Assessing the Impact of Commuting on Workplace Performance Using Mobile Sensing

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Commuting to and from work presents daily stressors for most workers. It is typically demanding in terms of time and cost, and can impact people's mental health, job performance, and, broadly speaking, personal life. We use mobile phones and wearable sensing to capture location-related context, physiology, and behavioral patterns of N=275 information workers while they commute, mainly by driving, between home and work locations spread across the United States for a one-year period. We assess the impact of commuting on participant's workplace performance, showing that we can predict self-reported workplace performance metrics based on passively collected mobile-sensing features captured during commute periods.

COMMUTING is a daily routine for workers around the globe. Not only is it costly, time-consuming, and stressful to many workers, but it can also negatively impact their physical and mental health. A multitude of factors associated with commuting, such as frequent stops, delays, congested traffic, and work and schedule demands can lead to frustration, social isolation, and boredom that in turn can contribute to increased anxiety and stress for workers. Furthermore, the after-burn of commuting may roll over into the work or home environment, having more residual impact than just time spent en-route. Prior studies show that the direct stress from commuting (e.g., physical discomfort, such as noise and pollution) or indirect stress (e.g., from reducing time available to address other demands in life) may lead to tardiness, increase in counterproductive work behavior (CWB), and decreased productivity at work.[1,2] In addition, researchers find that commuting is an important factor in play for employee turnover, job satisfaction, and cognitive failure at work.[3–5]

Despite its importance in everyday life, there are very few studies that explore commuting objectively. Most of these studies use specialized headmounts and electrodes, which we believe provide better cognitive data during driving but limit large-scale studies because of cost and their intrusive nature. Therefore, we propose a first-of-its-kind study to assess the workplace performance

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of N=275 commuters across one year using surveys to capture job performance along with mobile-sensing data from workers' phones and wearables. Using mobile-sensing technology, we can passively infer user's behavior or context not only for pre–post commute but importantly during commuting. We use location data passively collected from subjects' mobile phones to identify daily commute trips and weather. We passively collect continuous objective physiological data (e.g., heart rate, stress, etc.) from a wrist-worn wearable during commuting to infer worker's reaction to the commuting experience. The use of such off-the-shelf wearables and passive sensing could be useful on a fundamental level, primarily to promote further in-the-wild studies related to commuting, which is currently lacking. This is one of the aims of our study: to explore whether cheap off-the-shelf passive sensing devices are useful to draw objective insights into commuting.

Prior work on commuting indicates that stress, anxiety, and frustration, which result from negative commuting experiences, can lead to a less efficient workforce, decreased productivity, increased CWB, and reduced organizational citizenship behavior (OCB).[1,2] In this article, we hypothesize that objective data captured from passive sensors during commute periods can be used to assess the impact of commuting on workplace performance. We show that across the entirety of a worker's day, commuting periods are detectable using mobile phones and wearable sensors and that these commuting sensor data are informative of workplace behavior and performance.

RELATED WORK

Commuting induces stress and poor mood that results in a spillover effect on work performance and family relationships.[6] Studies show that postcommute performance can be significantly influenced by a negative commute experience.[1] Hennessy *et al.*[6] found in a study of N=114 participants that driver stress is related to subsequent acts of workplace aggression. This finding is in line with work that reports negative commute experiences, such as impedance and congestion, are associated with decreased task motivation, heightened negative emotions, including feelings of anxiety, frustration, irritation, and general annoyance.[3,4] Studies show that such behavioral stress reactions may lower performance efficiency of the employees when they arrive at the workplace.[7]

Researchers use the Conservation of Resources theory[8] to explain the relationship between commuting stress and job performance. As per this theory, people need to invest their resources to protect themselves from loss of resources, to recover from existing losses, and to gain new resources.[8] If an impedance (for example, traffic congestion) results in a loss of resource (in the form of time or energy), then people need to use their existing resources to rebalance their resource distributions. An exhausting commuting experience may require continuous loss of resources to cope with it. This leads to poor performance on the job because resources that were initially assigned to cope with the job and to do well on the task are now spent on dealing with the negative commuting experience.[8] Ma and Ye[5] reported that commuting distance is positively related to absenteeism and negatively related to job performance. There is strong evidence in the literature[1,6,7] regarding the influence of commuting on workplace behavior and job performance of employees.

Commuting has previously been studied in terms of physiological reactions. Researchers,[9] in a study conducted over multiple days, collect electrocardiogram, electromyogram, skin conductance, and respiration continuously while drivers (N=24) follow a set route. The authors show that these physiological signals provide a metric for measuring drivers' stress level. However, in this study, physiological monitoring is performed by special devices and electrodes connected to the power supply in the vehicle, not off-the-shelf mobile phones and wearables, as in our study. Vivoli *et al.*[10] reported that the highest mean levels of heart rate during driving are observed in heavy traffic and inclement weather. White *et al.*[11] found that commuting can lead to increased pulse rate and a higher systolic blood pressure, a biomarker of stress. Taken together, it is clear that commuting can elicit a physiologically measurable response in streams, such as heart rate.

Mobile phones and wearable sensing have been used widely for passive and *in situ* assessment of individuals across different contexts.[12] There is also a growing interest in the use of mobile sensing and machine learning to study workplace behavior, particularly with respect to the future of work and how passive forms of sensing can play a role in promoting wellbeing and efficiency of the workforce.[13,14] For example, researchers[14] use mobile phones, wearables, and Bluetooth beacons to predict job performance. Although there is an interest in workplace sensing to help more objectively characterize workers' behaviors, work-based tasks, and more broadly the workplace itself, there is a lack of research that studies commuting and workplace behavior or performance using passive sensing. We believe that passive sensing could help promote further research in commuting, particularly if we can establish that passive sensors are

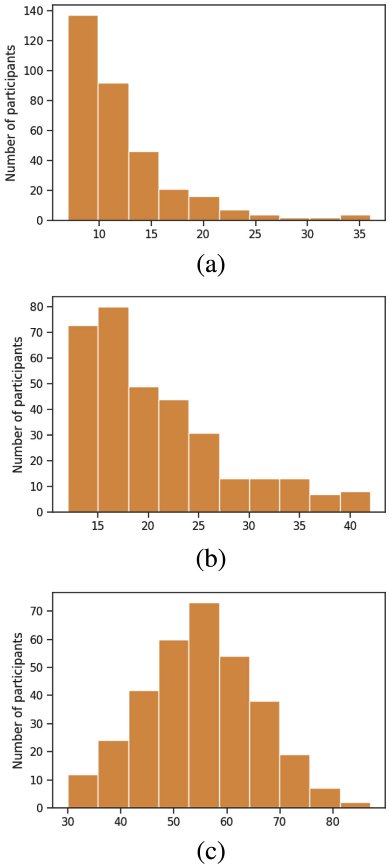

FIGURE 1. Self-reported responses to job performance questionnaires. The above figures show the distribution of the responses for various job performance metrics that we collect. (a) Interpersonal deviance. (b) Organizational deviance. (c) Organizational citizenship behavior.

capable of assessing participants' physiological reaction to commuting. We aim to investigate that through this study.

METHODOLOGY

In the following section, we discuss our study design, ground-truth, mobile-sensing system, and feature extraction process.

Study Design

We use the Tesserae study[15] dataset for our work. The study recruited 757 information workers across different companies in the United States for one year, where participants respond to several surveys. Participants are given a Garmin vivoSmart 3 wearable and a continuous sensing app is installed on their phone. The study protocol is approved by the Institutional Review Board. Please refer to the Tesserae study[15] for full details of the study design, participants, and data collection. Participants are instructed to maintain a data compliance level of 80% to warrant eligibility for monetary remuneration. Commute data are available from 60 to 300 days across a one-year period for participants in our commute dataset. In this article, we only include *N*=275 participants for whom we could identify the work and home locations via GPS with a high confidence level.

Demographic Descriptors

In our study, 34% of workers are identified as female and 66% as male. A bulk of the workers (*N*=121) belong to a single tech company in the mid-west and the rest come from other companies and organizations spread throughout the United States. A total of 94% of the participants report that they usually drive themselves to work, 4% report that they use public transportation, and the remaining 2% report carpooling and/or biking to work. The majority of the workers are in their 20s and 30s; in fact, 34% of participants are in their 20s, whereas only 10% are in their 50s.

Ground Truth

We assess the workers on two criteria of job performance with the help of self-reports: CWB and OCB. The distribution of the responses to these surveys is presented in Figure 1.

CWBs are actions that deliberately harm the organization or individuals at the organization. We use Bennett and Robinson's interpersonal and organizational deviance (IOD) scale[16] to measure CWB. The IOD contains 19 items, which the participant respond to using a seven-point frequency scale ranging from 1 (never) to 7 (daily). The Interpersonal Deviance score has a possible range from 7 to 49, and the Organizational Deviance score has a range from 12 to 84. Prior studies show that different subsets of CWBs such as tardiness, absenteeism, and workplace aggression can stem from negative commuting experience.[5,6]

OCBs are individual behaviors that are beneficial to the organization but are not directly recognized by the formal reward system of the organization. As such, these behaviors are discretionary and are responsible for creating better culture and climate in the workplace. We use Fox *et al.*'s Organizational Citizenship Behavior Checklist[17] to assess OCB of the participants. It includes 20 items and participants respond to it based on the frequency in which they engage in each behavior, using a scale ranging from 1 (never) to 5 (every day). It has a possible score range from 20 to 100. Existing literature show that commuting experience is related to OCB.[1,2] Therefore, we believe that sensing commute experiences can help us to better predict the OCB score of participants.

Mobile-Sensing System

Our passive sensing app is installed on workers' phones, which syncs to the Garmin wearable. It tracks commuters' physical activity, location, phone usage (i.e., lock/unlock), Bluetooth interactions, and ambient light levels. The phone application runs in the background and uploads the data to our secure server's backend periodically.

Features

We generate numerous aggregated sensing features for a 30-minute period prior to commute (i.e., precommute), across the complete commute period (i.e., commute), and during a 30-minute period after the commute (i.e., postcommute). In an empirical study, Friman *et al.*[18] used a window of 30 minutes to capture residual mood effects of traveling. We adopt the same window in our work. The 30-minute window gives us a "peek" into the precommute and postcommute physiology of a person—for example, their "state" as inferred from behavioral sensing data while readying to commute at the end of their working day and just after they get home. We believe that learning how sedentary or active or stressed a person usually is before commuting or observing their heart rate before commuting, and how the commute changes these states could be a signal to identify a person's response to their commute experience. In addition, this lets us capture stress responses that occur in anticipation, during, or in recovery from a stressor—for example, commuting—or manifestations of anxiety precommute and postcommute. We therefore study the postcommute period to assess the aftermath of the commuting event in our analysis. The features that we generate are as follows:

- *Activity:* duration, distance of active and inactive periods, energy expenditure, calories burnt, metabolic equivalent of task, walking intensity, and motion intensity;
- *Phone usage:* duration, count of phone usage, and data usage via cellular and Wi-Fi;
- *Heart rate:* heart rate (HR), heart rate variability (HRV)—time, frequency, and nonlinear measures;
- *Stress:* real-time stress and level of stress;
- *Weather:* sunrise, temperature, pressure, visibility, snow, sunset, precipitation, humidity, windchill, wind speed, wind gust, cloud cover, heat, and pressure;
- *Commute duration:* commute duration to home and work;
- *Commute variability:* variability in commute duration, arrival/departure time variability, variability in number of stops, and number of streets taken.

Features are generated for each commuting period (precommute, during, and postcommute of both home and work commute) of each day, separately. The sensing features that we use capture changes in movement, intensity, heart rate, energy expenditure, and phone usage. Real-time stress is inferred directly by the Garmin wearable based on heart rate variability, which is considered strongly associated with stress. We also compute several time domain, frequency domain as well as nonlinear measures of heart rate variability (HRV) features. We generate additional features known to be objective stressors during commuting such as the weather (e.g., snow storm, rain, poor visibility), which impacts commute anxiety. Research in commuting stress shows that the central determinants associated with commuting stress are *predictability/reliability* (i.e., the person knows how long it typically takes to reach their destination), *control* (i.e., the person has control over their commute time and distance), and finally, *impedance* (i.e., restricting movement because of traffic congestion, accidents, etc.). Kluger *et al.*[19] showed that commute variability is strongly correlated with commute-related stress. Uncertainty is low for a commute with low variability across days. As a result, commuting is more predictable, allowing commuters to maintain more sense of control. This is in line with findings in human physiology, in which decreased control and predictability of tasks (i.e., higher variability of commuting in our case) increases stress. Therefore, we also compute several commute-related variability metrics.

The formula used to quantify variability is

$$\sigma_{iX} = \frac{1}{D_i - 1}\sum_{j=1}^{D_i}\left|X_{ij} - \overline{X}_i\right|, X_i > 0$$

where

σ_{iX} = variability for metric X over D days of commute data available for person i;

X = {commute duration, arrival time, departure time, number of stops, number of streets taken };

X_{ij} = value for metric X on day j for person i;

$\overline{X}_i$ = average value for metric X over D days of commute data available for person i;

D_i = number of days for which commute data is available for a person i.

TABLE 1. Comparing mean variability in commuting pattern. Different commute variability metrics we compute are listed, along with how they differ between home and work commute.

Variability	Home commute	Work commute
Total Duration (minutes)	42.52	20.85
Arrival time (minutes)	72.23	40.69
Departure time (minutes)	67.27	35.27
Number of streets (*n*)	2.89	1.75
Number of stops (*n*)	0.94	0.64

Our mobile-sensing system logs GPS data from the users' smartphone every 2–10 minutes. We pass the sampled GPS coordinates through the density-based spatial clustering of applications with noise, which groups the points that are close to each other and computes the center of clusters. This allows us to understand user's mobility, i.e., the places that a person visits and their associated dwell time. We use this approach to identify home and work locations of the participants and their commute duration.

ANALYSIS AND RESULTS

In what follows, we present results from our commute study and discuss commute behavior and job performance.

Commute Behavior

We obtain a mean commute duration of 62 minutes and a standard deviation of 32 minutes on commute toward home. Whereas for commute toward work, we obtain a mean duration of 40 minutes and a standard deviation of 16 minutes. The results show that people spend more time commuting home from work (called home commute) than they do commuting to work from home (called work commute). Table 1 reports the distribution of the different commuting behavior variability that we compute. The variability metrics are significantly different between home and work commute (p-value < 0.10; Mann-Whitney U test). We observe that the home commute is more variable than the work commute in almost all metrics.

High and Low Job Performer Differences

Next, we analyze the differences in the commute-based sensing features of high and low performers. For this, we divide the participants into a high-performing group or a low-performing group, as defined in Mirjafari *et al.*'s work.[14] In summary, we run K-means clustering on the participant's OCB and CWB scores, setting the K=2. After running K-means five times, we divide the participants into two groups based on which cluster they most often fall into. Because CWB is a negative work behavior and OCB a positive behavior, the cluster with the higher OCB score but lower CWB score is considered to be representative of high performers, whereas the remaining cluster with lower OCB and higher CWB is designated as low performers. After clustering, 110 participants are grouped as low performers and 165 participants as high performers. We report the significantly different features (p-value < 0.10; Mann-Whitney U test) between the two groups in Table 2.

Predictive Modeling of Job Performance

Numerous existing studies claim that a negative commuting experience can and does deteriorate job performance, mostly via commuter stress.[1,3,6] If we can objectively assess that stress along with the physiological reaction to the commuting experience as a whole, it is reasonable that job performance would be predictable from objectively sensed commute data.

Table 3 shows the performance of different machine learning models trained on the commuting-

TABLE 2. Differences in commute-based sensing features. The statistically significant differences in the commute features of high performers and low performers in the workplace are reported.

Group	Differences in commute features
High Performers	Phone usage count during work commute is lower. Prework commute mean NN50 (HRV) is higher. Mean RMSSD, BBI, MRRI, HF (HRV) during work commute is higher. Work departure variability is lower. Work arrival variability is also lower. During work commute stress is lower.
Low Performers	Mean HR during both work and home commute is higher. Mean RMSSD, BBI, MRRI, HF (HRV) during home commute is lower. Prework commute steps is lower. Phone usage count during home commute is higher. Prehome commute stress is higher. Posthome commute stress is also higher.

TABLE 3. Prediction result. Results of different machine learning models when performing predictions on the job performance metrics are listed. We use MAE and Pearson correlation coefficient as the evaluation metric. Statistical significance is reported after t-test between best-performing model's predictions and baseline (*** $p < .01$, **$.01 \leq p < .05$, *$.05 \leq p < .10$).

Job performance metrics	Baseline MAE	Machine Learning Models			
		ExtraTrees MAE	NuSVR MAE	Adaboost MAE	Stacked Model MAE (std) / Pearson r
Counterproductive work behavior (7–84)	7.95	8.03	7.77	7.88	**7.34*** (3.18) / 0.53**
Interpersonal deviance (7–49)	3.94	3.87	3.82	3.91	**3.58*** (1.77) / 0.54**
Organizational deviance (12–84)	5.44	6.12	5.35	5.41	**5.29*** (1.35) / 0.52**
Organizational citizenship behavior (20–100)	8.43	8.54	8.30	8.38	**8.01* (3.71) / 0.54**

based sensing features to predict workers' workplace performance scores. To control for the differences in commute features that could be caused by having stopped at a location (e.g., shop, sport facility for a long time), we narrow down our dataset to two-way commutes where stops do not consist of more than 15 minutes. Despite this restriction, every commuter still has at least 52 days' worth of the two-way commute data. For predictive modeling, we use the average of each individual's commute features as the input to the model. This means that every participant has one set of features for their commuting period (i.e., precommute, during, and postcommute features for both home and work commute, separately), representing their entire commute experience in aggregate. We try four different machine learning models: ExtraTrees, NuSVR, Adaboost, and an ensemble model consisting of stacked models. In our implementation of stacking, each of the models outputs a prediction of their own for a given example. A final NuSVR model, also called metaregressor in stacking, then combines all the prior predictions (the outputs of the prior machine learning models), and trains on it to come up with a final output.

We normalize all our data before training machine learning models on it. We find that stacking generally outperforms other models when predicting job performance using commute-generated sensing features. We train the machine learning models using the leave one subject out cross validation approach. The final performance reported is the mean absolute error (MAE) of all the individual predictions and the true values. Along with that, we report the baseline score, which is the MAE we would obtain if we just used the mean score of the job performance metrics in the training set as the prediction each time.

In addition, for the best-performing model, we report the Pearson correlation coefficient between its predictions and true performance scores. We also run a t-test between predicted values of the stacked model and baseline values, finding that they are significantly different. We perform feature selection using the sequential forward selection (SFS) method. In this approach, the most relevant subset of features is picked by the algorithm. We report some of the most frequently selected features in Table 4, along with their importance score. The feature importance is calculated based on the normalized count of feature occurrences in the selection made by SFS.

DISCUSSION

We find several significant differences in the commuting patterns of high and low performers. High performers tend to a have higher HRV than low performers during commute. A higher HRV is generally considered to be good for health—people with a higher HRV are considered to be more fit and more resilient to stress. High performers' work departure and arrival variability is also lower, indicating consistency in the time they arrive and leave work. Low performers have a lower HRV during commute and as a result, a higher heart rate. Their real-time stress is higher during work commute. Interestingly, the stress level is higher for prework, prehome, and posthome commute states for low performers. In addition, low performers use their phone more during their commute in comparison to high performers. The physiological data (i.e., the heart rate, HRV, stress) seem to indicate that low performers are either more stressed or have a more negative experience during their commute than their counterparts. This motivates us to perform predictive

TABLE 4. Features selected. Some of the most frequently selected features by the sequential forward selection approach are shown.

Features for CWB	Importance	Features for OCB	Importance
Walking intensity (during work commute)	12.77	Work commute duration	7.33
Mean SD2 and SDNN (during home commute)	12.30	WiFi data sent/received (during home commute)	17.73
Mean NN50 (during home commute)	12.24	Max real time stress (during work commute)	2.06
WiFi data sent/received (during work commute)	6.65	Minimum temperature of the day	5.00
Real time stress (post-work commute)	12.54	Work commute variability	6.53
Mean LF/HF (pre-home commute)	9.12	Max real time stress (post-home commute)	22.60
Max real time stress (pre-work commute)	5.88	Mean motion intensity (during work commute)	4.02
Walking duration (during work commute)	6.43	Mean HR (during home commute)	8.86
Mean LFNu (post-home commute)	12.42	Minimum HR (during work commute)	16.47
Steps (during work commute)	9.65	Phone usage count (during work commute)	9.40

modeling using the commute data. In this respect, we find that the stacked model achieves a better MAE than the baseline prediction. We also obtain a moderate-to-strong correlation between its predictions and the true values. In addition, the t-test result between the baseline and predicted values of the stacked model shows that they are significantly different. These results indicate that the stacked model performs better than naive baseline averages. We show that the models' error (MAE) is less than 10% of the different ground truths, which leads us to conclude that commuting state presents a marker that provides us insight into work behavior and performance. We report some of the features selected by the SFS approach in Table 4. We run the entire pipeline 10 times and report the feature importance based on how often the same set of features are selected across each run.

The selected features capture several different aspects of commute that are explainable. Physical activity-related features such as walking distance and steps are related to active commuting. Studies show that commuters who are involved in active forms of commuting typically experience increased productivity at work.[5] Similarly, variability in commute duration may add to anxiety by affecting predictability, reliability, and control of the commute. Heart rate and HRV-related metrics are important features in our model. This is expected as they are indicators of physiological stress or stress response. We also see that the real-time stress metric (which is based on HRV) is present among the selected features. Negative commuting experience can add to stress, anxiety, and heighten frustration and irritation. Studies argue that feelings of stress caused by commute may lower the ability of employees to organize themselves leading to reduced effectiveness.[20] In addition, the behavioral reaction to such negative commutes, for example, in the forms of frustration can reduce the efficiency of the employees when they arrive at the workplace.[7] To cope with such stress and feelings of frustration and irritation, commuters may use their phone to try and improve their commute experience, such as using Google maps to help divert them away from congestion routes, or by listening to podcasts or music, or talking to someone on the phone—as a result providing a certain level of distraction and thereby alleviating stressors.

Finally, we believe that future work aimed at studying commuting that employs more complex modeling techniques such as deep learning could potentially obtain better results. The work here presents a proof-of-concept study about the use of passive sensing as a means to explore the relationship between commuting and workplace performance. The insight that focusing on the commuting period, something that is detectable with the help of sensors in a worker's life, could help us better understand workplace performance, is an important area of research for future of work. We envision a future where ubiquitous sensing technology can detect stress of individuals while they are commuting and offer interventions tailored to them such as music, podcasts, connecting them to friends and family, or offering tips for short stops (e.g., quick coffee stop).

Limitations

Our commute study has a number of limitations. First, we do not assess environmental factors along with job-related characteristics. Nor do we understand the contextual information of stress and anxiety related to noncommute issues that might contribute to what we measure making interpreting results difficult. Mediators such as job stress, work-related ruminations, and work satisfactions might have an impact on how a person experiences their commute. Our study is mostly related to tracking behavioral or physiological changes in the person during commuting. We do not look into subjective feelings about the commute. Another limitation is the lack of samples and diversity.

In addition, since the ground truth are self-reported, they could be subjectively biased. It is also worth noting that in this work, we focus on the between-person differences in the commute experience of individuals and its impact on work performance. As a result, we average the entire data of each individual during the analysis. Although not a limitation in and of itself, future researchers might want to explore the within-person fluctuations in performance as a result of differing commute experiences. Such a study of commute dynamics will help further our understanding of commuting and its impact on workplace behavior.

CONCLUSION

In this article, we used commute data of ($N = 275$) information workers collected using passive sensing devices to better understand commute behavior. We present results from the study and discuss commute behavior and job performance, specifically, how it relates to lower and higher performers. Our study represents a proof of concept using mobile-sensing technology to measure an individual's commuting experience and its impact on their job performance. We envision a future where mobile ubiquitous sensing technology better understands commuters' mental wellbeing and offers up interventions that help the commute experience, promote employee satisfaction, and increase workplace performance.

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