Using GPS Data to Understand the Relationship Between Mobility Behavior and Well-Being

Gabriella M. Harari

Department of Communication
Stanford University

Stanford Media & Personality Lab

(1) What do digital media reveal about who we are?

(2) How do digital media change who we are?

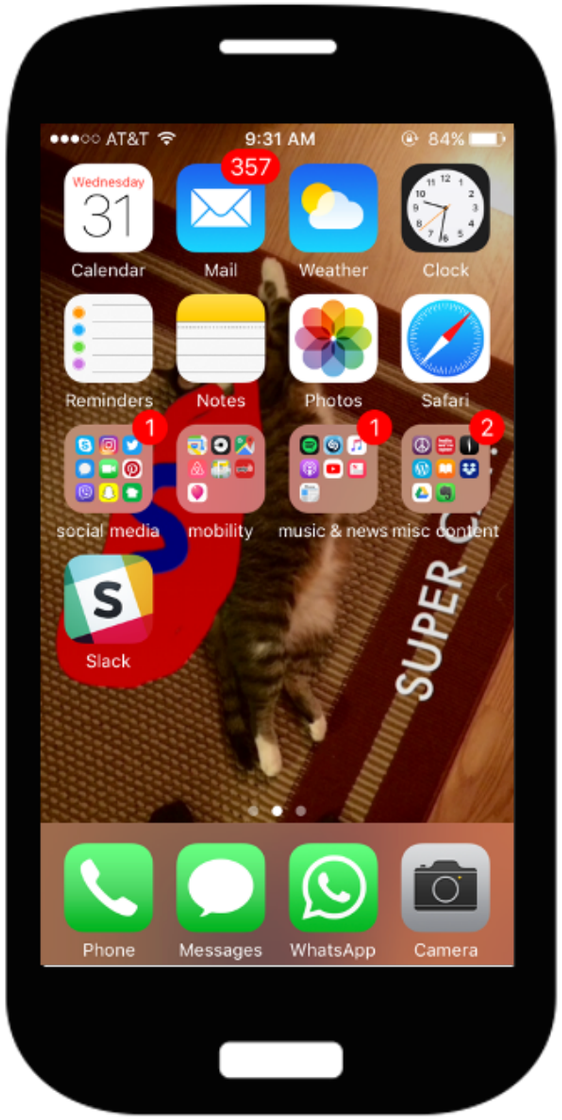
Today's Talk

(1) What do smartphones reveal about our behavior and psychological experiences?

Smartphone Sensing

Active Logging

How are you feeling today?

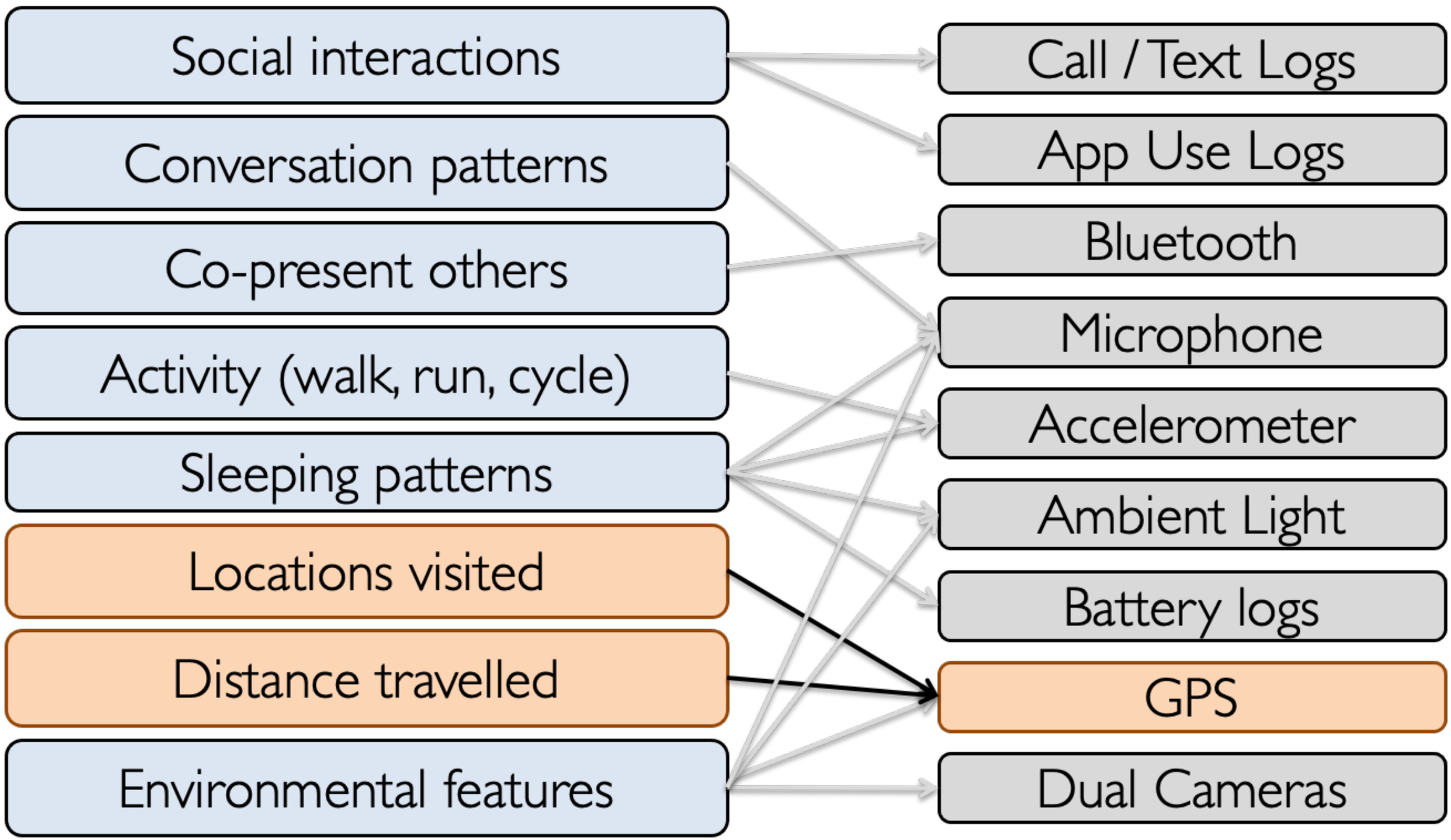


Passive Sensing

- Call / Text Logs
- App Use Logs
- Bluetooth
- Microphone
- Accelerometer
- Ambient Light
- Battery logs
- GPS
- Dual Cameras

Smartphone Sensing

Behavioral inferences from mobile sensing data



Individual Mobility Behaviors and Subjective Well-Being

Sandrine Müller,
Google

Heinrich Peters,
Columbia Business School

Sandra Matz,
Columbia Business School

Weichen Wang,
Dartmouth

(Müller, Peters, Matz, Wang, & Harari, 2020; *EJP*)

Understanding Subjective Well-Being

Cognitive and affective levels of well-being: includes positive and negative affect, as well as cognitive evaluations of one's life

(Diener, 2009)

Different temporal components, including:

- (i) more **enduring aspects of subjective well-being** that typically get measured over a two-week period (e.g., depression)
- (ii) more **short-term aspects of subjective well-being** that typically get measured in the moment (e.g. affect and stress)

Human Mobility

- Refers to the ways in which people interact with and move about their physical environment
  (González, Hidalgo, & Barabási, 2008; Williams, Thomas, Dunbar, Eagle, & Dobra, 2015)

- Previous research on mobility behavior has typically focused on population-level patterns (e.g. air travel, commuting, migration patterns)
  (Anderson, 2015; Belik, Geisel, & Brockmann, 2011; Crawford & Campbell, 2012)

- Less is known about individual mobility behaviors

Individual Movement Patterns

The GPS sensor allows researchers to passively assess patterns in a person's movement, such as:

- the **spatial range of movement** (e.g., distance a person travels)
- the **frequency of movement** (e.g., number of places visited)
- the **degree to which a person's movement is irregular** or conforms to a certain routine
- the **degree to which movement is evenly distributed** across time and space (e.g., entropy, or the amount of time person spends in different places)

Associated with mental health and well-being:

- **Depression** (Canzian & Musolesi, 2015; Saeb et al., 2017, 2016)
- **Loneliness** (Ben-Zeev et al., 2015; Doryab et al., 2019; Wang et al., 2014)
- **Anxiety** (Sano et al., 2018)
- **Affect and Mood** (Chow et al., 2017; DeMasi & Recht, 2017; LiKamWa, Liu, Lane, & Zhong, 2013; Ma, Xu, Bai, Sun, & Zhu, 2012; Sandstrom, Lathia, Mascolo, & Rentfrow, 2017; Servia-Rodriguez et al., 2017)
- **Happiness** (Jaques et al., 2015; Umematsu et al., 2019)
- **Stress** (Ben-Zeev et al., 2015; Sano et al., 2015; Umematsu, Sano, & Picard, 2019; Yamamoto et al., 2018; Zakaria, Balan, & Lee, 2019)
- **Energy** (DeMasi & Recht, 2017; LiKamWa et al., 2013; Sano et al., 2018)

*** Mostly focused on a narrow set of mobility behaviors and/or isolated indicators of well-being.**

Depression symptoms associated with:

(i) longer stays at home

(ii) lower circadian movement (i.e. a less regular 24-hour rhythm)

(iii) less transition time (i.e. amount of time spent in a non-stationary state per day)

(iv) lower normalized entropy (i.e. more variability of time spent at key locations)

(v) lower location variance

(vi) smaller number of location clusters visited

(vii) lower total distance covered

(Ben-Zeev, Scherer, Wang, Xie, & Campbell, 2015; Canzian & Musolesi, 2015; Farhan et al., 2016; Howe, Ghandeharioun, & Pedrelli, 2017; Saeb et al., 2017, 2016; Saeb, Zhang, Kwasny, et al., 2015; Yue et al., 2018)

Research Aims

- Examine the underlying behavioral dimensions that may characterize individuals based on GPS-based movement features.
- Investigate the relationship between movement patterns and multiple indicators of subjective well-being in a large sample of young adults.
- Explore these relationships for more enduring (*depression, loneliness*) and short-term aspects of well-being (*affect, stress, anxiety, and energy*).

Research Questions

1. What **underlying behavioral dimensions** might be used to characterize patterns in individual mobility behavior?

2. How do people's **mobility behavior tendencies** (over a two-week period) relate to their subjective depression and loneliness tendencies?

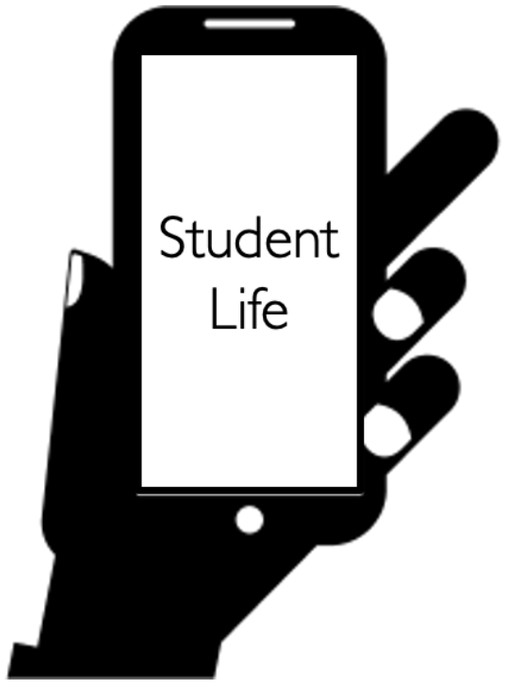
3. How do people's **daily mobility behaviors** relate to their daily affect, stress, anxiety, and energy level?

Method

- 778 students enrolled in a psychology online course at a large university in the United States, who participated for an average of 7 days (SD = 3 days).
  Age: M = 18.94, SD = 2.22
  60.49% female

- Self-tracking assignment to monitor behaviors to obtain insight into lifestyles and college experience, using one of 3 modalities:
  (i) a mobile app —> the focus of the current study.
  (ii) emailed surveys
  (iii) handwritten journal

- Completed one-time surveys and repeated surveys 4x per day (12pm, 3pm, 6pm, 9pm).
  M = 22 repeated surveys completed (SD = 10)



(Wang et al., 2014)

GPS data collected from app

- Time-stamped longitude and latitude coordinates. Outliers were removed.
- Overall number of GPS observations that were analyzed was 558,385 records.
  (M = 714 data points per person; SD = 313)
- Extracted features at two levels to assess both: (i) general movement tendencies over the entire two-week period, and (ii) daily-level movement patterns.

userid	deviceid	senseStartTi	senseStartTimeM	latitude	longitude
285764	351912060681237	08:32:02:978	1454315522978	52.2144859	0.1072277
285764	351912060681237	08:32:02:978	1454315522978	52.2144886	0.1072606
285764	351912060681237	08:32:02:978	1454315522978	52.2144952	0.107242
285764	351912060681237	08:45:00:010	1454316300010	52.2137459	0.1110568
285764	351912060681237	08:45:00:010	1454316300010	52.2109101	0.1150116
285764	351912060681237	08:45:00:010	1454316300010	52.2108887	0.1149992
285764	351912060681237	09:00:00:016	1454317200016	52.197969	0.1195136
285764	351912060681237	09:00:00:016	1454317200016	52.1979848	0.1195522
285764	351912060681237	09:00:00:016	1454317200016	52.1980592	0.1196755

List of mobility metrics
Displacement variance
Max. distance from home
Spatial coverage by convex hull approx.
Location variance
Max. distance between two locations
Radius of gyration
Total distance covered
Speed (mean)
Speed (variance)
Raw entropy
Time spent at each location
Entropy
Normalized entropy
Percentage of time spent at home
Displacement entropy
Routine index (max)
Circadian rhythm
Routine index (SD)
Number of clusters
Tiles sequence

Results

RQ1. What underlying behavioral dimensions might characterize patterns in individual mobility behavior?

Factor analyses of 23 GPS-based features characterizing movement tendencies

Distance

Variables	Factor 1: Distance Loadings
Spatial coverage by convex hull	**.99**
Maximum distance from home	**.99**
Location variance	**.97**
Standard deviation of displacements	**.96**
Maximum distance between two locations	**.95**
Total distance covered	**.92**
Radius of gyration	**.90**
Speed mean	**.53**
Spatial coverage by tiles	**.46**

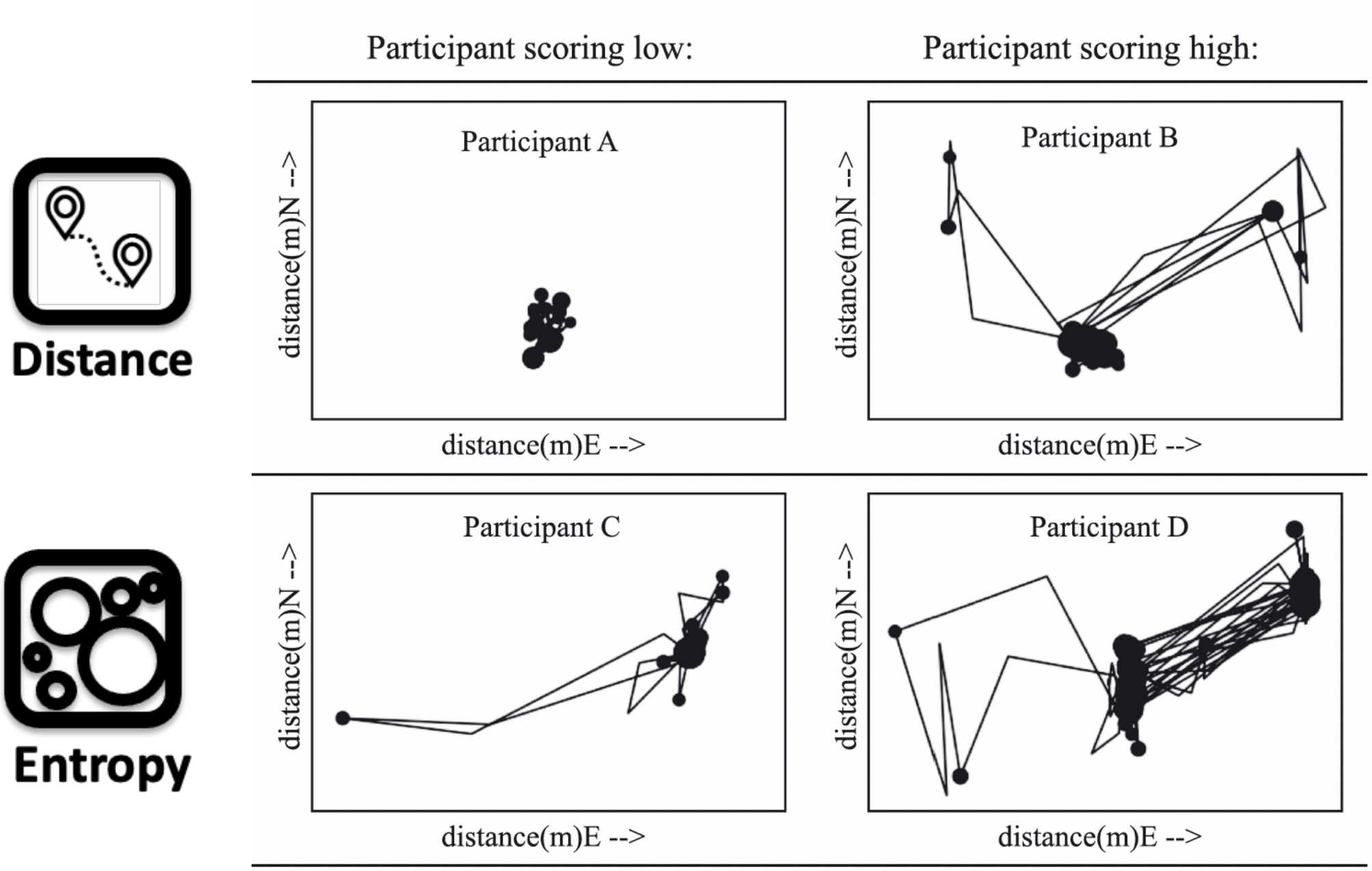
Entropy

Variables	Factor 2: Entropy Loadings
Raw entropy	**.91**
Normalized entropy	**.86**
Time spent at each location	**−.86**
Entropy	**.83**
Home stay	**−.76**
Displacement entropy	**.68**

Irregularity

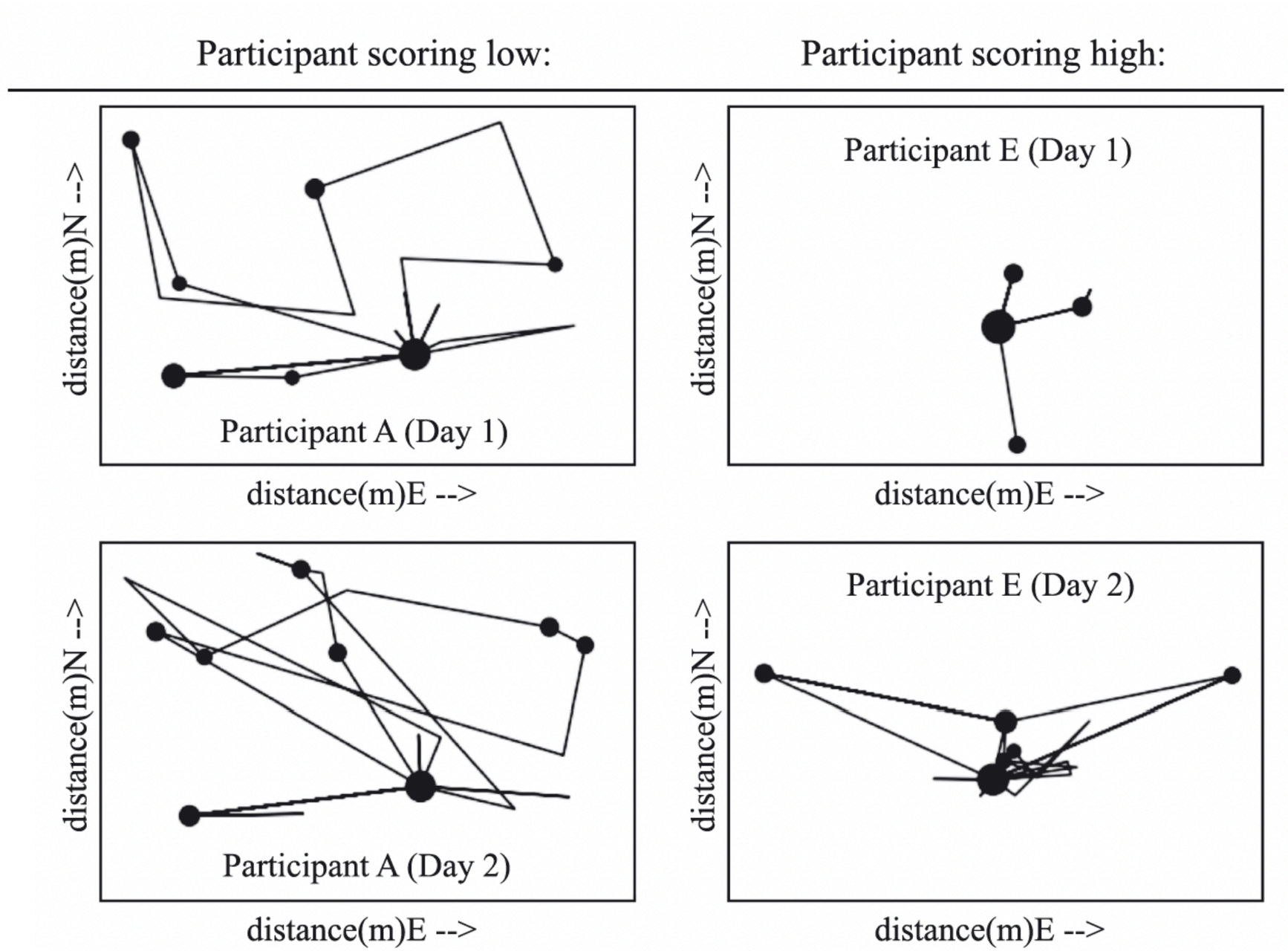
Variables	Factor 3: Irregularity Loadings
Tiles sequence edit distance	**.89**
Location sequence edit distance	**.88**
Location changes	**.86**
Circadian movement	**−.82**
Routine index	**.82**
Time in transit	**.78**
Number of locations visited	**.68**

RQ1: What underlying behavioral dimensions might characterize patterns in individual mobility behavior?



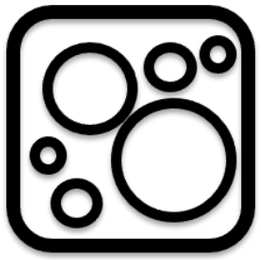
RQ1: What underlying behavioral dimensions might characterize patterns in individual mobility behavior?

Irregularity



RQ2: How do people's mobility behavior tendencies relate to their subjective well-being tendencies?

Correlations between movement and well-being tendencies

Factor scores reflecting two-week tendencies	Depression	Loneliness
 **Distance**	- . 04	.00
 **Entropy**	- . 05	- . 02
 **Irregularity**	- .12*	- .12*

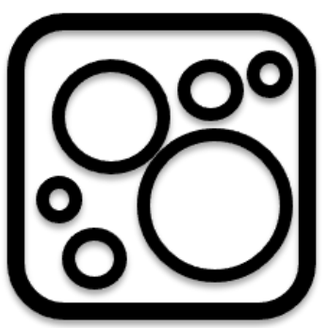
(* $p < .05$)

RQ3: How do people's daily mobility behaviors relate to their daily well-being?

Series of random intercept multilevel models with daily observations nested within individuals.

Distance

- On days when people travelled further distances, they also reported less anxiety and stress, and more positive affect.



Entropy

- On days when people showed higher entropy, they also reported less stress.

Irregularity

- On days when people showed higher levels of irregularity, they also reported less energy.

Summary

Distance

Entropy

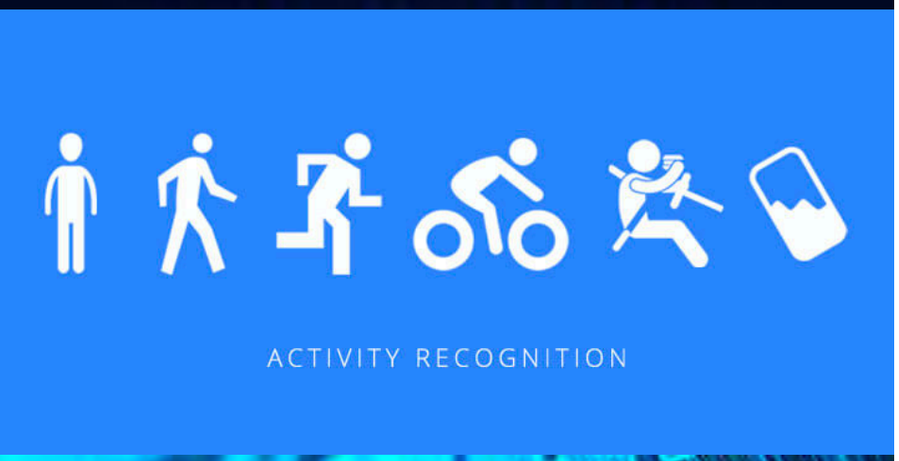
Irregularity

- GPS-based features map onto 3 latent behavioral dimensions.
- People who tend to have more irregular movement patterns tend to report being less depressed and lonely.
- People tend to report greater subjective well-being on days when they are actively engaging with and exploring their physical environment.

Implications

- Contributes to the broader literature on physical movement and subjective well-being
    - Field experiments are needed to test causal direction of observed relationships (e.g. nudging people to explore their environments)
- Development of better diagnostic tools for a range of mental illnesses
- Encouraging awareness of psychologically meaningful inferences that can be made about individuals based on their GPS data

Limitations and Directions for GPS Research



- **Practical:**

  Interdisciplinary research teams
  Technical expertise needed
  Handling big data

- **Analytical:**

  Data processing and feature extraction
  Developing measures
  Modeling strategies

- **Ethical:**

  Data security
  Privacy concerns
  Transparency and opt-in features

LIFE SENSING CONSORTIUM (LSC)

https://lifesensingconsortium.org/

Conducting High Impact Interdisciplinary Sensing Research

Building an Intellectual Community

Supporting Open Science Practices

Acquiring Research Funding

Saeed Abdullah

Assistant Professor, Penn State.

Gabriella Harari

Assistant Professor, Stanford.

Edison Thomaz

Assistant Professor, UT Austin.

Thank you!

contact: gharari@stanford.edu

- For more information:
  Müller, S. R., Peters, H., Matz, S., Wang, W., & Harari, G. M. (2020). Investigating the Relationships Between Mobility Behaviors and Indicators of Subjective Well-Being Using Smartphone-based Experience Sampling and GPS Tracking. *European Journal of Personality.* 714-732.

Sandrine Müller, Google

Heinrich Peters, Columbia Business School

Sandra Matz, Columbia Business School

Weichen Wang, Dartmouth

Stanford MAP Lab

Sam Gosling, UT Austin

Andrew Campbell, Dartmouth