Differentiating Higher and Lower Job Performers in the Workplace Using Mobile Sensing

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Assessing performance in the workplace typically relies on subjective evaluations, such as, peer ratings, supervisor ratings and self assessments, which are manual, burdensome and potentially biased. We use objective mobile sensing data from phones, wearables and beacons to study workplace performance and offer new insights into behavioral patterns that distinguish higher and lower performers when considering roles in companies (i.e., supervisors and non-supervisors) and different types of companies (i.e., high tech and consultancy). We present initial results from an ongoing year-long study of N=554 information workers collected over a period ranging from 2-8.5 months. We train a gradient boosting classifier that can classify workers as higher or lower performers with AUROC of 0.83. Our work opens the way to new forms of passive objective assessment and feedback to workers to potentially provide week by week or quarter by quarter guidance in the workplace.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**; • **Applied computing**;

Additional Key Words and Phrases: mobile sensing, workplace performance, mobile behavioral pattern

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1 INTRODUCTION

The increasing use of mobile sensing, machine learning and data analytics is offering new insights into health [3, 74], lifestyle [79], personality [16, 68, 75], cognition [78], and other human behaviors and traits [19, 27]. This passively collected sensor data from phones and wearables, while still in its early stages of research and development, holds the promise to significantly advance a broad spectrum of areas from precision medicine, advances in public health, to how we exercise, work and interact with each other on a daily basis. In this paper, we propose the application of mobile sensing to study workplace performance [40, 43]. Today, assessing workplace performance typically relies on subjective input such as peer ratings, supervisor ratings and self-reported assessments, which are manual, burdensome, potentially biased and unreliable. We propose a radically new approach to evaluating workplace performance using mobile sensing from phones, wearables and beacons. The use of unobtrusive assessments embedded in the work environment can produce a more objective measure of performance offering a better understanding of the workplace environment and the workforce both inside and outside of work. Specifically, we present new insights and initial results from an on-going year long study into behavioral patterns that distinguish higher and lower performers across different industries.

In [56, 60], the authors define workplace performance broadly as *a multidimensional construct indicating how well workers and employees perform their tasks, the initiative they take and the resourcefulness they show in solving problems*. A good workplace performer is one who is well aware of his or her role in the organization, and executes the underlying tasks and role well. The former behavior is termed in-role behavior [8, 70, 77] and the latter, individual task proficiency [8, 25, 70]. We can also think of a good performer as a good team player who helps colleagues in activities that contribute to the achievement of the overall objectives and goals of the organization, and one who is mindful of protecting the values and interests of the organization. Researchers [17, 18, 49, 50] describe this behavior as organizational citizenship behavior, and its opposite as counterproductive work behavior [11, 18, 58].

While many companies assess workers using different methods including self-reports, peer reviews or supervisor reports – and these may differ across different industries (e.g., tech, government, financial services), it is accepted that workplace performance [8, 70] can be assessed across four different dimensions: (1) *individual task proficiency (ITP)* [8, 25], which is proficiency at performing activities that contribute to transforming an organization's technical core, where the term technical core refers to the transformation of raw materials (objects, thoughts, or actions) into organizational products; (2) *in-role behavior (IRB)* [8, 77], which is the behavior required by an employee to accomplish their duties in an organization; (3) *organizational citizenship behavior (OCB)* [17, 18], which is the positive voluntary activity or behavior demonstrated by an employee, not necessarily recognized by the employer but it promotes the effective functioning of the organization; and finally, (4) *counterproductive work behavior (CWB)* [18, 58], which is the behavior demonstrated by an employee, that negatively affects the well-being of a company.

Many factors impact performance, making its assessment complex. In addition to personality, there are several cognitive states, behaviors and habits which impact performance at work. One factor, for example, is sleep. A study [41] of information workers found that the combination of less sleep and strong deadline pressure felt by workers leads to a longer focus duration while using their workplace computers. In another study of college students, researchers [42] found that cumulative hours of sleep loss with respect to the subject-specific daily need for sleep [69] is associated with more productivity. However, it was also found to be associated with shorter focus duration on their personal computers and smartphones and a proclivity to spend more time on social media. Other factors include stress, affect and anxiety. Research [30] found that a moderate amount of stress for example can help prolong focus and block distractions. However, in the workplace, high levels of stress are shown [41] to be associated with the reduced ability to focus. Other habits such as engaging in physical exercise or the use of alcohol, are reported as factors that affect performance in positive and negative ways, respectively. Figure 1 captures many of these factors as part of a multidimensional construct for workplace performance.

Factors affecting workplace performance have been previously studied [4, 6, 35, 60] using analyses of self-reported data where workers in organizations are asked to assess themselves against certain well established performance metrics. However, as reported in [5, 22, 60], data collected using this approach alone is prone to individual bias. Although these methods combined with bias correcting techniques [16, 24] and domain knowledge are useful in studies of workplace performance, there is a need for new research into more objective, unobtrusive and reliable methods. In this paper, we argue that passive sensor data from mobile devices and predictive analytics offers a novel approach to exploring workplace performance in a more objective manner. To the best of our knowledge our study represents the first time that mobile sensing data from phones, wearables and beacons is used to classify higher and lower performers across different industries. It provides a proof of concept of the use of mobile sensing in the workplace, identifies new insights into patterns that distinguish higher and lower performers, and ultimately opens the way to new forms of passive objective assessment and feedback to workers to provide day to day and week by week guidance. Specifically, the contributions of this paper are as follows:

- We collect a passive sensing data set from N=554 recruited participants' smartphones (i.e., Android and iOS), wearables (i.e., Garmin vivosmart) and bluetooth beacons inside and outside of the workplace. The cohort comprises three major sub cohorts: workers (N=138) at a midsize technology company, workers (N=217) from a consultancy company and finally a group we call "others" (N=199) that represent a collection of workers associated with universities (e.g., researchers) and small labs. Data is collected from workers over a period ranging from 2-8.5 months.
- We design a set of features which capture the mobility, activity, phone usage, physiological signals and movement within the workplace. Participants answer a wide range of self-reported surveys administered at the start of the study and a set periodically (i.e., 3 times per week) administered (e.g., ITP [8, 25], IRB [8, 77], OCB [17, 18], CWB [18, 58]) over the first two months of the study. Note, we only consider the job performance metrics (i.e., ITP, IRB, OCB, CWB) and health factors (e.g., heart rate, sleep) in our analysis and not the broader psychological factors (e.g., personality, affect, cognitive ability) shown in Figure 1. Considering these additional factors is part of our future work.
- We demonstrate that we can group information workers into higher and lower performers based on the four metrics of workplace performance (i.e., ITP, IRB, OCB and CWB).
- We identify sensing features which are significantly different between higher and lower performers with the goal of uncovering behavioral patterns associated with high performance in the workplace. In addition, we identify different patterns for higher/lower performance across different subgroups: for example, between supervisors and non-supervisors, and between employees of a consulting company and a tech company.
- We train a classifier to classify employees as higher or lower performers using their past week's mobile sensing features. The AUROC [23] of the trained model is 0.83. The model's precision for predicting higher and lower performers is 0.71 and 0.8, respectively, when the prediction model's threshold of the probability of occurrence is 0.65. The recall for predicting higher and lower performers is 0.84 and 0.64, respectively, for the same threshold.

2 RELATED WORK

There is a growing interest in studying workplace performance. New programs in the USA include the IARPA MOSAIC program [31, 44] that is studying new approaches to unobtrusive, passive and persistent measurement to predict an individual's job performance, and the NSF future of work program [48] that aims to advance cognitive and physical capabilities at work.

Most of the existing literature related to workplace performance relies on various types of self-reports and supervisory evaluations [6, 10, 65, 66]. Some of the earliest work [10] uses archival records, rating scales and job knowledge tests for job performance assessment. Sonnentag et al [65] report that performance ratings are the most widely used measure of assessment. Performance ratings often include a combination of peer ratings, supervisor ratings and self assessments. Some of the more objective methods being used are sales figures, production records, and lines of code written, but these metrics have drawbacks [10].

There is growing work [6, 21, 59, 66] on personality and its relationship to workplace performance. However, this work as a whole sometimes presents conflicting findings and views. Some researchers [6, 66] find that the only important personality trait associated with workplace performance is conscientiousness. While others show that extraversion and emotional stability [21] are important. Furthermore, other researchers [59] argue a combination of traits is important. In [29] the authors claim that there is bias toward a particular behavior due to the inclination of employees to associate themselves with a certain personality trait seen as ideal to their employers.

Mobile sensing is demonstrating promise across a number of areas including understanding lifestyles [38, 79], diagnosing disease [63], determining cognitive states of workers [61], studying human mobility patterns [9], and

Fig. 1. Multidimensional construct for workplace performance. Note, we only consider the job performance metrics (i.e., ITP [8, 25], IRB [8, 77], OCB [17, 18], CWB [18, 58] – as ground-truth) and health factors (e.g., heart rate, physical activity, sleep, etc. – as independent variables) and not the broader psychological factors (e.g., personality, affect, cognitive ability).

even predicting student academic performance [73]. Schaule et al. [61] present how office workers' cognitive load can be detected using physiological data from wearables. They demonstrate that physiological data relates to mental state and can determine when a person is busy and intellectually invested in their work [61]. In [73], the authors use the StudentLife app [72] to study academic performance showing that variation in conversation duration of students and the time spent studying are strong predictors of academic performance across the semester. The StudentLife study [72] also found that conscientiousness is the primary trait positively related to academic performance in college students. This is consistent with the findings of Higgins et al. [29] who conclude that both academic and job performance are influenced by conscientiousness.

Prior work in applied psychology, management studies and organizational behavior investigate how the four performance dimensions (i.e., ITP, IRB, OCB and CWB) we adopt in our study relate to a wide variety of different individual and group-level outcomes in organizations [20, 26, 33, 36, 53, 57, 76]. In addition, researchers show how these performance dimensions differ across a range of different demographic and individual traits (e.g., age, gender, personality, emotional intelligence) [15, 47, 51]. Prior research investigates the relationship between supervisors' overall ratings of employee performance [33, 36, 53, 57], allocation of reward [1] and employee turnover [14]. This body of research also investigates the relationship between OCB and CWB on the performance of business units (i.e., different sub-groups) within an organization [20, 54]. However, little is known about the daily real-world behaviors that separate higher and lower performers in companies. In our work, we aim to shed light on behavioral patterns that characterize higher and lower performers across various performance dimensions (viz. ITP, IRB, OCB and CWB) using mobile sensing methods, machine learning and predictive analytics. Mobile sensing methods offer the promise of unprecedented continuous assessment to study workplace behavior unobtrusively and objectively across daily, weekly, monthly, quarterly and yearly timescales.

3 METHODOLOGY

In what follows, briefly discuss our study set up, ground-truth, our mobile sensing and data collection system and feature extraction.

Table 1. Demographics of the participants across each cohort

Cohort	Male	Female	Total
A	109	108	217
B	112	26	138
C	15	6	21
D	72	75	147
E	12	19	31
Total	320	234	554

3.1 Study Design

Between early spring and late summer of 2018, we recruited 554 working professionals who live and work in the United States as part of a large scale longitudinal research study. Each worker agreed to participate in our study for a period of one year. As shown in Table 1, 217 participants work for a multinational consultancy company A, 138 work for a multinational technology company B, 21 work for a local software company C, 147 work for various smaller companies (which we collectively call group D), and finally, 31 work for a local university E. It is important to note that some of the workforce in company A work at different branches within the country, whereas the other groups work at their company headquarters. Among the participants in our study, 254 report holding a supervisory position in their company, 297 report holding non-supervisory position and 3 participants declined to mention their position in their companies.

For cohorts A, B and C, we established partnerships with the organizations who advertised the study to their employees. Workers have the option to either participate or not in the study. Those who join the study receive $750 for participating. The final amount of compensation varies depending on compliance levels, which is measured in terms of the average percentage of daily data streams collected from the participant. The minimum compliance percentage to earn the full amount is 80%. Furthermore, this amount is paid out in installments across the study period following a specific schedule with the goal of keeping people in the year-long study. Participants in cohorts D and E join the study through direct recruitment.

This study is conducted in accordance with the Institutional Review Board (IRB), an institution which protects the rights and welfare of human research subjects.

3.2 Ground Truth

Workplace performance is multifaceted and each dimension is composed of unique factors that influence it, as illustrated in Figure 1. For this reason, we use a number of gold standard questionnaires to collect data about each of these factors. The questionnaires are grouped into three categories: 1) job performance surveys, 2) a personality survey and 3) health surveys. We only consider the job performance surveys as ground truth in this paper, as shown in Table 2. We administer a battery of surveys at the beginning of the study period and periodically over the first 60 days of this year-long study. The job performance questionnaires are ITP [8, 25], IRB [8, 77], OCB [17, 18], CWB [18, 58]. The ITP survey is scored from 3 to 15, the IRB is scored from 7 to 49 and both the OCB and CWB surveys are scored from 0 to 8. A high value of ITP, IRB or OCB indicates higher performance, whereas a higher value of CWB indicates lower performance. Every participant in the study is required to respond to a set of periodic shorter self-reports (3 times per week – we call these the survey days) during the first 60 days of the study, as shown in Table 2.

Table 2. Performance surveys: (1) individual task proficiency (ITP), which is proficiency at performing activities that contribute to transforming an organization's technical core, where the term technical core refers to the transformation of raw materials (objects, thoughts, or actions) into organizational products; (2) in-role behavior (IRB), which is the behavior required by an employee to accomplish their duties in an organization; (3) organizational citizenship behavior (OCB), which is the positive voluntary activity or behavior demonstrated by an employee, not necessarily recognized by the employer but it promotes the effective functioning of the organization; and finally (4) counterproductive work behavior (CWB), which is the behavior demonstrated by an employee, that negatively affects the well-being of a company.

Survey	**Items**	**Answer Choices**
ITP	Please indicate how often you carried out these three behaviors today 1. Carried out the core parts of your job well 2. Completed your core tasks well using the standard procedures 3. Ensured your tasks were completed properly	Response scale: 1 (Very little) 2 (Somewhat) 3 (Moderately) 4 (Considerably) 5 (A great deal)
IRB	Please indicate your level of agreement with whether you... 1. Adequately completed your assigned duties 2. Fulfilled responsibilities specified in your job description 3. Performed tasks that are expected of you 4. Met formal performance requirements of your job 5. Engaged in activities that will directly affect your performance evaluation 6. Neglected aspects of the job you are obligated to perform 7. Failed to perform essential duties	Response scale: 1 (Strongly disagree) 2 (Moderately disagree) 3 (Slightly disagree) 4 (Neutral) 5 (Slightly agree) 6 (Moderately agree) 7 (Strongly agree)
OCB	Today, I... 1. Went out of my way to be a good employee 2. Was respectful of other people's needs 3. Displayed loyalty to my organization 4. Praised or encouraged someone 5. Volunteered to do something that was not required 6. Showed genuine concern for others 7. Tried to uphold the values of my organization 8. Tried to be considerate to others	Response scale: Yes/No
CWB	Today, I... 1. Spent time on tasks unrelated to work 2. Gossiped about people at my organization 3. Did not work to the best of my ability 4. Said or did something that was unpleasant 5. Did not fully comply with a supervisor's instructions 6. Behaved in an unfriendly manner 7. Spoke poorly about my organization to others 8. Talked badly about people behind their backs	Response scale: Yes/No

3.3 Data Collection: The Mobile Sensing System

Figure 2 illustrates the data collection and feature extraction process, which includes continuous sensing tools running on phones, wearables, beacons and backend servers for data collection and predictive analysis of workplace performance. The mobile sensing system is based on the StudentLife [72] data collection system. We continuously and passively collect mobile sensing data from participants' Apple and Android phones, Garmin wearables and beacons. The data is regularly uploaded and stored in our backend server databases. The mobile sensing system collects physiological, behavioral and mobility data from each participant in the study – all the sensing data is collected passively with no user interaction or burden. During enrollment each participant: 1) installs a data collection app on their phone called the PhoneAgent; 2) wears a Garmin vivosmart 3 wristband [37] which is paired with the PhoneAgent app on the phone in order to stream wearable data to the phone. Note, the Garmin typically lasts 4-5 days between charges in comparison to smartwatches that typically need to be charged each day – this significantly reduces the user burden to collect 24/7 wearable data; and 3) places one Gimbal bluetooth beacon [32] on their office desk and another near the entrance to their home. Participants are also asked to carry two mobile beacons on their person at all times – one in their wallet/bag and another on their keychain. The data collected from the PhoneAgent, wearable and beacons is summarized in Table 3. In what follows, we discuss each component of our continuous sensing collection system.

3.3.1 The Phone App: PhoneAgent. We develop the PhoneAgent, an app for the phone that tracks the participant's physical activity, location, phone usage (e.g., lock/unlock) and ambient light levels. This app runs in the background of Android and iOS smartphones to passively collect sensor data. The data is written to a file as a JSON object and uploaded to a server whenever the phone is connected to WiFi. The PhoneAgent app connects to the Garmin wearable and Gimbal beacons via bluetooth. The Garmin vivosmart 3 wearable streams real-time heartrate (HR), heartrate variability (HRV), floors climbed, steps, and calories burned data to the PhoneAgent over bluetooth. We stream this real-time data off the wearable to the PhoneAgent because in this way we get much finer grained data than the Garmin backend server provides to users.

3.3.2 The Wearable: Garmin Vivosmart 3. The Garmin vivosmart 3 wristband [37] is a commercial wearable and is mostly used for fitness monitoring, wellness monitoring and activity tracking. It periodically collects physiological data such as heartrate, heartrate variability and stress (which is a proprietary black box inference provided by Garmin). The Garmin (note, when we use the term wearable we mean Garmin) also captures sleep quality including the duration of light sleep, deep sleep, REM sleep and entire sleep time. The Garmin also allows users to input their weight, and automatically computes step count, calories burned, number of floors climbed and physical activity (e.g., walking, running, etc.) [37]. Participants are required to pair the Garmin with the PhoneAgent app on the phone via bluetooth. In addition, participants pair the Garmin with the off-the-shelf Garmin Connect app whose APIs provide access to the sleep data and daily summaries of other sensing streams described above. We periodically pull this data and store it in our database. These daily summaries (e.g., heartrate, physical activity and stress, etc.) are augmented with the finer grained sensor data that is streamed to the PhoneAgent, as discussed above.

3.3.3 The Beacons: Gimbals. We use static Gimbal beacons [32] to study time spent at the office and home as well as breaks taken away from a participant's desk. Beacons are low energy radio modules that transmit and receive radio signals to and from other bluetooth enabled devices [32]. The PhoneAgent app on the phone implements a Gimbal API library that enables the phone to detect encounters with beacons. To understand the protocol, consider smartphone A and beacon B. When A approaches B, A will receive the signal transmitted by B and report its signal strength. Generally, this signal strength increases as A and B are closer to each other. In this way, we can capture the mobility of participants at work. All encounter instances are logged by the PhoneAgent and uploaded to the server. A copy of these interactions is also saved on Gimbal servers and accessible through the

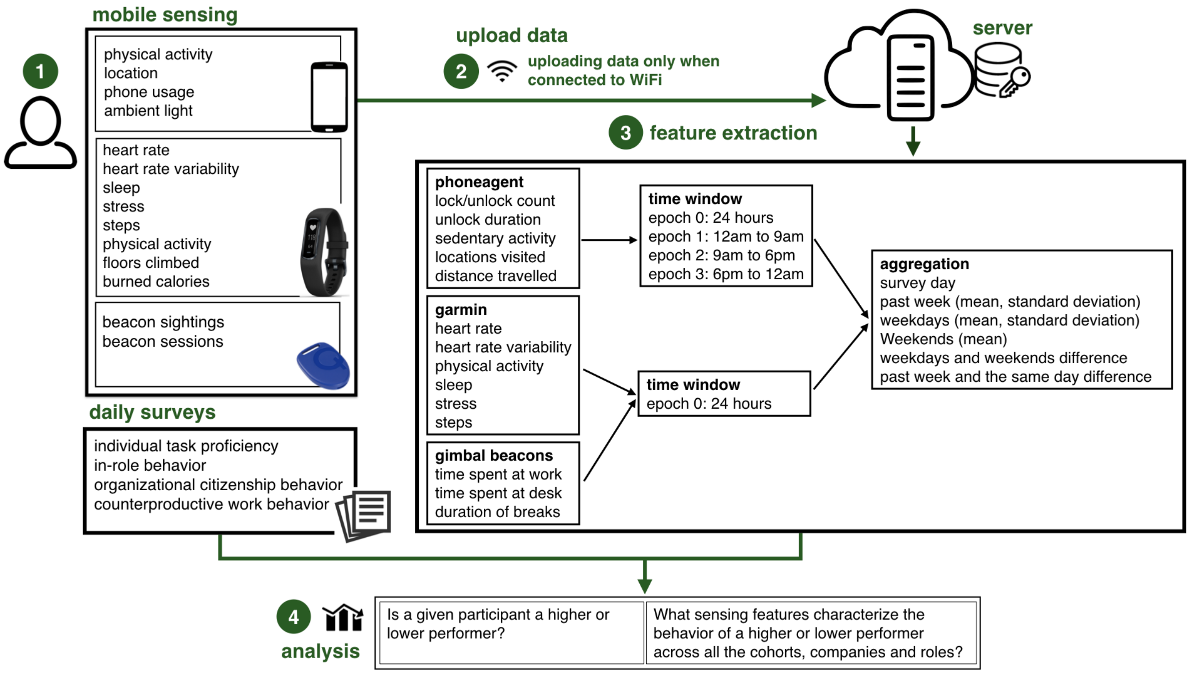


Fig. 2. We continuously collect passive sensing data from Android and Apple iOS smartphones, physiological data from Garmin Vivosmart 3, as well as sightings of Gimbal beacons. The sensor data is uploaded to the server using WiFi. We then compute features and study associations between the features and the self-reported performance.

Gimbal Server APIs [32]. In this paper, we only consider the time spent at their desk and the total time spent at work. We also consider "breaks" from the desk, which could be a meeting, or a work break for coffee, lunch, etc.

3.3.4 Dashboard. We compute the compliance rate for each participant based on whether we have collected their data for each 30 minute time interval; that is, each day we have 48 time slots of 30 minutes duration to check compliance. If we have data for a particular slot, we label it as 1, otherwise 0. We calculate a compliance percentage of each participant for each day based on these 48 time slots. A study portal allows participants and researchers to view compliance data. Participants can view compliance for different devices (e.g., PhoneAgent, Garmin and Gimbal) and report any issues they encounter to researchers. Using the study portal, we monitor the state of our sensing and data collection system. We find it helpful to stay in touch with participants to inform them if we observe any problems with their compliance rates. Participants are paid a final amount at the end of the study depending on their averaged compliance rate. The study has an overall compliance rate of 70% which means we have data from all streams (i.e., PhoneAgent, Garmin and Gimbal) for at least 17 hours per day.

3.4 Features

The features used in this study are inspired by insights drawn from prior work on mobile sensing discussed in the related work section. Given our understanding of the different factors affecting workplace performance [41, 42, 73], we calculate a total of 296 features based on the sensor data from the PhoneAgent, Garmin wearable and Gimbal beacons.

Table 3. Sensing streams collected from participants and computed features

Sensing Device	Feature Category	Features *
PhoneAgent	Mobility	Number of locations, total distance travelled **
	Activity	Physical activity and sedentary duration **
	Phone Usage	Unlock duration, number of unlocks **
Garmin Vivosmart 3	Heartrate	Averaged heart rate/heart rate variability
	Sleep	Start/end and duration of sleep, duration of deep/REM/light sleep, duration of wake-ups during sleep hours
	Stress	Duration of experienced stress levels (high/medium/low)
	Steps	Walking/running distance and duration, number of steps
Gimbal Beacons	Behavior at work	Duration at work places, duration at their desk, number of times they leave their desk (for durations of 5, 15 and 30 minutes)

* For each feature we consider: (1) features on the survey day; (2) mean values across days of the week, weekdays and weekends; (3) the standard deviation within a week across days; (4) the difference between the survey day and past week; (5) the difference between weekdays and weekends.
** We divide the day up into periods called epochs; epoch 0: 24 hours (whole day); epoch 1: 12am - 9am (night/early morning); epoch 2: 9am - 6pm (working hours); epoch 3: 6pm - 12am (evening)

Table 3 details the features we generate. Specifically, we extract aggregations of daily activity (e.g., sedentary duration), mobility (e.g., distance travelled and number of locations visited) and phone usage (e.g., number of lock/unlocks and unlocked duration) collected by the PhoneAgent. We consider various epochs for analysis across a day: night/early morning (12am - 9am, when people usually sleep), day (9am - 6pm, when people likely work) and evening (6pm - 12am, when people likely go home or visit other locations). We also consider a 24 hour epoch for the complete day. We assume that behaviors associated with each epoch may affect job performance.

We also extract physiological data and other features from Garmin (e.g., heart rate, sleep, stress and steps, as shown in Table 3). Research [62] has shown for example that heart rate and heart rate variability are associated with self-regulatory strength, effort, fatigue and burnout, which relate to performance. Sleep quality is one of the major factors that impact job performance. For example, the amount of sleep and daily variations of sleep across periods of time (e.g., week) might be a good predictor of performance. Different stress levels may influence performance. We therefore consider the stress level (e.g., low, medium and high) and its associated duration inferred by the wearable – note, the Garmin analyzes the heart rate variability while the user is inactive to determine the overall stress. Steps represent a proxy for engaging in physical exercise and may serve to influence performance.

We also extract features that capture indoor location at work using beacon data. We are interested in the following features that might directly reflect engagement at work:

- the time spent at work: captures the total duration a participant spends at work from the first sighting of the beacon at the work place to the last sighting.
- the time spent at desk: captures the percentage of time a participant spends at their desk each day.
- the number of breaks taken away from the desk that exceed periods of 5, 15 and 30 minutes (identified by the gaps in desk beacon sightings).

For each of the features mentioned above, we consider the features for the same day that the survey is administered and during the entire past week. We also consider weekdays and weekends. We calculate the standard deviation as a measurement of regularity during the week. Finally, we compute the changes between weekdays and weekends, and between the day the survey is administered and the past week.

4 ANALYSIS

We analyze the participants' performance metrics collected from the ground-truth survey measures (i.e., IRB, ITP, OCB and CWB) and then group each participant as a lower or higher performer according to their averaged (mean) performance scores using an unsupervised clustering method. We use a clustering algorithm to label the responses due to the absence of any prior work studying job performance measurements from surveys that defines cut-offs or thresholds indicating whether a worker is a higher or lower performer. We thus focus on a relative performance measure that categorizes participants into two relative groups of higher and lower performers. After identifying the performance group of each participant using a clustering method, we study associations in behavioral sensing features associated with higher and lower performers taking into account their work roles (i.e., supervisors versus non-supervisors). We categorize each participant as either higher or lower

Fig. 3. Correlations between the various workplace performance metrics. High ITP, IRB and OCB indicate higher performance whereas high CWB indicates lower performance. As shown above, ITP and IRB are highly positively correlated, whereas CWB is negatively correlated with ITP, IRB and OCB.

performer on survey days (that is, the day that a survey is administered). We identify common behaviors and behavioral patterns that characterize performers across the first 60 days of the on-going year-long study where we have ground truth assessments, namely, IRB, ITP, OCB and CWB self-reports. Questionnaires for each of these performance measures are administered once every three days over the first 60 days. Because surveys can be administered on any day of the week we ask users to respond to the question "Did you work today?" We only consider responses for days where participants state they are working and not for days when they report they are not working. Therefore, in most cases work days are during the common working week (Monday-Friday). Some workers work weekends but the common case for the study cohorts is working Monday-Friday.

We apply the K-means clustering method [2] where we consider the performance metrics as features for unsupervised clustering. We compute the mean of each metric (i.e., IRB, ITP, OCB and CWB) for every participant

Table 4. Statistics of job performance metrics

Job performance metrics	Range	Mean	STD
ITP	3-15	12.55	2.53
IRB	7-49	42.79	6.93
OCB	0-8	6.82	1.39
CWB	0-8	1.09	1.11

and then use these means as features for the K-means algorithm – we normalize mean scores as the measures have different ranges (see Table 4). After training the clustering model, 336 employees are deemed high performers and 218 low performers. Figure 4 shows the labels (viz. higher or lower performance) assigned to participants from the K-means algorithm. The K-means method is highly dependant on the initial centers to cluster the data points. Therefore, we set two initial points as representatives of higher and lower performers. The initial center for higher performers is a point with the maximum scores of ITP, IRB and OCB, and the minimum score of CWB. Conversely, the initial point for lower performers is the one including the minimum scores of ITP, IRB and OCB, and the maximum score of CWB. As shown in Table 2, ITP, IRB and OCB measure positive attributes associated with performance - the higher the score, the higher the performance. However, CWB represents a negative attribute associated with workplace performance - the higher the score, the lower the performance.

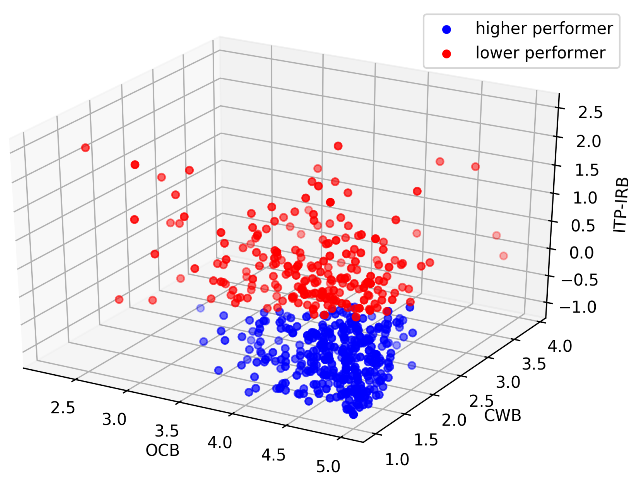


Fig. 4. Identification of participants as higher or lower performers. Blue dots represent higher performers. These participants have relatively high IRB, ITP and OCB values and low CWB values. Red dots represent lower performers. The ITP and IRB dimensions are reduced to one vector using principal component analysis (PCA) in order to visualize a 4D space in 3D. As shown in the correlation matrix (see Figure 3), ITP and IRB are highly correlated, hence the principal component explains over 90% of their 2D space variance. CWB is negatively correlated with both ITP and IRB. Therefore, a lower value on the principal component's axis demonstrates higher values of IRB and ITP.

Figure 5 shows histograms for the four performance dimensions (viz. IRB, ITP, OCB and CWB) across higher and lower performers. Looking at the histograms of the metrics after clustering, we note that those assigned as higher performers tend to have higher scores across all performance metrics other than CWB, particularly for ITP and IRB. After training the unsupervised K-means model based on the averages of metrics discussed earlier, we used this model to label ground-truth data points (i.e., higher or lower performance) corresponding to particular survey days – we implement this labelling approach for two reasons: 1) ground-truth scores are likely biased because they are self-reports, therefore, to reduce noise, we first run K-means on mean scores and then label every single data point based on it; and 2) even if a worker is on average a higher performer, they possibly have some days when they do not perform as well. As we run K-means on normalized mean scores, we first normalize survey day scores using the mean and standard deviation of mean scores. Then, comparing distances between scores of a survey and each of two centers of clusters, we identify whether a participant, on a given survey day, is a higher or lower performer. In total, there are 6701 performance surveys from 554 participants. 4264 of these responses are clustered in the higher performers group and 2437 in the lower performers group.

5 RESULTS

In what follows, we present results associated with differences in behavioral patterns that distinguish higher and lower performers. We then discuss the differences between supervisors and non-supervisors, and finally, differences that exist between different types of companies in our study, as shown in Table 1.

5.1 Behavioral Patterns of Higher and Lower Performers

As discussed in Section 3.4, our sensing features capture aggregation of daily data for both the day the survey is given on (aka the survey day – administered 3 times per week) and across the prior week excluding the survey day. In order to look at significant features and their differences between higher and lower performers, we take averages from the data points per participant (i.e., only one sample point for each participant in the dataset). We apply the Spearman correlation [64] and the Kolmogorov-Smirnov (K-S) test [64]. The Spearman correlation is a nonparametric measure to determine whether there is a monotonic relationship between two datasets. It does not assume that both datasets are normally distributed. The two-sided K-S test is also a nonparametric test that is useful to test if two independent samples are drawn from the same continuous distribution; it is also known for comparing two sub-samples from the same population. All participants in our study are not from the same company, but they are treated as the same population during training the K-means clustering model. We include all participants in the analysis regardless of which company they work for. The result of the Spearman correlation and the K-S test represents sensing features which are significant and different between average higher and lower performers at the subject level. As shown in Table 5, all of the features are the result of the Spearman correlation and the K-S statistical test where all p-values are less than 0.05.

5.2 Importance of Roles: Supervisors and Non-Supervisors

We are interested in identifying behavioral differences between higher and lower performers when considering job roles within a company, specifically, differences between supervisors and non-supervisors. As part of enrollment, participants complete an initial battery of surveys including job description in terms of whether they identify themselves as a supervisor of other employees or not. Table 6 shows the significant different sensing features for supervisors (N=254) and non-supervisors (N=297) for higher and lower performers. 165 supervisors are identified as higher performers and 89 lower performers. 168 non-supervisors are higher performers and 129 lower performers. In total, there are 2864 job performance surveys responses from supervisors and 3826 from non-supervisors. 1946 supervisors' surveys are clustered as higher performers and 918 as lower performers. 2325 non-supervisors' responses are grouped as higher performers and 1501 as lower performers.

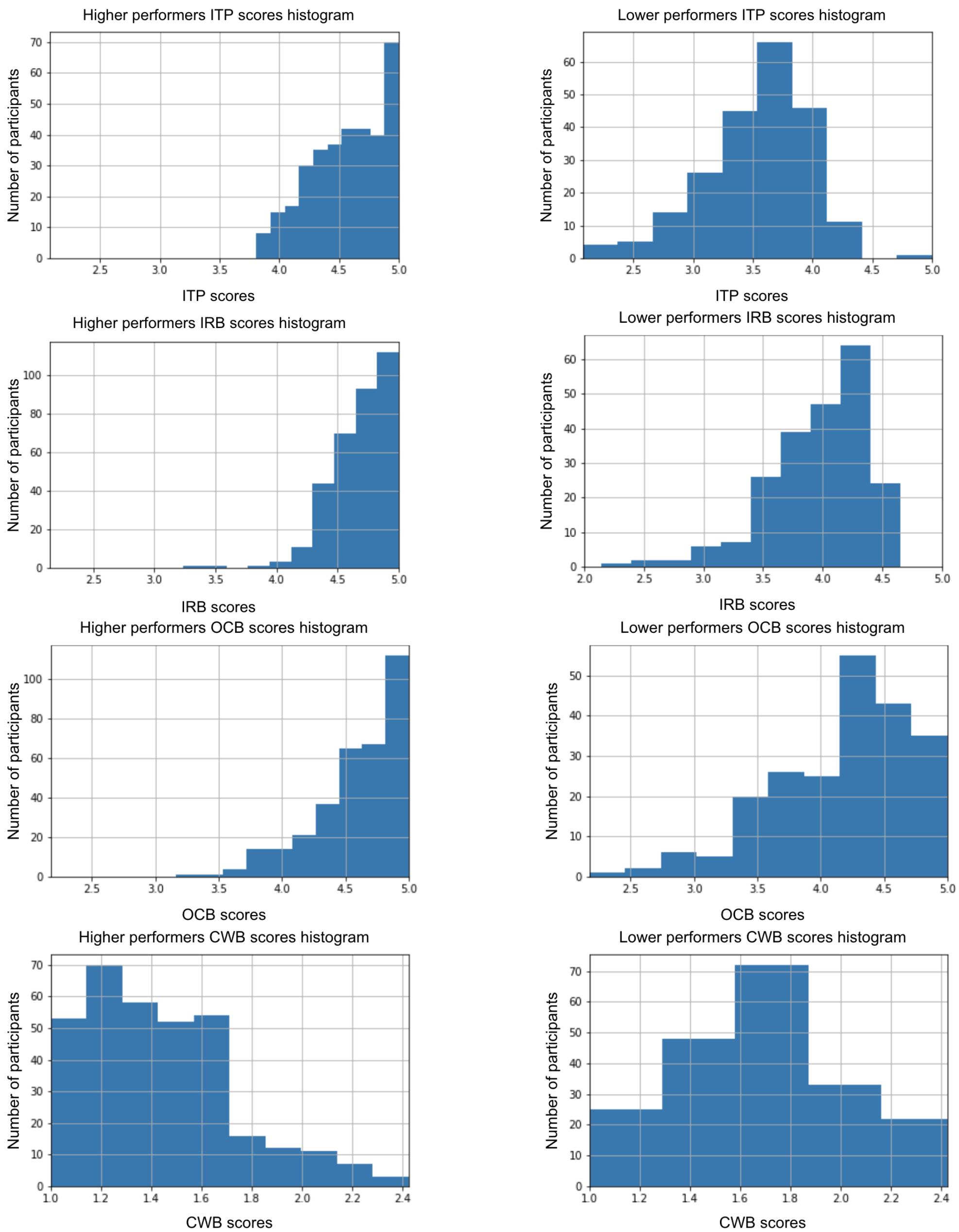


Fig. 5. Distribution of ITP, IRB, OCB and CWB within each performance group. All the performance metric scores are scaled for easy comparison. Row 1: Most higher performers have an ITP score ranging between 4.5 and 5.0, whereas most lower performers score between 3.0 and 4.5. Row 2: Most higher performers have an IRB score ranging from 4.5 to 5.0, whereas most lower performers score between 3.75 to 4.5. Row 3: most higher performers have an OCB score ranging between 4.5 and 5.0, whereas lower performers range from 4.0 to 4.5. Row 4: Most higher performers have a CWB score ranging between 1.0 to 1.6, whereas most lower performers score between 1.5 to 2.0 .

Table 5. Sensing features which are significantly different between higher and lower performers as the result of Spearman correlation and K-S statistical test. In terms of epochs shown in the table: epoch 0: the whole day; epoch 1: 12am - 9am (night/early morning); epoch 2: 9am - 6pm (working hours); epoch 3: 6pm - 12am (evening)

Device	**Feature**	**Period/Epoch**	**Behavior**
PhoneAgent	Number of times unlocking the phone	Survey day/3	Higher performers unlock their phones less during the evening periods (6pm-12am) on survey days.
Garmin	Duration of light sleep	Weekends/0	Higher performers have shorter light sleep periods during weekends.
	Duration of deep sleep	Survey day/0	Higher performer have longer deep sleep periods during survey days.
	Variation in heart beat rate	Past week/0 Weekdays/0	Higher performers have more regular heart beat rates during the past week particularly weekdays.
	Duration of awake time during sleep hours	Weekdays/0	Higher performers have longer awake time periods during sleep hours on weekdays.
	Amount of time being physically active	Survey day vs. past week/0	Higher performers are more physically active (i.e., the amount of time they are active) on survey days compared to any other day of the past week.
	Step distance	Survey day vs. past week/0	Higher performers are more mobile (i.e., greater “step distance” in meters) on survey days compared to any other day of the past week.
			Spearman p-value < 0.05 K-S p-value < 0.05

5.3 Companies: Tech and Consultancy Firms

We investigate how features are significantly different between higher and lower performers among the two largest cohorts in our study; these two companies represent different types of workforce: one being a tech company and the other an international consultancy company. These companies might have different norms and expectations associated with their workforce; for example, working hours, travel, communication protocols, out-of-office availability, among many other factors [46]. Therefore it is prudent to also investigate how behaviors of higher and lower performers may differ across these companies as case studies rather than drawing some universal results for all tech and consultancy companies. Table 7 shows the behavioral patterns in terms of mobile sensing features for each company. Company A (a consultancy company) has 217 employees participating in the study. The clustering model considers 127 participants as higher performers and 90 as lower performers. We have 2319 responses from Company A’s participants. 1506 responses are from higher performers and 813 from lower performers. Company B (a technology company) has 138 employees participating in the study. The clustering model identifies 84 participants as higher performers and 54 participants as lower performers. We have 1926 job surveys responses from company B’s participants. 1187 responses are from higher performers and 739 from low performers.

Table 6. Sensing features that demonstrate the patterns of higher performers for different job roles (viz. supervisor versus non-supervisor) as the result of Spearman correlation and K-S statistical test.

Role	Behavioral patterns attributed to higher performers in comparison to lower performers for different roles
Supervisor	**PhoneAgent** Higher performers regularly visit a smaller number of places during working hours (9am-6pm). **Garmin** Higher performers have shorter light sleep periods during the past week. Higher performers have longer deep sleep duration on survey days. Higher performers are more mobile (i.e., have greater step counts) during weekdays than weekends.
Non-Supervisor	**PhoneAgent** Higher performers visit a smaller number of places during weekday evenings (6pm-12am). Higher performers are less active (i.e., based on their overall stationary duration) over the past week particularly during weekday evenings (6pm-12am). Higher performers unlock their phones fewer times on survey days and during weekend evenings (6pm-12am). Higher performers use their phone less (based on the overall period of unlock duration) during weekday working hours (9am-6pm) than during the same period at the weekend. **Garmin** Higher performers are more mobile (i.e., have greater step counts) on survey days. Higher performers are more physically active (i.e., based on the amount of time they are active) on survey days in comparison to any other day during the past week. Higher performers have longer awake periods during sleep hours on weekdays. Higher performers have more regular light sleep periods during sleep hours on weekdays. **Beacon** Higher performers spend more time at work during weekends.
	Spearman p-value < 0.05 K-S p-value < 0.05

5.4 Classification of Higher and Lower Performers

A key goal of our paper is to classify higher and lower performers using the mobile sensing features, as discussed in Section 3.4. We aim to classify whether an information worker is on average a higher or lower performer based on the observed weekly sensing features within a certain period of time. We study several different classification models including support vector machine [12], logistic regression [52], random forest [7] and gradient boosting [13]. The gradient boosting classifier outperforms all models. We use the XGBoost [13] classifier to implement the gradient boosting technique. XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. We train the classifier using five repetitions of 5-fold cross validation (CV). The classifier's parameters are tuned using another level of 5-fold cross validation on the training set of each fold.

Table 7. Sensing features that demonstrate the patterns of higher performers within different companies as the result of Spearman correlation and K-S statistical test.

Company	Behavioral patterns attributed to higher performers in comparison to lower performers for different types of companies
Company A (Consultancy)	**PhoneAgent** Higher performers have regular periods of being stationary (i.e., based on their overall stationary duration) during evenings periods (6pm-12am) over the past week. Higher performers are less active (i.e., based on their overall stationary duration) during the evening periods (6pm-12am) on survey days compared to any other day of the past week. **Garmin** Higher performers are less mobile (i.e., based on "step distance" in meters) during weekends.
Company B (Tech)	**PhoneAgent** Higher performers are less active (i.e., based on their overall stationary duration) during working hours (9am-6pm) and the evening periods (6pm-12am) over the past week. Higher performers are less active (i.e., based on their overall stationary duration) during weekdays than weekends. Higher performers visit a fewer number of places during weekday night/early morning periods (12am-9am). Higher performers visit a greater number of places during weekday night/early morning periods (12am-9am) than during the same period at the weekend. **Garmin** Higher performers have more regular periods of mobility (i.e., based on "step distance" in meters) during weekdays. Higher performers have shorter light sleep periods on survey days.
	Spearman p-value < 0.05 K-S p-value < 0.05

Figure 6 shows the prediction model's performance in terms of the AUROC, precision and recall scores for higher and lower job performance labels. The evaluation metrics are all based on the majority vote technique [34]. The aim of utilizing this technique is to specify whether a worker is *on average* a higher or lower performer across the 60 day period. We use a 5-repetition 5-fold cross-validation training process on all data points at the survey level (i.e., based on the individual survey data points rather than averages of all participants survey data points). At each 5-fold cross-validation process, we first shuffle the data. Then, we run the K-means on the averaged scores of the job measurements scores (viz. IRB, ITP, OCB and CWB) associated with participants in the training set in order to get higher and lower clusters. Using these clusters, we label every single data point in the validation set by comparing the distance between the point and centroids of clusters. We train the classifier on the training set of the fold after finding the best parameters of the model through another level of 5-fold cross-validation on the training set using all the features discussed in Section 3.4. Finally, we classify the data points in the testing set. After a 5-fold cross-validation is complete, we get all the predicted probabilities returned by classifiers trained at each fold and identifying whether a data point is in the higher performer cluster or the lower one for all data points of each participant. We therefore compute the mean probability for each participant. We repeat the 5-fold cross-validation process five times. Therefore, we take an average of all the five mean probabilities for each participant. The averaged probability identifies whether a participant is on average a higher or lower performer. In addition, we determine whether a worker is on average a higher or lower performer for ground-truth, as discussed in Section 4. We report all the performance metrics (i.e., AUROC, precision and recall scores) in Figure 6. Specifically, we report the model's performance metrics in terms of different thresholds of occurrence probability. The default threshold is set to 0.5 as the problem is a binary classification problem. Therefore, if the predicted probability for a participant is more than 0.5, then the worker is predicted to be a higher performer, otherwise we consider them a lower performer. We change this threshold to a value in the ranged 0-1 in steps of 0.05 [0,0.05,0.1,0.15,...,0.9,0.95,1]. For example, if the threshold is 0.65, then the probability that indicates a worker is on average a higher performer is a value of more than 0.65, otherwise we consider them a lower performer. The precision and recall curves (shown in Figure 6 (b) and (c), respectively) would be more detailed if the threshold changed with a smaller step (e.g., 0.01 [0,0.01,0.02,...,0.98,0.99,1]). However, the trend of the curves remains the same regardless of finer increments.

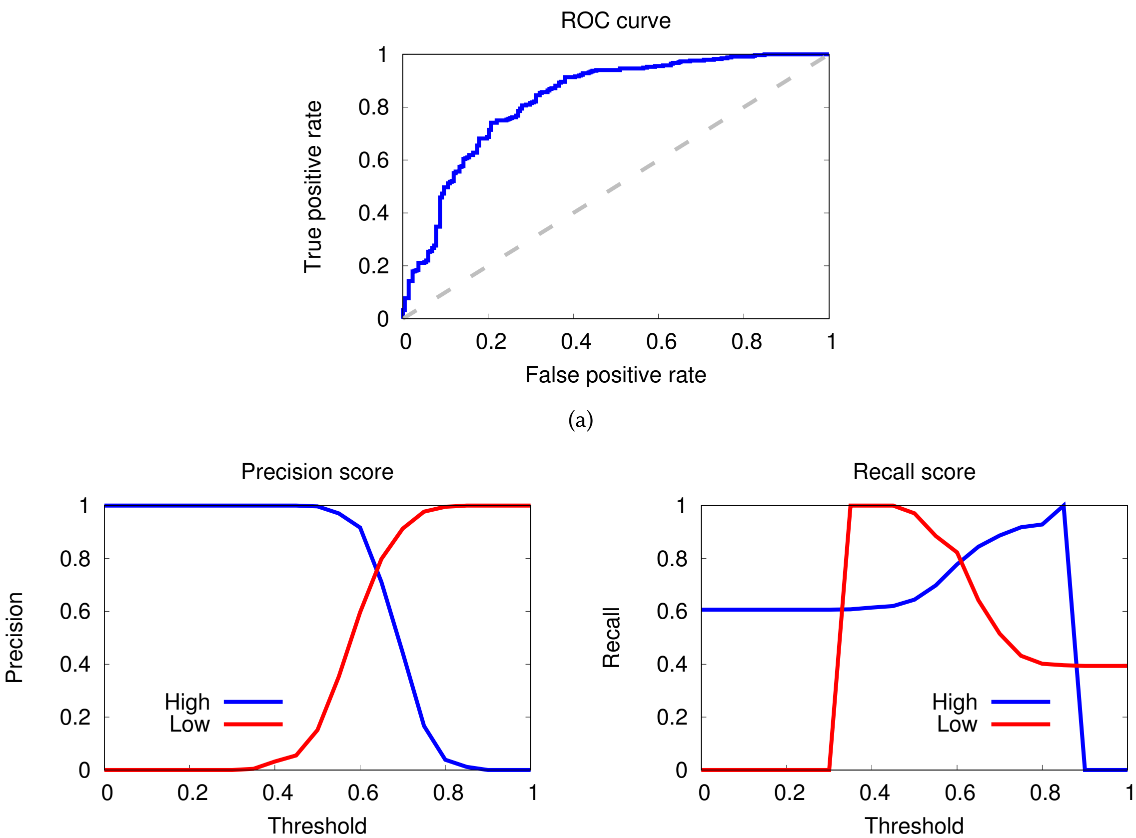
Figure 6 (a) shows the AUROC curve is 0.83. Figure 6 (b) shows different model precision scores when classifying higher and lower job performers in terms of different thresholds of the occurrence probability. Figure 6 (c) shows different model recall scores when classifying higher and lower job performers in terms of different thresholds of the occurrence probability. We also report the model's performance when the occurrence probability threshold is set to 0.65; in this case the precision and recall are 0.71 and 0.84, respectively, when predicting higher performers, and 0.8 and 0.64, respectively, when predicting lower performers. The F1 score at a threshold of 0.65 is 0.77 for higher performers and 0.71 for lower performers. We also train the model using different sensor modalities (i.e., phone and wearable) as features. Figure 7 (a) shows the ROC of the model's performance when only using Garmin sensing features when training the model. 7 (b) shows the ROC of the model's performance when only using PhoneAgent features when training the model. The AUROC scores for Garmin and PhoneAgent features are 0.72 and 0.65, respectively.

6 DISCUSSION AND LIMITATIONS

In this section, we discuss our findings and limitations. As shown in Tables 5, 6 and 7, our results indicate that focus and regularity of behaviors and routines (e.g., phone usage, places visited, mobility, activity, sleep and time spent at work) across weekdays and weekends offer important insights into higher and lower performers.

We find a number of interesting results associated with phone usage and higher performers. Higher performers tend to have lower rates of phone usage throughout the day based on the lock/unlock feature we compute. As shown in Table 6, higher performers who are non-supervisors unlock their phones fewer times on survey days (which are working days) and during weekend evening periods. In addition, these higher performers use their phone less during weekday working hours than during the same period at the weekend. As shown in Table 5, higher performers across all cohorts unlock their phones less during the evening periods on survey days. If we considered phone usage during working hours a distraction then this behavior would likely impact the performance of workers. However, research [45] shows that those who have a high level of commitment to work use mobile devices as a method for consistent and frequent communications with colleagues in work-related activities. A limitation of our results is that we do not have any additional information to indicate how phone usage relates to productivity. However, our results on phone usage of higher performers is a potentially important finding.

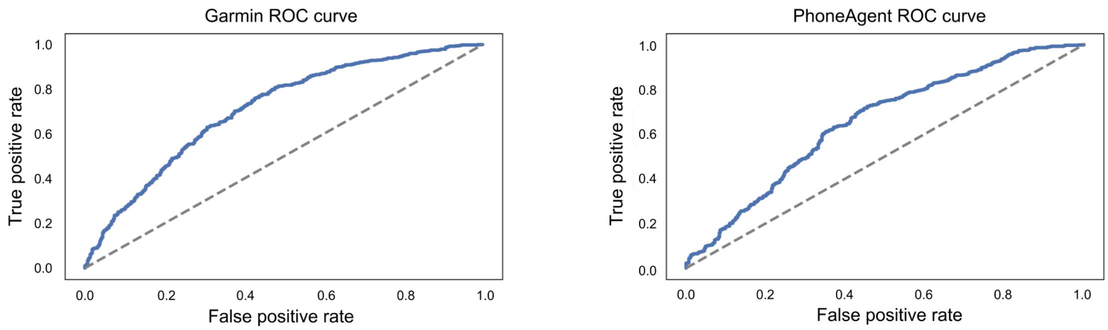
Physical activity and mobility have been shown to boost memory [67], improve concentration [28] and enhance creativity [39]. Therefore, regular activity could positively impact performance helping workers focus better, be creative at work, relieve stress and retain information. The level of activity and mobility during the working week is also strongly coupled with job demands. For example, a software engineer in a tech company may spend most of their working week at a workstation while a project manager/ consultant may be much more mobile.



(a) (b) (c)

Fig. 6. (a) The prediction model's ROC curve based on majority voting on the test set. The AUROC is 0.83. (b) Precision of the model when classifying higher and lower performers in terms of different thresholds of the occurrence probability. (c) Recall of the model when classifying higher and lower performers in terms of different thresholds of the occurrence probability.

When we consider the mobility of workers (e.g., their movement and places visited) and how active they are (e.g., stationary or moving around) across our study, our results offer a number of important insights. We assess higher and lower performers three times per week on survey days across the complete study period. As shown in Table 5, on these days we find that higher performers across all the cohorts are more active and mobile in comparison to lower performers. However, higher performers who work in the tech company are less active during working hours and evening periods during the week, as shown in Table 7. In addition, these workers are also less active during weekdays in comparison to weekends. Furthermore, higher performers who work in the consultancy company have regular periods of being stationary during the evenings and are less mobile at weekends. As shown in Table 6, higher performers who are supervisors are more mobile during weekdays than weekends. In addition, non-supervisors are also more mobile and active on survey days but less active during weekday evenings. When we consider the number of places visited during the week we find differences between performers. We find that higher performers who are supervisors regularly visit a smaller number of places during



(a) (b)

Fig. 7. (a) The prediction model's ROC curve when only using Garmin sensing features when training the model. The AUROC is 0.72. (b) The prediction model's ROC curve model's performance when only using PhoneAgent features when training the model. The AUROC is 0.65.

working hours, as shown in Table 6. In addition, non-supervisors also visit a smaller number of places during weekday evenings. When we consider higher performers in the tech company we find they visit a fewer number of places during weekday night/early morning periods (12am-9am). We also find these workers visit a greater number of places during the weekday in comparison to weekends. In this paper, we do not consider the semantics of the locations they visit. An exception to this is work location. We find that higher performers who work as non-supervisors spend more time at work during weekends, as shown in Table 6.

Another behavioral feature that separates performers is sleep. As shown in Table 5, higher performers across all cohorts experience longer deep sleep periods during survey days and shorter light sleep periods during weekends. In addition, higher performers have longer awake time periods during sleep hours on weekdays. We see these same sleep patterns when considering roles (viz. supervisor, non-supervisor) but not the type of company. Although, higher performers working in the tech company experience shorter light sleep periods on survey days. As a general comment, deep sleep is important in memory reactivation and consolidation [71]. The accumulation of deep sleep may therefore be a crucial factor that allows higher performers to retain and recall information that enhances their performance. However, our results also imply higher performers experience restless sleep periods, i.e, longer awake time periods during sleeping hours. We find one interesting physiological pattern associated with heart rate data from the wearable. As shown in Table 5, higher performers across all cohorts experience more regular heart beat rates during the week particularly weekdays.

The ground-truth surveys (i.e., IRB, ITP, OCB and CWB) administered in this study are widely used as validated measures of self-reported workplace performance. However, self-reported assessment of performance, captured in Figure 5, may be open to individual bias [55] that in turn would manifest itself as learning bias in trained models. While there are known techniques [55] for dealing with bias we plan to study any potential bias in our ground-truth surveys as part of our future work; for example, we could control for individual bias by collecting surveys more broadly, such as, from peers or supervisors working with an individual. This strategy may also be open to potential bias because of different types of relationships between peers, managers and individual workers. However, such additional data would allow us to apply different bias elimination techniques [55].

The results of the prediction, presented in Section 5.4, are based on a 5-repetition 5-fold cross validation technique. Our dataset contains several data points for each participant. During the training process, we might encounter data from the same participant in both training and testing sets. To mitigate this, we selected a group of participants at each fold and considered all their data as the testing set, and we trained the classifier on the remaining participants' data. We evaluated the performance of the trained model at the survey level on the testing set. However, we found our classifier did not perform as well as we anticipated. As discussed above, this might stem from self-reported bias.

7 CONCLUSION

Assessing workplace performance relies on subjective evaluations, such as, peer ratings, supervisor ratings and individual self assessments. In this paper, we present an alternative approach. We use objective mobile sensing data from phones, wearables and beacons to study workplace performance and offer new insights into behavioral patterns that distinguish higher and lower performers including roles (i.e., supervisors and non-supervisors) and different types of cohorts (e.g., high tech and consultancy). We present initial results from an ongoing year-long study of N=554 information workers collected over a period ranging from 2-8.5 months. We trained a gradient boosting classifier that can classify workers as higher or lower performers with AUROC of 0.83. Our results indicate that focus and regularity of behaviors and routines (e.g., phone usage, places visited, mobility, activity, sleep and time spent at work) across weekdays and weekends offers new insight into workplace performance that can distinguish higher and lower performers. Our work opens the way to new forms of passive objective assessment and feedback to workers to potentially provide week by week or quarter by quarter guidance in the workplace.

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