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Contextually Defined Postural Markers Reveal Who's in Charge: Evidence from Small Teams Collected with Wearable Sensors

Julius Dietzel, R. Elena Francu, Benjamin Lucas, and Mohamed Zaki

This is a Working Paper

Why this paper might be of interest to Alliance Partners:

Wearable sensor technology presents businesses with compelling opportunities to shed new light on human behavioural processes, within the broader spheres of ubiquitous computing and the internet-of-things (IoT). In B2C markets, wearable sensors are being put to use in areas such as personal health and fitness monitoring, often connected to cloud data platforms, while in B2B markets, such hardware is finding applications in healthcare and industrial safety.

Another new frontier application of wearable sensor technology is within the context of human resource management and organisational behaviour, where deploying wearable sensors has proven to be an effective, accurate and relatively non-invasive way of studying human interactions. Currently, such research builds largely on the domain of human activity recognition (HAR), focusing on defining and analysing behavioural markers of socio-psychological processes underlying social interactions, but in the future, presents possibilities to be extended into contexts such as organisational transformation, both in process planning / operations and physical space planning, built environment occupant behaviour analysis, and crossovers with building information modelling (BIM).

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Contextually Defined Postural Markers Reveal Who's in Charge: Evidence from Small Teams Collected with Wearable Sensors

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Abstract
Extant research shows that meaningful information about social interactions can be gained by studying 'honest signals'. Honest signals represent aspects of communication not captured directly by content semantics, but rather by factors such as body language and proxemics. In this regard, research employing wearable technology such as the sociometric badge developed by the MIT Media Lab has proven to be particularly useful for analyzing the interactions of humans in work environments. Such research has tended to take a dyadic or network perspective. However, in this study, inspired by human activity recognition research, we investigate the possibility of identifying employees and differentiating their group-functions based on behavior, with particular emphasis on identifying those in positions of leadership. Working with a high-resolution dataset collected using sociometric badges deployed during small team meetings in a European financial services firm, and applying multi-class classification, we reveal that individual accelerometer-derived posture movement (left-right and front-back) and speaking volume (from a microphone located closest to a focal participant, thus also capturing information pertaining to posture) are particularly strong features for identification. Across all models, we achieve an average of 73% accuracy, with reasonably balanced precision and recall across individuals.

Introduction

Wearable technology (WT) encompasses worn devices that collect information about a user, and / or relay and display information to that user. WT research overlaps with Human Activity Recognition (HAR) research, employing individual-level analysis based on machine learning classification and signal processing for human activity pattern recognition [1,2,3,4,5], or group-level analysis based on methodologies such as social signal processing and network analysis [6,7,8,9,10,11]. The latter is particularly complimentary to the domain of workforce analytics and wearable-enabled organizational behavior research [12,13,14,15] and the study of social dynamics within organizations more broadly [16,17]. However, one notable opportunity at the intersection of these perspectives is to leverage what is known about approximation using data from wearable devices at an individual level, and to transfer this approach into workforce analytics as a basis for developing approaches to machine learning-based employee identification. One area of application for such an approach is in the identification of leaders, a fundamental scenario in

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management and organizational science [18,19]. This also more broadly encompasses leadership style [20] and leadership performance outcomes [21].

As with the identification of any socio-interactive process, this idea builds around the innate human ability to 'read' one another, using 'honest signals' [22], dimensions of communication not captured directly by content semantics, but rather by factors such as body language and proxemics. Such social signals are able to capture attention, agreement and disagreement [23]. Among these, posture is a particularly interesting dimension; generally assumed relatively unconsciously, and able to capture exclusion or inclusion (i.e. facing toward or away from someone), engagement style (i.e. more face-to-face versus standing parallel), non-congruence versus congruence (where individuals more satisfied with an interaction also exhibit matching postures), and overall rapport [23]. Thus, our study addresses the following research question: can those in contextually defined leadership roles within teams be accurately identified using postural data? More specifically, this involves examining the role of posture as a social signal of hierarchical status, given a context where such positions are afforded to individuals. This is to treat posture not as a constant; a manifestation of a particular character or personality trait, but rather to examine posture as a function of social context.

To this end, we employ a small-scale field study format, which took place within the innovation department of a European financial services company. For this, employees were issued to wear sociometric badges during weekly team meetings [24]. Each sociometric badge is uniquely identified, serving as a class label for multi-class classification.

Human Activity Recognition

Human Activity Recognition (HAR) refers to the automatic detection of physical activities (e.g. sitting, lying, walking) by analyzing signals from wearable and ambient sensors [25,26]. Broadly speaking, two classes of HAR exist: wearable sensor-based HAR systems, using combinations of MEMS (micro-electrical mechanical systems) sensors and other sensors such as Bluetooth and infrared proximity sensors, and systems working with external sensors such as video recorders, cameras, and pressure sensors [27,28,29]. There are three main advantages in using wearable devices for social science research. Firstly, wearable HAR systems are less expensive, less computationally intensive, and less cumbersome. Secondly, these systems can be used in a relatively non-invasive manner, what makes them appropriate for a range of deployments in 'natural' settings [30,31]. Thirdly, participant acceptance is aided by the ubiquitous nature of wearable devices and portable electronics such as smartphones and consumer wearable technology [32,29]. Importantly, activity recognition systems have also gained traction in the consumer market. Various domains, such as healthcare, surveillance systems, sports coaching, fitness assessment, and smart homes involve HAR [33,29]. In academic research, two well-known applications of HAR are fall detection systems (i.e. for elderly care) [2], using threshold based methods and signal processing [34,1] and sports performance [35]. Mozos et al. [36] work towards a similar direction with a focus on measuring physiological markers of stress.

Broadening the HAR domain, the sociometric badge, or sociometer [24] is an example of a wearable HAR device which can gather complex data about social settings and the individual people within them. The device is capable of tracking and analyzing social signals via different sensors: a microphone picks up speech characteristics (e.g. tone of voice), an accelerometer detects body movement and posture, and infrared and Bluetooth sensors measure interpersonal distances [13]. Across a number of studies, researchers have found that behavioral outcomes in situations such as business plan contests [37], salary negotiations [38] or dating [39] can be accurately predicted by analyzing quantitative data from the sociometer. More recently, researchers have used the devices to study contagion in social networks [40] and social network diversity [41]. With HAR proving to be a useful approach to workforce and workplace analytics, Montanari, Nawaz, Mascolo, and Sailer [14] and Montanari, Nawaz, Mascolo, and Sailer [15] have also explored the use of Bluetooth-based wearable technology for human proximity measurement in this context. In the HAR domain, posture-related variables are particularly interesting, having been studied from a health perspective [42] as well as from a social science point of view, with posture seen as an important marker of social engagement [43], among other aforementioned social processes and outcomes. Posture has also been long recognized as a means of conveying and establishing dominance [44], a necessary ingredient for contextually defined leadership.

Materials and Methods

The focus of this study is on a small team within a large organization. The study was conducted by following four consecutive, equally structured meetings within the innovation department of a European financial services company. The sample comprised 13 subjects; 12 employees working and 1 independent researcher. Notably, the sample size between meetings varied throughout the field study due to distinct office locations and work-related travel, although six to ten subjects participated weekly. In terms of job roles, the division is broadly distributed into three, small functional teams comprising four, five, and two workers, respectively. The head of innovation (PID_1) overseas each work group and one peripheral manager (PID_2) gives a single team technological advice. Within the distinct teams, each employee performs a specific function. The specific job titles were Trainee, Architect, Project Officer, Senior Coach, General Manager, Innovation Manager and Head of Innovation.

The duration of the meeting ranged between 48 minutes in the first meeting to 23 minutes in the last meeting. Importantly, the participants were given a choice of where and with whom to sit. Participants had a choice between multi-tiered benches, office chairs, or standing positions. Before the study started, every employee signed a consent form to participate which informed the employees about the purpose of the study, the confidentiality of the data, and the opportunity to withdraw from the research project at any time. None of the participants requested to discontinue their participation or withdraw their consent. The participants also later confirmed that wearing the badges had been non-obtrusive and did not affect their social interaction behavior during the meetings.

Data Collection and Pre-processing

The variables used for feature selection collected from the sociometric badges are shown in Table 1. Each sociometric badge is uniquely identified, serving as class labels for multi-class classification. In each of the four meetings, employees present were equipped with sociometers for the duration of the meeting. In total 69290 seconds (1155 minutes) of data were collected, resulting in an average of almost 90 minutes per participant.

Table 1. Description of Variables.

Table Notes: This table shows all variables (features) used for feature selection.

Feature	Description
BM_activity	Body movement activity captured by accelerometer
Posture_left-right	Posture: left-right direction
Posture_front-back	Posture: front-back direction
Posture_activity	Absolute angular velocity of posture
Speech_profile_speaking	Amount of seconds someone spent speaking, while no one else was speaking
Speech_profile_overlap	Amount of seconds someone spent speaking, while someone else was speaking
Speech_profile_listening	Amount of seconds someone was being silent, while someone else was speaking
Speech_profile_silent	Amount of seconds someone was being silent, while everyone else was silent too
Audio_back_volume	Average volume (proportional to decibel) recorded by back microphone
Audio_back_pitch	Voice pitch (in Hz)

We extract this data, and then treated each row marked by a different timestamp as a separate instance, resulting in 69290 instances for classification of the 13 employees (Table 2). This was done to maximize the available information for classification, given the limitations of the relatively small dataset. Hence, time was not used formally as in time series analysis, but as a basis to create multiple training examples. At the same time, by using a one-second resolution, many instances were generated and the variance of each attribute was maximized. This also allows us to assess the validity of a very computationally simple and efficient approach versus formal signal processing techniques for example.

Due to the fact that the attributes are measured on different scales, each input feature was also standardized to be Gaussian distributed before feature selection and classification. The *z*-scores are obtained by subtracting the population mean from each attribute value and dividing the result by the attributes' standard deviation. Standardizing provided an equally scaled set of attributes with a mean of zero and standard deviation of one [45].

Table 2. Number of Instances per Participant.

Table Notes: This table shows the number of instances each participant contributed to the classification problem across the different meetings. Non-attendant participants are represented by grayed out entries. In total 69290 seconds (1155 minutes) were used to classify the individuals. PID = Participant ID (anonymized participant identifier). M1, M2, M3, M4 denote Meetings 1 to 4.

PID	M1	M2	M3	M4	Total
PID_1	2759		2004		4763
PID_2	2759	1772	2004		6535
PID_3		1772		1258	3030
PID_4	2759	1772		1258	5789
PID_5	2759	1772	2004		6535
PID_6	2759	1772		1258	5789
PID_7			2004		2004
PID_8		1772	2004	1258	5034
PID_9	2759	1366	2004		6129
PID_10	2759		2004	1258	6021
PID_11	1579	1772	2004		5355
PID_12	2759	1772			4531
PID_13	2759	1772	2004	1240	7775
Total	26410	17314	18036	7530	69290

A visual inspection of the raw data revealed interesting patterns between participants and meetings Figures 1 and 2 are stream plots showing posture left-right and posture front-back features for selected participants, normalized 1-0. The total area (all colors) in this plot shows the total motion recorded at timestamp *t* (i.e. for each instance) across four channels (Posture Left-Right and Posture Front-Back). Each section (color) represents the relative contribution of that variable to the total motion recorded. For illustration, Figure 1 shows PID_1 and PID_2 (the two most senior members among the participants) in the third meeting. Figure 2 shows PID_2 with PID_8 (a subordinate manager) in the third meeting.

Figure 1: Posture Features for PID_1 and PID_2 in Meeting 3

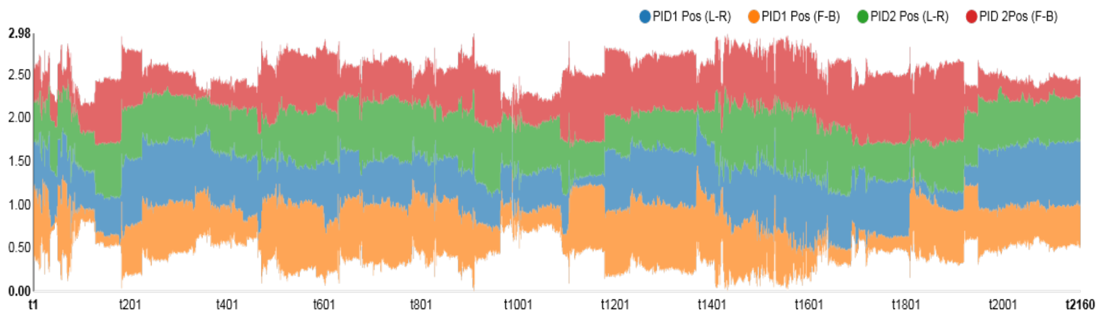
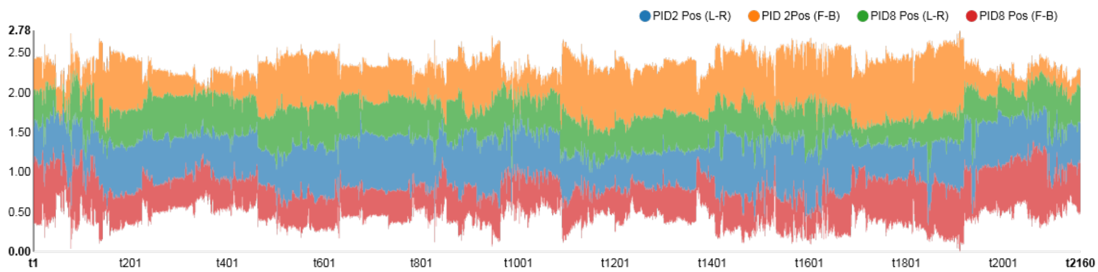


Figure 2: Posture Features for PID_2 and PID_8 in Meeting 3



Multi-class Classification

Classification employed the WEKA machine learning library, using the REP Tree[A], NB Tree[B] and Random Forest[C] (with consensus from ten trees) classifiers. The classifiers were run as a one-versus-all multi-class classifiers[D]. The three chosen classifiers were used within a forward-feature selection loop, within which a 10-fold cross-validation loop was also used. The algorithm starts by training the classifier based on one feature only. Then the most relevant features are continuously added and the classifier is trained again on the new feature subset. This process is iterated until the classifier reaches its maximal accuracy [46]. The same classifiers were then re-run using the features which produced the highest accuracy scores in the forward-feature selection exercise, also within a 10-fold cross-validation loop. Because of the design of the study and the focus on identification of individuals, classes were mostly well-balanced (except for instances where participants left meetings early for example). For refinement in future work, class-balancing could be performed using an oversampling technique such as SMOTE [47].

A. WEKA REP Tree: http://weka.sourceforge.net/doc.dev/weka/classifiers/trees/REPTree.html
B. WEKA NB Tree: http://weka.sourceforge.net/doc.packages/naiveBayesTree/weka/classifiers/trees/NBTree.html
C. WEKA Random Forest: http://weka.sourceforge.net/doc.dev/weka/classifiers/trees/RandomForest.html
D. WEKA Multiclass: http://weka.sourceforge.net/doc.dev/weka/classifiers/meta/MultiClassClassifier.html

Results

Feature Selection – Natural Classes

The results for the forward feature selection procedure for the natural class data are shown in Table 3. In particular, we were interested in assessing the relative roles of the postural (left-right and front-back) features, as well as the *Audio_back_volume* feature, the latter also capturing important information about posture. The optimal number of features ranged between six and nine features, with *six* being optimal only once in the case of Meeting 3 using NB Tree. Notably, in none of the twelve cases all available features were used to build the model, hence feature selection fulfilled its function to narrow the dimensionality of the problem as much as possible. The Random Forest classifier achieved the best results among the three classifiers used for feature selection.

The procedure resulted in a sharp increase in accuracy across the first three features for each model and each meeting, followed by a relative plateauing of accuracy scores thereafter. In eleven of twelve models, the same postural features accounted for the majority of predictive power. The feature subset which accounted for the sharp increase of accuracy consisted of the features *Posture_front-back*, *Posture_left-right* and *Audio_back_volume*. Almost half of the accuracy (49%) was explained by *Posture_front-back*, while *Posture_left-right* accounted for 37% of prediction ability on average. Additionally, *Audio_back_volume* contributed 7% on average. Importantly, *Audio_back_volume* can be considered something of an “audio posture” feature, since it is related both to how a participant sits (i.e. sitting up straight should increase the volume), as well as to overall posture tension/tone (i.e. when a participant holds their posture energetically, it is likely that their voice will project more, and be recorded louder).

Table 3: Feature Selection for Natural Classes

Table Notes: Gray= Highest overall accuracy achieved. Light blue= Postural features.

	REP Tree				NB Tree				Random Forest			
	Features	Accuracy	Change	Added feature	Features	Accuracy	Change	Added feature	Features	Accuracy	Change	Added feature
M1	10	64.40%	-0.30%	Speech_profile_listening	10	63.00%	-0.30%	Audio_back_pitch	10	68.40%	-0.60%	Speech_profile_silent
	9	64.70%	0.00%	Speech_profile_overlap	9	63.30%	-1.10%	Speech_profile_listening	9	69.00%	0.20%	BM_activity
	8	64.70%	-0.10%	BM_activity	8	64.40%	0.20%	Speech_profile_overlap	8	68.80%	0.30%	Audio_back_pitch
	7	64.80%	0.00%	Audio_back_pitch	7	64.20%	0.40%	Speech_profile_speaking	7	68.50%	0.50%	Speech_profile_overlap
	6	64.80%	0.90%	Speech_profile_speaking	6	63.80%	0.50%	BM_activity	6	68.00%	1.10%	Speech_profile_speaking
	5	63.90%	0.20%	Speech_profile_silent	5	63.30%	1.00%	Speech_profile_silent	5	66.90%	0.90%	Speech_profile_listening
	4	63.70%	1.30%	Posture_activity	4	62.30%	1.50%	Posture_activity	4	66.00%	2.70%	Posture_activity
	3	62.40%	2.00%	Audio_back_volume	3	60.80%	2.10%	Audio_back_volume	3	63.30%	4.80%	Audio_back_volume
	2	60.40%	16.90%	Posture_left-right	2	58.70%	14.20%	Posture_left-right	2	58.50%	23.80%	Posture_left-right
	1	43.50%	43.50%	Posture_front-back	1	44.50%	44.50%	Posture_front-back	1	34.70%	34.70%	Posture_front-back
M2	10	62.50%	-0.40%	Speech_profile_overlap	10	59.60%	-1.00%	Audio_back_pitch	10	67.30%	-0.70%	Speech_profile_overlap
	9	62.90%	0.30%	Speech_profile_speaking	9	60.60%	0.10%	Speech_profile_silent	9	68.00%	-0.40%	BM_activity
	8	62.60%	-0.20%	Posture_activity	8	60.50%	0.00%	Speech_profile_speaking	8	68.40%	0.30%	Speech_profile_speaking
	7	62.80%	0.20%	BM_activity	7	60.50%	0.20%	Speech_profile_overlap	7	68.10%	0.40%	Audio_back_pitch
	6	62.60%	-0.10%	Audio_back_pitch	6	60.30%	0.70%	Posture_activity	6	67.70%	0.60%	Speech_profile_silent
	5	62.70%	0.70%	Speech_profile_silent	5	59.60%	1.90%	Speech_profile_listening	5	67.10%	2.40%	Posture_activity
	4	62.00%	1.90%	Speech_profile_listening	4	57.70%	1.30%	Audio_back_volume	4	64.70%	2.80%	Speech_profile_listening
	3	60.10%	3.10%	Audio_back_volume	3	56.40%	1.80%	BM_activity	3	61.90%	6.70%	Audio_back_volume
	2	57.00%	21.70%	Posture_left-right	2	54.60%	17.60%	Posture_left-right	2	55.20%	28.10%	Posture_left-right
	1	35.30%	35.30%	Posture_front-back	1	37.00%	37.00%	Posture_front-back	1	27.10%	27.10%	Posture_front-back
M3	10	74.10%	-0.70%	BM_activity	10	73.10%	-0.30%	Audio_back_pitch	10	78.50%	-0.40%	BM_activity
	9	74.80%	0.20%	Speech_profile_listening	9	73.40%	-0.20%	Posture_activity	9	78.90%	-0.10%	Speech_profile_overlap
	8	74.60%	0.20%	Audio_back_pitch	8	73.60%	0.10%	Speech_profile_speaking	8	79.00%	0.10%	Speech_profile_listening
	7	74.40%	0.00%	Speech_profile_speaking	7	73.50%	-0.10%	Speech_profile_overlap	7	78.90%	0.80%	Audio_back_pitch
	6	74.40%	0.00%	Speech_profile_overlap	6	73.60%	0.10%	BM_activity	6	78.10%	0.40%	Speech_profile_speaking
	5	74.40%	0.40%	Posture_activity	5	73.50%	1.00%	Speech_profile_silent	5	77.70%	0.90%	Posture_activity
	4	74.00%	1.60%	Speech_profile_silent	4	72.50%	1.70%	Speech_profile_listening	4	76.80%	2.80%	Speech_profile_silent
	3	72.40%	3.20%	Audio_back_volume	3	70.80%	2.20%	Audio_back_volume	3	74.00%	6.50%	Audio_back_volume
	2	69.20%	26.90%	Posture_left-right	2	68.60%	25.00%	Posture_left-right	2	67.50%	34.20%	Posture_left-right
	1	42.30%	42.30%	Posture_front-back	1	43.60%	43.60%	Posture_front-back	1	33.30%	33.30%	Posture_front-back
M4	10	85.30%	-0.10%	BM_activity	10	85.40%	-0.40%	Speech_profile_overlap	10	87.30%	-0.70%	BM_activity
	9	85.40%	-0.10%	Audio_back_pitch	9	85.80%	0.40%	Audio_back_pitch	9	88.00%	-0.40%	Speech_profile_overlap
	8	85.50%	-0.40%	Speech_profile_overlap	8	85.40%	0.00%	Speech_profile_silent	8	88.40%	0.30%	Speech_profile_speaking
	7	85.90%	0.20%	Speech_profile_silent	7	85.40%	0.10%	BM_activity	7	88.10%	0.00%	Speech_profile_silent
	6	85.70%	0.20%	Posture_activity	6	85.30%	0.00%	Speech_profile_speaking	6	88.10%	0.20%	Audio_back_pitch
	5	85.50%	0.00%	Speech_profile_listening	5	85.30%	0.50%	Speech_profile_listening	5	87.90%	0.70%	Speech_profile_listening
	4	85.50%	0.60%	Speech_profile_speaking	4	84.80%	0.60%	Posture_activity	4	87.20%	1.10%	Posture_activity
	3	84.90%	2.50%	Audio_back_volume	3	84.20%	3.10%	Audio_back_volume	3	86.10%	3.90%	Audio_back_volume
	2	82.40%	16.30%	Posture_left-right	2	81.10%	13.90%	Posture_left-right	2	82.20%	24.60%	Posture_left-right
	1	66.10%	66.10%	Posture_front-back	1	67.20%	67.20%	Posture_front-back	1	57.60%	57.60%	Posture_front-back

A “good” feature here is characterized by its robustness across different individuals [30]. Hence, features are desirable which clearly differentiate the classes. The results gained from feature extraction are consistent with the honest signals argumentation [11]. Activity is an energy-based honest signal manifesting itself in social behaviors such as posture, body movement or tone of voice. It expresses each individual’s interests as well as their role in the social hierarchy [9]. For instance, Mast [48] showed that the individual dominance manifests itself in the amount of speaking time.

BM_activity was not a good identifying variable in this case since the employees were mostly stationary and did not move around. *Audio_back_pitch* performed far less well than expected. Research, for instance, has shown the associations between vocalic cues such as pitch, tempo or loudness and attributions of persuasiveness or dominance [49]. Also social scientists found that the deviation in voice pitch is significantly correlated with physiological stress [50]. Yet, *Audio_back_pitch* did not reach the prediction ability of the amplitude-based vocalic cue *Audio_back_volume*.

Likewise, the feature *speech_profile_overlap* had a negligible effect on the classification outcome. This might be due to the structured character of the meeting. Throughout the meeting, the participants were involved in a single conversation and most of the time only one employee spoke while the others were listening. Hence, the speech profiles of the non-contributing employees closely resembled each other. Another reason relates to the statistical independence of the speech profile features. For instance, the events *Speech_profile_speaking* and *Speech_profile_listening* are mutually dependent. Features showing similar trends are likely to carry similar information. Classifiers are sensitive to correlating features and since features that carry similar information will not improve the model performance, they are also less likely to be isolated during feature selection. Moreover, the speech profile features are time-based measures (second-by-second) causing high intra-class variability.

Multi-class Classification – Natural Classes

The multi-class classification results for the natural class data are summarized in Table 4. Identification results were best for Meeting 4, followed by Meeting 3, Meeting 1 and Meeting 2. The sample size varied as follows: Across the four meetings, the least employees (6) participated in Meeting 4, whereas nine employees were part of the study in Meeting 3. Yet, the largest sample size was recorded for Meeting 1 and Meeting 2 in which ten employees participated. In proposing a probabilistic argument, the likelihood that the algorithm correctly classified the instance is higher, where fewer classes exist. This is could be because mimicry, a sign of empathic understanding leading individuals to mirror certain behaviors of others [11], has more potential opportunities to manifest, thus confusing intra-class identification.

The occurrence and effect of influence and mimicry are certainly contingent on the number of people in a network. Thus, the effects have been the smallest during Meeting 4 which is supported by the researcher's perception of mentally focused employees during that meeting. This suggests that the classification approach works best, meaning that the social signature of each individual is most clearly established when an individual behaves actively, signals social behaviors in a consistent manner, is less susceptible to external influences, and does not mimic behaviors of others.

Table 4: Multi-class Classification Results for Natural Classes

		Recall	Precision	F-measure	Recall	Precision	F-measure	Recall	Precision	F-measure
		REP Tree (64.20%)			**NB Tree (64.20%)**			**Random Forest (68.90%)**		
M1	*PID_1*	0.948	0.956	0.952	0.944	0.955	0.95	0.959	0.973	0.966
	PID_2	0.674	0.676	0.675	0.664	0.655	0.659	0.74	0.688	0.713
	PID_4	0.68	0.614	0.645	0.679	0.618	0.647	0.704	0.658	0.68
	PID_5	0.422	0.409	0.415	0.399	0.395	0.397	0.444	0.496	0.469
	PID_6	0.522	0.581	0.55	0.522	0.584	0.551	0.594	0.629	0.611
	PID_9	0.632	0.536	0.58	0.657	0.549	0.598	0.681	0.6	0.638
	PID_10	0.604	0.655	0.629	0.613	0.644	0.628	0.693	0.693	0.693
	PID_11	0.859	0.839	0.849	0.855	0.847	0.851	0.874	0.872	0.873
	PID_12	0.736	0.765	0.75	0.73	0.766	0.747	0.762	0.778	0.77
	PID_13	0.437	0.486	0.46	0.447	0.502	0.473	0.515	0.564	0.538
		REP Tree (62.50%)			**NB Tree (60.30%)**			**Random Forest (67.90%)**		
M2	*PID_2*	0.585	0.568	0.576	0.523	0.559	0.54	0.662	0.623	0.642
	PID_3	0.551	0.683	0.61	0.432	0.701	0.535	0.616	0.747	0.675
	PID_4	0.72	0.675	0.696	0.712	0.669	0.689	0.761	0.722	0.741
	PID_5	0.605	0.64	0.622	0.595	0.64	0.617	0.656	0.698	0.677
	PID_6	0.655	0.761	0.704	0.676	0.692	0.684	0.715	0.8	0.755
	PID_8	0.573	0.545	0.558	0.564	0.52	0.541	0.609	0.614	0.612
	PID_9	0.638	0.595	0.616	0.626	0.593	0.609	0.667	0.614	0.64
	PID_11	0.688	0.702	0.695	0.694	0.604	0.646	0.715	0.75	0.732
	PID_12	0.657	0.558	0.603	0.657	0.548	0.598	0.705	0.627	0.664
	PID_13	0.581	0.566	0.574	0.554	0.554	0.554	0.682	0.625	0.652
		REP Tree (74.70%)			**NB Tree (73.20%)**			**Random Forest (78.80%)**		
M3	*PID_1*	0.838	0.846	0.842	0.852	0.818	0.834	0.886	0.874	0.88
	PID_2	0.648	0.638	0.643	0.605	0.559	0.581	0.701	0.704	0.702
	PID_5	0.652	0.716	0.683	0.649	0.739	0.691	0.713	0.769	0.74
	PID_7	0.603	0.655	0.628	0.548	0.62	0.582	0.668	0.726	0.696
	PID_8	0.753	0.728	0.741	0.727	0.721	0.724	0.789	0.773	0.781
	PID_9	0.821	0.767	0.793	0.824	0.743	0.782	0.863	0.781	0.82
	PID_10	0.757	0.696	0.725	0.737	0.713	0.724	0.791	0.734	0.762
	PID_11	0.873	0.889	0.881	0.863	0.913	0.888	0.876	0.923	0.899
	PID_13	0.778	0.788	0.783	0.782	0.768	0.775	0.807	0.815	0.811
		REP Tree (85.20%)			**NB Tree (85.30%)**			**Random Forest (88.20%)**		
M4	*PID_3*	0.824	0.836	0.83	0.821	0.839	0.83	0.875	0.877	0.876
	PID_4	0.855	0.767	0.809	0.846	0.777	0.81	0.862	0.813	0.836
	PID_6	0.984	0.974	0.979	0.981	0.977	0.979	0.987	0.988	0.988
	PID_8	0.678	0.73	0.703	0.696	0.723	0.71	0.742	0.773	0.758
	PID_10	0.935	0.947	0.941	0.936	0.942	0.939	0.955	0.956	0.956
	PID_13	0.837	0.86	0.848	0.84	0.864	0.852	0.868	0.883	0.875

Overall, in Meeting 1, accuracy amounted to 68.9%. Meaningful differences with respect to recall and precision can be detected between the employees. The precision scores ranged between 0.973 for PID_1 and 0.496 for PID_5 ($M = 0.695$, $SD = 0.137$) which was the biggest range (0.477) amongst all meetings. Evidently, PID_1 and PID_5 stood out due to extreme values in either direction. Notably, across all meetings the classification approach worked worst for PID_5. All three machine learning classifiers predicted more instances of PID_5 incorrectly (Random Forest: FP: 1245) than correctly (Random Forest: TP: 1225). It is important to note that it happened only once that more misclassifications than true predictions were computed for a class. Mostly, social signals of PID_6 were incorrectly identified as belonging to PID_5 (FP: 265). Disregarding PID_1 and PID_5, the other classes were fairly balanced (precision: $M = 0.685$, $SD = 0.093$).

The misclassification rate (error rate) for Meeting 2 was the largest compared to the other meetings. From all predictions made, the Random Forest classifier predicted 32.1% of instances incorrectly. The highest recall value was achieved for PID_4 (0.761) whereas the Random Forest classifier achieved the highest precision value for PID_6 (0.8). Notably, the instances of PID_5 were predicted much more accurate in Meeting 2 than in Meeting 1 (precision: 0.698, recall: 0.656). The fairly similar accuracy results achieved for Meeting 1 and Meeting 2 might stem from very similar samples. In both meetings, ten employees participated in the study and eight of ten employees even attended both meetings. Though, classification worked slightly better for Meeting 1 for which the accuracy ranged between 64.2% using REP Tree or NB Tree and 68.9% using Random Forest, and varied between 60.3% using NB Tree and 67.9% for Meeting 2 using Random Forest.

Nine participants participated in Meeting 3. The Random Forest classifier achieved 78.8% accuracy meaning that approximately four out of five instances were predicted correctly (recall: M = 0.788, SD = 0.075; precision: M = 0.789, SD = 0.067). In terms of recall, the classification approach again worked best for PID_1. 1775 of 2004 instances, equivalent to 88.6%, were correctly identified. In terms of precision, Random Forest achieved the highest value for PID_11 (0.923) whereas the least accurate results amongst all participants were obtained for PID_2 (precision: 0.704) and PID_7 (recall: 0.668).
The best recognition performance was achieved in Meeting 4. The accuracy amounted to 88.2%, 85.3% and 85.2% using Random Forest, NB Tree, and REP Tree, respectively. The correct predictions were consistently high across the participants, though the highest value was achieved for PID_6 (precision: 0.988, recall: 0.987), meaning that almost all instances belonging to that individual were predicted correctly. Misclassifications for that particular individual occurred very scarcely (FP: 15, FN: 16). In comparison to the other classes, classification worked less accurate for PID_8 (precision: 0.773, recall: 0.742). Confusion matrices for the Random Forest classifier are shown in Table 5.

Table 5: Confusion Matrices for Natural Classes

		PID_1	PID_2	PID_4	PID_5	PID_6	PID_9	PID_10	PID_11	PID_12	PID_13
M1	PID_1	2646	15	27	20	27	6	10	0	0	8
	PID_2	7	2042	300	203	107	33	27	0	0	40
	PID_4	11	272	1942	200	212	28	34	1	8	51
	PID_5	18	247	292	1225	253	345	76	0	14	289
	PID_6	13	170	210	265	1639	200	42	51	32	137
	PID_9	3	45	38	240	110	1880	133	21	127	162
	PID_10	6	84	44	76	46	187	1913	0	156	247
	PID_11	3	1	0	2	17	19	9	1380	148	0
	PID_12	2	4	8	22	19	150	160	127	2103	164
	PID_13	10	86	89	217	176	286	356	3	115	1421

		PID_2	PID_3	PID_4	PID_5	PID_6	PID_8	PID_9	PID_11	PID_12	PID_13
M2	PID_2	1173	8	159	52	11	229	21	4	25	90
	PID_3	25	1092	18	49	103	41	115	172	117	40
	PID_4	152	4	1348	9	10	221	5	1	0	22
	PID_5	111	37	60	1163	41	71	105	11	80	93
	PID_6	39	78	12	96	1267	26	21	88	60	85
	PID_8	290	6	241	41	11	1080	17	0	8	78
	PID_9	12	73	3	74	15	6	911	44	164	64
	PID_11	2	81	0	39	40	4	83	1267	160	96
	PID_12	16	65	0	49	31	3	148	54	1249	157
	PID_13	62	18	25	94	54	78	57	48	128	1208

		PID_1	PID_2	PID_5	PID_7	PID_8	PID_9	PID_10	PID_11	PID_13
M3	PID_1	1775	21	68	74	53	1	11	0	1
	PID_2	11	1405	43	68	120	133	148	6	70
	PID_5	82	79	1429	113	35	97	77	39	53
	PID_7	80	100	90	1338	210	7	170	5	4
	PID_8	69	117	18	147	1581	8	59	0	5
	PID_9	2	70	46	3	7	1730	23	38	85
	PID_10	11	130	46	87	31	43	1586	8	62
	PID_11	0	13	74	3	0	64	7	1755	88
	PID_13	2	62	44	9	9	132	79	50	1617

		PID_3	PID_4	PID_6	PID_8	PID_10	PID_13
M4	PID_3	1101	18	8	69	32	30
	PID_4	27	1084	0	118	0	29
	PID_6	6	0	1242	1	7	2
	PID_8	57	208	2	934	0	57
	PID_10	24	0	5	2	1202	25
	PID_13	40	24	0	84	16	1076

Discussion
Our results provide evidence of the role of context in defining postural behavior, and thus influencing the identification of employees. For example, PID_1, the most senior manager among the participants, participated in only meetings one and three. PID_2 also participated in only meetings one and three, with PID_8 only participating in meetings two and three. That is, even when contributing less total instances to the classification problem, these senior team members stood out. This result also illuminates the possibility of lower-ranked leaders 'stepping up' to take on a certain role in the absence of their superiors, and engaging in relatively unconscious behaviors to match. A number of more general overall findings also arise.

It was found that posture (*Posture_front-back*, *Posture_left-right)* is collectively the most powerful feature in recognizing individuals. In particular, the orientation angle in the front-back plane and left-right plane were found to be consistently powerful, irrespective of the dataset and applied classifiers. For instance, these kinetic features together contributed between 82.20% accuracy in Meeting 2, using Random Forest. Interestingly, Audio_back_volume, has potential as an "audio posture" feature, since, as discussed, it also captures some information about how a sociometric badge wearer is sitting, and to what extent they are projecting their voice (for example, in the same meeting, adding this feature increased the above to 86.10% for example).

In this study, we deliberately employed a minimal approach to classification here, by not formally factoring in the sequence or temporal structure of the instances. Additionally, in this study, feature consistency as a feature itself [51], was not formally measured, but rather was captured by maximizing the available amount of longitudinal categorical data available for classification (e.g. second-by-second individual instances).

According to Pentland [11], consistency of movements and vocalic cues is a sign of mental focus and indicates less susceptibility to influence. With respect to solving the classification problem at hand, logically, high consistency (low variability) leads to enhanced the recognition performance of each individual, whereas high variability caused less accurate results. This is illustrated by the fact that the highest accuracy across all meetings was achieved for Meeting 4. In relation to the other meetings, the relative amount of influence had been the lowest during that meeting, which seemingly contributes to ease of classification.

Some interesting individual level characteristics also emerge. For example, PID_5 was very difficult to identify in Meeting 1. A closer look at the postural position in left-right direction shows a higher variability in the data for that individual (M = 2.55, SD = 8.73, *range* = 75.03) compared to the others (M = 2.23, SD = 6.5, *range* = 50.78), possibly indicating increased openness to influence. Moreover, the bad recognition performance of PID_5 was attributable to very similar interaction patterns among the participants reflected in the number of misclassifications (see confusion matrix). This indicates that the non-linguistic behavior of PID_5 considerably overlapped with the other participants which might have been caused by him being mirroring signals of the group members. Since mimicry leads to reflexive copying of behaviors [11] it negatively affected the recognition performance.

Hence, if the classification approach faced homogenous behaviors in the group, the recognition performance decreased.

Individuals exhibiting extreme social behaviors, particularly those holding leadership positions within the group, rather than showing group-uniform behaviors were recognized more accurately. For instance, considering the recognition performance of PID_1 (the most senior manager present, meetings 1 and 2), it is evident that PID_1 is averagely identified the most accurately among all employees. For this individual, the classification approach worked very accurately for Meeting 1 (F-measure: 0.966 with Random Forest) as well as for Meeting 3 (F-measure: 0.88 with Random Forest). For both meetings, the recognition performance of PID_1 also varied considerably versus the other employees (F-measure = harmonic mean of recall and precision [52]).

Interestingly, PID_1 is characterized by a lower average orientation angle in the front-back plane (M = 42.15, SD = 6.86) compared to the orientation of the other participants (M = 68.82, SD = 7.98). A value of 90 indicates sitting up straight or standing upright, whereas a value of 0 indicates a flat position in either direction. The same was found to hold true for Meeting 3. Whereas the other employees showed an average orientation angle in the front-back plane of 65.31 (SD = 7.37), the orientation angle accounted to 50.28 (SD = 8.83) for PID_1. This notable finding can be explained by considering the seating arrangement during the meetings in more detail. PID_1 was the only one who sat comfortably and leaned back in an office chair rather than taking the same position as the group members.

Taking into account organizational structure, it is clear that PID_1 holds a senior post within the division. In fact, PID_1 is the head of the focal department and is responsible for its management and success. Theory on non-verbal communication and leadership impression suggests that leaning forward communicates interest whereas leaning backwards can potentially suggest less immediacy, or also informality and indifference [53,54,55,56,57], the latter two potentially being proxies for a particularly confident or authoritative member of a team.

Some notable differences can also be detected regarding paralinguistic speech characteristics. The dominant behavior of the department manager is manifested in averagely longer speaking segments. In Meeting 1, he spoke on average for 2.73 seconds per speech segment and in Meeting 3 he even spoke approximately 5 seconds per speech segment (Meeting 1: M = 1.72, SD = 0.81; Meeting 3: M = 2.11, SD = 0.84). Different studies [48,58,59] demonstrated that speaking time is strongly associated with individual dominance and constitutes a reliable predictor of emergent leadership. Burgoon and Saine [60] and Harper [61] showed that dominance is not only inferred from participation rate, but also conveyed by speaking loudly and frequently interrupting the conversational partner. Interestingly, the department manager spoke with the loudest voice (Meeting 1: M = 0.018, SD = 0.028; Meeting 3: M = 0.014, SD = 0.014) compared to the others (Meeting 1: M = 0.01, SD = 0.003; Meeting 3: M = 0.06, SD = 0.002) and also interrupted frequently (111 times in Meeting 3).

As shown, multiple factors such as postural position, voice volume or participation rate induce the most accurate recognition performance of PID_1. As the most senior manager, PID_1 took the lead during the meetings and also reinforced their dominant role by their non-verbal behavior. Interestingly, the department manager had not been present during Meeting 2, which was characterized by fairly balanced results across the employees, and the fact that none of the participants showed extreme interaction patterns. Evidently, the dominant role and position of PID_1 within the division can be clearly identified within the data.

Future Research Directions

Future research could focus more on a priori hypothesizing about the performance of specific features, building on our data-driven approach to feature selection. Additionally, future research could also take a more 'traditional' approach to HAR, focusing not only on individual identification but also on the identification of specific actions, which could include perspectives such as speech acts [62], and a more in-depth analysis of the behavioral proxies for hierarchy establishment. This could also build on the capabilities of the sociometric badges to facilitate the computation of non-verbal behavioral mirroring variables. Finally, future research will assess the impact of introducing or changing / switching leadership roles within contrived and natural settings, examining the associated changes in postural variables.

Next Steps

The next steps for this research include classification of employees grouped under job roles, identification of dyads, and model refinement using class balancing (e.g. under / over-sampling). Next steps will also include testing beyond this proof-of-concept analysis using larger sample sizes, and comparison across different teams and organizational settings.

References:

1. Genoud D, Cuendet V, Torrent J. Soft Fall Detection Using Machine Learning in Wearable Devices. InAdvanced Information Networking and Applications (AINA), 2016 IEEE 30th International Conference on 2016 Mar 23 (pp. 501-505). IEEE.
2. Gibson RM, Amira A, Ramzan N, Casaseca-de-la-Higuera P, Pervez Z. Multiple comparator classifier framework for accelerometer-based fall detection and diagnostic. Applied Soft Computing. 2016 Feb 29;39:94-103.
3. Gouverneur P, Jaworek-Korjakowska J, Köping L, Shirahama K, Kleczek P, Grzegorzek M. Classification of Physiological Data for Emotion Recognition. InInternational Conference on Artificial Intelligence and Soft Computing 2017 Jun 11 (pp. 619-627). Springer, Cham.
4. MacDonald K, Bahr R, Baltich J, Whittaker JL, Meeuwisse WH. Validation of an inertial measurement unit for the measurement of jump count and height. Physical Therapy in Sport. 2017 May 31;25:15-9.
5. Mooney R, Quinlan LR, Corley G, Godfrey A, Osborough C, ÓLaighin G. Evaluation of the Finis Swimsense® and the Garmin Swim™ activity monitors for swimming performance and stroke kinematics analysis. PloS one. 2017 Feb 8;12(2):e0170902.
6. Choudhury T, Pentland A. Sensing and modeling human networks using the sociometer. Innull 2003 Oct 21 (p. 216). IEEE.
7. Daggett M, O'Brien K, Hurley M, Hannon D. Predicting Team Performance Through Human Behavioral Sensing and Quantitative Workflow Instrumentation. InAdvances in Human Factors and System Interactions 2017 (pp. 245-258). Springer International Publishing.
8. Onnela JP, Waber BN, Pentland A, Schnorf S, Lazer D. Using sociometers to quantify social interaction patterns. Scientific reports. 2014 Jul 15;4:5604.
9. Pentland A. Social signal processing [exploratory DSP]. IEEE Signal Processing Magazine. 2007 Jul;24(4):108-11.
10. Wu L, Waber BN, Aral S, Brynjolfsson E, Pentland A. Mining face-to-face interaction networks using sociometric badges: Predicting productivity in an it configuration task.
11. Pentland A. Honest Signals: How They Shape Our World (Bradford Books). 2008
12. Pentland A, Choudhury T, Eagle N, Singh P. Human dynamics: computation for organizations. Pattern Recognition Letters. 2005 Mar 31;26(4):503-11.
13. Arena MJ, Pentland S, Price D. Honest Signals-Hard Measures for Social Behavior. Organization Development Journal. 2010 Oct 1;28(3):11.
14. Montanari, A., Nawaz, S., Mascolo, C., & Sailer, K. (2016, February). Experience in Deploying Wearable Devices for Office Analytics. Paper presented at the 1st International Workshop on Quantified Workplace, San Francisco, CA, USA.
15. Montanari A, Nawaz S, Mascolo C, Sailer K. A Study of Bluetooth Low Energy performance for human proximity detection in the workplace. InPervasive Computing and Communications (PerCom), 2017 IEEE International Conference on 2017 Mar 13 (pp. 90-99). IEEE.
16. Perry-Smith JE, Mannucci PV. From creativity to innovation: The social network drivers of the four phases of the idea journey. Academy of Management Review. 2017 Jan 1;42(1):53-79.
17. Perry-Smith JE, Shalley CE. The social side of creativity: A static and dynamic social network perspective. Academy of management review. 2003 Jan 1;28(1):89-106.

18. Goleman, D. (2003). What makes a leader. *Organizational influence processes*, 229-241.
19. Goleman, Daniel, and Richard Boyatzis. "Social intelligence and the biology of leadership." *Harvard Business Review* 86.9 (2008): 74-81.
20. Goleman, Daniel. "Leadership that gets results." *Harvard business review* 78.2 (2000): 4-17.
21. Mehra, Ajay, et al. "The social networking ties of group leaders: Implications for group performance and leader reputation." *Organization science* 17.1 (2006): 64-79.
22. Pentland, Alex. "To Signal Is Human: Real-time data mining unmasks the power of imitation, kith and charisma in our face-to-face social networks." *American scientist* 98.3 (2010): 204-211.
23. Vinciarelli, A., Pantic, M., Bourlard, H., & Pentland, A. (2008, October). Social signals, their function, and automatic analysis: a survey. In Proceedings of the 10th International Conference on Multimodal Interfaces (pp. 61-68). ACM.
24. Choudhury T, Pentland A. Characterizing social networks using the sociometer. Proceedings of the North American association of computational social and organizational science (NAACSOS). 2004 Jun.
25. Capela NA, Lemaire ED, Baddour N. Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients. PloS one. 2015 Apr 17;10(4):e0124414.
26. Catal C, Tufekci S, Pirmit E, Kocabag G. On the use of ensemble of classifiers for accelerometer-based activity recognition. Applied Soft Computing. 2015 Dec 31;37:1018-22.
27. Orr RJ, Abowd GD. The smart floor: A mechanism for natural user identification and tracking. InCHI'00 extended abstracts on Human factors in computing systems 2000 Apr 1 (pp. 275-276). ACM.
28. Turaga P, Chellappa R, Subrahmanian VS, Udrea O. Machine recognition of human activities: A survey. IEEE Transactions on Circuits and Systems for Video Technology. 2008 Nov;18(11):1473-88.
29. Yazdansepas D, Niazi AH, Gay JL, Maier FW, Ramaswamy L, Rasheed K, Buman MP. A multi-featured approach for wearable sensor-based human activity recognition. InHealthcare Informatics (ICHI), 2016 IEEE International Conference on 2016 Oct 4 (pp. 423-431). IEEE.
30. Bulling A, Blanke U, Schiele B. A tutorial on human activity recognition using body-worn inertial sensors. ACM Computing Surveys (CSUR). 2014 Jan 1;46(3):33.
31. Mannini A, Sabatini AM. Machine learning methods for classifying human physical activity from on-body accelerometers. Sensors. 2010 Feb 1;10(2):1154-75.
32. Choudhury T, Consolvo S, Harrison B, Hightower J, LaMarca A, LeGrand L, Rahimi A, Rea A, Bordello G, Hemingway B, Klasnja P. The mobile sensing platform: An embedded activity recognition system. IEEE Pervasive Computing. 2008 Apr;7(2).
33. Aggarwal JK, Ryoo MS. Human activity analysis: A review. ACM Computing Surveys (CSUR). 2011 Apr 1;43(3):16.
34. Igual R, Medrano C, Plaza I. Challenges, issues and trends in fall detection systems. Biomedical engineering online. 2013 Jul 6;12(1):66.
35. Chambers R, Gabbett TJ, Cole MH, Beard A. The use of wearable microsensors to quantify sport-specific movements. Sports medicine. 2015 Jul 1;45(7):1065-81.

36. Mozos OM, Sandulescu V, Andrews S, Ellis D, Bellotto N, Dobrescu R, Ferrandez JM. Stress detection using wearable physiological and sociometric sensors. International journal of neural systems. 2017 Mar;27(02):1650041.
37. Stoltzman WT. *Toward a social signaling framework: Activity and emphasis in speech* (Doctoral dissertation, Massachusetts Institute of Technology). 2006.
38. Curhan JR, Pentland A. Thin slices of negotiation: predicting outcomes from conversational dynamics within the first 5 minutes. Journal of Applied Psychology. 2007 May;92(3):802.
39. Madan A, Pentland AS. Vibefones: Socially aware mobile phones. InWearable Computers, 2006 10th IEEE International Symposium on 2006 Oct 11 (pp. 109-112). IEEE.
40. Alshamsi A, Pianesi F, Lepri B, Pentland A, Rahwan I. Beyond contagion: Reality mining reveals complex patterns of social influence. PloS one. 2015 Aug 27;10(8):e0135740.
41. Alshamsi A, Pianesi F, Lepri B, Pentland A, Rahwan I. Network diversity and affect dynamics: The role of personality traits. PloS one. 2016 Apr 1;11(4):e0152358.
42. Dunne, L. E., Walsh, P., Hermann, S., Smyth, B., & Caulfield, B. (2008). Wearable monitoring of seated spinal posture. IEEE transactions on biomedical circuits and systems, 2(2), 97-105.
43. Pentland, A., & Heibeck, T. (2010). Honest signals: how they shape our world. MIT press.
44. Weisfeld, Glenn E., and Jody M. Beresford. "Erectness of posture as an indicator of dominance or success in humans." *Motivation and Emotion* 6.2 (1982): 113-131.
45. Witten IH, Frank E, Hall MA, Pal CJ. Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann; 2016 Oct 1.
46. Kohavi, R., & John, G. H. (1997). Wrappers for Feature Subset Selection. Artificial Intelligence, 97, 273-324.
47. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research. 2002;16:321-57.
48. Mast MS. Dominance as expressed and inferred through speaking time. Human Communication Research. 2002 Jul 1;28(3):420-50.
49. Burgoon JK, Birk T, Pfau M. Nonverbal behaviors, persuasion, and credibility. Human communication research. 1990 Sep 1;17(1):140-69.
50. Taylor CJ, Freeman L, Olguin Olguin D, Kim T. Deviation in Voice Pitch as a Measure of Physiological Stress Response to Group Processes. InAdvances in Group Processes 2016 Jul 13 (pp. 211-242). Emerald Group Publishing Limited.
51. Olguín-Olguín D, Pentland A. Sensor-based organisational design and engineering. International Journal of Organisational Design and Engineering. 2010 Jan 1;1(1-2):69-97.
52. Lara OD, Labrador MA. A survey on human activity recognition using wearable sensors. IEEE Communications Surveys and Tutorials. 2013 Jul;15(3):1192-209.
53. Burgoon JK, Guerrero LK, Floyd K. Nonverbal communication. Routledge; 2016 Jan 8.
54. Howell JM, Frost PJ. A laboratory study of charismatic leadership. Organizational behavior and human decision processes. 1989 Apr 1;43(2):243-69.
55. Leathers DG, Eaves M. Successful nonverbal communication: Principles and applications. Routledge; 2015 Oct 16.
56. Remland, M. S. (1984). Leadership Impressions and Nonverbal Communication in a Superior-Subordinate Interaction. Communication Quarterly, 32(1), 41-48.

57. Roter DL, Frankel RM, Hall JA, Sluyter D. The expression of emotion through nonverbal behavior in medical visits. Journal of general internal medicine. 2006 Jan 1;21(S1).
58. Mullen B, Salas E, Driskell JE. Salience, motivation, and artifact as contributions to the relation between participation rate and leadership. Journal of Experimental Social Psychology. 1989 Nov 30;25(6):545-59.
59. Stein RT, Heller T. An empirical analysis of the correlations between leadership status and participation rates reported in the literature. Journal of Personality and Social Psychology. 1979 Nov;37(11):1993.
60. Burgoon JK, Saine TP. The unspoken dialogue: An introduction to nonverbal communication. Houghton Mifflin Harcourt (HMH); 1978.
61. Harper RG. Power, dominance, and nonverbal behavior: An overview. InPower, dominance, and nonverbal behavior 1985 (pp. 29-48). Springer New York.
62. Pentland, B. T., Pentland, A. P., & Calantone, R. J. (2017). Bracketing off the actors: Towards an action-centric research agenda. Information and Organization, 27(3), 137-143.