Table S2. Study findings for studies with nonclinical samples. F: Female; M: Male; pat: patient; contr: healthy control; *P < .05; **P < .01; °: Significance not reported; ¥: Human labeled, not objective

Main Author;year	**Feature category**	**Sensor**	**Feature;description**	**Results on outcome**
Asselbergs [3];2016	Physical activity	Accelerometer	Vigorous activity	r = .116**
	Device	Screen	Screen active frequency	r = .034
	Device	Screen	Screen active duration	r = -.074*
	Device	Phone	Images taken	r = .062
Baras [4];2016	Social	SMS log	SMS recieved	r = .542°
	Social	SMS log	SMS sent	r = .573°
Becker [5];2016	Physical activity	Accelerometer	Vigorous activity	β = 0.08
Ben-Zeev [17];2015	Social	Microphone	Speak duration	*P* = 0.048*
	Location	GPS+WIFI	Geospatial; log-transformed total distance	*P* = 0.022*
	Physical activity	Accelerometer	Kinesthetic; number of active periods	*P* > 0.05
	Subject	Multi sensor	Sleep duration; measured with screen, accelerometer, sound and light	*P* = 0.028*
Berke [8];2011	Social	Microphone	Speaking duration	r = -.73
Canzian [9];2015	Location	GPS	DT; Total distance covered	r = -.0252
	Location	GPS	DM; Maximum distance between two location clusters	r = -.0161
	Location	GPS	Coverage area; distances from locations to center	r = -.0090
	Location	GPS	Standard deviation of displacement	r = .0210
	Location	GPS	DH; Maximum distance between home and location	r = -.0175
	Location	GPS	Ndif; The number of different places visited	r = -.0203
	Location	GPS	Routine index; difference between daily mobility behavior	r = .0359
Cho [1]; 2016	Social	Call log	Call frequency	F/M: r = 0.049/-0.052
	Social	Call log	Call duration	F/M: r = 0.059/-0.031
Chow [10];2017	Location	GPS	Home stay (10AM-6PM)	Std. β = 0.03
DeMasi [11];2016	Subject	Accelerometer	STD of sleep	β = 7.2**
	Physical activity	Accelerometer	Activity (daytime)	β ≈ 0
	Physical activity	Accelerometer	STD stillness activity	β = -3.3**
	Physical activity	Accelerometer	Entropy	β ≈ 0

Edwards [12];2016	Physical activation	Pedometer	Activity (Step counter)	F = 11.85**
Farhan [13];2016	Location	GPS	Location variance; Variability in a subjects GPS location	r = -.15
	Location	GPS	Normalized distance; The amount of movement normalize with time period	r = -.13
	Physical activity	GPS	Movement speed	r = -.09
	Physical activity	GPS	Activity (duration)	r = .06
	Location	GPS	Entropy; The variability of the time the participant spent at the location clusters	r = -.16*
	Location	GPS	Normalized Entropy	r = -.21**
	Location	GPS	Home stay	r = .18*
	Location	GPS	Number of clusters	r = -.09
	Physical activity	Accelerometer	Activity	r = -.11
	Physical activity	Accelerometer	Inactive	r = .10
Mark [19];2016	Subject	Accelerometer	Sleep duration	β = 0.02**
	Physical activity	Accelerometer	Activity	β = 0.0001
Matic [16]; 2011	Physical activity	Accelerometer	Activity	r = -.26*
	Location	FM-position	Breaks; time spent in break room or balcony	r = -.21
Mehrotra [18];2016	Device	Notification	Acceptance; % notifications clicked	|r| < .2**
	Device	Notification	ST; time from arrives until seen	|r| < .2
	Device	Notification	DT; time from seen until acted upon	|r| < .2
	Device	Notification	RT; Response time (ST + DT)	|r| < .2**
	Device	App	App frequency (number of lunched apps)	|r| < .2
	Device	App	App duration	|r| < .2
	Device	Screen	Screen active duration	|r| < .2**
	Device	Screen	Screen active frequency	|r| < .2
	Device	Screen	Screen unlocks	|r| < .2**
Mestry [2]; 2015	Device	App	Communication apps used	r = -.33**
	Location	Internet	Distinct location visited – found through Telephony Manager	r = .09
	Device	Data usage	Network data transmitted	r = .07
	Social	Call log	Call duration (incoming)	r = .22
	Device	Screen	Screen active duration (between 9pm-10pm)	r = -.03
Pillai [20]; 2014	Subject	Accelerometer	Sleep onset latency	r = .21*
	Subject	Accelerometer	Sleep duration	r = .05

	Subject	Accelerometer	Sleep efficiency	r = -.15*
Saeb [6];2015	Location	GPS	Entropy	r = -.42
	Location	GPS	Normalized entropy	r = -.58*
	Location	GPS	Location variance	r = -.58*
	Location	GPS	Home stay	r = .49*
	Location	GPS	Transition time	r = .21
	Location	GPS	Circadian rhythm	r = -.63**
	Location	GPS	Number of clusters	r = -.09
	Physical activity	GPS	Activity	r = -.08
	Device	Screen	Screen active duration	r = .54*
	Device	Screen	Screen active frequency	r = .52*
Saeb [7];2016	Location	GPS	Location variance	r = -.43*
	Location	GPS	Circadian movement	r = -.48*
	Location	GPS	Speed mean	r = -.06
	Location	GPS	Speed variance	r = -.06
	Location	GPS	Number of clusters	r = -.44*
	Location	GPS	Entropy	r = -.46*
	Location	GPS	Normalized entropy	r = -.44*
	Location	GPS	Raw entropy	r = .22
	Location	GPS	Home stay	r = .43*
	Location	GPS	Transition time	r = -.32
	Physical	GPS	Total distance	r = -.18
Wang [14];2015	Subject	Camera	Image brightness, contrast and saturation	All three not significant
	Subject	¥ Camera	Label: laying down; if person, during EMA, was laying down	r = .51**
Wang [15];2014	Subject	Multiple-sensor	Sleep duration; light, lock-state, accelerometer and microphone	r = -.382*
	Social	Call log	Call frequency	r = -.387*
	Social	Call log	Call frequency (evening)	r = -.345*
	Social	Call log	Call duration	r = -.328*
	Location	Bluetooth	Co-located Bluetooth deices	r = -.362*

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