



Feasibility of Using Behavioral Marker via Mobile Sensors in Measuring Physical Activity : A Pilot Study

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◆ Background

- Direct observation of behaviors is the main assessment method of behavior analysis(Pierce & Cheney, 2013). However, data collection is limited due to practical difficulties of collecting vast amount of information with accuracy(Gardner, 2000).
- Recently, mobile sensors have emerged as an effective and efficient way to measure passive data for behaviors (Rohani et al., 2018), as mobile sensors allow the collection of data as they occur, thus minimizing the loss of data.
- However, the use of passive data in behavioral research has not been fully investigated in terms of reliability and validity, calling for further research to confirm the consistency between the collected passive data and the participant's self-reports. (Singh & Agarwal, 2016).

◆ Purpose

- The purpose of this study was to test the feasibility of using passive data collected via mobile sensors in explaining self-report regarding physical activity.

◆ Method

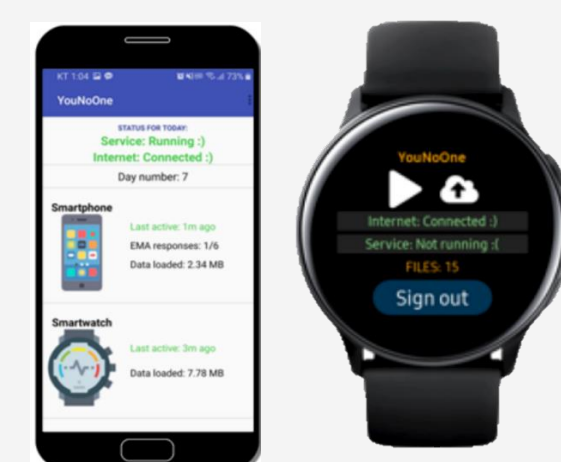
Participants

- 15 college students (Age mean=28.4; male N=9, female N=6)

Procedure

- For 15 days
- YouNoOne, mobile sensing software, on smartphone and smartwatch(Samsung Galaxy Gear S3, Active)
- Data collection

Passive data	Self-report (EMA*)
<ul style="list-style-type: none">- Heart rate(HRM)- Step counts- Significant motion counts	Q. Your status in last 10 minutes? 1. Status (study, rest, exercise, eat, on transportation, talk) 2. Intensity (1~5) 3. Location (home, study place, workplace, outside) 4. Ability to move (yes or no)
- 24 hours / 7days	- 6 times a day



YouNoOne

* Ecological Momentary Assessment

Data Analysis

- Hierarchical linear regressions were conducted to examine explanation power of passive sensing data on self-reported physical activity in SPSS 25.

◆ Results

- After controlling for the location and ability to move, passive data significantly and uniquely accounted for the self-reported status of physical activity($F(5,63) = 27.046$, $p < 0.01$, $\Delta R^2 = 0.067$), but not the intensity.

Table 1. Effect of passive sensing data on self-reported status of physical activity

Predictor	B	SE	β	t
Block 1				
Constant	.03	.04		.65
Dummy1_location	-.03	.11	-.02	-.24
Dummy3_location	-.03	.12	-.02	-.22
Dummy4_location	.67	.09	.70	7.72
Dummy5_location	-.03	.11	-.02	-.22
Dummy6_location	..22	.13	.16	1.73
R² = .511				
Block 2				
Constant	.06	.10		.56
Dummy1_location	-.02	.11	-.02	-.20
Dummy3_location	-.03	.12	-.02	-.24
Dummy4_location	.67	.09	.70	7.67
Dummy5_location	-.05	.14	-.04	-.35
Dummy6_location	.23	.13	.16	1.74
Dummy_ability	-.03	.10	-.03	-.32
$\Delta R^2 = .512$				
R² = .001				
Block 3				
Constant	.60	.26		2.29
Dummy1_location	-.05	.11	-.04	-.47
Dummy3_location	-.08	.11	-.06	.73
Dummy4_location	.71	.10	.73	7.76
Dummy5_location	-.12	.14	-.10	-.88
Dummy6_location	.22	.13	.15	1.78
Dummy_ability	-.14	.11	-.14	-1.26
HRM	-.01	.00	.26	-2.17
Step_counts	.00	.00	-.03	-.21
SigMotion_counts	.01	.00	-.25	2.58
$\Delta R^2 = .580$				
R² = .067*				

Table 2. Effect of passive sensing data on self-reported intensity of physical activity

Predictor	B	SE	β	t
Block 1				
Constant	.03	.04		.59
Dummy1_location	-.03	.12	-.02	-.22
Dummy3_location	-.03	.13	-.01	-.20
Dummy4_location	1.07	.10	.82	9.19
Dummy5_location	-.03	.13	-.01	-.20
Dummy6_location	..22	.14	.11	1.58
R² = .682				
Block 2				
Constant	.01	.11		-.04
Dummy1_location	-.03	.12	-.02	-.24
Dummy3_location	-.02	.13	-.01	-.17
Dummy4_location	1.1	.10	.82	9.58
Dummy5_location	-.00	.15	-.01	-.02
Dummy6_location	.22	.14	.11	1.54
Dummy_ability	-.03	.11	-.03	-.30
$\Delta R^2 = .683$				
R² = .001				
Block 3				
Constant	.17	.31		0.55
Dummy1_location	-.04	.12	-.03	-.33
Dummy3_location	-.04	.13	-.03	.33
Dummy4_location	.94	.10	.85	10.32
Dummy5_location	-.02	.16	-.01	-.14
Dummy6_location	.23	.15	.12	1.53
Dummy_ability	-.02	.13	-.01	-0.13
HRM	-.00	.00	.05	-0.49
Step_counts	.00	.00	-.07	-.80
SigMotion_counts	.01	.00	-.06	-.55
$\Delta R^2 = .688$				
R² = .005				

◆ Discussion

- The significant R^2 suggests that passive data accounts for 6.7% of the self-reported status of physical activity, and thus suggests that passive data is feasible in measuring physical activity.
- However, passive data did not significantly explain the self-reported intensity of physical activity. A possible reason may be that there is less variation possible in intensity, compared to status. This further suggests that passive data may not be sensitive enough to detect subtle changes in the intensity of physical activity.
- The results indicate that passive data collected via mobile sensing can partially explain the self-reported status of physical activity and has the potential to be used to measuring behaviors in the context of physical activity.
- However, further studies should include various sensors to measure physical activity and should use more reliable self-report questionnaires to enhance the explanation power of passive data on self-reported physical activity data.

Reference

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