Birds of a Feather Clock Together: A Study of Person–Organization Fit Through Latent Activity Routines

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Organizations often strive to recruit and retain individuals who would be a "good fit" with their core values, beliefs, and practices. Person–Organization (P–O) congruence is known to explain employee satisfaction, commitment, and absenteeism. This paper proposes a new measure of P–O fit by empirically investigating the similarity of routine within an organization. This measure of *routine fit* is motivated by the theory of *entrainment*, which refers to the synchrony of individual and community behaviors. We use unobtrusive bluetooth sensing to examine how the concurrence of latent activity patterns is related to job performance and wellbeing. Routine fit echoes traditional constructs of congruence as it is significantly related to higher task performance and lower workplace deviance. However, it is also related to greater stress and higher arousal. Prior work in organizational psychology has used single-occasion survey instruments to infer uni-dimensional models of fit. These methods are limited by subjective perceptions of employees. In contrast, we demonstrate a data-driven and multidimensional approach to study normative routines in an organization as a measure of P–O fit. We discuss the potential of our approach in designing technologies that understand the congruence of employee routines and positively impact employee functioning at the workplace.

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

Additional Key Words and Phrases: person–organization fit, routine, group behavior, entrainment, passive sensing, activity patterns

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1 INTRODUCTION

One of the primary interests of organizational research for decades has been to augment individual efficiency at the workplace [11]. While a large body of literature has studied employee performance

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through the lens of an individual's intrinsic traits [4] , other research has strongly argued that, these characteristics best explain employee functioning at work only when they are considered in conjunction with the organization's characteristic [81]. In particular, individuals tend to thrive in organizations that share their values and beliefs [14, 17, 85]. Therefore organizational studies have recognized this concept of person–organization congruence or "person–organization fit" as critically important [12, 13]. For instance, the *Attraction-Selection-Attrition* (ASA) framework posits that congruence between workers and organizations leads to mutual attraction and selection of talent [28, 98]. In fact, it says that workers whose beliefs, values, and practices are congruent with the organization have better outcomes, such as performance and wellbeing.

Past work on person–organization fit has often relied on static surveys, which are vulnerable to a variety of biases [5]. These surveys capture the similarity between the job aspects an individual values and those that the organization values [89]. Consequently, these methods only represent an individual's perception of their values compared to an organization's values [37]. Therefore, the major limitation of such estimates of fit is their subjectivity [47]. In contrast, due to methodological constraints, objective measures of fit have only studied a single dimension of the employee (e.g., the level the organization values authority versus the level an individual values authority) [39]. These drawbacks prevent researchers from assessing more general ideas of fit, for which congruence is often a function of multiple dimensions, such as measuring employee activity patterns.

Researchers could address the limitations of the previous methods by an unobtrusive yet objective assessment of employee behavior at the workplace. Sensors embedded in the environment can provide empirical estimates of normative group activity to better explain the employee experience. For example, how teams coordinate through electronic media and other devices can be indicative of task performance [46]. Activity levels of call-center employees along with their face-to-face interactions (measured by wearable badges) do correlate with team performance [115]. Similarly, camera-based sensing of workplace interactions help explain mood [76]. Even employee smartphone and desktop engagement have been related to their behavior at work [77, 113]. Thus, measuring employee functioning through technologies and systems embedded in an employee's workday provide a unique perspective to understand both performance and wellness.

Building on this research, we utilize bluetooth sensors at the home and workspace to computationally infer individual routine patterns, and subsequently their similarity with the latent activity pattern of the organization [35]. We adopt this congruence of latent routines as a notion of P–O fit, or *routine fit*, and explore its relationship with theoretically-grounded measures of employee job performance and wellbeing. Specifically, we address the following two research questions:

RQ1. What is the relationship between routine fit and different aspects of job performance?
RQ2. What is the relationship between routine fit and different aspects of wellbeing?

This paper contributes to the literature in several key ways. First, this work leverages the power of passively sensed activity routines in cohorts to explore how they can be meaningfully used as person–organization variables and provide an objective measure of fit. Secondly, our work goes beyond prior work that relies on single-occasion survey instruments and demonstrates the association between job outcomes and a data-driven representation of behaviors over multiple time periods. Finally, our findings encourage future endeavors that incorporate the activities of an individual's peer group. We discuss opportunities to design various employee-facing as well as organization-facing workplace tools in a privacy-preserving way to understand and eventually improve the workplace experience. Broadly, our research contributes to the growing interest in the "Future of Work at the Human-Technology Frontier,"[1] wherein we present new technology-facilitated and -augmented means to improve workplace "health", performance, and functioning.

[1] https://www.nsf.gov/eng/futureofwork.jsp

Table 1. Some of the different pairs of P-O values used to study fit and the outcomes they have predicted.

Person Variable	Organizational Variable	Outcome(s)	
Subordinate values	Supervisor values	Organizational Commitment	[17, 79]
Actual job enrichment	Desired job enrichment	Work Motivation	[20, 67]
Pay Received	Referent Other's Pay	Propensity to Leave	[32, 107]
Cultural values	Key informant values	Satisfaction	[85]
Personality	Benchmark personality	Performance	[14]

2 RELATED WORK

2.1 Person–Organization Fit

Both recruiters and aspirants are always looking for a prospect that matches their values. The concept of a person fitting into an organization is rooted in the interactionist perspective of socialization [61] that emphasizes neither individual variables (such as personality and attitudes) nor situational variables (such as rules and norms) in isolation can entirely explain how the people in a community behave [81]. The extent to which these variables resemble in an organizational context is known as "person–organization fit" [81].

The literature delineates two different models to explain "fit" [12, 81]. The first is *supplementary*, where individuals of an organization embody characteristics similar to, or appreciated by, their peers — used to expand an existing workforce by multiplying the same kind of employees. The other model, which is *complementary*, finds an individual with characteristics that complete the requirements of their organization — used to identify people that can fill voids in personnel roles. Another key difference is that the complementary model typically profits an organization itself, which could end up benefiting employees transitively. In contrast, the supplementary model places the individual as the primary beneficiary, extending on person-to-person relationships within a company. Our method is reflective of the supplementary approach since it focuses on disentangling the relationship of fit with individual functioning by operationalizing routines of multiple employees [85]. Any subsequent mentions of "fit" refers to the *supplementary* approach.

The pertinence of supplementary fit in organization behavior is exemplified by the *Attraction-Selection-Attrition* (ASA) framework that states, *"Attraction to an organization and attrition from it produce restriction in range in the kinds of people in an organization. This restriction in range of people yields similar kinds of behavior from the people there, making it appear as if the organization were a determinant of their behavior"* [98]. In the past, inter-person congruence has been used to explain both the satisfaction and tenure of employees [85, 110]. Through self-reported assessments of the congruence (or incongruence) of individuals, ASA posits that organizations implicitly tend to move to a psychologically homogenous state [28]. This paper complements prior ideas of fit by exploring if routine homogeneity between employees within an organization, measured with sensors placed in the physical environment, can illustrate a new type of congruence.

2.2 Measuring Fit with respect to Job Outcomes and Wellbeing

The effect of P–O fit on the employee experience depends on the intrinsic nature of the variables representing the person and the organization (Table 1). The congruence or discrepancy between these variables is used to explain a target variable. Inequity in pay is related to an employees disposition to leave [32, 107]. Congruence in job enrichment - assignment to tasks of higher responsibility - is connected to motivation [20, 67]. The approach this paper takes is to consider an individual's routine behavior as the person variable and the latent routine behavior of their organization as the other variable. This section discusses the different P–O variables inspected by prior work, the methods to match them and the outcomes they have been shown to affect.

Caldwell and O'Reilly III mapped job norms with individual attributes to form benchmark templates and found significant correlations of fit with performance [14]. O'Reilly III et al. measured fit by first establishing a template through the responses of "key informants" and correlating this to individual preferences of other employees [85]. They found fit to be positively correlated with commitment and job satisfaction while being negatively correlated with intent to leave an organization. Chatman used the *Organizational Culture Profile*, based on the Q-methodology, to find significant relationships between satisfaction and intention to stay in the job [17]. The underlying method to ascertain congruence in most of these methods is highly subjective as Q-methodology relies on manual sorting by participants. Moreover, the templates or scales used to determine what is "ideal" or considered the standard are crafted theoretically and not empirically. These methods are also difficult to scale across a large set of individuals to apply a truly data-driven approach. More generally, these methods have been critiqued as being problematic and thus limited in inferring fit on multiple dimensions [36].

The methods described up until now obtain the P-O variables from separate scales and then combine these values to gauge congruence. Yet, there are techniques where participants directly record their perceived difference with the organization – known as *molar* approaches [37]. This method has been shown to express significant correlation to job attractiveness, sacrifice, commitment and embeddedness [13]. While measuring congruence between two variables is considered "reductionist", self-reported molar methods are subject to its own biases [26]. Participants of these studies are expected to internally summarize their judgement of personal and situational variables before reporting a single value to the survey instrument.

Irrespective of approach, in general, surveys administered over single-occasions have limitations [37, 47]. A notable pitfall is capturing perceptions of individuals that may be inconsistent over time. Moreover, in organizational contexts, the insecurity that employers can access survey responses causes alter self-presentation [33]. These can be mitigated by an empirical data-driven characterization of longitudinal information from individuals.

Traditionally, all the discussed measures of organizational fit measure similarity between an individual and their community through static survey instruments that typically assess an individual's attitudes (e.g. goal-oriented, demanding, competitive), values (e.g. growth, collaboration) and other intrinsic qualities like personality (e.g. innovativeness, experimental, responsible). To the best of our knowledge very little work has been done to understand fit through activity and behavioral data. While, existing work focuses on who an employee thinks they are vis-a-vis the organization, we are centrally interested in exploring *what they actually do in comparison to their colleagues.*

2.3 Entrainment and Fit

Acting in accordance to "how things are done" while adjusting to the standards or conventions of a social group is a form of *normative social influence* [29]. Conforming to the behaviors of the social system helps individuals find themselves in states of social harmony [6]. Social and situational norms are known to elicit appropriate and acceptable behaviors within a system [63]. We consider alignment to group routines as a manifestation of normative behaviors, that emerges from social influence. This sameness of routine or the synchrony in an individual's behavior with respect to that of others is formally known as *entrainment* [65, 88].

Even outside the workplace humans can be observed to match routines or tempos at an activity level. When drivers on the freeway accelerate and decelerate in synchrony, the flow of traffic is safe and consistent. Entrainment functionally corresponds to normative social influence, as it too is an adjustment towards a harmonic state [1]. In organizations, highly efficient teams have been studied to match the rhythm of the environment, by either modifying their cycle or altering the environment's pace [1]. Getting "entrained" into an organization, is considered a kind of *temporal fit* and a lack of which has been connected to a dip in performance [65]. Consider how an employee's rhythms get displaced from the people around them once they get off a transcontinental flight. According to the theory of entrainment, jet-lag is an extreme case of temporal disharmony between an agent and their system. Pérez-Nordtvedt et al. argue that a mismatch in the tempo, or pace, between individuals and the environment can lead to a reduction in performance at the organizational level [88]. Even though organizational entrainment has intrigued the community, attempts to explain it have been mostly theoretical. In one of the empirical approaches, Labianca et al. showed that milestone tracking towards deadlines helps improve task completion among teams [68]. Another study demonstrated the "temporal distance" within teams can affect performance [42]. Most of this work has relied on laboratory experiments and simulations. In comparison to such work, this paper deals with large scale longitudinal data distributed across multiple organizations to estimate a form of temporal discrepancy, referred to as *routine fit* throughout the paper.

2.4 Computationally Studying Group Activity and Congruence

Manually disseminated survey instruments that capture information of a single splice of time are an extremely cumbersome means to extract behavioral norms within a group. Although via tangential interests, the field of computer science has made some progress towards this.

Keegan et al. quantitatively identified emergent "behavioral motifs" in online behaviors of crowd contributed knowledge communities [64]. Similarity of within-group behaviors has been studied from the perspective of polling [22]. Zheng et al. found that individual voting patterns on Doodle polls is influenced by knowledge of which choice the majority favors in order to meet expectations of peers[118]. Savarimuthu et al. has computationally shown that norms within virtual agents emerge in a bottom-up fashion, i.e., the interactions of individuals in a group can define the normative behaviors which are not restricted to structural constraints of a system[96]. This phenomenon has been observed in groups of multiplayer gaming as well [60], where teammates that do not conform to established norms are penalized. Comparing the sequential activities of contributors in Open Source Software communities has also found that codebases that get entrained tend to evolve together [70]. These studies on publicly visible group engagement demonstrate the influence of normative group behaviors. Though these are not specific to the workplace, analysis of group activities and their effect on individuals set up the bedrock of this paper.

Analysis of linguistic cues in communication to estimate the similarity of individuals has also gained attention. Alignment in choice of words reflects the development of shared beliefs [34]. Word usage in historical organization emails can indicate if an individual is likely to retain their job, leave on their own or be laid off [48]. However, harmonic functioning at work does have aspects apart from the propensity to stay that explain daily behavior. On similar lines, this paper inspects the alignment of an individual's activity tempo to their organization and how that associates to their formal task efficiency, citizenship, deviance, and stress.

The advent of unobtrusive sensing and passive data sourcing in computing has made the study of activity similarity interesting to the information and data science community. Computing similarity between people as a one-to-one model to understand social ties has multiple applications for recommendation systems. These methods typically operate at the behavioral level to identify links between individuals. Zheng et al. have used location acquisition of individuals to recommend friends based on how similar the history of visited places between two different people is[118]. Location-mining and modeling sequential activity has shown to be effective in clustering users who are similar [73, 108]. These methods are not limited to geo-temporal data. Lv et al. have furthered this idea of linking individuals through the regularity of visiting semantic locations like "home" and "work". The use of sensed data to associate individuals has gained significant popularity in recent years, however, these models tend to be interpersonal and do not particularly clarify the standardized behavior of a group as a whole [74]. Thus there is poor grounding to use these techniques to understand individual conformity to a normative group.

Other work in the CSCW community has attempted to disentangle person-to-person resemblance and person-to-group similarity. The latter is considered a better representation of normative group behaviors and conformity. Begole et al. have been able to extract activity rhythms of individuals and infer the schedules of teams that they belong to [7]. Although without sensing physical behavior, Saha et al., measure role-ambiguity in the workplace (a form of P–O fit) with the help of social media data. The work most relevant to this paper is the method proposed by Eagle and Pentland, to eigen-decompose aggregated individual activity behaviors and depict group behaviors to gain an understanding of latent behavioral norms[35]. Using that very method, this paper explores the relationship between the activity routines of a person, with respect to their organization, and their job performance and wellbeing.

3 DATA

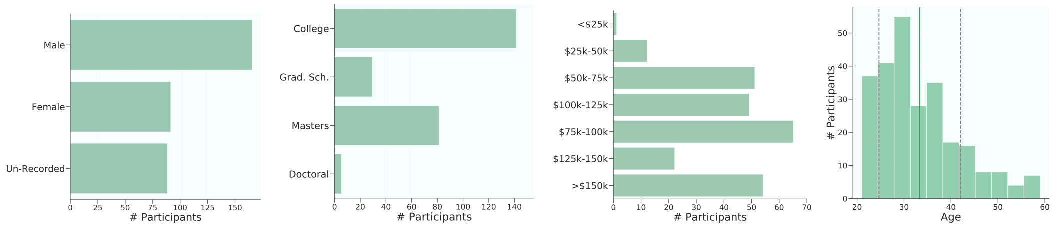
3.1 The Tesserae Project

This paper analyzes data acquired from a larger ongoing project that harnesses the sensing capabilities of commercially available technologies to understand workplace performance longitudinally [78]. This expands on earlier works employing multimodal sensor streams to infer individual features such as mood and other mental health states [10, 76, 90, 94, 114].

This dataset represents a sample of 757 information workers recruited from multiple field sites across the United States. The enrollment was coordinated from January 2018 through July 2018. Participants were asked to stay in the study for up to a year or through April 2019. The most recent data in the sample of participants analyzed for this paper is dated November 11, 2018. This study was approved by the Institutional Review Board (IRB) at the researchers' institutions. Individuals recruited from the same field site are grouped together and typically belong to the same organization (barring C6 – comprising of independent employees recruited remotely). Throughout the paper, we sometimes refer to these groups as "cohorts". Of the six cohorts, we selected four cohorts (each belonging to a different organization) of a sizeable sample to answer the research questions we are interested in. Since we apply a data-driven approach to identify normative routines, C5 was dropped as it contains far too little members to aggregate data on. C6 was excluded because it represents a cluster of employees who are not actually tied to the same organization, they are simply clubbed together on the basis of their remote recruitment. Using our approach on an artificial group of individuals, such as C6, is inaccurate as this cohort is neither socially bound nor expected to conform to the same workplace norms.

To infer participant activity and physiological context, various off-the-shelf technologies were given to the participants; 1) Bluetooth beacons (*Gimbal*)—two static (to track their home and work location) and two portable devices (to carry on their person), 2) Wearable—a smartwatch (*Garmin Vivosmart 3*) to capture heart rate, stress, and physical activity, and 3) Phone Agent—a smartphone application [114] to track phone usage (e.g., screen lock/unlock and GPS locations). On top of this, some participants explicitly consented to provide their historical social media data [93]. The models discussed in this paper primarily use data from the bluetooth beacons to build a model of routine fit. The beacons behave like access points that can be scanned by phone agent. Apart from this, data from the wearable is used to understand individual arousal levels – as a measure of wellbeing. The workings of both these technologies are clarified in following sections.

On entering the study, participants completed an initial battery to record details about demographics, job performance, personality and mental health traits via psychometrically validated survey instruments. To measure the daily fluctuations in these constructs, Ecological Momentary Assessments (EMAs) containing abbreviated versions of our initial ground truth instruments are disseminated periodically (Table 3). Literature on developing self-report instruments for organizational research has argued that these assessments are more robust against criterion contamination in comparison to organizational evaluations [54, 111]. This paper analyzes the daily measures, based



(a) Gender (b) Education (c) Income (d) Age

Fig. 1. Summary of the participant demographic information.

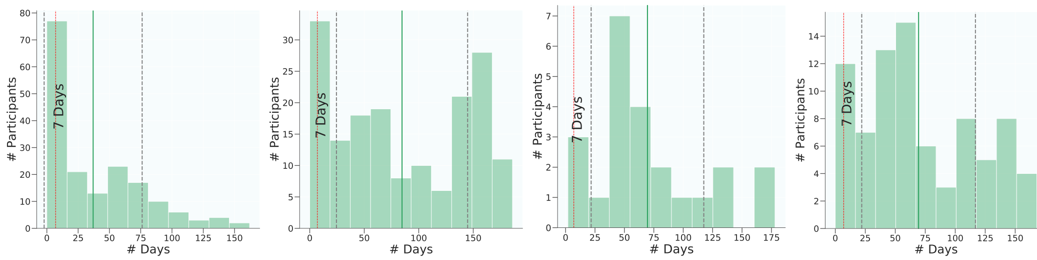
on the situational state of the individual. These constructs, their measurement and relationship to P–O fit is elaborated in the subsequent sections.

Participant Privacy and Consent. Given the sensitive nature of the dataset used (from the Tesserae project), participant privacy was a key concern. In addition to the informed consent form, the participants were provided with a technical specification document that described the data sensed by each stream as well as methods to store and secure it. After reading this, the participants could specifically consent to each sensing stream they wished to provide data on. Participants could clarify their queries about the sensing streams through in-person discussions as well as e-mails. We had cases of initially eager individuals who later chose to decline participation after reading the details. Some of them anticipated challenges to comply with the study while others had apprehensions regarding data collection. Although none of these individuals expressed concerns about the beacons, some were uncomfortable with the wearable and phone agent tracking them passively. For the enrolled individuals, their data was deidentified and stored in secured databases and servers which were physically located in one of the researcher institutions, and had limited access privileges. The study was approved by the relevant Institutional Review Boards.
In addition to these safeguards, the sensing streams have in-built privacy and security features. Specifically, the bluetooth beacons randomize MAC addresses on each broadcast and can only be tracked by authorized devices. Moreover, the beacons do not track the user's location or movement and only provide coarse signals of their presence.

3.2 Presence Sensing

For the purpose of studying the routine behaviors, we primarily process the data from the Gimbal beacons within an organization. Bluetooth beacon technology can approximate an individual's presence in its vicinity. Although it provides a coarse understanding of location it presents a tighter accuracy radius, approximately 1-4 meters [71]. Unlike location sensing through mobile devices, which exposes an individual's every movement, presence sensing through beacons only relies on relative location, i.e., if they were near the beacon or not. Participants were asked to attach the static beacons to immobile objects at home and work. These objects essentially emit signals making them "observable" so that the participant's phone can discover them through periodic scans. It is not uncommon to employ bluetooth-like near field technologies to capture spatio-temporal data [105]. Additionally, bluetooth helps estimate indoor mobility and interactions [30, 71]. Dey et al. noted that individual are at room level proximity to their phones (within 5-6 meters) for 90% of the day [30]. Thus it is reasonable to consider the phone as a surrogate of the individual's presence.

Typically the beacon designated for the home location was placed on the front-door and the one for work was situated on the individual's desk. An extended period of time away from either the home beacon or work beacon helps estimate when the individual left a particular place and entered another. Furthermore, the discontinuity in the presence of an individual near their desk



(a) C_1 (b) C_2 (c) C_3 (d) C_4

Fig. 2. The amount of data collected per participant varies based on when they enrolled as well as how compliant they were in terms of maintaining the beacons

indicates sessions in time that they are away from it. This could indicate casual breaks or scheduled meetings. An aggregation of these behaviors helps explain their routine [35].

Participants with home and work beacons located in the same place (based on Gimbal's GPS coordinates) were dropped from the study. These individuals were assumed to work from home, i.e, they do not find themselves colocated with their peers often. Other participants who were excluded had accidentally swapped their designated beacons. Individuals with less than 7 days of data were dropped as well. This decision helps maintain consistency with the self-report measures — some of which have a temporal resolution of a week. After filtering, the beacon data of 343 participants were analyzed (Table 2) to compute routine fit. Fig. 1 summarizes the demographic information of the selected participants, and Fig. 2 presents the amount of daily data provided by each cohort, with an overall average of 62.41 days of data for the selected participants. For each cohort, the majority of bluetooth data spans the months August, September, and October.
Note: In the dataset, 20% of the participants were "blinded" for external validation, i.e. their survey responses were obscured. Due to this, the job performance and wellbeing measures of only 249 (of the participants with adequate bluetooth) could be used for exploring specific relationships

Routine fit is computed using the information obtained from these beacons, and in turn applied to evaluate the overall functioning and mental health of employees. This includes examining both an individual's job performance (in-role behavior, citizenship behaviors, counterproductive behaviors) as well as their psychological wellness (stress, arousal, and anxiety).

Table 2. 4 cohorts from the larger dataset were sampled for this paper. Each of these represents a unique field site tied to a specific organization.

Cohort	C_1	C_2	C_3	C_4
All Participants	294	177	26	89
Non-Colocated Beacons	176	168	23	81
After 7 Day Filter	113	139	20	71

3.3 Job Performance Measures

Prosperity of an employee is generally studied from the lens of their performance at the workplace. There are three independent dimensions on which job performance can be described: task performance, organizational citizenship behavior, and counterproductive work behavior [92, 111]. Prior work has demonstrated personality congruence in an organization is related to work outcomes [66]. Given that personality fit is important, and personality informs typical behaviors, it motivates exploring if fit on objective behavioral routines is also predictive of performance [14].

3.3.1 Task Performance. This refers to metrics that assess how an individual accomplishes tasks directly pertinent to their formal role in an organization. An employee's organizational productivity is known to be linked with their job satisfaction and commitment to work [87, 117]. Moreover, just like employee satisfaction and commitment, their success in completing job-related tasks have

Table 3. The responses to the EMAs help determine the job performance and psychometric measures. *Garming Vivosmart 3* wearable supplied the arousal durations.

	Job Performance			Psychometric		Arousal Duration(s)	
	IRB	**OCB**	**CWB**	**Stress**	**Anxiety**	**Stressful**	**Restful**
Mean	42.81	6.85	1.14	1.97	1.69	20882	20275
Std	5.23	0.98	0.87	0.55	0.51	7694	6843
Max	49.00	8.00	5.99	3.37	3.36	41777	37480
Min	23.02	2.40	0.00	1.00	1.00	2775	1691
Scale	7-49	0-8	0-8	1-5	1-5	-	-

been associated with the fit between a person and organization's attitudes [8]. This was gauged using the In-Role Behavior (IRB) [117] — 7-item Likert scale prompted 3 times a week.

3.3.2 Citizenship Behavior. This reflects actions that are not directly recognized as rewards but encourage welfare within the organization. While citizenship has not been specifically studied from the lens of organizational fit, individuals involved in altruistic activities at work tend to be more satisfied [87]. These behaviors can either be directed towards other individuals(e.g., aiding a peer) or to the larger organization (e.g., volunteering in activities outside one's core responsibilities). This was measured using the Organizational Citizenship Behavior scale developed by Dalal et al. [23] — 8-item dichotomous scale prompted 3 times a week.

3.3.3 Counterproductive Work Behavior. Deviant behaviors are actions that sabotage the organization or the individuals within it. Plagiarism, disrespect of peers, deliberate lack of productivity are a few instances of this performance dimension. While deviance in terms of fit has not been studied exclusively, related measures like satisfaction are well-studied outcomes [62]. The CWB assessment instrument was developed by Dalal et al. [23] – 8-item dichotomous scale prompted 3 times a week.

3.4 Psychometric Characteristics

Beyond an employee's task accomplishment, measuring their general wellness is important to infer their success in an organization. P–O fit has looked at wellness from the perspective of satisfaction, commitment and propensity to leave, but there is little literature measuring mental health directly using the supplementary model of fit.

3.4.1 Anxiety. For an individual, the state-based anxiety is an expression of the magnitude of subjective feelings of tension, apprehension, and nervousness. High anxiety is a marker of poorer worker wellbeing [24]. In the context of organizational fit, Edwards and Van Harrison demonstrated that the disparity between an individual's job demands and their expectations can explain anxiety[40]. A single item instrument developed by Davey et al. was administered daily to compute fluctuations in anxiety[25] — 1-item Likert scale prompted daily.

3.4.2 Stress. At an organizational level, stress can be viewed as the effect of external demands of one's workplace [69]. The relationship between stress and employee job performance has been studied comprehensively in the past work [102]. Arbour et al. have tried investigating the link between stress and the congruence of individual cultural expectations with the organizational cultural values[3]. However, their results show there is no relationship between the two. This paper re-evaluates this criterion for routine-based fit. The study disseminated a daily single-item omnibus question to explore this phenomenon, *"Overall, how would you rate your current level of stress?"*. This instrument was internally validated within the program metrics of the overall project by robustly correlating it with other measures – 1-item Likert scale prompted daily.

3.4.3 Arousal. External stressors can lead to a "fight-or-flight" response in an individual. This is linked to the *Sympathetic Nervous System* (SNS) that influences physiological responses such as heart rate and is associated to both anxiety and stress. The participant's wearable devices use an optical heart-rate (HR) sensor, combined with heart-rate variability (HRV) to compute their stress score periodically throughout the day. This score is categorized as either "restful" or "stressful". The Garmin device directly provided the daily time a user spent in each state. According to *Firstbeat Technologies,* (the analytics behind Garmin's *HealthAPI* [2]) when an individual exhibits low HR and high but uniform HRV they are considered to be in a recovery state or at rest as the effect of the SNS on the body diminishes [106]. Typically this indicates relaxation, such as sitting or sleeping. On the contrary, when an individual's HR increases and their HRV drops below their baseline (rest) their SNS dominates, activating the body into a stress state. We use this measure to validate the results from the reported stress levels and go beyond the construct of subjective (perceived) stress.

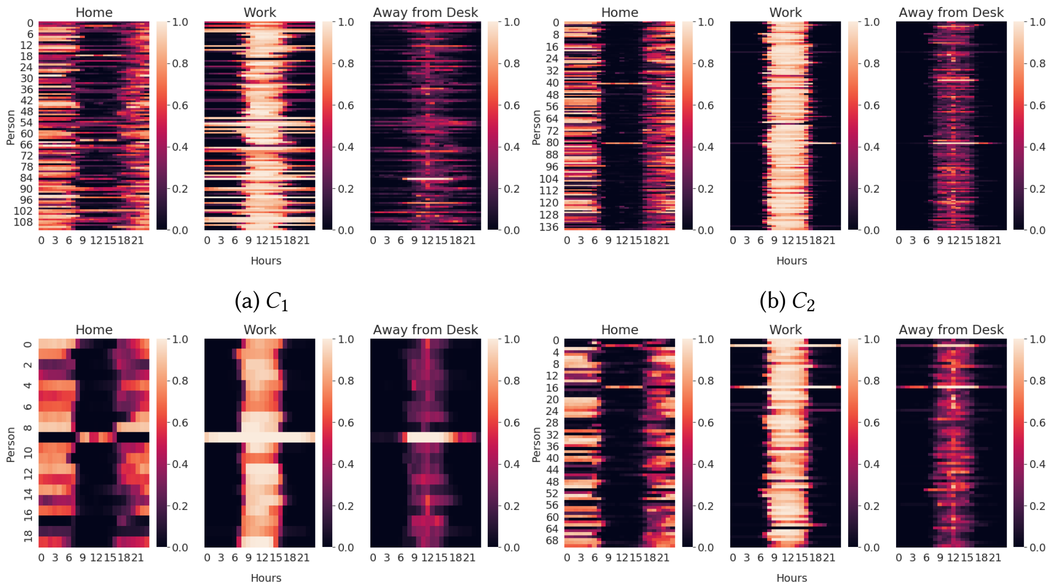
4 METHODS

4.1 Aggregating Activities into Routines

Throughout the day an employee is engaged in a multitude of activities such as commuting, taking calls, creating slide decks and attending meetings. A routine is simply a sequence of such activities. We scope the concept of routine through an objective perspective of mobility. Using non-invasive bluetooth beacons we infer the state of an individual – if they are at home, work or away from their desk (when at work). The temporal pattern of these states in a given day forms the routine for a day. This section elucidates our approach to quantify individual-level and organization-level daily routines (as a function of their presence at specific places).

4.1.1 Operationalizing Individual Routines. The phone agent installed on participant smartphones periodically scans the vicinity to locate other active bluetooth devices. Whenever a static beacon belonging to that individual is observed within a reasonable threshold of signal strength (-90 RSSI), the individual's presence at home or work can be determined. The instances at work are further deconstructed into sessions away from the desk – 5 contiguous minutes outside the range of the desk beacon is labeled as being "away". This data is chunked, or bucketed, in an hourly fashion to obtain the fraction of time at each hour an individual spends at *home*, at *work* and *away from desk* (when at work). The time at work directly represents an employee's habitual work hours, and the periods away from desk explain their internal schedules, such as meetings or breaks. The segments at home (and away from it) not only helps to infer commute times but also indicates spillover effects of work. How employees divide their time between home and work can influence their job behavior [19]. Moreover, according to the social-ecological model [16] human behavior is a function of contextual factors that bleed beyond a person's immediate surroundings. For example, periods at home can illustrate work done from home or even absent days. Therefore, to understand job performance, we must consider contexts outside of the workspace as well. Unlike the approach described in Eagle and Pentland which uses boolean representations, this method of fractional values per hour makes the data more granular and of higher temporal resolution [35]. Using this method, each day is characterized by the 24 hour pattern of 3 different possible states the employee can be found in. This produces a 72 (= 24x3) dimensional vector that coarsely represents the routine for a given day. Our study aims to characterize these routines in terms of individual mobility, or more accurately their presence near certain artifacts (front door/work desk), but this method can be extrapolated to any temporal activity.

4.1.2 Composing Organizational Routines. We construct several routine vectors for each individual, proportional to each day they logged data in the study. The mean of these vectors represents the average routine of an individual. Practically, a third person observing the participant is most likely to see this behavior. A collection of individual routines belonging to the same organization



(a) C_1 (b) C_2 (c) C_3 (d) C_4

Fig. 3. Every row of a heatmap illustrates the routine of an individual in an organization. Each column corresponds to an hour of the day. Brighter cells reflect individual presence – based on the beacon visibility.

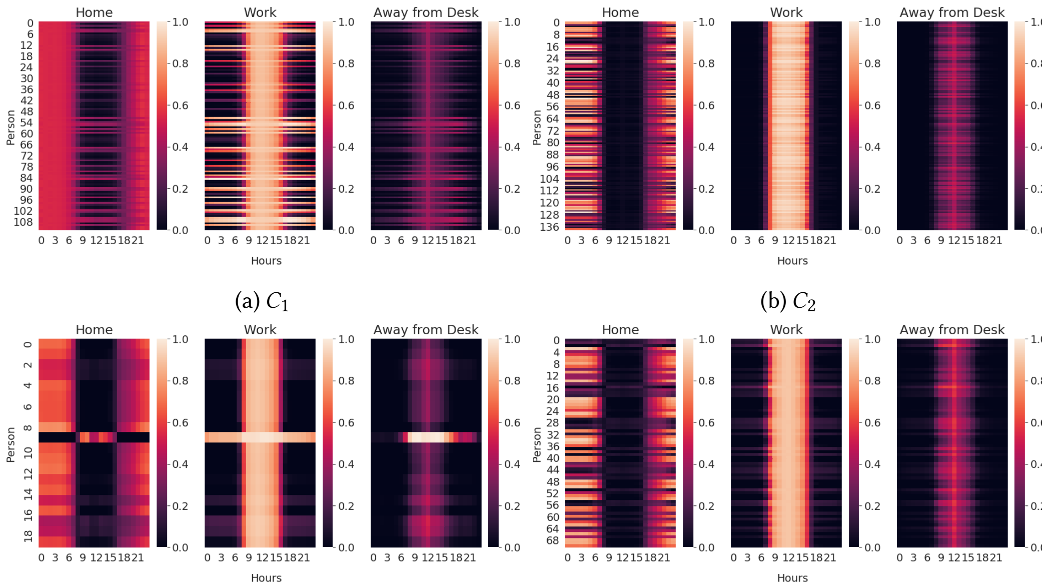
depicts the "real" behavior or *observable cohort routine*. Fig. 3 visualizes the aggregated behavior of each of the 4 cohorts. Even though, all the participants that were analyzed are primarily involved in information work, the organizations they work for are very different. C_1represents a large multinational company primarily operating in the service sector. On the other hand, $C_2$is part of a manufacturing company that builds consumer products, C_3belongs to a small 50 people firm, and $C_4$is made of university staff. On eyeballing these it is quite evident that individuals in $C_2$and C_4demonstrate largely consistent routines. C_3shows regularity as well. Compared to these, members of C_1show a lot more variation in the routines. We can attribute this to the fact that the $C_1$is a large consultancy where employees have diverse routines dictated by their specific client and project requirements. Hereon, whenever the paper mentions an individual's routine, we are referring to the average of their daily routines.

4.2 Computing Person–Organization Routine Congruence

In this section, we elaborate the computation of congruence between these operationalized routines. Methodologically, we adapt the eigen-decomposition method to aggregate behaviors of groups originally proposed by Eagle and Pentland [35]. Generally speaking, this technique identifies the primary patterns within data by assessing it in a latent space or "eigenspace" [109]. The following components of the paper contextualize this method in terms of our research questions.

4.2.1 Estimating Latent Routines.

One can imagine taking a mean of all the average individual routines in an organization to quantify the routine of a cohort. However, this means routine vector for a cohort is not necessarily comparable to normative group behaviors within an organization. It only reflects how much time on average do employees spend at different places throughout the day, washing out the variance in the data and misrepresenting the behaviors of many employees. Thus arises a need to distinguish latent group behaviors that sufficiently represent the normative behavior for a given group. In



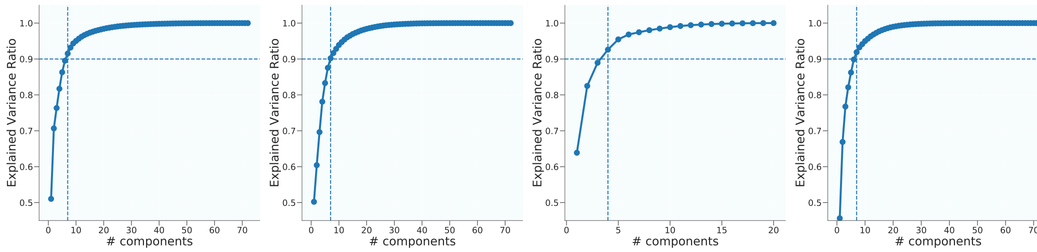
(a) C_1 (b) C_2

(c) C_3 (d) C_4

Fig. 4. Latent organizational routines can be depicted using different sets of eigenvectors. Here the originally observed routines are projected on the most prominent eigenvector

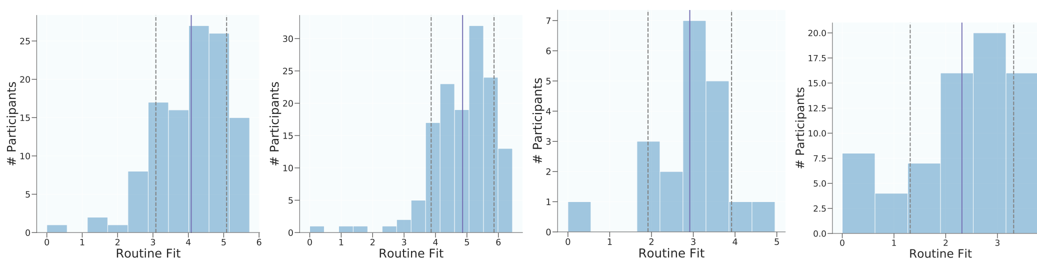
order to do this, a *Principal Component Analysis* (PCA) needs to be performed. This identifies the *eigenvectors* or principal components of the observable cohort routine. These represent the most characteristic behavioral patterns shared by members of a cohort. However, these do not necessarily correspond to interpretable routines in themselves. Rather, these vectors reflect the underlying latent structure that empirically emerges from the patterns observed in the cohort. Any individual's routine can be practically expressed as a linear combination of these eigenvectors (Eq:1). Prior to this, the individual routines must first be mean-adjusted, i.e., an individual behavior should be contrasted from the mean activity of cohort. The mean adjustment ensures that the primary principal component is independent to the mean of the data [80]. For any individual I, this adjusted routine will be referred to as $\Phi1(I)$. The PCA is applied on a collection of the mean-adjusted individual routines belonging to a cohort and eigenvectors are obtained. Fig. 4 illustrates the cohort routines when they are expressed using only the most important eigenvector – the behavior that explains maximum variance in the cohort. Relative to the observed cohort routine (Fig. 3), the projected routine (Fig. 4) is able to highlight prominent behaviors. These represent the normative patterns within an organization. For e.g., every cohort shows a distinctly bright vertical column around 1200hrs in the "away from desk" block, indicating a commonly agreed upon lunchtime or regularly scheduled meeting that causes most employees to leave their desk.

4.2.2 Identifying Normative Routines and Explaining Behavioral Variance. Given that we describe multiple employees in a high-dimensional space to explain routines, individual's could differ from each other in many different ways (across every hour on every feature). Furthermore, each individual can be compared to every other individual as well, implying a large set of comparisons. However, as already demonstrated earlier, a small set of latent patterns in behavior can explain a large part of the observed cohort routines. Fig. 5 illustrates the cumulative variance explained by the eignvectors. Despite constructing the observed cohort routine with routines of multiple unique individuals, the PCA demonstrates that the normative behaviors can be expressed with



(a) C_1 (b) C_2 (c) C_3 (d) C_4

Fig. 5. The cumulative variance explained by subsequent eigenvectors across different cohorts. We consider vectors that explain 90% variance to be reflective of normative behaviors



(a) C_1 (b) C_2 (c) C_3 (d) C_4

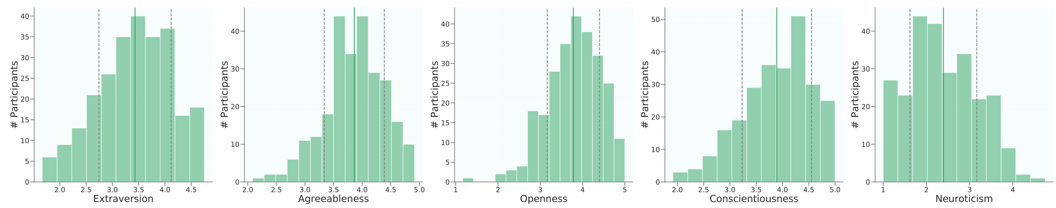
Fig. 6. Distribution of "Routine Fit" across different cohorts

about 10 latent behaviors (explaining 90% of variance). Although challenging to interpret in their native form, each of these latent patterns is comparable to the actual routine such that they contain the same number of dimensions. The 10% of unexplained variance omitted from the normative patterns represents the irregular routine behaviors. These are discarded in the form of eigenvectors that show least variances. In other words, these are the behaviors that are outside of the norm, accounting for individual differences within the population. For subsequent computations, we label the set of eigenvectors that explain these patterns as $U_1, U_2, ..., U_E$ (where E is the number of behaviors that explain 90% variance) – henceforth referred to as *latent cohort routines*.

4.2.3 Quantifying Routine Fit. The underlying latent cohort routines explain 90% of the observable cohort routine, but it is important to understand to what extent it can explain the routine of an individual within the organization. On projecting a single individual's routine onto the different latent cohort routines, we infer the different weights corresponding to each behavior; referred to as $w_1, w_2, ..., w_E$. These weights denote the emphasis particular latent routines have in explaining the individual routine (mean-adjusted to $\Phi1$). Having this information, for any given individual I, it is possible to reconstruct their activity routine based on the latent cohort routines as $\Phi2(I)$. Essentially, figure 4 illustrates $\Phi2$ if it was computed with only the primary eigenvector. The subsequent analyses consider $\Phi2$ computed with the first E vectors, which represents 90% of the observed routines. For individuals that behave very similar to the norms of their organization their reconstructed routines and actual routines will be equivalent.

$$\Phi2 = w_1U_1 + w_2U_2 + ... + w_EU_E \tag{1}$$

We conceive the *Routine Fit* $RF(I)$ of on individual (I) as the measure of similarity between the original activity routine of an individual, $\Phi1(I)$, and the reconstructed activity routine $\Phi2(I)$.



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

Fig. 7. Distribution of *Big Five* personality traits in the dataset

For this, we first compute the Euclidean distance $D(I)$ between $\Phi1(I)$ and $\Phi2(I)$. At this step, it is important to note that routine fit only compares the congruence of routines within a cohort, but not across them because of how diverse they are (Section 4.1.2). Because the absolute value of $D(I)$ is dependent on the normative routine of the cohort, it is a relative measure. As a result to control for inter-cohort differences in samples, these measures are standardized within the cohort as Z-Scores. Each of these standardized distances is subtracted from the cohort's maximum distance presenting a measure of similarity hereby called *routine fit*.

Fig. 6 shows how the measures of routine fit vary across cohorts. Between $C_1$and C_2, the two cohorts of comparable sizes we observe that on average C_2has a higher routine fit than C_1. This insight supplements what we know from the observed cohort routine depicted in Fig. 3. This distribution between the routine fit of $C_1$and $C_2$is also expected because these cohorts are part of organizations that operate differently. $C_1$is largely made up of consultants that work with individual clients and often have independent schedules. On the contrary, employees of $C_2$are engaged in research and development of consumer products and tend to rely on high internal collaboration. Therefore, the mean fit of $C_2$is bound to be higher than C_1because the employees of each cohort find themselves in different social contexts .

$$D(I) = \sqrt{\sum_{i}^{\mathcal{A}} (\Phi1(I)_i - \Phi2(I)_i)^2} \tag{2}$$

$$D(I) = ZScore(D(I)) \tag{3}$$

$$RF(I) = \max_{I \in C}(D(I)) - D(I) \tag{4}$$

Equation 4 represents our measure of routine fit and is analogous to the conceptualization of fit described by Edwards et al. in equation 5 where the P is the person variable, E is the environment (or organization) variable and c is the theoretical maxima of fit within that organization [37].

$$F = c - |P - E| \tag{5}$$

In terms of our approach, P is equivalent to $\Phi1$, reflecting the individual's routine as it is observed in the real world. E is equivalent to $\Phi2$, describing the expected individual routine, given the normative patterns of their cohort.

Note: Although using difference metrics to measure some form of P–O fit is common in the literature, we are aware that the use of polynomial regression models has been encouraged as a means to mitigate its many limitations [38]. A polynomial regression method uses higher-order terms to decipher more complex relationships between the P–O variables such as directional differences. Despite this, we choose to use a Euclidean distance to gauge congruence due to the high-dimensional nature of our P–O variables, i.e., $\Phi1(I), \Phi2(I)$*. Given the multiple dimensions used to describe our vectors, constructing a* *polynomial regression model that exhaustively captures the interactions between all dimensions is too complex to interpret meaningfully.*

4.3 Measuring Relationships with Routine Fit

After computing the routine fit of every individual, linear regression models were built to examine its monotonic relationships with each of the different outcome variables, Y [27]. These models included covariates for demographic information and intrinsic personality traits (Equation 6). The different attributes of the big-five personality traits are correlated with different measures of job performance and mental health [4]. As mentioned in Section 3.1, this data was collected during participant enrollment using the Big Five Inventory-2 (BFI-2) instrument (Fig. 7) [103] – agreeableness (3.86 ± 0.53), conscientiousness (3.89 ± 0.66), extraversion (3.43 ± 0.69), neuroticism (2.39 ± 0.77), openness (3.78 ± 0.62). The demographics variables were chosen based on previous work [13, 85] – age (continuous), education level (ordinal), income (ordinal). None of the control variables were found to be significantly correlated with routine fit.

$$Y \sim age + education\_level + income + personality\_traits + routine\_fit \tag{6}$$

Additionally, we measure the *Variance Inflation Factor* (VIF) [82] for the covariates to check for multicollinearity among them. We perform this measurement iteratively for each covariate. At every successive step, the VIF of the covariates was found to be less than 1.4, which is far smaller than the conventional thresholds ($VIF = 5$ or 10) for excluding covariates. Therefore, the inflation of error caused by including these covariates in the model (Equation 6) is inconsiderable.

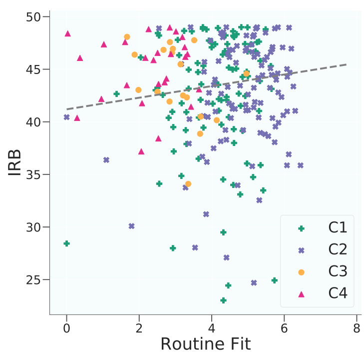
5 RESULTS

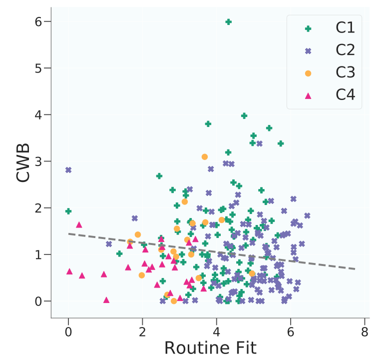
5.1 RQ1: Routine Fit and Job Performance

The results of the linear regression show significant associations between routine fit and in-role behavior (IRB) as well as counter-productive work behaviors (CWB), as depicted in Table 4. There were no significant relationships found with the ITP and OCB test scores. This section unpacks the significant relationships by theoretically grounding it with the relevant literature.

5.1.1 Positive correlation with In-Role Behavior. We find that there is positive correlation between an individual's routine fit and in-role behavior (Table 4a). Employees with home-work-desk patterns congruent to others in the organization tend to exhibit higher task performance. This is aligned with the ASA theory given that workers who are congruent with their organizational patterns would be more likely to thrive as compared to those who are less congruent [98]. Moreover, this method shows a significant correlation with performance after controlling for the typical effects of personality [4]. One possible explanation for this lies in the conceptualization of organizational routine by Feldman and Pentland [44]. They describe routines as "sources of stability" that "encode organizational capabilities and knowledge". Moreover, routine behavior of an employee is informed by organizational structure where macro-level changes only occur for the purposes of improved performance [44]. These effects are also grounded in the notion of entrainment — or the synchronization of routines — within the organization system. Syncing up with the task rhythm of a team is known to help increase coordination and task efficiency [52]. These results support expanding the idea of team-based synchronicity to an organizational level. Individuals who are keyed into the dominant organizational tempos (i.e., have high routine fit) would produce greater task performance [88]. For instance, being co-present to work with other colleagues would enhance productivity. Individuals with less routine fit could be lacking in task efficiency because of sub-optimal habits that implicitly the organization discourages.

Table 4. Significant relationships between Routine Fit and job performance based on the linear model (equation 6). Only significant covariates are reported. (. p<0.1, * p<0.05, ** p<0.01, *** p<0.001)





	Std. Coeff		
In-Role Behavior			
Openness	0.115	.	▲
Extraversion	0.119	.	▲
Agreeableness	0.204	**	▲
Conscientiousness	0.349	***	▲
Routine Fit	0.114	*	▲
R^2 = 0.283			

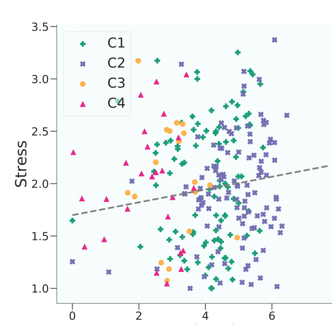
(a) IRB

	Std. Coeff		
Counter-productive Work Behavior			
Age	-0.121	.	▼
Agreeableness	-0.138	**	▼
Conscientiousness	-0.249	***	▼
Routine Fit	-0.117	*	▼
R^2 = 0.179			

(b) CWB

5.1.2 *Negative correlation with Counter-productive Work Behavior.* Next, we observe that there is negative correlation between an individual's routine fit and counterproductive work behavior (Table 4b). Congruence in home-work-desk patterns reflects a lower likelihood to be involved in deviant behaviors at the workplace. Early work on organization fit scarcely focused on deviant work practices. Prior work on P–O fit has shown counterproductive work behaviors are inversely related to job-satisfaction [62, 75]. Sharkawi et al. observed a negative correlation of fit with an individual's propensity to counterproductive activities [99]. Iliescu et al. found the congruence of vocational interests (or lack of it) to be related with CWBs [57]. Non-conformity to the normative routines have been studied in other fields of psychology to understand its relationship with behavioral deviance [72]. An individual's within-person routine irregularity has also been linked with deviant acts like crime [86]. From a social context Bernburg and Thorlindsson studied the link between routines, differential social relationships and deviant behaviors [9]. In light of this, the negative relationship between routine fit and CWBs could indicate a lack of social connectedness.

Table 5. Significant relationships between Routine Fit and reported stress the linear model (equation 6). Only significant covariates are reported
(. p<0.1, * p<0.05, ** p<0.01, *** p<0.001).



	Std. Coeff		
Reported Stress			
Neuroticism	0.351	***	▲
Routine Fit	0.113	.	▲
R^2 = 0.186			

5.2 RQ2: Routine Fit and Psychometric Characteristics

As per the results of the linear regression, used to model the relationship between routine fit and different wellbeing measures (equation 6), we find that an individual's routine fit and reported stress are correlated. Additionally, we observe that routine fit is linked to their resting arousal and stressful arousal duration. None of the other psychometric constructs were found to have significant relationships. This section elucidates these results in light of organizational psychology literature.

5.2.1 Positive Correlation with Reported Stress. Based on the results returned by the linear model, the routine fit shows a positive relationship with self-reported stress (Table 5). Before understanding this relationship it is important to note the distribution of the self-report responses as depicted in Table 5. The responses are skewed towards a lower score, reflective of low stress, with a mean of 1.97 on a scale of 1-5 with a max of 3.37. This indicates the general level of stress reported by participants is of low intensity. Most of the previous literature has only claimed relationships of fit and stress indirectly through other measures, such as strain and intent to leave. In fact, Arbour et al. found no significant association between stress and the congruence of behavioral norms in an organization[3]. Siegall and McDonald studied the relationship between value congruence and burnout, an extreme form of stress and found a strong negative correlation[101].

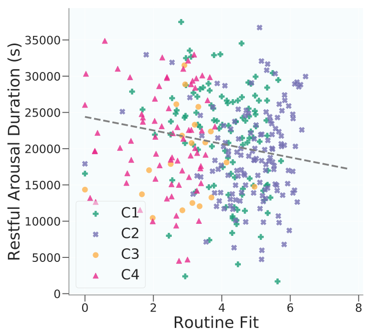
Given the ground truth data of our study does not capture the full range of the stress scale, there are little to none extremely high stress values reported. Another important detail to note is that the stress instrument used in this study does not capture valence. With this in mind, it is possible that the individuals with higher stress reports are relatively more focused in workplace activities [97]. In their study, Mark et al. state that, "People are happiest doing rote work and most stressed doing focused work"[77]. The interlinking between routine fit and stress could be indicative of high engagement work that is being performed by individuals following routines congruent to their peers. Moreover, the high routine fit could also represent a lack of autonomy in terms of work flexibility. When workers are not given sufficient agency to make decisions on task-related choices, including periods of work and schedule, they tend to be more stressed [50, 58]. In this regard a low routine fit could reflect resources being allocated to other aspects of life, such as one's social ties, subsequently reducing perceived stress [49, 51].

5.2.2 Positive Correlation with Stressful Arousal. On testing the relationship between routine fit and arousal duration, there emerged a significant positive relationship with stressful arousal duration and a negative one with restful arousal duration (Table 6). Individuals with lower routine fit spend a longer amount of time in the restful state than those with a higher routine fit. On the other hand, the relationship of stressful arousal with routine fit indicates that high fit individual spends more time in higher arousal periods. This could either be indicative of physical activity or the response of an external stressors like a challenging task. We also know that the restful and stressful durations correspond to increase in HRV and decrease in HRV respectively [106]. In fact, decrease in HRV is actually reflective of an individual being in an attentional state [84, 91]. Thus, individuals with high routine fit spending longer durations in the stressful arousal state could be indicative of their involvement in engaging activities. The positive correlation with stressful arousal supplements the previous result where individuals with high fit also reported higher stress.

5.3 Post-Hoc Analyses

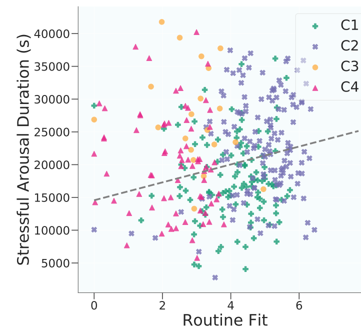
The final subsection presents tests to validate routine fit as an objective construct. First, we control for the time spent at a location to demonstrate divergent validity. Following this, we test a random-effects model to evaluate consistency within the dataset.

Table 6. Significant relationships between Routine Fit and different arousal measures based on the linear model (equation 6). Only significant covariates are reported (. p<0.1, * p<0.05, ** p<0.01, *** p<0.001).



	Std. Coeff		
Restful Arousal Duration			
Age	-0.186	**	▼
Agreeableness	-0.142	*	▼
Conscientiousness	0.258	***	▲
Routine Fit	-0.125	***	▼
R^2 = 0.139			

(a) Resting Arousal



	Std. Coeff		
Stressful Arousal Duration			
Conscientiousness	-0.206	**	▼
Routine Fit	0.151	*	▲
R^2 = 0.107			

(b) Stressful Arousal

Table 7. Significant relationships between Routine Fit and previously found significant relationships after controlling for durations (. p<0.1, * p<0.05, ** p<0.01, *** p<0.001).

	IRB	CWB	Reported Stress	Resting Arousal	Stressful Arousal
Home	***	**	.		***
Work	.		*		
Away from Desk	.	*			*
Routine Fit	***	***	***	**	***
R^2	0.95	0.90	0.90	0.85	0.81

5.3.1 *Controlling for Presence Duration.* Recall that, the routine fit of an individual is computed based on the duration of their presence at different beacon locations. This method begs to question if the relationships between routine fit and the different dependent variables are simply the effect of an individual's time at home, work or desk. To untangle this, we test the relationship of routine fit with our outcome variables by including these duration variables as covariates to the linear regression model:

$$Y \sim duration_{home} + duration_{work} + duration_{away\_from\_desk} + routine\_fit \quad (7)$$

The results of the regression depicted in Table 7 show that the relationship between the calculated measure of routine fit with different job performance variables and psychometric constructs, still hold in models controlling for the duration variables. This is because routine fit models similarity in patterns across 72 different features in a high dimensional space, capturing information that cannot be acquired by matching 3 dimensions of duration [35]. Therefore, this provides evidence routine fit expands upon simplistic measurements of duration to explain the outcome variables.

5.3.2 Generalizability of Routine Fit across Cohorts. We determined the relationship of an employee's routine fit to their job performance and psychometric characteristics using a dataset comprised of four different cohorts. As described in Section 3.1, all of these cohorts are similar in that they represent employees involved in information work. Having said that, these cohorts vary in many different aspects such as organization size, workforce diversity, and company culture. Therefore, it is reasonable to argue that routine fit has a different relationship to performance and wellbeing outcomes for different cohorts. Even though Section 4.2.3 describes the use of Z-scores to standardize routine fit, we only adjust for observable differences and not the subjective differences between cohorts. This motivates us to empirically validate the effect of different cohorts by testing a random-effects model:

$$Y \sim age + education\_level + income + personality\_traits + routine\_fit + (1 + routine\_fit | cohort) \quad (8)$$

Equation 8 extends on the linear model used in our analysis (equation 6 by incorporating a random term, $(1 + routine\_fit | cohort)$. This random term tests if the slope of routine fit and the outcome variable (Y) varies across cohorts. We apply this model to find that routine fit does not vary significantly across cohorts for most of the outcome variables except for stressful arousal, for which the variation is only weakly significant ($p = 0.084$). This indicates that, even though the cohorts vary in nature, the findings presented in Section 5.1 and 5.2 are consistent across them.

6 DISCUSSION

A sizeable chunk of literature on P-O fit has focused on intrinsic congruence of individuals with respect to their organization. Typically researchers study the similarity between cultural values, personality traits, salaries, and job enrichment to investigate this concept (Table 1). This work takes an alternate approach to assess fit objectively by studying the congruence of activity patterns – in the form of latent mobility routines. Moreover, this measure is data-driven and aggregated through passively sensed data from a longitudinal field study, alleviating many of the pitfalls of survey studies. By considering routine congruence as a metric of P-O fit, the paper identifies relationships similar to past work in that both performance increases and deviant behavior decreases with increased fit. The temporal similarity captured in this measure also unpacks a new relationship with stress illustrative of focus and low autonomy — a dimension insufficiently explored previously.

6.1 Theoretical Implications

The organizational research literature has always positioned fit as a positive outcome [61, 81, 85, 98]. In fact, it is not only the research community but also the personnel recruiting units of companies that give importance to an individual's alignment or affinity to an organization's internal system and expectations. Yet, our study of fit at a behavioral congruence level expounds that resemblance has its benefits as well as pitfalls.

Routine fit shows a significant relationship, both theoretically and statistically, with performance and deviant behaviors, which reinforce these long-held beliefs about the importance of P-O fit to organizational and workplace outcomes [44, 52, 88, 98]. However, the associations routine fit uncovers between P-O congruence and reported stress, as well as arousal, dispute if fitting in is necessarily a favorable outcome within an organization. Entrainment, or aligning with the tempo of a system, has been associated with reduced autonomy in the workplace [50, 51]. Similarly, prior work in P-O fit has associated high similarity as an obstacle to creativity, inventiveness and innovation [18, 43]. Therefore, the homogeneity of individuals to the behaviors of the organization could exhibit itself in the form of an implicit stressor. This finding motivates further investigation into understanding how an employee's routine-fit interacts with individual and organizational characteristics that determine wellbeing.

From the social dynamics perspective, this work gives us more reason to believe that the activity patterns of individuals should not be isolated while studying workplace outcomes, such as job performance or employee wellbeing. Previous work implying that any form of activities affect employee performance or wellbeing has taken an insular focus on the individual behaviors [46, 76, 77, 113, 115]. The findings in our paper encourage compounding these behaviors with the activities of the social system an individual is found embedded in.

Methodologically, this paper reinforces the use of "eigenbehaviors" as a computational method to glean normative behaviors from large-scale passively sensed data. It also presents an application of this method for practical purposes to measure individual outcomes in community settings [35].

6.2 Design Implications

Our paper establishes significant relationships between similarity of within-group activity routines, gathered through passively sensed behaviors, and certain job performance outcomes and wellbeing. Though these results are specific to our sample, the CSCW community can use this method to envision a variety of both employee-centric and organization-centric technologies, which seek to (self)-monitor and understand workplace outcomes and are also privacy-aware.

Technologies for the Organization. First, our approach can facilitate developing technologies that organizations can use, with employee's consent, to use embedded technologies to assess routine conformity of employees in the context of their policies. Based on these findings, organizations can experimentally test causal effects of synchronizing employee routines and inform if and when coordinating routines is helpful or even detrimental. Next, personnel management has many alternatives to modify their organization's landscape, for example, open-offices or activity-based working. These decision-making bodies can use workplace technologies, such as bluetooth beacons and desktop activity, to objectively validate the effects of structural and cultural changes on employee functioning, both in terms of productivity and wellbeing. For instance, in our dataset, although routine fit is associated with better job performance attributes, it is also linked to higher stress. Therefore, organizations must quantify these trade-offs before practically applying routine fit for decision-support technology. Furthermore, such a technology can help an organization reflect on its tolerance for activity-based heterogeneity in their population and make informed decisions about the flexibility in routine behavior they are willing to permit. These insights enable organizations to support employees demonstrating low fit from the lens of behavioral diversity [18]. In fact, organizations define "deep diversity" to be an encouraging feature – teams composed of divergent perspectives have been argued to be more creative [53].

Technologies for the Prospective or Current Employee. Second, the use of technologies for job-seeking (e.g., Indeed) as well as human resource management (e.g., performance evaluation software for managers) has increased in recent years [59]. A data-driven approach such as routine fit, that quantitatively expresses the behavioral signature of a community can be a new kind of descriptor for an organization. As a result, such tools can also provide job-seekers an unambiguous means to assess their fit along the dimension of their own routines [98]. With this information, job seekers can eventually ascertain the extent to which an organization's norms, which they may aspire to join, align with their personal values, beliefs, and work ethics, and use this information objectively in their decision-making processes.

Further, these activity-based latent organizational descriptors can objectively depict the normative activity within a cohort or even a single employee. In turn, this can facilitate employee-facing or cohort-facing tools that enable employees in their acculturation process, i.e., learning and inculcating the organization's norms. Finally, current employees can also benefit from tools that allow them to assess and understand their P-O (or routine) fit with the organization. These would provide employees with more agency to reflect and positively influence their performance and wellbeing. To new employees in particular, knowledge of fit offered by such tools can serve to break the ice and build workplace relationships, facilitate ways to better forge quality collaborations. At the same time, when employees are aware of their (lack of) fit they can carve their unique place in the company, and be empowered to adopt measures that define boundaries between one's own preferences and the expected organizational norm.

6.3 Implications for Aggregated Sensing of Community Behaviors

In our work, the key source of data to quantify routine fit were features engineered from passively-sensed bluetooth beacon data. These low-cost technologies can be easily embedded into the individual's environment; in fact they are already present ubiquitously. Most off-the-shelf smartphones, with consent from the stakeholders, can easily leverage their built-in bluetooth sensor to infer movement or peer colocation [112]. With the increase of home automation, this technology has become even more omnipresent, making it easier to estimate the presence of individuals at different places in real-time [104]. We see opportunities to harness this potential for a variety of different communities beyond the workplace, whose behaviors have been of interest to researchers in CSCW and other related fields [90, 94, 114]. For instance, phenomena such as routine congruence have value in other situated communities like university campuses. Social rhythm, or entrainment, has been helpful in explaining sleep hygiene of students [15]. Similarly, non-conformity to normative wakefulness and sleep patterns has been shown to be indicative of low self-control [31]. Along these lines, routine fit can be used to help describe the variances in high and low performing students. In turn, this can encourage studying the behavioral contrast with respect to students' social groups (or interaction patterns), and how it can explain their mental wellness.

Additionally, the results of this paper encourage the use of other large scale infrastructure administrated by large organizational units to be used to understand community behaviors. For instance, companies or universities can apply the same method using WiFi access points to personalized RFID swipes [55]. These channels could provide more granular information at a larger scale as well as capture other kinds of behaviors, for e.g., entering into the leisure room, using the communal gym or recreation center, patterns of offline social interaction, or swiping a meal pass at the food court [56]. Subsequently, these could provide valuable insights toward understanding a community's health in an unobtrusive, real-time fashion, and then leveraging these insights to improve community or organizational resources that address gaps in wellbeing.

Further, the idea of routine fit is not confined to movement patterns. All the other sensed behaviors that can be socially witnessed have the potential to be extrapolated onto this model as additional dimensions. Previous work in the workplace has shown the effect of interactions on individual performance [76]. Keeping in mind other studies that discuss coordination, congruence in both online and offline activities can be explored in terms of both individual and team performance [46]. Similarly, the synchronicity of digital activity in terms of desktop and smartphone activities can be investigated through this lens; a source of data that has already been explored in the CSCW and HCI literature to understand a variety of workplace outcomes [77, 113].

6.4 Privacy and Ethical Concerns

We acknowledge that the analysis presented in this paper is not possible without access to large scale behavioral data of employees both inside and outside their workplace. Collecting this information raises serious privacy concerns. As described in Section 3.1, we took multiple precautions to ensure the participants were aware of the type of data they were providing, the right to opt-out of the study, the means to communicate with researchers, and the method of storing and securing their data. However, in practical scenarios, companies might not explicitly educate employees of the privileges to their data. Even though it can be argued that many companies are already monitoring employee activity (communication, browsing, card access), many of these surveillance streams are considered unjustified and abusive of employee rights [116]. Albeit for the greater good of improving efficiency and workplace wellbeing, may it be organizational or individual, the findings in this paper may seem to encourage oversight of the grave privacy concerns that underlie granular activity data collection and modeling using ubiquitous technology [100]. Therefore, we suggest some solutions below:

A potential approach to alleviate the privacy implications of these results would be to introduce a disparity in the organization-centric view of this information (or the tools we suggest designing) and the individual-centric view (the prospective or current employee-facing tools). The former should only be studied at an aggregate level. An organization should not have the ability to single-out employees who are not congruent, as this information can be exploited both intentionally or inadvertently towards negative consequences – e.g., denying compensation or benefits to, or firing a non-congruent employee in extreme scenarios. In fact, even when presented with aggregated employee information, the organization-centric tools we present above need to administer caution in how this information is made actionable. For instance, our approach does not get at causality between the observed routines and the various job performance and wellbeing outcomes. Therefore, organizations using such correlational results for organizational change without rigorous experiments for causal inference can be problematic. This can lead to organizations self-prescribing rigid structures for routines as well as reorganizing employees in a brute-force manner without sufficient employee feedback or assent.

Further, we believe that the employee-facing tools should incorporate affordances and mechanisms that allow them to have agency over how the information about their organization's normative behavior is appropriated in the personal context of the employee. Employees tend to interact with such tools when they want to gain an increased awareness of their state to adjust it to meet their goals [41]. Notably, even though P-O fit is generally considered preferable, the effects of exposing an employee's routine fit, in this manner and via the tools we describe above, needs to be studied more extensively before considering deploying such interfaces in the wild [45].

Most importantly, employees enrolled in company programs that analyze behavioral data must be incentivized adequately. When participants are remunerated appropriately for providing their data, they show greater motivation to participate [21]. However, there is a fine line between compensation and coercion. Employees must not feel obligated to expose such data for research unless they truly see in value in it.

6.5 Limitations & Future Work

The primary motivation of this paper is the theory of Person–Organization (P–O) fit. The organization in itself is a high level, intangible entity that governs the employee with respect to their work. Nevertheless, there are other entities that an individual might need congruence with in order to succeed, including the job itself or the supervisor [66]. The current method does not quantify many of these attributes, such as, the effect of an individual's micro-level environment or normalize for tangible factors that affect social interactions and potentially congruence. Thus like other notions of fit [66], routine congruence might also have hierarchical variations at different levels. Moreover, this study motivates in-depth analysis into the relationship of routine fit with traditional types of P–O fit, such as work enrichment, role ambiguity, personality fit, and culture fit (Table 1).

The ground truth measures of this study are based on individual self-reports, however, the answers recorded by these surveys are subject to many different biases – a desirability bias to impress employers often emerges [33]. While self-reports have been a mainstay, supervisor facilitated assessments are known to introduce unique variance to performance evaluations [47]. Thus an employee's actual outcomes could be based on metrics that are not captured in this dataset. Moreover, our current work has been confined to examining linear relationships of routine congruence with these metrics. Similar to the unidimensional or low-dimensional variables used to measures fit, there exists an opportunity to explore non-linear connections between multidimensional behavioral congruence and ground truth measures [36, 39].

Relatedly, P–O fit varies on multiple factors and activity based routine is only one of these (Table 1). With a growing need to increase diversity in the workplace, the common ideas of P–O fit have already been disputed [83]. How a data-driven metric of fit like ours varies across individuals who are vastly different based on various personal characteristics such as race, gender, sexual orientation, cultural background, and faith is yet to be explored. We realize that the effects of fit, or the lack thereof, on specific populations could be very different from what would be observed in a sample of information workers. In fact, although our study quantifies routine fit, it presents new opportunities to explore the psycho-social underpinnings that define it. Even though the method of measuring routine fit does not directly incorporate a cohort's demographic composition, such factors can dictate the congruence of routines. For example, individuals belonging to specific minorities might find it challenging to assimilate into the normative routine. Therefore, future investigations can explain if routine fit of an individual is associated with cohort-level characteristics, such as sexual and racial diversity.

Finally, an interesting future direction to explore with this type of longitudinal data is the progressive entrainment of individuals with longer tenures versus those who did not retain their jobs. Applying this same method over a temporal sliding window could also help inspect the assimilation or acculturation of an individual into an organizational community. Similar to the prospective studies related to tenure, investigating entrainment as a temporally varying construct will also invite the opportunity to understand how it is related to seasonality. Especially if the differential perception of seasonal effects is related to an employee's routine fit.

7 CONCLUSION

Our work leverages ubiquitous bluetooth sensing to empirically assess if the congruence between an employee's activity routines and their organization's latent routines is associated with their job performance and wellbeing. Unlike previous constructs of person–organization fit, *routine fit*, which is measured through sensing movement patterns, objectively characterizes an individual on the basis of multiple dimensions. Moreover, we demonstrate how routine fit is a data-driven approach to glean an organization's normative behaviors and meaningfully explain variances in employee functioning. Our approach is similar to traditional methods that rely on value-congruence, in that routine fit is also associated with high task performance and low workplace deviance. This indicates that when individuals synchronize with their organization's tempo they coordinate better and get more socially embedded. However, routine fit also shows a positive correlation with perceived stress and arousal, implying high engagement work or possibly a loss in autonomy. These findings provide evidence that collective sensing of aggregate behaviors, on the basis of P–O congruence or "fit", is an objective way to disentangle workplace functioning.

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