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Capturing Individual and Group Behavior with Wearable Sensors

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Abstract

We show how to obtain high level descriptions of human behavior in terms of physical activity, speech activity, face-to-face interaction (f2f), physical proximity, and social network attributes from sensor data. We present experimental results that show that it is possible to identify individual personality traits as well as subjective and objective group performance metrics from low level data collected using wearable sensors.

Introduction

Organizational behavior is the systematic and scientific analysis of individuals, groups, and organizations. Its purpose is to understand, predict, and improve the performance of individuals, and ultimately, the organizations in which they work. There are three building blocks that make up the field of organizational behavior: the individual, groups, and the organization (Tosi, Mero, and Rizzo 2000). At the individual level several aspects such as personality, perceptions, attitudes, and judgment are studied. At the group level, one is concerned with the way groups are formed, group dynamics and group performance. At the organizational level different types of organizational structures and they way these structures affect the performance of the organization are studied.

Human behavior modeling has been approached from disciplines such as behavioral science, social science, cognitive science and artificial intelligence among others. Researchers have developed several models of human behavior, from cognitive and affective states to human activities. However, to the best of our knowledge, few researchers have focused on measuring and modeling organizational behavior using low level data from environmental and wearable sensors.

One of the first attempts to measure face-to-face interactions between people using wearable sensors was the *sociometer*(Choudhury and Pentland 2003). This wearable sensor package was used to learn social interactions from sensory data and model the structure and dynamics of social networks (Choudhury 2004). Pentland describes several statistical learning methods that use wearable sensor data to make reliable estimates of users' interactions (Pentland 2006). He presents a detailed description of eigenbehavior modeling for learning and classifying user behavior from proximity and location data, and influence modeling for predicting the behavior of a subject from another subject's data.

Our research group has developed several wearable sensing platforms to automatically capture individual and collective patterns of behavior, predict human behavior from unconscious social signals, identify social affinity among individuals working in the same team, and enhance social interactions by providing real-time feedback. Our latest platform uses *sociometric* badges to measure and analyze organizational behavior (Olguin-Olguin et al. 2009).

We instrumented a group of 67 nurses working in the Post Anesthesia Care Unit (PACU) of a Boston area hospital with *sociometric* badges capable of measuring physical activity, speech activity, face-to-face interaction, and physical proximity. Using the data collected with these sensors we have been able to identify different personality traits and estimate the overall group's perception of workload, difficulty to obtain information, quality of group interaction, productivity and stress, as well as the average patient recovery time and daily number of delays.

Background and Hypothesis

Personality

Over time researchers have tried to describe and measure personality traits (individual tendencies to react emotionally or behaviorally in a specific way) using various tests. The most popular model is the "Big Five" model that describes five personality traits (Tosi, Mero, and Rizzo 2000):

- (N) Neuroticism. Being highly emotional, tense, insecure, suffering from depression, and easily upset, suspicious and having low self confidence.
- (E) Extroversion. Tendency to be sociable, liking to be with others, energetic and forceful.
- (O) Openness. Being imaginative, curious, cultured, broad minded, having broad interests and tending to be self-sufficient.
- (A) Agreeableness. Tendency to be more tolerant, trusting, generous, warm, kind, good-natured, and less likely to be aggressive, rude and thoughtless.

- (C) Concscientiousness. Being responsible, dependable, persistent, punctual, hard working, and oriented toward work.

Hypothesis 1 Personality traits manifest themselves in the the way individuals speak, move, and interact with others. Therefore it is possible to identify personality traits from individual behavioral sensor data.

Group Behavior

The study of groups has been a focus across the social and behavioral sciences for over 50 years. Poole et al. have described nine different interdisciplinary perspectives on small groups (Poole et al. 2004). We are particularly interested in two of these nine perspectives: the *social-evolutionary perspective* which posits that group structure and interaction reflect evolutionary forces that have shaped human social behaviors over thousands of years, and the *social network perspective* which considers groups as interlinked structures embedded in larger social networks. The social-evolutionary perspective treats groups as aggregates of individuals and views group behavior as the product of individual behaviors that scale up to the group level; whereas the social network perspective uses members attributes and social network properties as inputs and treats performance, efficiency, cohesiveness, attitude, and belief convergence as the model outputs.

Hypothesis 2 Aggregate individual behaviors described in terms of physical activity, speech activity, face-to-face interaction, physical proximity, and social network attributes are predictive of group performance.

Method

Participants

The sample was composed of 67 nurses who worked in the Post Anesthesia Care Unit (PACU) of a Boston-area hospital. Each nurse wore a sociometric badge every day for a period of 27 days. In total we collected 3,906 hours of data. The mean number of hours each participant wore a badge was 7.18 hours per day ($\pm$4.17).

At the end of each day the participants were asked to answer a job performance survey that included the following questions:

- Q1. How would you rate your workload today?
- Q2. How hard was it to obtain the information that you needed to do your job?
- Q3. How would you rate the quality of your work group interaction today?
- Q4. How satisfied do you feel with your job performance today?
- Q5. How productive do you think you were today?
- Q6. How much stress were you under today?

Each question could be answered according to the following 5-point likert scale: (1 = very low) (2 = low) (3 = average) (4 = high) (5 = very high). In total we collected 226 valid surveys. At the end of the study 39 participants also answered a NEO-FFI (NEO Five Factor Inventory) questionnaire (Costa and McCrae 2008) that contains 60 questions and is designed to measure the five personality traits described in the background section.

Experimental set-up

The hospital has 50 Operation Rooms (OR). After surgery is completed, patients are taken to the Post Anesthesia Care Unit (PACU), where they are kept under supervision until they recover from anesthesia. Thereafter they are admitted to the floor units where they convalesce before being discharged. Patients without assigned beds on the floors are kept in the PACU until vacancies on the floors can be found. The PACU is a critical intermediary step in the surgical patient throughput system and it consistently experiences delays of various kinds. These delays cause hold ups in the OR resulting in schedule disruptions, overtime work and productivity losses. This translates into loss of revenue for the hospital since the health-care system reimburses a fixed sum for a particular surgical procedure irrespective of the patient's length of stay in the hospital (Samarth 2007).

We placed base stations next to each bed and phone in the PACU in order to detect when the nurses were in close proximity to a bed or a phone and track their location and displacement patterns. There were 37 beds in the PACU, with only 30 being used during the study and 12 phones distributed around the room for patient scheduling.

Procedure

Table 1 shows the list of features that were calculated on a per-minute basis from the sensor data grouped by behavior description. The daily average and standard deviation of the per-minute features were calculated for each participant. Table 2 shows the notation that we use when we refer to the daily features. We used correlation analysis to identify personality traits from the individual daily features, and stepwise multiple linear regression analysis to predict the overall perception of workload, difficulty to obtain information, quality of work group interaction, job performance, productivity, and stress, as well as the average patient recovery time and number of delays from the daily features aggregated across subjects.

Measurements

Physical activity

A 3-axis accelerometer signal should be sampled at $f_s \geq 30$ Hz in order to capture the range of human movement since 99% of the acceleration power during daily human activities is contained below 15 Hz (Mathie et al. 2004). The acceleration signal vector magnitude ($|\vec{a}'_i|$) provides a measure of the degree of movement intensity that includes the effect of signal variations in the three axes of acceleration (Karantonis et al. 2006). $|\vec{a}'_i|$ is calculated on the normalized i^{th} acceleration sample as follows:

$$|\vec{a}'_i| = \sqrt{a'^2_{x_i} + a'^2_{y_i} + a'^2_{z_i}} \quad (1)$$

Behavior Description	Variable	Sensor features calculated every minute
Physical activity	Intensity	(F^1) Mean signal magnitude (F^2) Standard deviation of signal magnitude (F^3) Power or energy per minute
Speech activity	Speech volume	(F^4) Mean volume modulation (F^5) Standard deviation of volume modulation
	Speaking time	(F^6) Speaking time in minutes
	Voiced speaking time	(F^7) Voiced speaking time in minutes
Face-to-face interaction (f2f)	f2f time	(F^8) f2f time in minutes
	Number of people with f2f	(F^9) Number of different people
Proximity	Time in close proximity to other people	(F^{10}) Time in minutes
	Time in close proximity to a bed	(F^{11}) Time in minutes
	Time in close proximity to a phone	(F^{12}) Time in minutes
Social network	Degree centrality	(F^{13}) Using f2f network (F^{14}) Using proximity to bed network
	Contribution index	(F^{15}) Using f2f network (F^{16}) Using proximity to bed network
	Betweenness centrality	(F^{17}) Using f2f network (F^{18}) Using proximity to bed network

Table 1: Per-minute sensor features

Daily feature	Notation	Calculation
Average	F_μ^n	$\frac{1}{\sum_{k=1}^K h(k)} \sum_{k=1}^K F^n(k)h(k)$
Standard deviation	F_σ^n	$\sqrt{\frac{1}{\sum_{k=1}^K h(k)} \sum_{k=1}^K [F^n(k)h(k) - F_\mu^n(k)]^2}$
Percentage of time	$F_\%^n$	$\frac{1}{\sum_{k=1}^K h(k)} \sum_{k=1}^K F^n(k) > 0$

Table 2: Daily sensor features, where $h(k) = 1$ if $F^1(k) > 1$ (when wearing the badge), and $h(k) = 0$ if $F^1(k) \leq 1$ (when not wearing the badge)

The mean accelerometer signal magnitude is calculated as follows:

$$F^1(k) = \frac{1}{f_s T} \sum_{i=1+f_sT(k-1)}^{f_sTk} |\vec{a}_i'| \qquad (2)$$

where $T = 60$ seconds, f_s is the accelerometer sampling frequency, and k is the k^{th} minute.

The standard deviation of the accelerometer signal magnitude is calculated as follows:

$$F^2(k) = \sqrt{\frac{1}{f_s T} \sum_{i=1+f_sT(k-1)}^{f_sTk} [|\vec{a}_i'| - F^1(k)]^2} \qquad (3)$$

The signal power or energy per minute is calculated as follows:

$$F^3(k) = \frac{1}{f_s T} \sum_{i=1+f_sT(k-1)}^{f_sTk} |\vec{a}_i'|^2 \qquad (4)$$

It can be shown that when the badge is static and not being worn $F^1(k) \leq 1$.

Speech activity

The speech signal must be sampled at at $f_s \geq 8000$ Hz since the voice frequency band ranges from 300 to 3400 Hz approximately. The voiced speech of a typical adult male has a fundamental frequency between 85 and 155 Hz, and that of a typical adult female between 165 and 255 Hz. (Baken 1987).

Several speech enhancement and speech recognition front-end systems based on band-pass filter banks have been shown to be effective in detecting speech (Ellis et al. 2002; Mouchtaris et al. 2005). The *sociometric* badges have an analog band-pass filter bank that divides the speech frequency spectrum $[85, 4000]$ Hz into four frequency bands: f_1 from 85 to 222 Hz, f_2 from 222 to 583 Hz, f_3 from 583 to 1527 Hz, and f_4 from 1527 to 4000 Hz.

We compute the speech volume modulation from the output of filter 1, since that is where the majority of the speaking energy resides:

$$v(i) = |(f_1(i) + f_1(i-1)) - (f_1(i-2) + f_1(i-3))| \qquad (5)$$

Feature $F^4(k)$ (mean volume modulation per minute) is then obtained as:

$$F^4(k) = \frac{1}{f_s T} \sum_{i=1+f_sT(k-1)}^{f_sTk} v(i) \qquad (6)$$

The standard deviation of volume modulation per minute is calculated as:

$$F^5(k) = \sqrt{\frac{1}{f_sT}\sum_{i=1+f_sT(k-1)}^{f_sTk}[v(i) - F^4(k)]^2} \quad (7)$$

The amount of speaking time per minute is simply calculated by counting the number of samples in one minute where the volume modulation is $v(i) > 0$:

$$F^6(k) = \frac{1}{f_sT}\sum_{i=1+f_sT(k-1)}^{f_sTk} v(i)h(i) \quad (8)$$

where $h(i)$ is the step function:

$$h(i) = \begin{cases} 1 & \text{if } v(i) > 0 \text{ (speaking)} \\ 0 & \text{if } v(i) = 0 \text{ (not speaking)} \end{cases}$$

We determined an experimental threshold value for each of the four band-pass filters in order to detect voiced and unvoiced speech. We coded these threshold values using a bit mask. The experimental values that we found are: $b_1(i) = 1$ if $f_1(i) > 2$, $b_2(i) = 1$ if $f_2(i) > 78$, $b_3(i) = 1$ if $f_3(i) > 78$, and $b_4(i) = 1$ if $f_4(i) > 31$; otherwise these bits are set to zero. These values are within the range $[0, 255]$ for an 8-bit analog-to-digital converter. The bit mask for detecting voiced speech is $b(i) = b_1(i) \wedge b_2(i) \wedge b_3(i) \wedge b_4(i)$. With this we can determine the amount of voiced speech per minute:

$$F^7(k) = \frac{1}{f_sT}\sum_{i=1+f_sT(k-1)}^{f_sTk} v(i)b(i) \quad (9)$$

Face-to-face interaction (f2f)

IR transmissions can be used as a proxy for the detection of face-to-face interaction between people (Choudhury and Pentland 2003). In order for one badge to be detected through IR, two *sociometric* badges must have a direct line of sight and the receiving badge's IR sensor must be within the transmitting badge's IR signal cone of height $h \leq 1$ meter and radius $r \leq h\tan\theta$, where $\theta = \pm 15°$.

We define the amount of face-to-face interaction $F^8(k)$ as the total number of IR detections per minute divided by the IR transmission rate (TR_{ir}). Feature $F^9(k)$ is simply the number of different badge IDs detected every minute. In this particular experiment the IR transmission rate was set to $TR_{ir} = 30$ IR packets per minute

Proximity

RSSI (radio signal strength indicator) is a measure of the signal strength between transmitting and receiving devices. An average threshold was determined experimentally in order to detect when two badges were in close proximity to each other (at a distance of less than 3 meters) by collecting RSSI measurements over an extended period of time under different environmental conditions. The range of RSSI values for the radio transceiver in the badge is $[-128, 127]$ and the experimental average threshold was found to be $\text{RSSI}_{th} = 50$. The time spent in close proximity to another person $F^{10}(k)$, a bed $F^{11}(k)$, and a phone $F^{12}(k)$ are calculated by dividing the number of radio packets with $\text{RSSI} > \text{RSSI}_{th}$ by the radio transmission rate (TR_{radio}). In this particular experiment the radio transmission rate was set to $TR_{radio} = 12$ radio packets per minute.

Social network

The social network attributes (features F^{13} through F^{18}) can be calculated using the number of IR and radio detections as the link strength between two actors. We have used conventional social network analysis as described in (Wasserman and Faust 2005). In particular, we measured individual and group degree and betweenness centrality as well as contribution index (Gloor et al. 2003). Betweenness centrality is a measure of power and influence within a group. Degree centrality measures the number of direct interaction partners. Contribution index measures how much of a sender or a receiver within a group somebody is.

Results

A correlation analysis of the daily badge features with each subject's answers to the daily job performance survey revealed weak but significant correlations ($r \leq 0.2$ with $p \leq 0.05$). However, when we aggregated the sensor features across subjects, the overall group perception of job performance (average of daily surveys across subjects) was highly correlated with the daily group behavior in the PACU. In order to do this, the answers to the daily survey were standardized across participants and the mean and standard deviation across subjects of the daily badge features described in table 2 were calculated. We will use the following notation to distinguish between daily features calculated across days and daily features calculated across subjects:

$\mu(F^n)_D$ denotes the average of daily feature F^n across days for a particular subject.

$\sigma(F^n)_D$ denotes the standard deviation of daily feature F^n across days for a particular subject.

$\mu(F^n)_S$ denotes the average of daily feature F^n across subjects for a particular day.

$\sigma(F^n)_S$ denotes the standard deviation of daily feature F^n across subjects for a particular day.

Table 3 shows the correlation coefficients found between the daily badge features (mean and standard deviation across days) from each participant's sensor data and the results of their personality test grouped by behavior description.

These results confirm Hypothesis 1: *Personality traits can be identified from sensor data*. The results can be interpreted in terms of each personality trait (without implying causality) as follows:

- Neuroticism. The higher the daily percentage of f2f time, and the more variation across days in the daily percentage of f2f time, the more neurotic. These results are in accordance with (Hough 1992), who found that Emotional Stability (the opposite of Neuroticism) is correlated with effective teamwork (balanced f2f time and low variation over time).
- Extroversion. The lower the daily average time in close proximity to a bed or phone, the lower the daily variation

Behavior Description	Feature	Personality Dimension N	E	O	A	C
Physical activity	$\mu(F^2_\sigma)_D$	-0.03	-0.07	0.37*	-0.14	-0.09
Speech activity	$\sigma(F^5_\mu)_D$	0.07	-0.16	-0.18	-0.43**	-0.006
	$\sigma(F^5_\sigma)_D$	0.09	-0.13	-0.24	-0.41**	0.12
	$\sigma(F^6_\sigma)_D$	0.11	-0.006	-0.36*	-0.18	0.02
Face-to-face	$\mu(F^8_\%)_D$	0.35*	-0.08	0.004	0.06	-0.18
	$\sigma(F^8_\%)_D$	0.41*	-0.09	0.02	0.06	-0.26
Proximity	$\sigma(F^{11}_\%)_D$	0.06	-0.18	-0.16	-0.34*	0.16
	$\mu(F^{11}_\mu)_D$	-0.003	-0.36*	0.11	-0.26	0.18
	$\mu(F^{12}_\mu)_D$	0.15	-0.39*	0.22	-0.24	-0.11
	$\sigma(F^{12}_\mu)_D$	0.25	-0.27	0.32*	-0.18	-0.20
	$\mu(F^{12}_\sigma)_D$	0.12	-0.36*	0.22	-0.20	-0.14
	$\sigma(F^{12}_\sigma)_D$	0.31	-0.34*	0.17	-0.31	-0.08
Social Network	$\sigma(F^{17}_\mu)_D$	0.30	-0.07	0.46**	-0.16	-0.42**
	$\mu(F^{18}_\mu)_D$	0.18	0.01	0.26	-0.28	-0.37*
	$\sigma(F^{18}_\mu)_D$	0.13	-0.0008	0.20	-0.28	-0.36*

Table 3: Correlation coefficients between monthly badge features and personality traits. $*p < 0.05$, $**p < 0.01$.

in time in close proximity to a phone (phone call length), and the less variation across days in the daily variation in time in close proximity to a phone, the more extrovert. One could interpret these results as the nurses having more time to interact and talk with others when they are not in close proximity to a bed looking after a patient or making phone calls to schedule patients' transfers, therefore being more sociable (or extrovert).

- Openness. The higher the daily variation in physical activity, the less variation across days in daily variation in speaking time, the more variation across days in the daily average time in close proximity to a phone, and the more variation across days in the daily average betweenness centrality (f2f network) across days, the more open. There is evidence for the benefit of physical activity on cognitive performance (openness to experience being a trait-based contributor to predicting cognitive performance) (Lochbaum, Karoly, and Landers 2002). The betweenness centrality correlation coincides with that obtained by (Gloor et al. 2008), who used our sensing platform in a bank and found that people who exhibit more fluctuating betweenness centrality also tend to exhibit higher levels of openness.

- Agreeability. The less variation across days in the daily average speech volume modulation, the less variation across days in the daily variation in speech volume modulation, and the less variation across days in the daily percentage of time in close proximity to a bed, the more agreeable. Previous research indicates that speech is perceived as more agreeable or accommodating when it is well modulated (Pentland 2007). The nurses might also be perceived as more agreeable when they spend a similar amount of time with each patient (less variation in proximity time across patients).

- Conscientiousness. The less variation across days in the daily average betweenness (f2f network), the lower the daily average betweenness (f2f network), and the less variation across days in the daily average betweenness (bed proximity network), the more conscientious. These results seem to be in accordance with those found by (Wehrli 2008): Conscientiousness is negatively correlated with betweenness centrality.

Tables 4 to 8 show the results of the multiple linear regression analysis for the overall group perception of workload ($R^2 = 0.49$), difficulty to obtain information ($R^2 = 0.42$), quality of group interaction ($R^2 = 0.69$), productivity ($R^2 = 0.63$), and stress ($R^2 = 0.77$) from the aggregated daily features across subjects.

In the case of workload, the most predictive features were the variation across subjects in physical activity and in speech activity. In the case of difficulty to obtain information, the average physical activity intensity, and the variation across subjects in the time in close proximity to a bed were the most predictive features. The best predictors of quality of group interaction were the group's physical activity, speech activity, proximity to other people, proximity to a bed, and social network attributes. Voiced speech activity seemed to be the best indicator of the group's perception of productivity. Finally, several attributes seemed to play an important role in determining the group's stress level: physical activity, speech activity, face-to-face interaction, and proximity to a phone.

Tables 9 and 10 show that it is also possible to explain the variation in the average patient recovery time in minutes ($R^2 = 0.73$) and the average daily number of outgoing delays ($R^2 = 0.56$) from the aggregated features across subjects. In the case of patient recovery time physical activity intensity and speech activity across subjects played an important role. When estimating the daily number of delays the variation across subjects in physical activity and proximity to a phone were the most predictive features.

These results confirm Hypothesis 2: *Aggregate group behavior is predictive of group performance* (subjective in the case of the job performance survey, and objective if we consider the patient recovery time and the daily number of outgoing delays in the PACU as the group's outcome).

Conclusions

We have shown how to obtain high level descriptions of human behavior in terms of physical activity, speech activity, face-to-face interaction, proximity and social network attributes from sensor data. We presented experimental results that show that it is possible to identify individual personality traits as well as subjective and objective group performance metrics from low level sensor data. While we could not predict the individual perception of job performance from sensor data for each individual, we were able to estimate the overall group performance by aggregating the daily sensor features across subjects.

This is a first attempt to measure and model organizational behavior at the individual and group levels. In future work we plan to extend this research to multiple groups and entire organizations in order to better understand and improve organizational performance. Future work includes modeling, simulation and optimization of individual and group behavior from sensor data.

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Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\sigma(F_\sigma^3)_S$	-0.61	0.37	0.30	10.16	0.005	0.39	4.54
$\sigma(F_\mu^7)_S$	0.47	0.49	0.40	7.71	0.004	0.37	-3.54

Table 4: Prediction of group's perception of workload (Q1) from badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\mu(F_\mu^3)_S$	0.50	0.25	0.16	5.62	0.03	0.28	-15.82
$\sigma(F_\mu^{11})_S$	-0.51	0.42	0.32	5.87	0.01	0.25	5.90

Table 5: Prediction of group's perception of difficulty to obtain information (Q2) from badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\mu(F_\mu^1)_S$	-0.52	0.27	0.18	6.21	0.02	0.37	91.44
$\mu(F_\mu^3)_S$	-0.50	0.35	0.22	4.22	0.03	0.36	-34.55
$\sigma(F_\sigma^{10})_S$	-0.51	0.61	0.51	7.88	0.002	0.28	6.15
$\sigma(F_\mu^{11})_S$	0.47	0.66	0.52	6.67	0.003	0.28	-5.14
$\mu(F_\mu^{15})_S$	0.56	0.67	0.52	5.24	0.007	0.28	-0.66
$\mu(F_\mu^{16})_S$	0.48	0.69	0.52	4.55	0.01	0.28	0.52

Table 6: Prediction of group's perception of quality of group interaction (Q3) from badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\sigma(F_\mu^7)_S$	0.71	0.50	0.44	16.84	0.0007	0.17	-1.84
$\mu(F_\sigma^7)_S$	0.74	0.63	0.56	13.58	0.0003	0.15	-2.25

Table 7: Prediction of group's perception of productivity (Q5) from badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\mu(F_\mu^1)_S$	0.67	0.45	0.38	13.82	0.002	0.44	-218.247
$\sigma(F_\mu^1)_S$	-0.55	0.45	0.34	6.50	0.008	0.45	-22.10
$\mu(F_\mu^3)_S$	0.65	0.61	0.51	7.93	0.002	0.39	77.78
$\mu(F_\%^7)_S$	0.46	0.64	0.51	6.15	0.004	0.39	417.85
$\sigma(F_\mu^7)_S$	0.49	0.75	0.63	7.80	0.001	0.34	-5.78
$\mu(F_\mu^9)_S$	0.58	0.76	0.63	6.45	0.003	0.34	-0.03
$\sigma(F_\mu^{12})_S$	0.46	0.77	0.63	5.38	0.007	0.34	-7.02

Table 8: Prediction of group's perception of stress (Q6) from badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\mu(F_\mu^3)_S$	-0.62	0.39	0.32	10.81	0.004	28.59	155.58
$\mu(F_\mu^6)_S$	-0.67	0.58	0.50	11.12	0.0009	24.38	461.19
$\mu(F_\sigma^6)_S$	-0.61	0.60	0.49	7.38	0.002	24.74	-645.57
$\sigma(F_\sigma^6)_S$	0.70	0.73	0.63	9.44	0.0006	20.96	-697.09

Table 9: Prediction of average patient recovery time in minutes from badge features across subjects

Predictors	R	R^2	adj R^2	F	p	RMSE	β
$\sigma(F_\mu^2)_S$	0.46	0.21	0.12	4.48	0.05	3.95	-189.53
$\sigma(F_\mu^{12})_S$	-0.60	0.56	0.48	10.37	0.001	3.02	206.63

Table 10: Prediction of average daily number of delays (going out of the PACU) from badge features across subjects