

# An exploratory analysis of mobile phone sensor-derived mobility patterns and experiential avoidance using digital phenotyping

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## Background

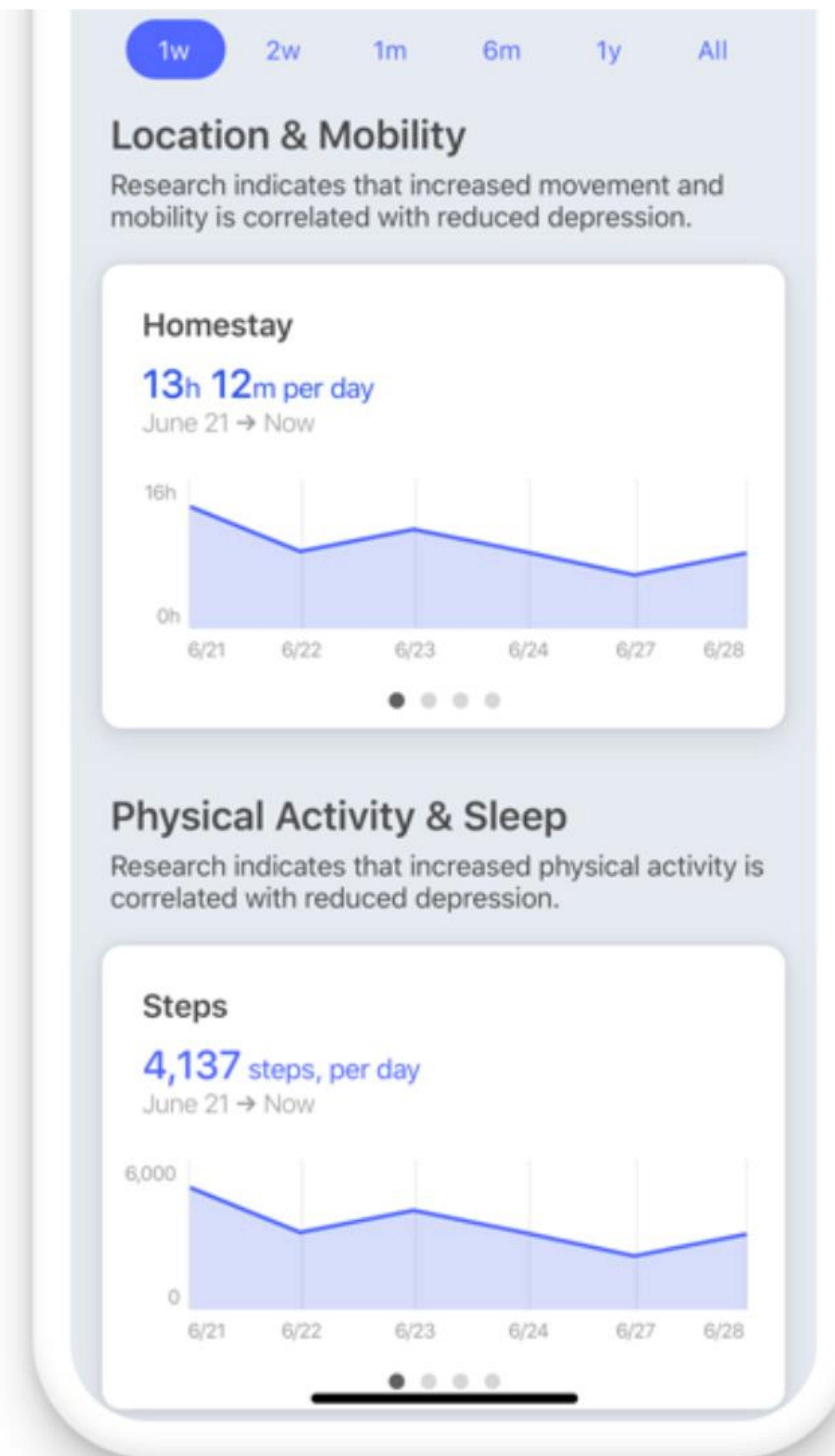
Digital phenotyping refers to the moment-by-moment in-situ capturing of social and behavioral experiences in naturalistic settings as lived by the individual (1). Using mobile phone sensor data, digital phenotyping has traditionally been applied to the medical model of mental health, whereby passively-collected behavioral phenotypes are mapped onto diagnostic constructs (2-3). While this approach can revolutionize proactive technology-driven care, current pathology-oriented research in this domain is not well aligned with contextual behavioral initiatives that emphasize acceptance and mindfulness-based approaches to understanding health and wellness. Thus, we aimed to apply digital phenotyping principles to investigate the relationship between weekly mobility patterns and psychological flexibility.

## Method

De-identified user data were extracted from 58 treatment-seeking individuals ( $M$  age = 28.2) who were using the Blueprint mobile application as part of their standard course of outpatient care. Individuals provided consent to share their health data upon enrolling on the platform.

Weekly mobility pattern features were extracted from pedometer and GPS sensors (see 2 for detailed information on feature extraction and pre-processing procedures used in the study). Features were averaged across weeks for subsequent analysis. Experiential avoidance was measured on a weekly basis using the Acceptance and Action Questionnaire II (AAQ-II). Multiple imputation methodology was used to account for missingness in the self-report (AAQ-II) data.

A multilevel time series model was used to explore the within-subject contemporaneous relationships between mobility patterns and experiential avoidance.



## Descriptive Statistics

<b>Sample size (N)</b>	58
<b>Mean Age (SD)</b>	28.2 (4.2)
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<b>Experiential Avoidance (AAQ-II)</b>	
Mean score (SD)	26.2 (5.4)
Mean 12 week within-subject point change (SD)	-10.2 (4.9)
<b>Homestay</b>	
Mean (SD)	18.2 (7.7)
Mean 12 week within-subject point change (SD)	-1.8 (0.8)
<b>Physical Activity</b>	
Mean (SD)	2,202 (986)
Mean 12 week within-subject point change (SD)	210 (54.4)
<b>Location Variance</b>	
Mean (SD)	3.8 (0.9)
Mean 12 week within-subject point change (SD)	0.5 (0.2)

## Daily Mobility Features Extracted

### Homestay

- **Definition:** Hours spent at home per day
- **Data Source:** GPS (iPhone) + Address Verification

### Physical Activity

- **Definition:** Number of steps taken per day
- **Data Source:** Pedometer (iPhone or connected wearable)

### Location Variance

- **Definition:** Variability of daily stationary state locations
- **Data Source:** GPS (iPhone)

## Results

Participants completed 81% of the weekly assessments sent via the Blueprint mobile application. Two outliers were removed due to technical issues resulting in GPS feature inconsistencies.

Results indicated that experiential avoidance was significantly predicted by location variance,  $b = -0.61$ ,  $t(204.3) = -2.4$ ,  $p = 0.03$ , and homestay,  $b = 0.55$ ,  $t(213) = 2.1$ ,  $p = 0.04$ , but not physical activity,  $b = -0.1$ ,  $t(210.1) = -0.9$ ,  $p = 0.09$ .

## Conclusion

Our study provides preliminary evidence supporting the feasibility of using real-time mobile phone sensor data as a continuous passive indicator of experiential avoidance. Digital phenotyping may thus represent a scalable and context-sensitive solution for improving population-wide contextual behavioral prevention and intervention efforts. However, recent events (i.e., COVID-19) elucidate the challenges to maintaining adequate ecological validity when relying solely on daily mobility metrics that may be influenced by outside events.

## References

1. Insel, T. (2018). Digital phenotyping: A global tool for psychiatry. *World Psychiatry*, 17(3), 276-277.
2. Saeb et al., (2015). Mobile phone sensor correlates of depressive symptom severity in daily life behavior: An exploratory study. *J Med Internet Res.*, 17(7) 175
3. Insel, T. (2017). Digital phenotyping: Technology for a new science of behavior. *JAMA*, 318(13), 1215-1216

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