Digital Trails of Work Stressors

Talha Oz[1,2]

[1] Analytics R&D, Humanyze, Menlo Park CA 94025, USA
[2] Computational and Data Sciences, George Mason University, Fairfax VA 22030, USA
toz@gmu.edu

Abstract. This paper proposes a novel strategy to identify work stressors using metadata from most available workplace technologies such as e-mail and calendar. Stressor measurement has predominantly been done by self-reported questionnaires; yet it has proven imperfect due to selectivity and response biases. By addressing the questions of *What work stressors can be diagnosed by digital exhaust without violating employee privacy? How to model such stressors and make use of the model most effectively?* this paper makes scientific as well as practical contributions to organizational design. The proposed strategy allows continuous monitoring of stressor levels and making quick data-driven decisions throughout an organization. It guides interventions by enabling benchmarking, experimentation, retrospective cohort analysis, and trend analysis of stressors. Besides, it can inform survey design by help determining what questions to ask and to whom, and response interpretation by identifying stressors on which different measurement methods converge or diverge. Thus, with the proposed strategy, stressor measurement becomes less disruptive and more cost effective.

Keywords: Work Stress, Employee Experience, People Analytics.

1 Introduction

A positive employee experience boosts performance and productivity, while a negative one can have very serious individual, organizational, and societal effects [1]. To safeguard the psychological wellbeing of their employees, organizations can choose from two intervention strategies: mitigating organizational stressors (external stressful conditions impinging upon employee) and increasing individual resilience (e.g. by wellness programs and counseling services) [2]. The former strategy is proactive and preventive, and directed at work design; while, the latter approach is often reactive and recuperative, and directed at individual cognitive and emotional processes. Accordingly, organizations with preventive measures in place not only benefit from the removal of adversarial effects of stressors in the first place, but they also mitigate the need for and costs of secondary interventions [3]. Since "it only makes sense to redesign jobs when strains can be attributed to objective stressors—and not primarily to appraisal processes" [4], we need an objective concept of stressor to develop a work environment that does not cause psychological damage to *most* employees in the first place.

Organizational psychologists have identified several methods to measure stressors. Surveys in which participants are asked to rate the characteristics of their jobs without interpretation is the dominant method for measuring stressors. The main advantage of surveying is the possibility of depth and breadth of information one can obtain about stressors. Achieving that fully, however, is very difficult: since participating in surveys take time and effort of employees, increasing sampling frequency reduces participation rate and thus increases selectivity bias. Besides, general well-known response bias issues of surveys such as transient mood effect, personality trait effect, social desirability, memory weakness, and many other effects of survey-item characteristics and contexts distort the reality of work [5]. Aggregating employees' job ratings (at some level) may cancel out some of these biases. Yet, aggregation of self-reports might reflect "a shared perception of job characteristics, rather than any 'objective' reality" because of social information processing and convergence in trait affect in work groups [6–8]. Also, some complex constructs (for example those that depend on social networks) do not lend themselves to aggregation because of their emergent nature (think of a workplace where social cohesion is high in general but with a few individuals excluded) [9].

Another self-report technique to identify stressors is making employees record their activities in diaries. Since employees' recording and others' reviewing is too costly, this method appears not scalable and hence inapplicable beyond research.

Since trained and experienced observers can rate work characteristics more objectively than the job incumbents, observer-based measures of job stressors have also been developed [10, 11]. Yet, this third-party solution has its own issues, including observability problems in both organizational coverage (observers cannot see important aspects of the work of many employees) and temporal coverage (it would be very costly to hire independent observers for long periods) aspects [12, 13].

Stressors are also studied at a macro level by analyzing employee handbooks, job descriptions, and national job databases. To pinpoint the "location" of stressors within an organization in "time" however, a better unit of analysis (such as enacted job characteristics that are more proximal to the individual's experience of strain) is needed [6].

In this paper, we propose an alternative method to measure job stressors, which can be coupled with other methods to improve the accuracy and speed of stressor identification. This strategy paves the path to more informed and rapid intervention cycles. It is unobtrusive, observational, and employs existing technologies in the workplace. Accordingly, in the remaining of this paper, I address: *What work stressors can be diagnosed by exploiting digital exhaust without violating employee privacy, and how? How can the findings be used and what is the scope of this strategy?*

2 People Analytics

Big data from workplaces, along with methods of computational and data sciences bring new opportunities and challenges for organizational psychology [14–16]. Depending on particular insights sought after, organizations decide on what data to collect (and how to analyze and interpret) [17]. In identifying stressors, we argue, metadata from readily available workplace technologies can be exploited.

Common technologies of workplace include systems such as e-mail, calendar, and unified messaging apps (such as Slack), video conferencing, file sharing platforms, as well as ID badges and room occupancy systems --from which physical locations and co-presence (face-to-face interactions) can be inferred. Data from such technologies allow organizations to understand the ways in which employees interact, organize their time, and use their workspace [18–20]; our goal here is to add stressors into this list.

Beyond metadata, some researchers have tapped into partial or full message content, e.g. [21, 22]. Yet, due to commercial and privacy concerns, most companies are unwilling to share their communication content with researchers or people analytics vendors. Hashing the content may be a solution to this problem; however, then it does not lend itself to semantic analysis, and does not allow studies like [22] and [21] (in which the authors examined sentiment and psychological categories of words, respectively). Sharing only the metadata, rather, frees companies from commercial and privacy concerns on one hand, and researchers from the scientific concerns of reproducibility and generalizability on the other. Accordingly, our strategy employs only metadata.

3 Work Stressors and Their Digital Trails

Work stressors can be categorized into physical stressors (poor physical working conditions), task-related job stressors (high time pressure, high task complexity, monotonous work, and interruptions), role stressors (unclear or conflicting role expectations, too much or too complicated work, and facing illegitimate tasks), social stressors (relationship problems with coworkers, supervisors, and customers), work-schedule-related stressors (overtime and night-shift work), career-related stressors (job insecurity, underemployment, and poor career opportunities), traumatic events (major accidents), and stressful change processes (mergers, downsizing, and adapting to new technologies) [4]. We acknowledge that not all of these work stressors are identifiable by digital trails of workplace technologies, but many of them are.

3.1 Methodology

A single metadata record represents an enacted event (e.g. a message sent, a file edited, or a meeting setup) and it is this atomic unit on which we model the stressors. From a calendar system, for a meeting, we learn its date (start and end times), its location, its organizer, list of invitees and their responses (accept, reject, tentative), timings of the invitation and responses, meeting recurrence frequency (if it is repeating), and when it is updated or canceled. From e-mail and other messaging platforms, for a message, we get its timestamp, sender, receivers, and thread-id (if it is a forwarding or a response message) from which we can calculate response time. File sharing platforms provides us with the information of which file edited when by whom, from which we can infer collaborations. From ID badges, we can infer an individual's physical location (e.g. at desk, meeting room, cafeteria, or elsewhere), and face-to-face (pairwise) interaction time and duration. When such events along with their attributes are collectively examined, emergent work conditions such as organizational stressors can be captured.

A stressor model in this strategy describes how to synthesize such metadata to measure the intensity of that stressor. Provided the events (metadata) an employee experiences for a particular time interval (at least one week), the model returns a single numeric value representing the intensity of the stressor impinging upon the employee. Simply checking the stressor measurements against some acceptable ranges (normative values) allows us to classify an individual's condition as safe or critical. Beyond that of individual, reviewing a stressor's aggregated scores for groups by teams, job functions, countries, etc., help identify collective behavior and processes fueling the stressors.

Conveying the local norms found the be a superior strategy to make people change their behaviors [23]. In this regard, merely sharing group-level benchmarking scores with the employees is expected to be in and of itself an effective intervention. Besides, continuously monitoring stressors enable early and preemptive solutions.

Another benefit of modeling stressors this way is its facilitation of running real experiments that allows causal inferences. For example, executives can conduct A/B tests to measure the effectiveness of two competing policies (or any hypotheses for that matter). Similarly, organizations can conduct retrospective cohort analysis [24] on stressors in which the test cohort is made up of those who left the organization (due to distress), and the control group is made up of that still working (without distress). Executives can thus discover which stressors contribute to what extent in their employees' decisions to leave. Hence, they can work more effectively in reducing the turnover rates.

Identification of stressors unobtrusively help reduce the cost and increase the effectiveness of surveys as well. It allows targeted surveying by helping identify what questions to ask and to whom, and thus reduces the survey costs.

3.2 Modeling Stressors with Digital Trails

Overload and work-life imbalance. Governments require companies to objectively measure work hours to prevent overwork; yet, as work can easily spill over via information and communication technologies, simply monitoring building check-in and check-out times is not effective. In this regard, by surveying employees and analyzing their email metadata, researchers found that the share of emails responded outside work hours is the most predictive email feature of work-life imbalance [25]. Sheer number of meetings and emails also found to be associated with increase feelings of overload and low job satisfaction [26–28].

Work-life stressor can be measured by calculating the time allocated for work after hours and on the weekends (just by looking at the timestamps retrieved from file sharing platforms, communication tools, and calendar APIs). Beyond time, identifying the parties (whether managers, coworkers, or customers) driving those interactions allows more targeted interventions. Besides, we can measure the sheer number of incoming messages and meeting invites during work hours and add the amount of double-booked and partially overlapping time slots into the equation. Comparing the measurements by such a model (I built at Humanyze) to responses to "my workload is manageable" survey item found to be highly correlated ($r=.78$, $p \leq 0.05$; that company survey had 264 participants and the responses I was provided were aggregated to eight business areas).

Undesired meeting characteristics. Employees are stressed about meetings when they are too lengthy, start late, get cancelled or postponed, when there is short notice and a lack of participation [29]. Lateness to meetings is another problem: it correlates with low job satisfaction for the perpetrator, but also causes stress on other meeting attendees as they feel frustrated, concerned, and distracted [30, 31].

We know when a calendar event is created (invitations sent) and meeting start time, from which we can infer if it was a short notice; combining with meetings postponed and cancelled, we can model uncertainty stressors. By integrating sensor data, we can identify meetings that did not start/end on time and that took shorter/longer than what was planned. Thus, scheduling reliability stressor can be modeled. Beyond measurement, simply a nudge can be sent in advance to habitually late joiners before meetings.

Late or no response. Under time pressure and deadline, waiting for a response for prolonged periods can elevate stress. Indeed, email response time between the manager and direct reports is found to be the most predictive email feature in satisfaction with the manager [25]. Similarly, not getting response can evoke frustration, powerlessness, hopelessness and inadequacy [32].

Organizations can calculate response time between all pairs of individuals. By aggregating and analyzing it across various combination pairs of roles, job functions, managerial hierarchy, country, etc. we can identify patterns of late-response stressors.

Interruptions. Self-interruption, i.e. frequently switching attention between tasks, throughout the day reduces performance and job satisfaction [33, 34]; and interruptions by others –be it in the same or different context– causes stress and frustration [35, 36].

Self-interruptions can be modeled by the burstiness of emails and clusteredness of meetings (time series analysis). Individuals whose emails and meetings are too scattered then can be targeted for training. To model others' interruptions stressor, from sensor data, we can detect how often others come to an employee's desk and interact.

Lack of social support. Social support has both a moderating effect [37] and buffering effect [38] on stress response, negative effect on turnover intention [39], and a positive effect on productivity and job satisfaction [40]. Supervisor support in addition to group cohesion is also shown to be related to lower levels of stress [41]. Diversity and Inclusion (D&I) brings challenges organizations need to address [42]. If not handled well, it can cause lower self-esteem, depression, and anxiety especially for the minorities and disadvantaged [43]. Although scholars have observed less D&I issues in online communication than offline, it has been shown that these issues do not fully go away [44].

Social support stressor can be modeled after embeddedness of employees in their social network (the lower the worse). We can model supervisory exclusion stressor by measuring the inequalities of time managers spent with their direct reports. D&I stressor can be modeled by examining communication bias between different demographics, which can be measured by calculating attribute assortativity coefficient within teams and across the organization (e.g. amount of emailing or formal/informal meeting between same versus different genders) [45]. This attribute could be gender,

race, religion, or anything that can be discriminated against. This enables interventions on the cultural fault lines.

Major Changes. Major changes such as mergers, acquisitions and downsizing elevate employee stress [46, 47]. The stressors can be related to group processes, social integration, and communication aspects of post-acquisition integration process [48, 49].

This stressor can be modeled by measuring the change in communication styles before and after the major change. By observing the evolution of communication network over time at groups level, we can identify groups closing the gap and the silos.

Spatial (Dis)organization. Office layout may cause employees to have a sense of lack of privacy (e.g. in open areas), lack of space (e.g. for formal meetings or informal mingling), and a sense of ineffective design (e.g. meeting rooms too small or afar). Besides, remote workers feel less connected [50].

Crowdedness stressor can be modeled using ID badges by measuring occupancy ratio of places. We can also measure the extent to which a space (e.g. meditation room, kitchen) is used as intended. Thus, real estate investments can be prioritized in favor of those prone to spatial layout stressors. Remoteness stressor can be modeled by measuring employees' ratio of face-to-face communication over that of virtual. Similarly, their seat distance to their top collaborators is a spatial stressor. Measuring them also helps solving a spatial optimization problem that relates to productivity, i.e., restacking.

4 Conclusion

Organizational psychologists have been calling for an alternative stressor measurement method free from biases of self-reports, and the proposed strategy is a response to that call. Beyond merely identifying the presence of certain types of stressors —unlike most of the traditional job-stressor instruments [11] — the strategy proposed here allows measuring stressors' frequency, duration, and severity. Besides, one of the most important advantages of this method is that once the algorithms for the proposed metrics are implemented, they can be continually computed and assessed.

The proposed strategy allows benchmarking, experimentation, cohort analysis, and trend analysis of stressors. Besides, it can also be used to inform survey design (e.g. by help determining what questions to ask and to whom) and response interpretation (e.g. by identifying stressors on which different measurement methods converge or diverge). Thus, stressor measurement becomes less disruptive and more cost effective.

To ensure this strategy be ethical and effective, several steps need to be taken (see [51] for a detailed discussion). It needs to be opt-in and both the participants and non-participants need to be protected by aggregating the results at group level (instead of providing each individual's values, a behavior should be reported as a distribution over a group). Individuals can be grouped by their teams, offices, roles, or job functions and then benchmarked against each other. Thus, by conveying the local norms, i.e. benchmarking stressor measurements, at risk groups can be effectively incentivized to change

their behaviors [23]. Of course, decision makers should interpret metrics in context, along with other information, and not follow the numbers blindly.

The strategy introduced in this position paper has several limitations. First of all, it is not inclusive of all work stressors. For example, some career-related (e.g. job insecurity) and role-related (e.g. facing illegitimate tasks) stressors are unobservable to the metadata. Content analysis could solve this problem to some extent, but for ethical and privacy reasons we limited our scope to stressors that can be measured solely from the metadata. Given the limitations of this strategy and others, organizations that want to measure work stressors cannot solely rely on one particular strategy, instead they should consider combining multiple methods of measurements.

5 References

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