# A Multisensor Person-Centered Approach to Understand the Role of Daily Activities in Job Performance with Organizational Personas


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Several psychologists posit that performance is not only a function of personality but also of situational contexts, such as day-level activities. Yet in practice, since only personality assessments are used to infer job performance, they provide a limited perspective by ignoring activity. However, multi-modal sensing has the potential to characterize these daily activities. This paper illustrates how empirically measured activity data complements traditional effects of personality to explain a worker's performance. We leverage sensors in commodity devices to quantify the activity context of 603 information workers. By applying classical clustering methods on this multisensor data, we take a *person-centered* approach to describe workers in terms of both personality and activity. We encapsulate both these facets into an analytical framework that we call *organizational personas*. On interpreting these organizational personas we find empirical evidence to support that, independent of a worker's personality, their activity is associated with job performance. While the effects of personality are consistent with the literature, we find that the activity is equally effective in explaining organizational citizenship behavior and is less but significantly effective for task proficiency and deviant behaviors. Specifically, personas that exhibit a daily-activity pattern with fewer location visits, batched phone-use, shorter desk-sessions and longer sleep duration, tend to perform better on all three performance metrics. Organizational personas are a descriptive framework to identify the testable hypotheses that can disentangle the role of malleable aspects like activity in determining the performance of a worker population.

CCS Concepts: • **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**; • **Applied computing** → *Law, social and behavioral sciences*; *Psychology*.

Additional Key Words and Phrases: Wireless sensor networks, media access control, multi-channel, radio interference

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## 1 INTRODUCTION

Apart from sleeping, work occupies the largest amount of time of an individual's day [100]. To exact a particular quality of life, it is essential for an individual to have an occupation where they can sustain, grow, and contribute. For employers, understanding how workers perform is integral for organizational productivity and overall organizational health. Therefore, employees, employers and organizational researchers often seek factors to determine the likelihood of maximal job performance.

Certain theoretical frameworks describe an individual's performance to be a function of both their inherent personality and the activities that they perform to adapt to situations [35, 94]. Yet, in practice, personnel management only incorporates personality-assessments to forecast job performance because traditional organizational research considers personality traits to be the most robust predictor of workplace functioning [2, 76]. However, personality assessments have limitations. First, the instruments used to measure personality rely on self-reports, which are vulnerable to feigning and self-presentation leading to subjective results [47]. Secondly, since changes in personality are only observed over long periods of time [86], its rigidity presents an inflexible view of a worker's job outcomes. In contrast, a worker's activities can be objectively measured and be flexible to changes. While traditional personality assessments can relegate a worker's potential, by learning how actions determine workplace experiences, personnel management units can recommend day-level activities to improve


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their performance despite the limitations of their traits. Prior work has shown that job performance is related to activity-based features like commuting time [80], workplace mobility [53], and social interactions [73]. Nevertheless, these studies concentrate on specific aspects of activity and also ignore personality traits. Because of this they fail to dissociate the effects of the two constructs. While, prior research has extensively investigated the aspirational personality types that succeed in the workplace [45], disentangling the role of day-level activities in determining job performance, independent of the worker's personality, can provide a more holistic understanding of workplace functioning and establish a basis to look beyond personality and investigate activity patterns for improved personnel management.

Accordingly, we aim to empirically validate that personality and activity context are independently associated with job performance. However, unlike personality, activity context can vary at a day-level. Moreover, personality assessments are subjective to the recorder's perceptions but activities can be objectively examined, i.e., irrespective of the observer they are consistent in terms of the actor, the action taken, the duration and time of incidence [79]. Indeed, self-report instruments to study activity context fail to capture objective moment-by-moment *in situ* information that represents a person's situation accurately, consistently and at scale [97, 103]. To bridge this gap we harness the multimodal sensing capabilities of ubiquitous off-the-shelf devices embedded in a worker's everyday life. Pervasive technologies like smartphones [77], wearables [62] and social media [92] provide strong evidence that digital phenotyping can identify objective markers associated with individual experiences. This addresses past calls for more data-driven methods to investigate performance [102]. This also overcomes some common problems with the use of self-reported personality, such as social desirability and acquiescence [81]. Uncovering the relationship between sensed activities and performance not only has practical advantages, but also sets up theoretical advancements. The literature recognizes the traits that describe high-performing individuals but does not explain what they do [34]. Additionally, activity patterns are sensitive to situational demands, which are occluded in self-reported personality measures. Further, from an intervention standpoint one's activities and habits are more readily electable for changes, which in turn can encourage positive job performance outcomes [75]. This new perspective to complement the worker's personality construct with aspects of their day-level activity aspects can further illuminate the factors related to job performance [102].

To represent an individual as a totality of their activity context and personality we present the concept of an *organizational persona*. In psychology, a *persona* refers to consistent patterns or regularities in perceivable actions and beliefs[98]. We consider an organizational persona to be the intersection of two components; *activity*, which is sensitive to situational dimensions and demands; and *personality*, which is develops intrinsically. In our study, the use of off-the-shelf commercial technologies for large-scale passive sensing in the wild helps us capture a worker's activity context – information that can describe the change in an individual's state [1, 33]. Subsequently, we illustrate the use of classical machine learning techniques on this multimodal sensor data to identify personas in a diverse organizational population. These personas enables us to explore if the co-occurrence of activity characteristics coupled with inherent personality traits can improve our understanding of workplace functioning.

In this paper we specifically document:

**Discovering Organizational Personas:** We describe an automated unsupervised clustering approach to discover meaningful organizational personas, which are composites of a trait-based *personality facet* and a dynamic, longitudinal *activity facet*.

**Interpreting Organizational Personas:** We provide meaning to the four different personas we uncover by elaborating the various facets they are composed of.

**The Role of Personas in Understanding Job Performance:** We examine how personas can reveal the association between an individual's activity context and their workplace functioning independent of pre-established relationships of personality to job performance.

Table 1. Definition of the key concepts explored in this paper, i.e, "personality traits", "activity context" and "job performance".

| Description | Examples |
|---|---|
| **Personality Traits** | |
| The characteristics that describe variation in individual dispositions and motivations are broadly defined as personality [34, 64]. While some of its aspects can change with external factors, such as significant life-events, personality represents a set of stable propensities that are expressed irrespective of situations [34]. These patterns, known as *personality traits*, explain much of an individuals functioning. | An individual's proactiveness, diligence and ability to moderate impulses is governed by the "conscientiousness" trait [64]. In academic settings this trait is strongly related to curricular scores [9]. Alternatively an individual's knack for learning and creativity is linked to the "openness" trait [64]. At the workplace, this is associated with high training proficiency [9]. |
| **Activity Context** | |
| The attributes that describe the implicit situational information surrounding an individual is known as context [33]. The four commonly accepted components of context are location, identity, time and activity [1]. This paper focuses on *activity-context*, which describes "what is occurring in the situation" [33]. While personality traits are agnostic to situational-changes, activity-context is sensitive to changes in an individual's surroundings. | In their qualitative study, Paruthi et al., describe how implicit factors that surround an individual can effect their intention to exercise [80]. This includes features of activity-context, such as commute duration and social interactions [80]. Similarly, Olguín et al., have used sensing to show how the communication activity an individual is embedded in is associated with their job satisfaction and productivity [74]. |
| **Job Performance** | |
| The set of functions that a worker intentionally performs to contribute to the goals of an organization represents their *job performance* [87]. Unlike activity-context, which implicitly characterizes the setting a worker is immersed in, job-performance refers to explicit behaviors that effect an organization's overall health and effectiveness | Moorman demonstrates that workers that help colleagues with job-related tasks and exhibit responsible participation in the civic-affairs of the organization tend to have greater job satisfaction [69]. |

Organizational personas provide a descriptive lens to interpret how passively-collected activity data can complement personality to explain job performance. These personas are automatically assessed constructs that can go beyond conventional personality-based interpretations to generate new hypotheses about activity and job performance. We situate our findings in theories of organizational behavior and discuss how a more nuanced, dynamic, and grounded understanding of activities of an individual explains their performance.

## 2 RELATED WORK

Table 1 compares and contrasts the primary themes discussed in this paper, namely, personality traits, activity context and job performance. Job performance is defined as, "those actions and behaviors that are under the control of the individual and contribute to the goals of the organization" [87]. Job performance is a multi-dimensional construct that includes task performance (i.e., fullfilling organization assigned duties), citizenship behaviors (positive behaviors, beyond the assigned responsibilities and unrelated to organizational objectives) and counterproductive work behaviors (voluntary behaviors that harm the organization and workers).

### 2.1 Personality Traits and Job Performance

The variability in job performance is generally the product of within-person variances in intrinsic propensities and situational factors[30]. The personality of an individual is one such dispositional attribute that has been widely studied to explain job performance. The *Five Factor Model* (FFM) [64] of personality and its association with job performance has been studied extensively in the literature. These traits are described as; conscientiousness, neuroticism, extraversion, agreeableness, and openness. In this section, we elaborate on the known relationships between these traits and specific job performance metrics.

Conscientiousness, the trait that represents being dutiful, organized and focused has always been considered a strong predictor of job performance [3, 9, 93, 101]. On the other hand, these same studies describe neuroticism, or the tendency to be less emotionally stable and being anxious, as a negative indicator for job performance. This could be driven by high neuroticism is associated with low job satisfaction [26]. One's ability to socialize and assert themselves in the company of others, or extraversion, is typically correlated with high performance in people-facing roles and training proficiency [9, 10]. The latter could be because individuals with high extraversion are able to assimilate easily into newer settings. Agreeableness describes kind, compassionate characteristics, often found in people who are trusting and more helpful. Much like extraversion, this trait typically correlates with performance in jobs involving significant social interaction [9, 10]. Lastly, openness is a measure of intellectual curiosity, adventuresomeness, and inquisitiveness. Work involving creativity and innovation can be gauged through this trait [11, 38].

A majority of these studies are based on one-time survey instruments that collect subjective self-reported data. Having said that, not all of this research has been entirely agnostic to the concept of context. Barrick and Mount, specifically studied the effects of occupational role as a sample characteristic [9]. While certain traits like conscientiousness are favorably correlated for all types of work, other traits like extraversion only show strong correlation for certain roles like management and sales.

Although personality has consistently provided a strong signal representing job performance, it is operationalized as a fairly stable construct that does not typically vary on a daily basis. It is restricted to what a person *is* and agnostic to what they *do*. This motivates our examination of mutable everyday actions in determining job performance and understanding how it can accompany the existing influence of personality.

## 2.2 Activity States and Job Performance

The motivation to look for new indicators of job performance, which are flexible compared to personality, arises from various frameworks describing how individual's cope or interact with their ecology [35, 94]. In psychology the *Lewin's Equation* theoretically establishes that an individual's performance is a function of both personality and context [94]. Even in interaction research, Dunn et al. postulated that there is a relationship between context (temporal, physical, social, and cultural) and performance [35]. Their framework, *Ecology of Human Performance* (EHP), considers the dynamic setting of an individual to be fundamental to assess occupational outcomes. These concepts assert that situations, or the state an individual finds themselves in, can restrict or enable performance over and above their intrinsic traits. Yet, "context" or "situation" is a broad, nebulous term. We primarily adopt the daily activities as a proxy of context [1, 33]. It represents the actions or procedures that have been adapted to maintain or recover a setting as a response to changes in it [1, 95]. Moreover, actions taken by an entity are salient to describing a situation and certain situations are known to impact psychological outcomes [36, 79]. This leads us to believe there is some value to studying the association between daily activities and performance. In fact, an interview study by Paruthi et al. demonstrated that certain activities like commuting or staying in the office can be indicative of specific behaviors in individuals [80]. Our work aims to empirically examine these theoretical notions. A coarse understanding of these activities can be inferred from non-invasive sensing in a way that is scalable and dynamic. This can provide information on what an individual is *doing* in addition to their *being*, and provide a more holistic representation of functioning [35, 94].

Despite the fact that organizational psychology research overwhelmingly focuses on personality aspects that determine job performance, some prior work in the domain has tried to investigate the activity of workers. For example, Mintzberg followed detailed activities of the working life of five CEO's for a week that culminated in the book *The Nature of Managerial Work*[66]. Similar work has been extended to longer time windows and larger samples to understand better a long-standing question, the influence of everyday work activities on job performance. Leesman, a company that analyzes workplace behavior and employee experience, surveyed individual movement across 1700 workplaces [53] to understand employee performance in different corporate real-estate cultures. Profiles that exhibited higher movement show an increase in satisfaction with respect to individual tasks, away from their desk, as well as creative thinking. Therefore, companies need to understand their employees' day-level activities better so that they can design their workspaces, teams and even task flows in efficient ways. Modern technology is capable of replicating these event markers at a much larger scale [22] and help extend this question to larger scales. While most prior studies focused on constructs like agenda and sequence of meetings, break times, time spent at desk we further this line of inquiry by including more granular features that can be obtained from passive sensing individual activities in a workplace.

Previous work in the space of ubiquitous computing has shown how unobtrusive sensing technologies can be used to understand worker behaviors and perceptions. For example, social-activity has been sensed through wearables to understand aspects of job satisfaction [73–75]. Olguín et al., have used wearables to determine that task completion is affected by both physical activity and speech activity [74]. In 2016, Mark et al. computationally analyzed the digital activity of individuals with respect to their email interactions, to understand how batching notifications as opposed to self-interruptions impact task performance and stress [61]. Their *in-situ* study found relationships that deviated from theories in the literature. The new findings were uncovered because passive sensing could overcome the challenges, faced by survey instruments, to acquire appropriate representative data of an individual's dynamic context. Thus, using large scale-sensor studies to unobtrusively quantify activity within such spaces provides researchers a deeper understanding of workspace paradigms [67]. While most of these works imply that an individual's activities can impact their workplace experience, they are limited in contrasting the effects of an employee's activities from their personality traits. Thus such work is insufficient in motivating the organizational researchers to explore new constructs outside personality. This paper distinguishes itself from prior mobile-sensing studies on workplaces by specifically disentangling if an individual's day-level activities are significantly associated with performance independent of their personality and to what extent to this effect exists.

The primary reason why activity is an interesting marker to study with respect to job performance is because of its variability and sensitivity to change. Since, activity is fundamental in describing the state, situation or context of an individual it often varies along with it. Moreover, unlike personality traits, activity context is malleable — it can be manipulated by policy and cultural changes local to an organization. Consider *Activity-Based Working* (ABW) which is a relatively recent trend within office spaces where there are no designated desks and allows flexibility of movement and diverse settings to work[6]. Brown et al. modified the spatial layout of office spaces and studied the impact on interpersonal interactions through wearables [19]. Recently, Montanari et al. have used proximity based sensing to understand employee interactions in ABW settings [68]. Although earlier work has suggested that the misuse of this design can lead to loss of productivity [6], they found that ABW flattens office hierarchies and promotes lateral communication. Thus, studying the additive information contained in empirically measured day-level activities can provide actionable insights for design and personnel management.

### 2.3 Personas in the Workplace

A *persona* is the perceivable aspect of an individual that can help understand their overall functioning and motivations. We adopt this term to define a person-centered construct that encapsulates both an individual's personality traits and their activity states. This idea is based on the theory that individuals must be described as totalities, containing all the interactions of the sever traits and states they embody [41, 105, 111]. While not explicitly using the term, the concept of personas has been studied in the scope of the workplace.

Beside Big-5 personality traits individuals with proactive characteristics (crafting their own task objectives) have been associated with high job performance [8, 28]. In organizational psychology, the leader persona and its role in an organization has drawn attention [29]. Across different cultures, prototypical good leaders are considered charismatic/transformational, team-oriented, and participative[32]. Similar to the leadership profile, emotion regulation has been studied in the organizational setting through distinct activity-based classes [44] — some of which act on the surface, others deeply regulate. Each of these groups shows specific associations to exhaustion and job satisfaction. Woo and Allen's multifaceted approach to understand the propensity to leave an organization found different classes with diverse characteristics of both reasoning and actions [110].

Generally, however, this research is based on data collected through self-report survey instruments and interviews. To counteract the limitations of these studies, Van Knippenberg and Sitkin, in their meta-analysis found the need to encourage empirical studies in organizations that can be more informative than subjective measurement scales [103]. Consequently, Meyer et al. demonstrated a leader's effectiveness can be operationalized as a factor of passively sensed *micro-behaviors* like question-asking and mimicry are linked to a leader's ability to empathize [65]. Although devoid of sensor data, a longitudinal study of absenteeism found distinguishable patterns related to work and health [59]. These studies either successfully demonstrate or sufficiently motivate how certain passively sensed activities can be used to understand a leader's performance.

Comparably, our work intends to delineate common characteristics of workers to depict their job performance by analyzing multimodal sensor data. We use an automated method to unify information represented by trait-based features (personality) with dynamic features (activity) in order to derive semantically meaningful personas.

## 3 STUDY AND DATA

### 3.1 The Tesserae Project

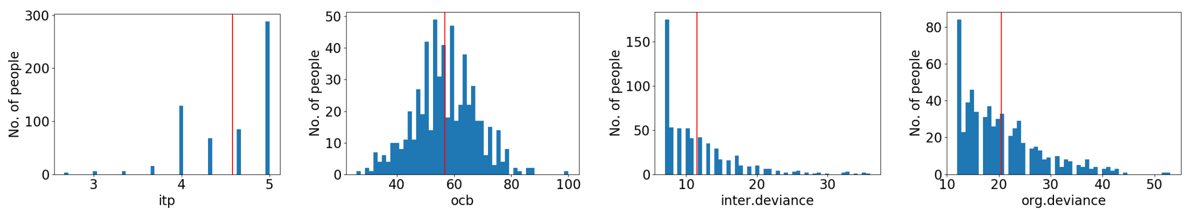
This paper studies data from a larger project [63, 91] that builds on previous efforts to use multimodal sensing to infer individual behaviors and mental states [60, 85, 92, 106]. The objective is to leverage the sensing capabilities of commercially available technologies and understand workplace performance longitudinally and in-the-wild.

This dataset comprises of 757 information workers from different field sites across the United States. A rolling enrollment was conducted from January 2018 through July 2018. Participants were either compensated by direct payments or through a set of weekly lotteries, based on the specific field site's requirements. Participants were requested to remain in the study for either up to a year or through April 2019. This study was approved by the Institutional Review Board (IRB) at the researchers' institutions. To ensure data privacy of the participants, the data was de-identified and stored in secured databases and servers with limited access privileges that were physically located in one of the researcher institutions.

Participants were requested to complete an initial set of questionnaires related to demographics, job performance, personality, intelligence, affect, anxiety, alcohol and tobacco use, exercise, sleep, and stress, administrated via validated psychometric survey instruments. The analyses presented in this paper are only concerned with the job performance and personality metrics that the participants recorded.

In addition to the above, participants were provided with 1) Bluetooth beacons (*Gimbal*)—two static (to track their home and work location) and two portable devices (to carry on the person), 2) Wearable—a smartwatch (*Garmin Vivosmart*) to capture heart rate, stress, and physical activity, and 3) Phone Agent—a smartphone application [106, 107] to track phone usage (for e.g. screen lock/unlock and GPS locations).

**Demographics.** A random sample of 154 participants was "blinded" for external evaluation of the project metrics [63]. Our findings are based on the remaining 603 "non-blinded" participants of which 253 reported they were female. On average a participant in the study was 34 years old (stdev. = 9.34). A majority of the participants possessed a college degree (52%), another significant proportion reported having a master's degrees or graduate




(a) ITP (b) OCB (c) Inter.Deviance (d) Org.Deviance

Fig. 1. The distribution of our participants for different job performance variables with the red line indicating the mean

Table 2. Descriptive statistics of the job performance variables and personality traits

| Measure | Mean | Std.Dev | Range | Scale |
|---|---|---|---|---|
| ITP | 4.58 | 0.5 | 2.67-5 | 1-5 |
| OCB | 56.87 | 10.73 | 26-100 | 20-100 |
| Inter Deviance | 11.5 | 5.37 | 7-36 | 7-49 |
| Org Deviance | 20.48 | 7.56 | 12-53 | 12-84 |

(a) Job Performance

| Measure | Mean | Std.Dev | Range | Scale |
|---|---|---|---|---|
| Neuroticism | 2.46 | 0.78 | 1-4.92 | 1-5 |
| Conscientiousness | 3.89 | 0.66 | 1.92-5 | 1-5 |
| Extraversion | 3.44 | 0.68 | 1.67-5 | 1-5 |
| Agreeableness | 3.87 | 0.56 | 2.08-5 | 1-5 |
| Openness | 3.82 | 0.61 | 1.67-5 | 1-5 |

(b) Personality

level certification (43%), while few had doctoral degrees as well (4%). In terms of annual income, roughly the same proportion of participants earned between 50-100k USD (43%) and more than 100k USD (48%) per year.

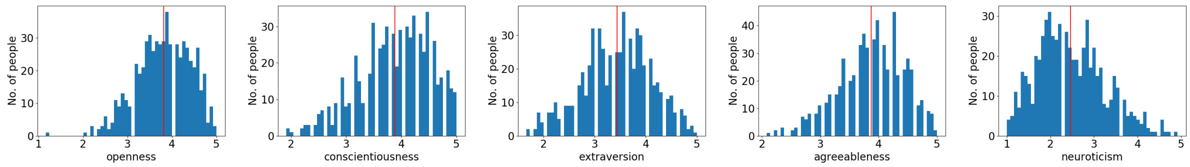
## 3.2 Self-Reported Data

*3.2.1 Job Performance.* Individual success in the workplace can be described along three different dimensions: task performance, organizational citizenship behavior, and counterproductive work behavior [87, 104].

**Task performance:** This refers to behaviors typically rewarded by the management. It is characterized by a worker's proficiency at tasks that transform raw materials (objects, thoughts, or actions) into products or services [18, 104]. For example, in firefighting the task performance can be assessed on the basis of rescue operations, or, in software development it can be associated with bug fixes and feature deployment. While task performance focuses on a worker's accomplishment of employer-prescribed roles and duties, it does not account for their experiences during downtime (e.g., lateness, interpersonal interactions (e.g., collaboration) or destrutive behaviors (e.g., plagiarism) [104]. The project used the Individual Task Proficiency (ITP) scale to quantify this [46].

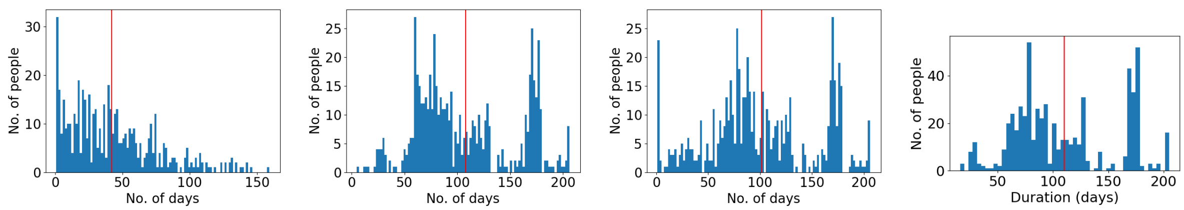
**Organizational Citizenship Behaviors:** These behaviors are not typically rewarded by management, but promote welfare within the organization [15, 70, 78, 96]. Such "extra-role" behaviors are voluntary and can either be *individually targeted* (e.g., aiding a peer) or *organizationally targeted* (e.g., volunteering in extra-professional activities) [83]. Contemporary notions of worker performance argue that at an aggregate, citizenship behaviors are as crucial as task performance in determining overall organizational outcomes [18]. Additionally, citizenship is one of the performance metrics that is related to factors like job satisfaction, which can predict organizational committment, turnover and absenteeism [69]. We measure this using the Organizational Citizenship behavior Checklist (OCB-C) [42].

**Counterproductive Work Behaviors:** This refers to behaviors intended to jeopardize the organization or the individuals within it [23, 90]. Examples include stealing from a peer, insulting a colleague, purposefully




(a) Openness (b) Conscientiousness (c) Extraversion (d) Agreeableness (e) Neuroticism

Fig. 2. The distribution of our participants for different job performance variables with the red line indicating the mean




(a) Bluetooth Beacon (b) Wearable (c) Phone Agent (d) Study Duration

Fig. 3. The distribution of participants by the number of days they provided data in each stream.

doing tasks incorrectly. Recently, such behaviors have been considered to be a dimension of job performance because they can effect organizational outcomes by potentially disrupting goods and services produced and utilized by the organization [23]. Sometimes this is considered as the most important metric when assessing overall workplace effectiveness [87]. This is captured using the Interpersonal and Organizational Deviance (IOD) scale [13] which can separately distinguish the interpersonal deviance from the organizational deviance. Throughout the paper, we refer to these measures as “inter.deviance” and “org.deviance”.

Broadly, there are two approaches to assess job performance metrics. The first kind involves the worker rating themselves, also known as “self-report”. The other kind has the supervise rate the worker and is referred to as “other-report”. While, self-reports can suffer from social-desirability effects, other-reports can be inflated by *halo error* — rating based on overall impression bias as opposed to specific instrument categories [17, 24]. Moreover, meta-analysis of job performance survey instruments show that there is a high convergent validity between the two approaches [17, 24]. As a result of this, this project adopts validated self-report instruments to quantify each of our performance metrics [13, 42, 83]. Figure 1 shows the overall distribution of the participants across the metrics. Table 2a provides the statistical summary for each job performance variable.

*3.2.2 Personality Traits.* The initial ground truth assessment recorded during participant enrollment computed the personality traits described via the Big Five Inventory-2 (BFI-2) [64, 99]. The BFI-2 measures five different factors of personality — **agreeableness** (compassion, respectfulness, trust), **conscientiousness** (organization, productiveness, responsibility), **extraversion** (sociability, assertiveness, energy level), **neuroticism** (anxiety, depression, emotional volatility), and **openness** (intellectual curiosity, aesthetic sensitivity, creative imagination)

The overall distribution of our participants for their personality trait metrics is presented in Figure 2. The statistical summary for the BFI variables is provided in Table 2b.

Table 3. 30 activity features representing the objective situations of the participant were derived and examined, this table shows a subset of them; : Wearable, : Phone Agent, : Beacon

| Context | Representative Features | Stream |
|---|---|---|
| Physical | Distance On foot, Still Duration | |
| Sleep | Sleep Duration, Sleep Debt | |
| Mobility | Locations Visited | |
| Screen | Unlock Duration, Unlock Count | |
| Desk | Desk Session Duration, 30 Minute Break Count | |

### 3.3 Passively Sensed Data

This paper is focused on understanding activity context and complementing this with trait-based attributes to identify personas among information workers. While personality is a static representation of an individual, agnostic to the time and space they are in, their activity is not. It can in fact be considered an artifact of one's situation, or in a broader sense their *context* [1, 95]. Unlike personality, which is a trait, activities are more flexible to alteration based on external demands, the state of the individual and their immediate objectives [35, 40]. Our research is interested in examining unobtrusively sensed day-level activities with respect to job performance, beyond a worker's intrinsic traits.

To infer activity we used contextual information sensed through the devices provided to the participants. In comparison to the self-reported personality measures, the use of ubiquitous sensing enables us to describe *objective situations* — characteristics that "exist" regardless of who perceives it, e.g., what is happening, when it is occurring [79]. The latest data analyzed in this paper was logged on August 23, 2018. At this snapshot, the mean study period for the participants was 110 days (Figure 3d). The participants were required to maintain the battery of each of the devices provided to them. The varying compliance to charging the devices led to different sensor streams collecting different amounts of data. On average, Bluetooth beacons recorded 42 days of data, the wearable collected 108 days of data and the Phone Agent collected 101 days of data (Figure 3). For each participant, the feature values were summarized as the mean (of their study duration), in order to represent the sensed activity of their average day (Table 3). To describe the features, we have semantically segregated similar features into multiple sets :

**Physical Activity**: The Phone Agent used the Google activity Recognition API [4] to measure the duration of different physical activities. Additionally, the wearable provided the distance traveled on foot.
**Sleep**: The Garmin API provided information was supplemented with the phone unlock signals to infer an individual's sleep duration. Besides this, the dataset also computes sleep debt or deficit.
**Mobility**: The number of locations a participant visited and the distance between these locations was calculated using the GPS coordinates logged by the phone agent. A DBSCAN clustering algorithm was used to identify significant locations across all the data-points.
**Phone Use**: The Phone Agent recorded timestamps when the participant either locked or unlocked the screen. This was used to infer the number of unlocks as well as the duration of phone use (by measuring the time between an unlock and a lock).
**Desk Activity**: The Gimbal API [5] in conjunction with the phone agent captured moments when particular beacons are within the range of an individual. Using the sightings of the static bluetooth beacon placed on a participant's desk, desk sessions and break sessions (of varying intervals) were inferred.

## 4 DISCOVERING ORGANIZATIONAL PERSONAS

We operationalized an organizational persona as a combination of a *personality facet* and an *activity facet*. To obtain these facets, we employed a clustering method to identify mutually exclusive, homogeneous group of characteristics, which can be used to describe our participants. This paper posits personas as a framework to comprehensively understand worker performance both in terms of personality as well as activity. The following segments report the streamlined procedure and rationale we propose for identifying the personality and activity characteristics of a worker population in a meaningful way.

### 4.1 Feature Selection

For inferring the personality aspect of our personas we use a set of well-established traits as features [64] (Section 3.2.2). However, given the scope of this work, recognizing the right set of activity features from multimodal-sensor datasets that characterize an individual is subjective. This section clarifies our assumptions and criteria.

The ubiquity of passive sensing can capture so much data, it becomes tempting to harness all the contextual information it can gather. Yet, context is a nebulous term that can encompass many different characteristics of an individual's situation [1, 35, 95]. This paper centers on a specific fragment of context, *activity* — what someone does. activity is a mutable attribute, thus making it interesting to investigate in studies of performance and wellbeing. Contrary to personality, the malleable nature of activity presents the opportunity to manipulate it for experimental studies. This dynamic nature of activity primarily motivates our choice of features.

At a formal level, the features of interest express how an activity is performed (for e.g., duration, distance, count) and/or when it occurs (for e.g., throughout the day, from midnight to 6am, 6am to noon, etc.). The activity contexts shown in Table 3 can be extended on the basis of such qualities leading to a total of 30 features. Excessive features can add noise and latency to the modeling algorithm [16, 55]. Thus to mitigate these effects we filtered out the most distinguishable features within our sample. Features like "outgoing calls" were rejected due to its sparse signal, i.e, event-contingent activities that occurred less than once a day were dropped. This was followed by a step-wise *Variance In ation Factor* method [71] that eliminated features with high multicollinearity, for e.g., the phone unlocks from 6pm to 12am can be explained by other features. For this step, a VIF threshold of 10 was used and the topmost feature was removed successively. Carefully curating features that depict activities followed by a few computational heuristics helped minimize our activity information to a set of 16 features.

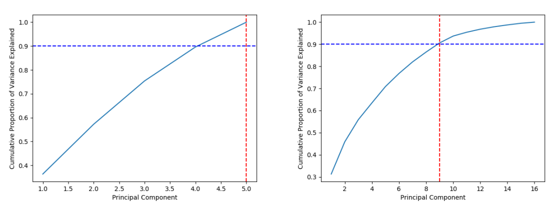
### 4.2 Person-centered Approach

The selected features were fed into clustering algorithms to characterize the dominant patterns of personality traits and day-level activities. The use of classical clustering methods is motivated by a methodological perspective known as the *person-centered* approach [111]. Not only is "clustering" a popular method in organizational research [41, 105, 111], the person-centered approach views the individual as an "integrated totality" [41]. This is an alternative to *variable-centered* approaches that study human-centered data since those methods often treat individuals as a collection of isolated features [111].

Even in practice, compared to variable-centered methods, person-centered methods can simplify the main effects and interactions of a large set of features through cluster representations. For example, we can consider taking a variable-centered procedure to unpack the role of personality and activity by building multiple linear regression models. These models test the relationship between activity features and job performance metrics after controlling for personality traits. Table 4 shows which of the 16 shortlisted features exhibit significant associations with performance, when analysed through the lens of a variable-centered method. However, given a large number of separate models corresponding to each of the features, this framework is susceptible to false positives [111]. Theoretically, a variable-centered approach should account for multiway interactions between the features, but this requires including multiple interaction terms (multiple two-way terms, multiple three-way,

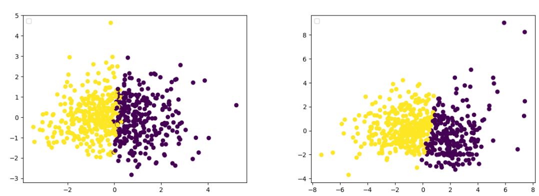
Table 4. Standard coefficients of activity features when using multiple different regression models for each activity (an example of the variable-centered approach). These are useful for describing the variables but not the individual.
$M : performance\_metric \quad personality\_traits + activity_i$ ('-':p<1, '.':p<0.1, '*':p<0.05, '**':p<0.01, '***':p<0.001)

| Activity Feature | ITP | OCB | Inter Deviance | Org Deviance |
|---|---|---|---|---|
| Locations Visited (12am-6am) | - | - | $3{:}61\ 10^{1*}$ | $6{:}58\ 10^{1**}$ |
| Locations Visited (12pm-6pm) | - | - | $2{:}77\ 10^{1*}$ | $5{:}25\ 10^{1**}$ |
| Distance-On foot | $1{:}85\ 10^{5*}$ | $3{:}82\ 10^{4*}$ | - | |
| Unlock Duration (12am-6am) | - | - | $2{:}31\ 10^{4*}$ | - |
| Unlock Duration (6am-12pm) | - | - | $5{:}39\ 10^{4**}$ | - |
| Unlock Duration (12pm-6pm) | - | - | $5{:}74\ 10^{4**}$ | - |
| Unlock Count (12am-6am) | - | - | - | $1{:}12\ 10^{1*}$ - |
| Unlock Count (6am-12pm) | - | - | - | $3{:}78\ 10^{2*}$ - |
| Unlock Count (12pm-6pm) | - | - | - | $5{:}49\ 10^{2*}$ - |
| Desk Session Duration | - | $8{:}66\ 10^{4*}$ | - | - |
| 30 Minute Break Count | - | $3{:}20\ 10^{1*}$ | - | - |



(a) Personality (b) Activity

Fig. 4. 5 PCs for personality and 9 for activity are needed to explain 90% variance in their respective feature spaces



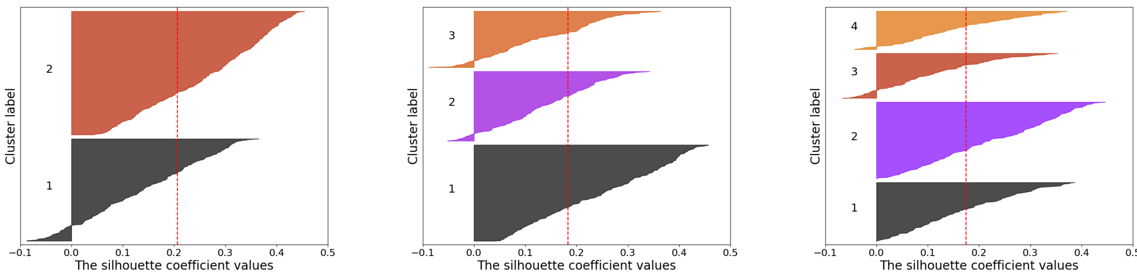
(a) Personality (b) Activity

Fig. 5. A representation of $k$-means clustering of the data along the first 2 PCs — explaining approximately 60% variance in the personality and 40% variance in activity.

and eventually n-way terms) [111]. Therefore in studies that describe individuals along multiple-dimensions, regression models can often get bloated and challenge interpretability. On the contrary, taking all the activity features as a whole is more conceptually grounded and domain-driven [111] way to capture the interplay of dimensions. A person-centered method is a minimalist technique to meaningfully understand the nature of the individuals in a sample by capturing the interactions within the features concurrently. *Note: This process is not meant to supersede regressions, it is simply an alternate lens to examine individuals [44].*

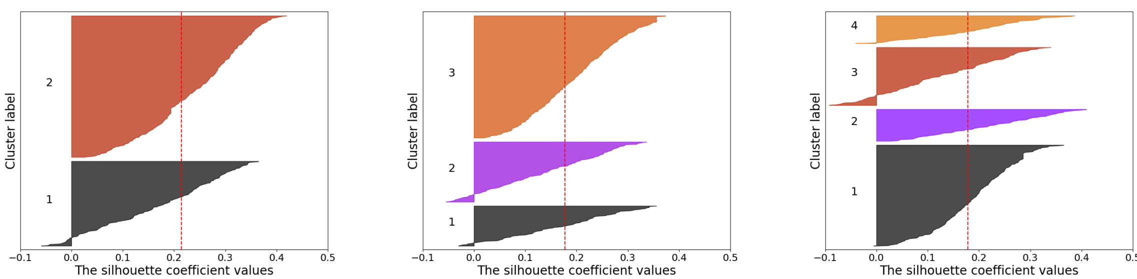
## 4.3 Clustering Procedure

Before proceeding with clustering, we transformed the selected features for the best possible algorithmic results. To make the comparison across dimensions more equitable, we standardized our features into Z-scores [52] – the number of standard deviations a participant differs from the mean. This transformed the features into values of comparable order and maintained their relative distribution with respect to their mean. This was followed by a *Principal Component Analysis* (PCA) to overcome the loss of precision in distance measures of high-dimensional spaces [82]. This dimensionality reduction technique transforms data into orthogonal dimensions. Based on a 90% threshold for explanatory variance we retained all 5 principal components in the personality facets the first 9 for the activity facet (Fig 5).




(a) $k = 2$ (b) $k = 3$ (c) $k = 4$

Fig. 6. Silhouette plots for different $k$ in the personality space. The red vertical line represents the average silhouette score




(a) $k = 2$ (b) $k = 3$ (c) $k = 4$

Fig. 7. Silhouette plots for different $k$ in the activity space. The red vertical line represents the average silhouette score

Table 5. Silhouette scores per clustering algorithm; $k$ represents the number of clusters

| | Activity | | Personality | |
|---|---|---|---|---|
| | score | $k$ | score | $k$ |
| K-Means | 0.214 | 2 | 0.207 | 2 |
| Hierarchical | 0.205 | 2 | 0.195 | 2 |
| Affinity Propagation | 0.074 | 47 | 0.153 | 46 |
| DBSCAN | -0.289 | 2 | -0.241 | 2 |

Given our unsupervised approach, we first investigated which clustering method would be most suitable for our data. We tested these methods on the different feature spaces (personality and activity). The $K$-Means method was chosen and then applied to both feature spaces based on the best average silhouette score [88] (Table 5). DBSCAN understandably performs poorly due to the lack of uneven density in the data [37]. Hierarchical clustering [108] is the next best method, but there is no *a priori* reason to assume a hierarchical distribution in the data. On both feature spaces, Affinity Propagation exhibits a low score [43]. This could be due to a large number of small clusters it tends to identify; these could have high variance leading to a low average. Thus, given the shape of the points in our feature space, the K-Means method appeared to be the most suited algorithm for clustering. Moreover, it also ensures the homogeneity of variance between clusters, making it an ideal candidate for subsequent statistical analyses.

For K-Means, to determine the number of clusters we used the Silhouette Method [88]. Fig. 6 and 7 visualize the silhouettes based on how closely each point in a cluster is matched to the cluster. When clusters have a majority of points with their silhouette score greater than the average, it is considered a good count [88]. We find that the highest average silhouette score in both cases is at $k = 2$. Within each cluster a large proportion of the points (y-axis) have silhouette scores exceeding the average, indicating grouping with similar points.

To summarise, we identified two distinct clusters in the personality feature space and two dominant groups in the activity feature space for our participants. Each feature space corresponds to a *facet* in the organizational persona. For simplicity, we labeled the personality facets as $P_1$and $P_2$; similarly, the activity facets were labeled as $C_1$and $C_2$. Table 6 shows the distribution of the participants across the personas.

Table 6. Number of participants in each persona

| | $P_1$ | $P_2$ |
|---|---|---|
| $C_1$ | 120 | 106 |
| $C_2$ | 210 | 167 |

## 5 INTERPRETING ORGANIZATIONAL PERSONAS

Fundamentally, we envision an organizational persona as a construct that encapsulates the most discernible aspects of inherent traits (personality) of dynamic states (day-level activities) shared by a population of workers.

### 5.1 Meaningful Representation of Clusters

The high dimensionality of our feature spaces can make interpretation of clusters challenging [12]. Once the clusters were identified, we performed an additional post-hoc test to quantify the most important features. We performed an ANOVA comparing the cluster means for each feature. If the $F$-statistic value (ratio of between-group variance and within-group variance) was significantly greater than 1, that feature was considered to sufficiently discriminate between clusters and thus non-trivial in describing a cluster [21]. For the personality clusters, all the features were retained, i.e. every trait was a good discriminator among the clusters. For the contextual clusters, however, two features were pruned out and the remaining 14 features were used to interpret these clusters (Table 7). A meaningful rendition of the clusters helps explain the attributes of the participants and the interactions between those features in a ground-up way. Additionally, it sheds light on the exemplary aspects of the persona that can be subsequently situated in the organizational domain.

### 5.2 Personality Facets

A descriptive summary of different personality composites in our sample replicates findings known in the literature. We unpack these facets by situating these constructs within established person-centered typologies, such as the ARC taxonomy [27]:

$P_1$ **-** *High Conscientiousness, openness, extraversion and agreeableness, Low Neuroticism*:
This group scored high on all the personality factors except neuroticism. In fact, this group was below average with respect to that particular trait. Neuroticism is also the only negative trait in the Five Factor Model [64]; a lower score indicates better emotional stability. Also note, the high conscientiousness in this group as it is known to be a strong indicator for certain forms of task performance. Also worth noting is the resemblance of this cluster to the "Resilient" personality type based on the ARC taxonomy [27]. This type is known to be most robust to psychological adaptability. In their approach, Gerlach et al. demonstrate that this composition of traits is often considered desirable, making it a role-model class [45].

$P_2$ **-** *Low Conscientiousness, openness, extraversion and agreeableness, High Neuroticism*:
These individuals are generally the polar opposite of $P_1$in relation to conscientiousness and neuroticism. Their conscientiousness was 16.67% less than $P_1$and neuroticism was 49.2% higher than $P_1$. In terms of the ARC taxonomy, this group is similar to the "Undercontrolled" type that tends to be relatively antisocial [27].

Fig. 8 shows how each cluster varies along different traits with Table 9 depicting their absolute values.

Table 7. Results of ANOVA, comparing each cluster along different features; only features with F statistics significantly greater than 1 were retained; ♥: Wearable, ▯: Phone Agent, ʙ: Beacon

| Feature Name | Source | p-value | F-stat |
|---|---|---|---|
| **Explanatory Features** | | | |
| Locations Visited (6am-12pm) | Phone Agent | $2{:}55 \quad 10^{97}$ | 645.92 |
| Locations Visited (12am-6am) | Phone Agent | $2{:}17 \quad 10^{74}$ | 445.35 |
| Locations Visited (12pm-6pm) | Phone Agent | $1{:}33 \quad 10^{71}$ | 423.28 |
| Unlock Duration (12am-6am) | Phone Agent | $1{:}20 \quad 10^{51}$ | 278.44 |
| Unlock Duration (6am-12pm) | Phone Agent | $1{:}60 \quad 10^{43}$ | 225.55 |
| Unlock Duration (12pm-6pm) | Phone Agent | $2{:}23 \quad 10^{41}$ | 212.15 |
| Unlock Count (12am-6am) | Phone Agent | $4{:}07 \quad 10^{37}$ | 186.15 |
| Unlock Count (6am-12pm) | Phone Agent | $3{:}27 \quad 10^{25}$ | 117.96 |
| Unlock Count (12pm-6pm) | Phone Agent | $9{:}44 \quad 10^{22}$ | 99.30 |
| Desk Session Count | Beacon | $2{:}38 \quad 10^{16}$ | 71.23 |
| Sleep Duration | Phone Agent, Wearable | $5{:}10 \quad 10^{14}$ | 59.50 |
| Still Duration (6am-12pm) | Phone Agent | $1{:}59 \quad 10^{11}$ | 47.21 |
| 30 Minute Break Count | Beacon | $2{:}90 \quad 10^{8}$ | 31.60 |
| Desk Session Duration | Beacon | $3{:}85 \quad 10^{8}$ | 31.02 |
| **Pruned Features** | | | |
| Sleep Debt | Phone Agent, Wearable | $1{:}03 \quad 10^{1}$ | 2.66 |
| Distance On-foot | Wearable | $5{:}60 \quad 10^{1}$ | 0.34 |

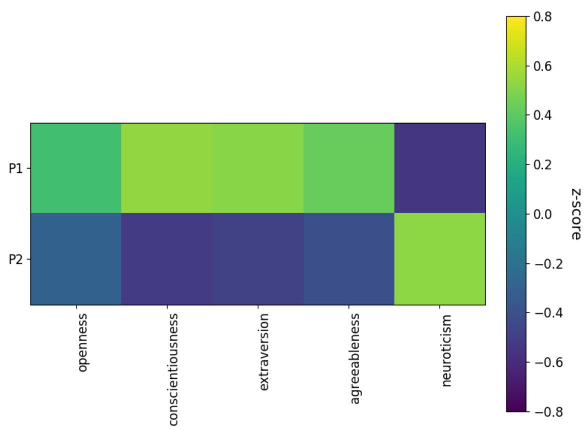



Fig. 8. The Z-Scores of the personality clusters help distinguish the relative difference between the clusters features

Table 9. Absolute value of personality features across clusters ▲: values higher than mean, ▼: values lower than mean

| | $P_1$ | | $P_2$ | | Mean |
|---|---|---|---|---|---|
| Openness | 3.92 | ▲ | 3.69 | ▼ | 3.82 |
| Conscientiousness | 4.20 | ▲ | 3.50 | ▼ | 3.89 |
| Extraversion | 3.73 | ▲ | 3.09 | ▼ | 3.44 |
| Agreeableness | 4.09 | ▲ | 3.61 | ▼ | 3.87 |
| Neuroticism | 2.01 | ▼ | 3.00 | ▲ | 2.46 |
| *Participant Count* | 330 | | 273 | | 603 |

## 5.3 Activity Facets

While the patterns emerging from clustering personality traits in our sample echoed conventional psychological constructs, the activity-based facets have not been explored in typical studies of organizational research. This section describes the clusters in terms of the confluence of action-strategies individuals in our sample employ to adapt to daily contexts. The dominant activity patterns in the passively-sensed data are described as follows:

$C_1$ - *High Mobility, Interruptive Phone Use, High Desk Dwelling, Low Sleep*:
Individuals exhibiting this activity facet are relatively the most mobile. We see this pattern practically throughout the day (across all three 6-hour windows). In the morning from 6am to 12pm, members of this group visit about 7 distinct locations. It is worth pointing out that this does not necessarily imply a greater amount of physical activity since the average time they remain still is only 12 minutes less than the average. Similarly, this group is almost indistinguishable in terms of distance covered (note the poor $F$ statistic on Table 7). This gives us reason to believe that commute might be one of the cardinal activities of their day.
Another distinct aspect of this group is interruption-heavy phone use. This tag is borrowed from Mark et al.'s description of email use [61]. Here an interruption refers to both self-interruptions (user checks devices from internal motivation) or through notifications (external motivation). Since members of $C_1$ exhibit lower duration of contiguous phone use and complement this with a high number of device unlocks it could indicate a greater disposition to interruptions. Despite these digital interruptions, their duration at desk exceeds the average. They also exhibit fewer instances of leaving their desk (*break count*).
On average they sleep 20 minutes less than the average individual of our population. This could either be because of more commute (visit about 1 location more than average at night) or because of interruptions (unlock the phone 5 more times than average).
Considering the concurrence of such action markers, $C_1$ could represent workers who travel frequently and mostly work from the desk where they collaborate or communicate often, but remotely.

$C_2$ - *Low Mobility, Batched Phone Use, Transient Desk Dwelling, High Sleep*:
Members of $C_2$ log far fewer distinct locations throughout the day. The amount of time they are still is slightly higher than average, but their physical movement is not significantly lower (Table 7).
Interestingly, in contrast with to $C_1$, these individuals demonstrate contiguous phone use or "batching" [61]. They unlocked the phone fewer times than usual, but their duration of use was longer. For example, from 12am to 6am, they unlocked their phones around 6 times less than $C_3$, but they used the phone for 35 minutes longer. Another divergent aspect of this cluster is their desk activity is an inverse of the previous group. They log far more desk sessions, but the average duration is shorter and the number of breaks is higher. This ties in with their phone use patterns as well.
In addition to these qualities, this set of individuals end up sleeping longer as well. Even though they use their phone longer, the fewer interruptions could indicate better resting due to lack of interference.
These workers spend most of their time in one place but not necessarily at their desk. This implies more frequent physical collaborations within a site, and digital tasks being coordinated into chunks.

Fig. 9 shows how each of these groups differs for different contextual factors. The absolute values for the activity attributes of these clusters can be referred to in Table 10. In terms of specific activities, individuals are typically consistent throughout the day, i.e. if an individual performs one activity more frequently or for longer during the day then they are likely to do the same at night.

### 5.4 Combining Facets to Construct Personas

Each personality facet combines with each activity one to give rise to a persona. With 2 facets of each kind, this approach renders 4 personas, referenced subsequently in the form of $P_iC_j$. We perform a $\chi^2$ test to measure the association between the two facets and found no significant association ($p = 0.59$) between them. Therefore individuals of the same personality facet are equally likely to exhibit qualities of any of the two activity facets; and vice-versa. This is an important result for us to establish independence between our two constructs before comparing its effect on job performance.

Without the distinction mentioned above, it would be a struggle to elucidate the effect of personality and activity patterns on job functioning independent of the other factor. This two-faceted approach provides the

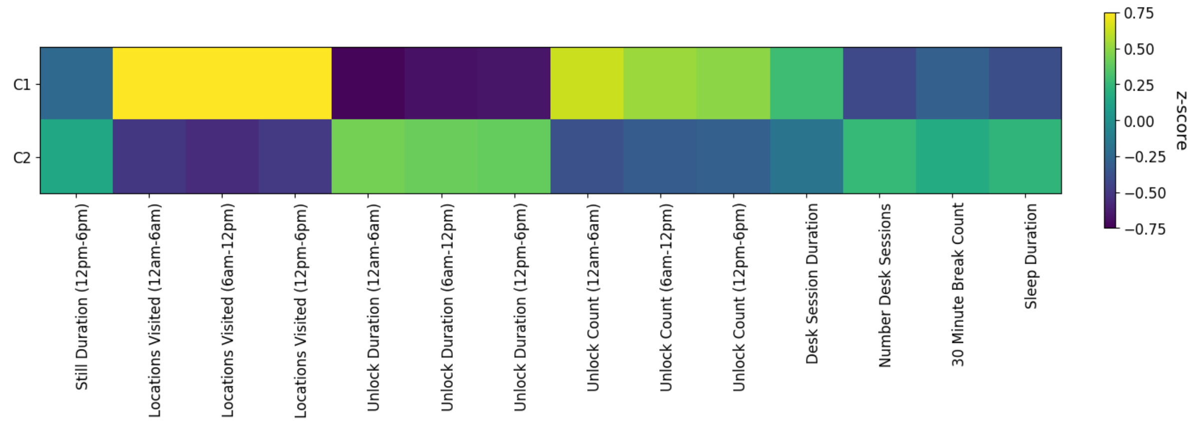



Fig. 9. Heatmap showing the Z-Scores of contextual clusters

Table 10. Absolute value of activity features across clusters;
▲: values higher than mean, ▼: values lower than mean

| | $C_1$ | | $C_2$ | | Mean |
|---|---|---|---|---|---|
| **Physical Activity** | | | | | |
| Still Duration (12pm-6pm), *minutes* | 433.23 | ▼ | 453.43 | ▲ | 445.43 |
| **Mobility** | | | | | |
| Locations Visited (12am-6am) | 3.20 | ▲ | 1.37 | ▼ | 2.11 |
| Locations Visited (6am-12pm) | 7.36 | ▲ | 2.43 | ▼ | 4.44 |
| Locations Visited (12pm-6pm) | 3.87 | ▲ | 1.58 | ▼ | 2.51 |
| Distance-On foot, *meters* | 4836.65 | ▲ | 4713.79 | ▼ | 4760.69 |
| **Phone use** | | | | | |
| Unlock Duration (12am-6am), *seconds* | 568.53 | ▼ | 2671.83 | ▲ | 1846.57 |
| Unlock Duration (6am-12pm), *seconds* | 293.59 | ▼ | 1418.34 | ▲ | 978.56 |
| Unlock Duration (12pm-6pm), *seconds* | 332.28 | ▼ | 1361.40 | ▲ | 957.61 |
| Unlock Count (12am-6am) | 12.06 | ▲ | 6.37 | ▼ | 8.59 |
| Unlock Count (6am-12pm) | 40.53 | ▲ | 24.08 | ▼ | 30.51 |
| Unlock Count (12pm-6pm) | 21.19 | ▲ | 12.79 | ▼ | 16.08 |
| **Phone use** | | | | | |
| Desk Session Duration, *seconds* | 1379.38 | ▲ | 827.86 | ▼ | 1040.65 |
| Number Desk Sessions | 15.02 | ▼ | 31.37 | ▲ | 25.01 |
| 30 Minute Break Count | 3.70 | ▼ | 5.10 | ▲ | 4.55 |
| **Sleep** | | | | | |
| Sleep Duration, *hours* | 6.84 | ▼ | 7.36 | ▲ | 7.16 |
| Sleep Debt, *hours* | 1.38 | ▲ | 1.30 | ▼ | 1.33 |
| *Participant Count* | 226 | | 377 | | 603 |

flexibility to test the isolated effect of each factor as well as the interaction effect of each cluster. The following

Table 11. Significance of main effect and interaction effect of different facets of persona on measures of job performance ('-':$p$<1, '.':$p$<0.1, '*': $p$<0.05, '**':$p$<0.01, '***':$p$<0.001)

| | ITP | OCB | Inter.Deviance | Org.Deviance |
|---|---|---|---|---|
| Personality | $8.03 \times 10^{-17}$*** | 0.028* | $7.79 \times 10^{-6}$*** | $3.03 \times 10^{-12}$*** |
| Activity | 0.031* | 0.026* | - | 0.012* |
| Personality:Activity | - | - | - | - |

section will detail how to test this in a $m \times n$ design where $m$ is the number of personality facets and $n$ represents the different types of activity configurations.

# 6 USING ORGANIZATIONAL PERSONAS TO ANALYZE JOB PERFORMANCE

Once the personas have been rendered and sufficiently described, they can be used to understand employee performance at the workplace holistically. To express the functionality of these personas beyond simply considering individual personality profiles we perform a factorial analysis including the activity-facet of the individuals as a factor. This is followed by measuring the effect size of these activity configurations in reflecting the individual's functioning at the workplace. Thus, we illustrate how personas can uncover variability in job performance while being cognizant of the worker's mutable activities (reflective of their ecological setting [1, 35, 40, 95]).

## 6.1 Significant Main Effect

*6.1.1 Analyses.* The two personality facets along with the two activity facets inform a $2 \times 2$ factorial design for ANOVA. This analysis will help reveal:

- If personality type effects individual job performance irrespective of their daily activity pattern — *Do personality clusters from our person-centered approach replicate relationships in the literature?*
- If day-level activity pattern effects individual job performance independent of their personality type — *Do regular dynamic-activity patterns add new information over and above personality type?*
- If personality and daily activity have a combined effect different from the sum of their whole in determining job performance — *Do the two independent factors (personality and activity context) interact significantly?*

.

We used a two-way non-parametric ANOVA test to compute the main effects of a worker's personality facet and activity facet with respect to the 4 job performance measures we collected from the initial enrollment survey (ITP, OCB, interpersonal deviance and organizational deviance). For our data, apart from the case of OCB, the distributions of all other job performance metrics failed the normality test (verified through the *Shapiro-Wilk's test* and the *Levene's test* [20, 89]). Thus, as opposed to a simple two-factor ANOVA, we conducted the *Aligned-Rank Transform* test [49, 109] — a robust measure that accounts for non-normality and can accommodate multiple categorical variables as independent variables (personality facet and activity facet).

*6.1.2 Findings.* The results of the previously described tests are recorded in Table 11. As prior work in organizational studies has posited, the personality facet of a worker is, in fact, potent in distinguishing job performance — across all 4 metrics, task performance (ITP), citizenship (OCB), interpersonal deviance (Inter.Deviance) and organizational deviance (Org.Deviance) [9, 10, 39]. The personality facet of the persona construct reinforces those results and illustrates that intrinsic qualities, even when compounded have an association with performance.

Noting the results in Table 11 it is clear that an individual's activity facet does hold significance in explaining certain aspects of job performance. We find the activity facet has a significant main effect on ITP, OCB and Org.Deviance, i.e., the means of the facets $C_1$ and $C_2$ are distinct. This implies that even on holding out the effect of a worker's composite personality, their day-level activity patterns do describe their performance.

Table 12. Effect size of the two different organizational persona facets in explaining different performance metrics. $\eta^2$ indicates the effect of each factor when the individual is described in terms of both personality and activity.

| | ITP | | OCB | | Inter.Deviance | | Org.Deviance | |
|---|---|---|---|---|---|---|---|---|
| | $\eta^2$ | partial $\eta^2$ | $\eta^2$ | partial $\eta^2$ | $\eta^2$ | partial $\eta^2$ | $\eta^2$ | partial $\eta^2$ |
| Personality | 0.954 | 0.954 | 0.434 | 0.855 | 0.982 | 0.987 | 0.855 | 0.972 |
| Activity | 0.063 | 0.784 | 0.492 | 0.870 | 0.005 | 0.253 | 0.120 | 0.828 |

It is also important for us to note that our analyses found no interaction effect between the two patterns that represent a persona (Table 11). This result is key in our interpretation of the effect of each facet, as the lack of interaction indicates their effects are not confounded.

## 6.2 Effect Size

*6.2.1 Analyses.* The previous test shows us that there is indeed a significant effect of an individual's configuration of daily activities and their performance. We also established this effect is not confounded with their personality profile in any way either. Therefore, passively sensed activity data can provide new information to explain workplace experiences. This section quantifies that effect, i.e., how much new information does accounting for situational activities provide. Considering the mixed-factorial design of the ANOVA, we compute the $\eta^2$ and the partial-$\eta^2$ for the personality and activity facet [25, 54, 57].

*6.2.2 Findings.* The ANOVA depicted that a worker's activity facet explains task performance, citizenship behavior, and organizational deviance. Table 12 records the $\eta^2$ and the partial-$\eta^2$ of both facets. The partial-$\eta^2$ approximates the effect of a facet if we had a single independent variable ($IV$) in our ANOVA, without controlling for other effects. Since we use 2 $IV$s (personality and daily activity), the $\eta^2$ reflects the individual effect of each factor when both accounting for both facets of a persona.

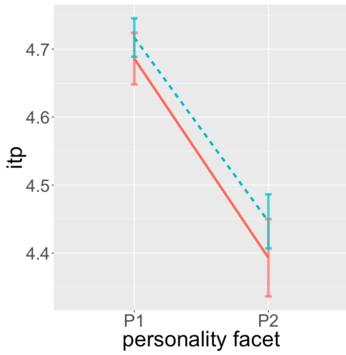
In terms of task performance (ITP), both personality and activity have a large effect — partial-$\eta^2 = 0.92$ for personality and partial-$\eta^2 = 0.78$ for activity. However, the $\eta^2$ value infers that personality is alone responsible for explaining most of the variance in task performance. Once those effects are held out, the activity facet still retains a significant but small effect. Though the incremental delta of information the activity facet provides over a worker's personality is minimal, it still helps improve our understanding of task performance.

For citizenship (OCB), the individual effects of personality and activity are very similar, partial-$\eta^2 = 0.85$ and partial-$\eta^2 = 0.87$ for activity respectively. Evaluating the $\eta^2$ value elicits a similar result. These values suggest that considering the activity facet actually explains close to 50% ($\eta^2 = 0.49$) of citizenship behavior.

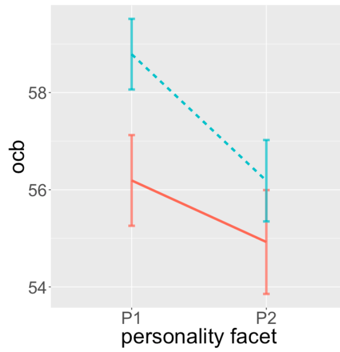
The tests on organizational deviance again show a large effect of personality, but there is still a considerable effect of an individual's activity facet. On noting the effects of both the factors, personality accounts for a majority of the variance ($\eta^2 = 0.85$) but activity does help complement this effect by explaining a significant segment of the remaining variance ($\eta^2 = 0.12$). The incremental variance explained by the daily dynamic activities represents the proportion of performance that can be varied with changes in activity variation.

## 6.3 Interpretation of Effects

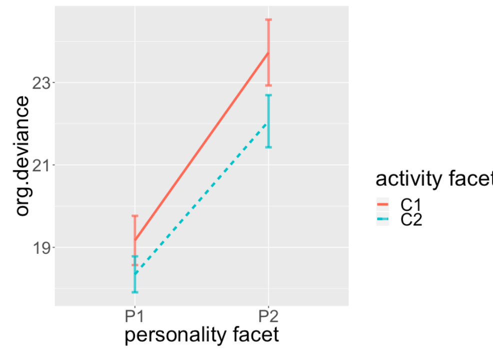
The results discussed in the previous sections quantitatively establish the significance of passively sensed activity patterns in investigating job performance. The configuration of day-level actions an individual adapts provides a signal of work functioning beyond a worker's intrinsic qualities. Thus, by incorporating the activity-facet, the persona construct can provide a signal that complements the known effects of personality to provide a more




(a) ITP




(b) OCB




(c) Org.Deviance

Fig. 10. Main effect plots showing the effect of the 2 IVs (personality facet and activity facet) on job performance. Personas exhibiting $P_1$ personality score better on all metrics. Personas demonstrating $C_2$ activity patterns rate better on all metrics.

wholesome understanding of workplace outcomes. Besides this, the person-centered approach that personas represent provide a descriptive lens to understand these effects.

Fig 10 illustrates how each of the four personas varies in terms of different job performance metrics. To summarize, we find the personality facet $P_1$, (high conscientiousness and low neuroticism) to have significantly better task performance and citizenship than $P_2$. This falls in line with the unambiguous similarity of the $P_1$ facet with the "Resilient" class [27] and the "Role Model" class [45], as well as the known relationship of the aspirational traits that it comprises [9, 10]. It is also intuitive to observe $P_2$ has higher organizational deviance given its resemblance to the "Under-Controlled" type [27], which has been equated to antisocial behaviors.

While the persona construct retains the dominating relationship between personality and performance, it also uncovers new relationships of activities and worker functioning. Among the two facets, the activity composite depicted by $C_2$ (low mobility, batched phone use, and high sleep) appears to have more aspirational qualities. Personas with this facet have higher task performance and citizenship along with lower deviance. In comparison to the $C_1$, personas with this facet logged far fewer locations visited in the day. Given the duration of stillness that this facet exhibits is comparable to the average, the greater number of locations could represent commute. Prior research shows that greater amount of commute and higher variability can lead to stress, strain and also an inability to perform non-work responsibilities [50, 84]. In $C_1$'s case, the complex commute is also indicative of poor satisfaction [72] which in turn is related to poor citizenship behaviors at the workplace [69]. The patterns of phone-use by individuals in $C_1$ indicate interruptions. These could be self-initiated (distractions) or be external notifications (intrusion). Distractions can encourage procrastination and intrusions lead to disrupting task-flow that gives individuals the perception that their performance is lagging behind [7, 48]. In contrast $C_2$ have more compartmentalized use of their phones that could support to better task organization. While phone-use could cause interference, breaks from desk represent greater social interaction and collaboration that generally tempers deviant behaviors [14] and boosts citizenship [51]. Given that the personality facet and activity facet are independent of each other (section 5.4), these findings show how individuals sharing similar personality profiles could still differ based on the composite activities they are involved in regularly.

## 7 DISCUSSION

We refer to *organizational persona* as a framework for evaluating a subpopulation's job outcomes through a person-centered approach. It is a descriptive tool that furthers the interpretation of a worker's experience by incorporating ecologically-measured day-level activities. Not only can this method be scaled through ubiquitous technology, but it also displays the utility of sensed workplace data for informing personnel management in a dynamic way that is not shackled by static measures like personality. It encourages greater insight into malleable contexts of individuals at workplaces, leading to new testable hypotheses.

### 7.1 Implications and Opportunities

**Organizational Research.** Our findings suggest that harnessing off-the-shelf commercial sensing technologies to capture everyday activity states help further dissect workplace performance beyond internal traits like personality. Even though we demonstrate our approach on a sizeable dataset with participants from multiple cohorts of information workers, we do not claim that the personas that emerge are in themselves generalizable. However, we demonstrate that classical machine-learning methods and sensor fusion can identify such personas which serve as a descriptive analytical framework to render new hypotheses between the relationship of situational information and job performance. Organizational personas provide a dynamic lens that illuminates the association between everyday activities and workplace functioning, while still preserving the effect of inherent personality. Our results are not intended to invalidate the role of personality nor substitute it. Rather, we emphasize the importance of considering markers like activity that depict objective situations to evaluate a worker's job performance along dimensions like task performance, citizenship behavior, and organizational deviance.

**Personnel Management.** In the EHP framework proposed by Dunn & Brown [35] (introduced in Section 2.2 earlier), they mention the need to "alter" and "adapt" situational context to support occupational performance. Activity is an attribute of context that is a product of external ecology, like an employee's workspace, the nature of their work, the characteristics of their peers or even their own lifestyle [1, 95]. Comparing organizational personas helps inform personnel management teams of the kinds of changes to activities, habits, and environment that can be encouraged for certain personalities. Since malleability is salient to dynamic constructs like activity states, the insights presented by personas provide a set of testable hypothesis for organization research. For example, in our participant pool, individuals resembling a "resilient" personality ($P_1$– high conscientiousness, low neuroticism) score higher on citizenship behavior than those sharing a likeness to "undercontrolled" personality ($P_2$– low conscientiousness, high neuroticism) [27]. However, through a persona representation, we learn that the activity facet is as effective as the personality facet in determining citizenship behavior (Section 6.3). Actually, workers that demonstrate an activity configuration like $C_2$(low mobility, batched phone use, high sleep) are associated with greater citizenship irrespective of inherent personality. This implies individuals described by the $P_2C_2$ persona are better than $P_2C_1$ on the grounds of citizenship, even though $P_2$overall has low citizenship (Fig 10). Thus, despite the restrictive limits of one's intrinsic personality, personnel management can use personas to account for situational variations (in terms of activity configurations) and glean a more holistic understanding of worker performance. Since personality is a relatively steady construct [86], it renders an insular explanation of performance that deems it preordained and inflexible. On the contrary, personas show that the mutable activity context of a worker is related to performance (even if it is a weak effect). This furnishes optimistic opportunities to investigate methods to improve workplace functioning notwithstanding inherent traits of individuals.

**Workplace Sensing.** Moreover, all this information can be obtained from sensors ubiquitously present in the workspace. As is, the described method of deriving organizational personas is retrospective, not predictive. Yet, because the activity-context can be varied, this paper encourages new opportunities to test changes in worker environments. For instance, It would also be interesting to study personas within sub-populations of organizations to understand organizational culture. Using a similar method as the one proposed in this paper, we can attempt to identify the core groups of people that succeed in specific organizations, if and how these groups differ across organizations, and how significantly does differing from this group affect an individual's performance. In fact, activity based personas can be imagined as tools to study new notions of person–organization fit as well.

Recent work with unobtrusive sensing has demonstrated difference in daily workplace routines impact employee performance and wellbeing [31]. Similarly, this work encourages new multimodal interpretations of fit that not only compare personalities within organizations but also activity states. In fact, we believe such an approach also bears potential in revealing job performance dynamics across groups of individuals during times of organizational crises, upheavals, or unanticipated policy changes or enforcement within the organizations. For example, changes to personality are only gradually perceived, but passive sensing could detect sudden changes in activity facets that correspond to high performance or low performance. Furthermore, there is more to context, or ecology, than simply activity. This work encourages inspecting other mutable aspects of context like the semantics of *location* [1] or social interactions.

All-in-all the organizational personas offer not only a stylistic representation of the different kinds of workers, but they also reveal testable hypotheses that can be verified with further experimentation. Moreover, this method can be extended to more sophisticated contextual information to construct more in-depth personas with richer explanatory variables. In summary, the utility of this kind of information is an antecedent to further study the role of activities (or more broadly, objective situations) in the workplace and encourage the use of passive sensing to elicit more robust illustrations of job performance in comparison to an over-reliance on static measures.

### 7.2 Limitations and Future Work

The first limitation we would like to acknowledge is the form of our data. Since our participants comprised entirely of information workers recruited through rigorous hiring policies, we do have a skewed sample with respect to our data. Applying personas on a more diverse enrolment of participants (e.g., blue collar workers, or focusing on organizations in non-Western countries and cultures) could bring forth starker differences in activity context (or even explain their triviality in comparison to personality for certain occupations). Even though the personality facets identified by the organizational persona framework replicates results in the literature, we do not expect the activity facets to generalize. Rather, the unsupervised person-centered methodology can be applied to other populations and unearth the organizational personas in them, and in turn tease apart the effect of objective situations, like activity, on their performance.

Recruitment aside, at a practical level our means of sensing individual activity has shortcomings. The use of passive sensing through off-the-shelf, commercially available technologies affords to capture data of individuals in a non-invasive way. This mitigates the challenges with self-reported data, such as obtrusiveness and recall bias; making it convenient to deploy sensors at scale and perform longitudinal studies in field settings. However, researchers must not lose sight of the fact that data captured by sensors is only a representation of the actual situation of the worker. An accelerometer can be used to infer if a participant is engaged in physical activity, but this information does not completely describe what events in their surroundings actually elicit such actions. Thus we caution the use of personas as a singular indicator of job performance as it is limited to *measurable* activity context. It is an additional medium to explore an individual's suitability for their workplace. To truly explore how a worker behaves given their situation [56], the data funneled into the persona must be a more explicit representation of a situation. One way to do so could be to introduce additional sensors that capture the complementary dimension of an individual's context. Alternatively, more nuanced feature engineering can extend upon our findings by generating more theoretically grounded constructs to represent a worker's situation. Future work can also explore the use of qualitative observations, field site insights, or independently audited information about an organization's culture to augment these measurable attributes of activity context.

In terms of the data processing, the paper aggregates daily activities to characterize the situational information that surrounds the worker. While the literature informs us that activity context is sensitive to the changes in an individual's ecology [1, 95], the persona framework in itself does not account for temporal variations in the activity information. Although the current iteration is only limited to providing testable hypotheses for future experiments to verify, researchers can conceive a temporal analysis with modified iteration organizational personas. Over a longer study, this framework could be modified to incorporate changes in a worker's activity-context based on seasonality, organizational factors (e.g, new projects, new roles, relocation) and personal factors (e.g., family events). However, such a study would require granular assessments of job performance as well. In theory the organizational persona of a worker can change over windows when their context changes. Arguably, experimental testing is the most robust indicator of causality, but modifying our framework to temporal variation can render new insights towards causal inferences.

Finally, personas have limitations as an analytical framework. Since we adopt a person-centered approach that uses clustering it arguably risks ignoring individual differences that are distinct from the exemplary attributes of their facets. However, personas must not be evaluated as a substitute for variable-centered approaches but rather a complement that yields a distinct perspective to characterize the workers in an organization. Organizational personas, much like other classification schemes, describe job performance through a coherent minimalist illustration of personality and activity contexts shared by workers [58].

## 8 CONCLUSION

This paper is motivated by person-centered approaches to use dynamic multimodal sensing data to provide an analytical framework, known as *organizational personas*, to inspect job performance from a unique descriptive perspective. We demonstrate how this composite construct furnishes evidence that a worker's activity context (a representation of their daily objective situation) can explain workplace performance beyond the static effects of implied by their intrinsic personality. This paper describes how to identify and meaningfully describe these personas using standard clustering methods. Furthermore, we document the functional utility of the personas. The comparative analyses of these personas help us understand how the extent to which a variation in mutable activities can explain performance. We believe our work encourages harnessing pervasive technology embedded in an individual's everyday to gather activity information and in turn improve the understanding of personnel performance as well as inform subsequent efforts to alter it.

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