterative design process was instrumental in uncovering and addressing real-world issues that might have been overlooked in the lab."

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Junmo Lee, Bongshin Lee, Uichin Lee

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