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Productivity, Work Pressure, and Wellness Are Related

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Abstract

The research conducted in this article was used to prove that work stress has a measurable impact on wellness and productivity of professionals. Research was conducted by placing typical work patterns of subjects in perspective, identifying sources of data for various aspects of the subject's interactions with work during the day, classifying and organizing collected data based on criteria related to time, groups, etc. and then used to draw conclusions via corelation of work stress periods with periods of productivity. The research concluded that work stress does in fact have a measurable impact, not just on individual subjects, but also has long term consequences for organizations/groups.

Keywords: Work-life, productivity, health, wellness, flow, organizational resources, personal resources, positive.

INTRODUCTION

In recent years, there has been extensive research into the challenges that working professionals face with respect to productivity and wellness; there is literature that focuses on what effects work stress and other detrimental work-initiated pressures can have on health. One thing to note though, is that often, the thrust of such research explores ways that productivity can be affected by detrimental factors; for instance, in *Burnout and Work Engagement: A Thorough Investigation of the Independency of Both Constructs* by *Demerouti, Mostert*, the authors make the contention that there are factors that can be used to prove that the corelation between cynicism/dedication and exhaustion/vigour can be used to determine patterns of burnout during work engagement. In *Optimal Experience in Work and Leisure* by *Csikszentmihalyi* and *LeFevre*, it is posited that having the optimal *flow* during work has the most effect on the quality of experience during working rather than leisure. Keep in mind that here we speak of leisure as discretionary time free from obligation (Brightbill, 1960; Kelly, 1982), or as the pursuit of freely chosen recreational activities (Dumazedier, 1974; Roberts, 1981). Authors like Neulinger argue that leisure can also involve time spent in activities that provide intrinsically rewarding experiences (Neulinger, 1974; Iso-Ahola, 1980), although a case can be made that the *absence* of activity could also constitute leisure time.

With all the literature that explores these topics together, there is *some* acknowledgement that productivity is affected by work pressure in multiple ways, and that attributes like personality are not necessarily promising indicators of job performance (e.g., Hurtz & Donovan, 2000). However, we believe that one question remains to be effectively researched and answered.

We know that work stress and pressure can have a significant impact on the life and wellbeing of working professionals. However, at this point of time, such stress is assumed to be part and parcel of the life of a person pursuing a career; we explain away such pressures as being inherent to the nature of work, rather than as *indicators of some sort of deficiency in optimal performance of work*. With this perspective, it becomes clear that work stress isn't just something to be accepted. To achieve flow (defined as the process of optimal experience (Csikszentmihalyi, 1975, 1982; Inghilleri, 1986b), it is important that factors that affect flow be identified and assessed in terms of their impact on well-being as well. For instance, while it is known from a survey that undesirable interruptions constitute 28 percent of the knowledge worker's day, which translates to 28 billion wasted hours to companies in the United States alone (Spira & Feintuch, 2005), we do not yet have an accurate picture of how these interruptions impact general well-being of the individual. While we have statistics that tell us about monetary losses for organizations to the tune of 700 billion dollars per year (Bureau of Labor Statistics, http://www.bls.gov/), what are the losses in terms of mental/physical health and well-being that are being ignored or underestimated? While most scholars agree that burned-out employees are characterized by high levels of exhaustion and negative attitudes toward their work (cynicism; Maslach, Schaufeli & Leiter, 2001), it is only in recent decades that organizational psychologists have started to become interested in flow at work (Bakker, 2005).

When dealing with productivity analysis on office-goers, research throws up some observations that would be considered obvious in the modern world today; for instance, employees who operate from a well ventilated office with sufficient lighting, high standards of hygiene and relatively sound-proofed spaces are more likely to exhibit high degrees of efficiency and effectiveness at their jobs (Duru, Shimawua, 2017). Even in academia, research has shown that in academic institutions, patterns of physical and mental harassment, rudeness, and exclusionary behaviour have a significant negative impact on job productivity (Anjum, Ming, Siddiqi, Rasool, 2018).

The question we seek to answer here is, is there a way to quantify and assess the effect of work stress on both wellness and productivity? A few attempts have been made in the past that involve active interactions with subjects like the experience sampling method (Csikszentmihalyi, Larson, & Prescott, 1977; Csikszentmihalyi & Larson 1987; Hormuth, 1986, Larson & Csikszentmihalyi, 1983). The remainder of this research article aims to document an alternate method that was utilized, involving collection of data across various sources on individuals representing professions.

MOTIVATIONS

On a side note, it should be noted that this question was not merely an academic consideration for the authors.

The impetus for conducting this research stemmed from specific events in author's lives; a trusted colleague, and a separate dear friend, both of whom appeared to be in the best of health but succumbed seemingly without warning to catastrophic health incidents that resulted in a loss of life.

Amidst the grief came a desire for understanding; these weren't sedentary individuals with unhealthy eating habits working long hours in a chair; to all intents and purposes, these were highly active individuals who understood the need for a healthy diet and fitness routines; so how did things come to such a pass? What were we missing? Were there patterns hidden here that we didn't see until it was *too late* to intervene?

It eventually became our firm conviction that research was necessary and vital to understanding how such events could be anticipated; just as important, how such events could be *mitigated* beforehand to prevent such tragedies from repeating themselves.

MATERIALS AND METHODS

Answering this question took us on a long journey spanning many years.

To begin with, we realized that treating our experiences as one-offs to be analysed wasn't going to work; we needed more data and we needed to cast our nets wider.

We started off by looking at friends, family, and colleagues. Anyone who was willing to listen and engage… we built up profiles of these individuals; *what is your profession? What do you work on? How long do you work?* Once we did this, the next step was to dig a little deeper.

We were looking for patterns; we figured that collecting as much information as we could, would be a good start. We initially had our subjects maintain work diaries in which to record as much information as they could about their day-to-day jobs. This was messy, time-consuming, and ultimately doomed to become unwieldy and unsustainable as the number of subjects grew. At that point of time, we decided to try a slightly different tack.

Statement of hypothesis

To start the statistical analysis, we formulate our null and alternate hypothesis along the lines below. Note that our *assumption* at the start was that the alternate hypothesis would be borne out by the data.

Null hypothesis (Ho)

Increase in undesirable work outcomes has no effect on Stress Management score

Alternate hypothesis (Ha)

Increase in undesirable work outcomes does reduce Stress Management score

Control variables employed

In order to ensure widest spread of data, data was collected in the following proportions from subjects:

- Across multiple job disciplines (criteria explained in section *Organizing subjects based on profile* below)
- Equal numbers of men and women
- Equal proportions of shift-based employees (morning shift and night shift)
- Split in equal proportions across managerial/individual contributor roles
- Spanning multiple countries (United States, India)

Organizing subjects based on profile

(Note: At the outset, we obtained explicit permission from our subjects to collect each data attribute that we utilized in our research)

Some of the information that we collected at the beginning was still useful. Since it was important that we have a wide spread of working professionals represented in our subject list, we identified some key "profiles" of working professionals that we wished to study, and aligned them to specific jobs/professions to aid in classification and segregation. These included:

- Sales professionals
- Software developers
- Support engineers
- Product Managers
- QA engineers

It should be noted that the majority of these subjects were engaged over a period of *5 years* in terms of collection of data for our study.

Evolving quantifiable categories of information to collect

We spent some time interviewing subjects from each of these profiles. Instead of trying to rely on manual recorded observations, we first started with a set of specific questions:

- *What measures do you usually employ in your job profile to determine that your goals have been achieved?*
- *What conditions/outcomes during the course of your specific job profile would be considered as a failure to achieve your goals?*
- *Based on previous questions, how would you categorize your job performance?*

Asking these questions and arriving at a consensus resulted in a set of "criteria" for productivity/wellness for each job profile being evaluated.

General wellness criteria among profiles

For individuals belonging to these profiles, we intended to make a general case for analyzing wellness; accordingly, we captured certain common data across all profiles (like Heart rate, Sleep, Steps and Fitness activity)

Sales Professionals

This profile corresponds to working professionals who work in sales to win deals that result in additional revenue for their employer.

For such individuals, success would be categorized under the following categories:

- Bringing in new sales leads that result in opportunities for increased revenue for the company
- Successfully closing deals with customers to realize additional revenue (and doing it as quickly as possible)

Conversely, there are a few scenarios that could be judged as a "failure" in productivity:

- Failure to bring in new leads over the course of a financial year
- Failure to close out deals, resulting in dropping these opportunities and preventing revenue from being realized
- Failure to *adequately* pursue open opportunities through available methods like customer in person meets, calls, emails/meetings, etc.

Armed with objectives for "gauging" productivity, we captured data from specific data sources:

- Sales related data (CRM)
- Emails/Meetings
- Travel information

Software Developers

This profile corresponds to software engineers who are directly or indirectly responsible for maintaining the code base of products/services/projects in an organization, whether it be by contributing to new features or fixing existing issues.

For such individuals, success would be categorized under the following categories:

- Timely contributions to the source code management system (which would imply quick closure of assigned defects, fast closure of requests for enhancements or new features)
- Good quality contributions (which would imply minimizing of defects arising from changes/fixes to the product, infrequent changes happening on touched source code files, etc.)

Failure in such cases in terms of productivity would include:

- Leaving open assigned defects opened for a long period of time without closure
- Bad quality of code contributions resulting in increased issues, and requiring more code rewrites, slowing down development, etc.

An attempt was made to capture data in these categories:

- Code check-ins in source code management systems utilized by subjects
- Bugs/feature requests in project management software
- Emails/Meetings
- Software App Usage

Support Engineers

This profile corresponds to working professionals who are responsible for directly interfacing with customers utilizing products/services from their organization (with the purpose of customer assistance/support, preliminary analysis, communication with backend teams, and closure of reported issues).

For such professionals, success criteria would include:

- Number of customer issues (aka "tickets") resolved
- Reduced time to resolve filed tickets

On the flip side, failure would include scenarios like:

- Taking too long to resolve tickets
- Having a higher number of critical/high priority tickets open without resolution

To account for such scenarios, we captured data in the following categories:

- Incident management system tickets
- Emails/Meetings

Laying out patterns for a working professional's day

To properly assess the data required to answer this question, it must be framed in a manner that can be tied to typical patterns of work and leisure that working professionals undergo. We started by taking a time interval of 1 day (24 hours) out of the life of a person; we can roughly categorize periods of the day in the manner below. Note that in this instance we are assuming that the subject works in the morning shift; in the case of working professionals who work in different shifts, the time periods and associated tasks/behaviours would change accordingly.

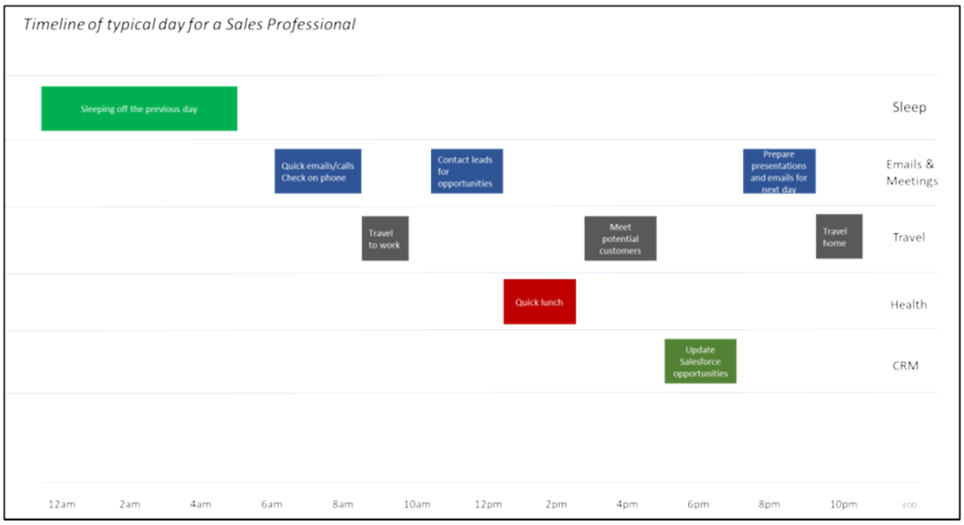
- *Sleep period:* This is the number of hours of the day during which a subject would typically be in a sleep state. The actual quality of sleep during this period would have to be judged by multiple factors (i.e., REM periods, number of times that subject woke up, amount of sleep, how closely it fit circadian rhythms, etc.).
- *Post sleep morning period:* Typically, this is the time just after the subject has woken up, where the subject would indulge in activities that would eventually transition into typical activities during the day; this could include time to brush, take a shower, morning constitutional, breakfast, etc. Note that it's possible that activities during this period may also include preparatory work for the rest of the day or may include physical activities from the point of view of exercise.
- *Office commute period:* This can vary from person to person (and may not even exist for a subject who works remotely 100% of the time). The time period can vary depending on the commute to work distance, condition of traffic based on time of day, etc.
- *Working hours:* This would be the period where a subject is *expected* to engage in most productive activities from the context of the job/profession.
- *Return commute period:* At the conclusion of the day, if the subject is working from an office, this period would coincide with the return journey back to subject's home.
- *Pre sleep period:* Usually associated with a "winding down" of the day (and can also include physical activities), including dinner and relaxation activities followed eventually by commencement of the sleep period.

At this point of the methodology, we had essentially constructed a "picture" of a person's day based on time periods of *presumed activity*. This point is crucial; even aside from the fact that these patterns of time periods can vary depending on "shifts" in which a working professional can operate, it also doesn't fully consider the *quality* of activities that are undertaken during these periods. We instinctively (which is to say, without the need for explicit measurement) can ascertain that it is very rare for a working professional to have periods of activity that occur with such consistency, and even in the event of said periods actually coinciding with the "expected" activities, it is rare that there not be some sort of interruption or negative effect on quality of the activity, be it physical, mental, psychological or otherwise.

The decision was then made to more finetune our picture of working professionals by relying on *sources of data* that are available throughout our subject's day.

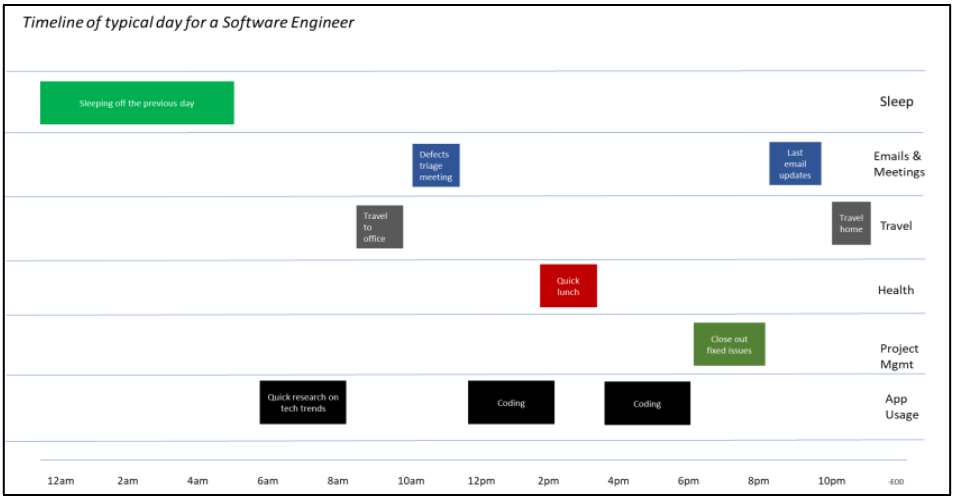
Timeline for a Sales Professional

To accomplish this, we interviewed sales professionals to build a "picture" of the sales professional's day. To do this, we create a timeline that models all 24 hours of a person's day, and then placing (based on their feedback) typical periods of activity. Accordingly, we come up with the following diagram for a particular sales professional:



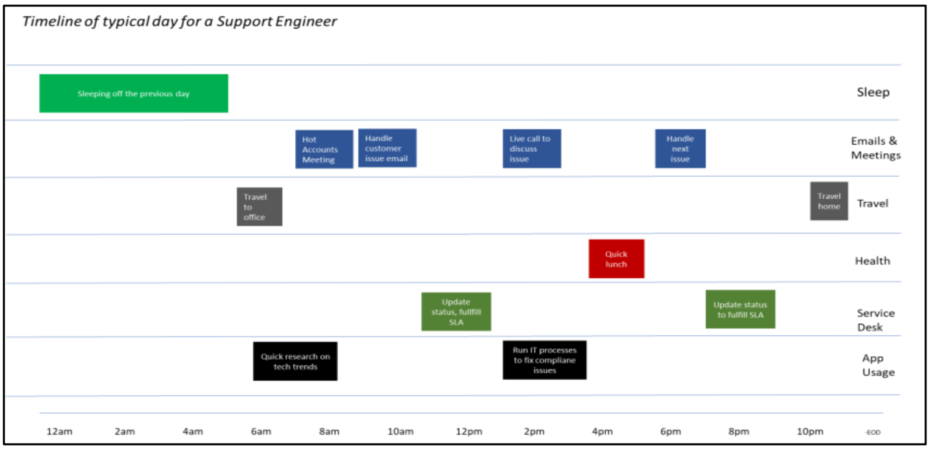
Timeline for a Software Developer

In a similar fashion, we came up with a representative timeline for software developers



Timeline for a Support Engineer

A similar timeline was created for support engineers as follows:



Organizing the set of subjects and data capture

As we mentioned before, our original plan was to have our subjects maintain work diaries that they would write into over time. There were several problems with this approach; for one thing, it wasn't very reliable as a *comprehensive* record of activities since it depended on frequency and accuracy of written entries; for another, it could potentially *detract* from the efficiency with which work activities were undertaken, thus potentially undermining the study.

Once we had this realization, we realized that our only recourse would be to *automate* the collection of data from the subjects. Accordingly, we went back to the subjects, and determined what productivity tools were utilized for our subjects to do their day-to-day jobs? We gathered the answers to this question across all profiles and came up with a list of services/information to be gathered. Over time, we researched methods for gathering this information in an automated fashion (web services, APIs, software/apps, etc.), and began the process of monitoring and collection of information from subjects.

Accordingly, with appropriate disclosures of our intentions and with explicit permission obtained, we arranged for the capture of data from multiple subjects, using appropriate data sources to feed into our research. To briefly summarize the extent of data capture from subjects:

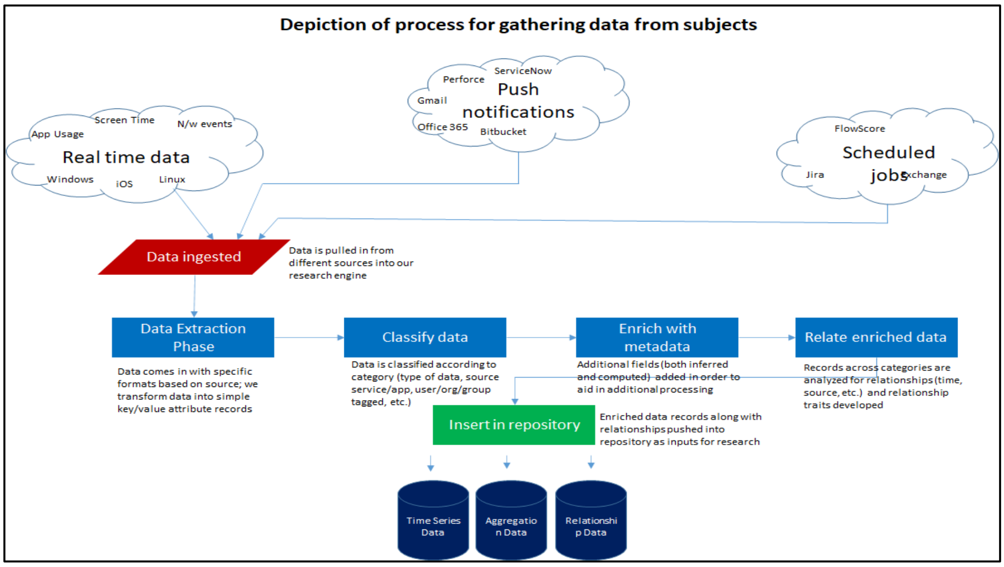
- **Health information:** We collected information about sleep, heartrate, fitness activities, etc. In addition, we also sync a health *score* that fitness tracker tools that subjects make use of.
- **Emails/meetings:** We collected emails/meetings information from popular office suites like Microsoft Office 365, Microsoft Exchange, Gmail, etc. with subject's consent.
- **Business desktop apps:** We collected information about screen time (defined as time spent actively working on a screen of a desktop PC, laptop, mobile, etc.), actual software/processes that the subject was working on, and factors that can influence degradation of work undertaken using business apps (i.e., network interruptions, machine restarts, etc.).
- **Business critical services:** We collected information from services that are utilized in some form or the other by subjects for specific purposes, i.e., CRM data from Salesforce, service desk tickets, tasks/issues filed in project management systems.
- **Mobile phone apps:** Given that cellular phones are now a critical medium of communication and work for professionals, we collected information from phones related to screen time, apps used and duration of usage, etc.

Relating collected data based on specific organizing criteria

Finally, we evolved a system for *relating* the data was collected on multiple criteria to put them into proper context. These organizing criteria fell into the following:

- **Time based**: Data is related based on time of day, hour, day, week, month, year, etc.
- **Organized groups:** Data is aggregated and related based on groups of subjects, by role (i.e., engineers versus managers), by geographic proximity, by organization, etc.

The diagram below summarizes the data collection process:



RESULTS

Based on gathered information, the following results/conclusions were reached:

- We found corelations between factors that impede productivity, and their effect on stress management on the part of subjects
- Intensity of stressful work periods would directly corelate to workplace stress
- Workplace stress would lower productivity across subjects regardless of performance/achievement levels

Corelation between factors that impede productivity and stress management

There appears to be a direct corelation between frequency of factors that impede productivity during intense sessions of productivity and work stress. Some of these factors appear to be tied to the nature of the subjects' profession:

- ➢ For developers, repeated failed attempts to solve a tricky problem, or a sudden influx of severe defects uncovered in submitted work causes high levels of stress
- ➢ For QA, inability to uncover quality defects, and large workloads of defects that require closure with tight deadlines causes high levels of stress
- ➢ For sales, the inability to close important deals and make revenue causes high levels of stress
- ➢ For support, struggling with a high influx of incidents, or dealing with ageing escalations that appear to have no resolution cause high levels of stress
- ➢ For product managers, declining customer satisfaction rates and product revenue cause high levels of stress

Other factors (that appeared in our research) appear to corelate to stress regardless of the nature of the subjects' profession:

- ➢ Influx of negative emails
- ➢ Excessive meetings

Intensity of stressful work periods directly corelates to increased stress

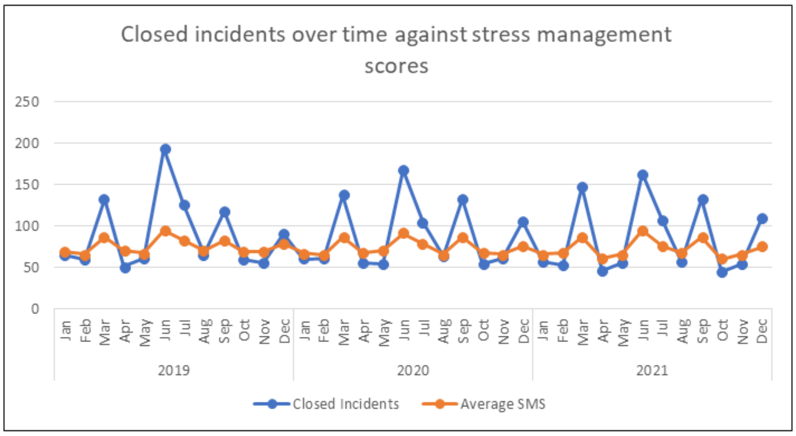
It was further observed that the more prolonged the period of workplace problems, the more cumulative the effects of stress. Short bursts of workplace issues would result in dip in Stress Management scores but would pick up again as issues were resolved; the dip was noticeably longer lasting as workplace issues increased in intensity and duration.

Impact of increased stress lowers productivity regardless of performance level of subjects

It was also observed that a general dip in Stress Management scores occurred as workplace issues increased, regardless of the performance level of subjects. High performers or low, the only difference was in the intensity of the dip (smaller dips in Stress Management scores for high performers). This could possibly be explained by a better ability to handle stress, and could result from factors like better time management, optimizing techniques, etc. and would be the subject of another report.

DATA AND ANALYSIS

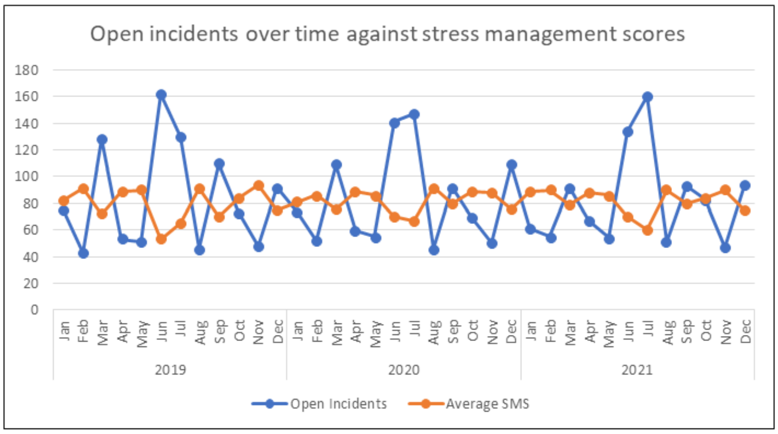
- A common convention was followed across all the subjects for which data (from which below tables/graphs were derived) was collected. We identified multiple disciplines (i.e., sales, support, developers, etc.), and obtained permission from sets of individuals belonging to each discipline to collect their data over a period of 3 years
- These individuals were segregated into “high performers” and “low performers” based on criteria that was specific to their discipline (i.e., salespersons with highest/lowest revenue being brought in, support with highest incident closure rates, etc.).
- We took the *median* of data collected across high and low performers for every day of the time for which data was collected and performed aggregations accordingly to populate tables for our research. This was done to get as accurate a representation as possible of a general trend that can be applied to individuals that fall into either category of performance.



Closed incidents over time against stress management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Closed Incidents	65	59	133	51	61	193	125	66	118	59	55	90	64	70	144	61	55	183	101	69	118	59	54	92	73	69	173	56	45	165	89	79	132	69	59	104
Average SMS	66.00	65.00	87.00	68.00	70.00	95.00	80.00	66.00	85.00	68.00	65.00	76.00	66.00	73.00	86.00	66.00	70.00	93.00	76.00	66.00	84.00	67.00	65.00	75.00	72.00	68.00	91.00	68.00	57.00	91.00	75.00	73.00	90.00	68.00	65.00	80.00

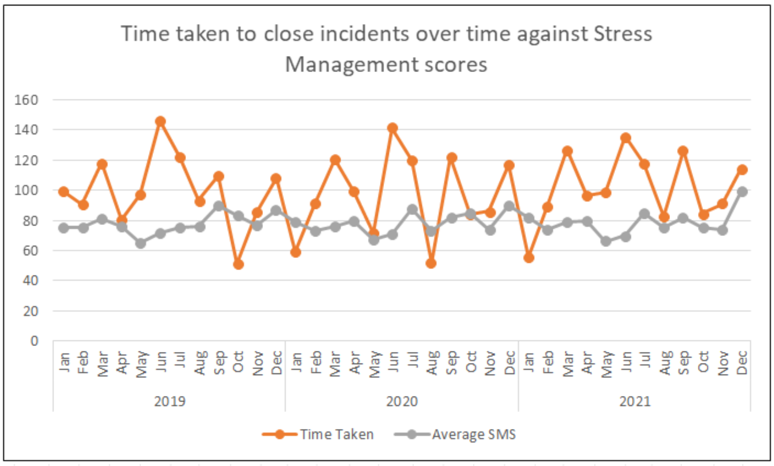
Graph 1.0: Support Engineers: Impact of consistently resolving filed issues on ability to handle stress



Open incidents over time against stress management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Open Incidents	65	59	133	51	61	193	125	66	118	59	55	90	57	53	124	42	63	220	146	71	119	60	65	92	67	59	133	34	72	216	172	76	130	61	61	82
Average SMS	89.00	86.00	68.00	85.00	90.00	54.00	70.00	89.00	70.00	88.00	85.00	75.00	90.00	89.00	75.00	91.00	85.00	50.00	65.00	84.00	70.00	88.00	90.00	78.00	86.00	90.00	70.00	92.00	83.00	50.00	53.00	82.00	65.00	86.00	87.00	84.00

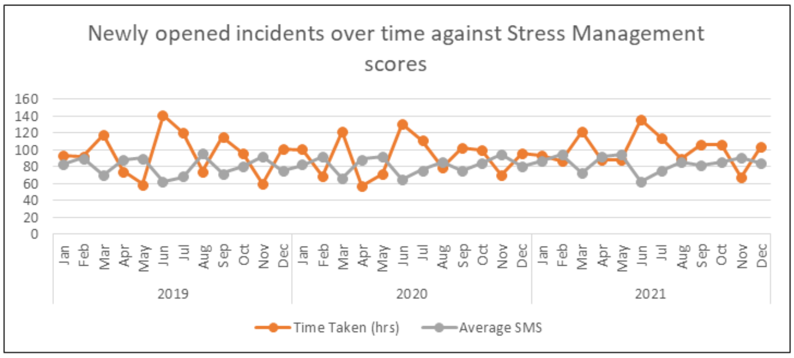
Graph 1.1: Support Engineers: Effect of excessive open issues on ability to handle stress



Time taken to close incidents over time against Stress Management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Closed Incidents	65	59	133	51	61	193	125	66	118	59	55	90	59	48	132	61	54	172	128	59	139	59	58	104	51	55	156	61	63	165	129	48	152	51	52	104
Time Taken	100	90	118	80	97	146	122	93	110	52	86	108	59	91	121	99	72	141	120	52	122	84	86	117	55	89	127	97	99	136	118	83	126	85	91	114
Average SMS	75	75	81	76	65	72	75	76	90	83	77	87	79	73	76	80	67	71	88	73	82	85	74	90	82	74	79	80	66	70	85	75	82	75	74	99

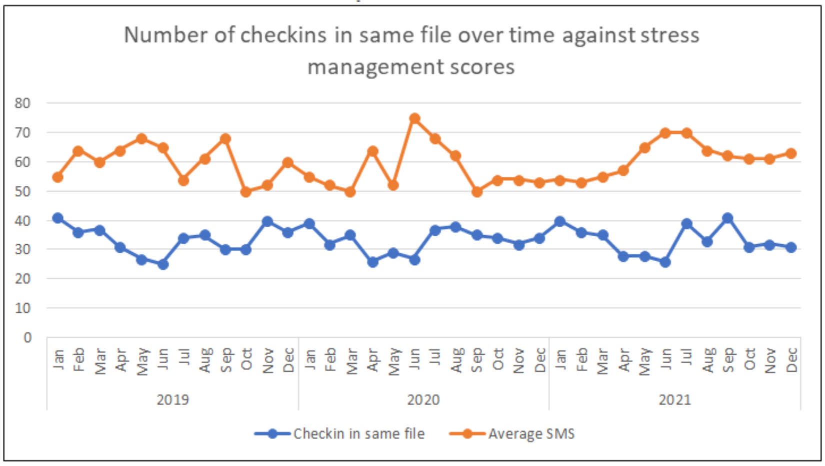
Graph 1.2: Support Engineers: Impact of time taken to solve problems on ability to handle stress



Newly opened incidents over time against Stress Management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Open Incidents	75	43	128	53	51	162	130	46	110	73	48	92	71	47	138	52	45	149	104	54	95	71	38	75	63	42	126	47	42	164	115	55	83	84	39	80
Time Taken (hrs)	94.6	63.9	122	64.9	59.2	137	124	58.5	109	99.4	75.5	104	98.6	72.2	117.7	87.8	65.5	128.7	113.2	73	100.9	97.2	90.8	94.7	93.3	80.4	124.6	70.7	82.9	137.9	111.1	58.1	108	106	64.8	101
Average SMS	83	90	70	88	90	62	68	95	72	80	92	75	82	92	66	89	92	65	76	86	75	84	94	80	87	94	73	92	94	62	75	85	81	85	91	84

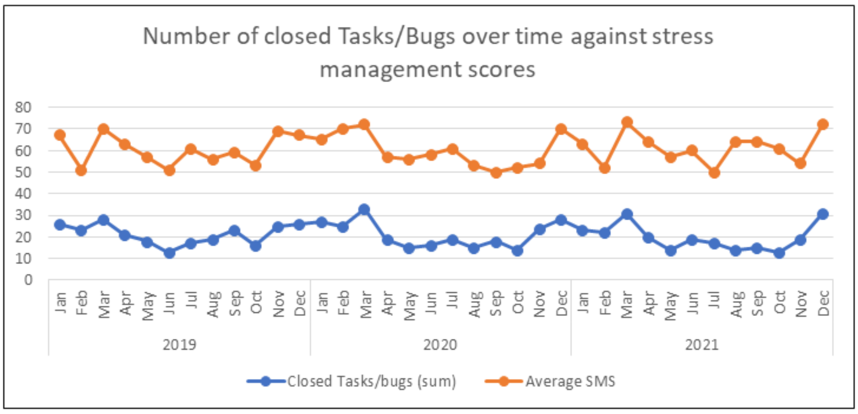
Graph 1.3: Support Engineers: How does a sudden increase in issues affect the ability to handle stress



Number of checkins in same file over time against stress management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Checkin in same file	41	36	37	31	27	25	34	35	30	30	40	36	39	32	35	26	29	27	37	38	35	34	32	34	40	36	35	28	28	26	39	33	41	31	32	31
Average SMS	55	64	60	64	68	65	54	61	68	50	52	60	55	52	50	64	52	75	68	62	50	54	54	53	54	53	55	57	65	70	70	64	62	61	61	63

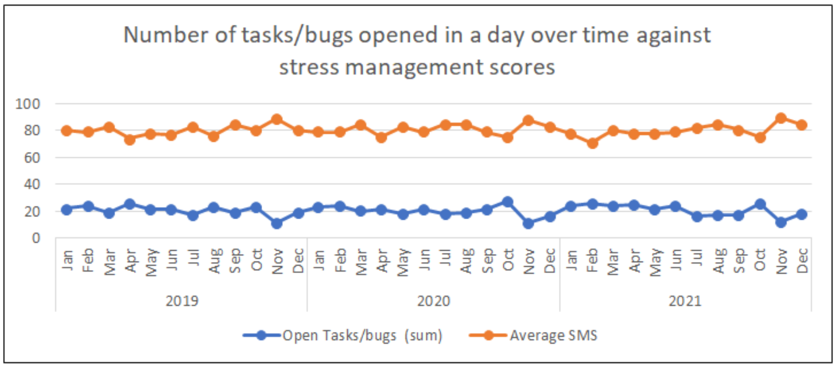
Graph 2.3: Developers: How having to address repetitive problems in software affects ability to handle stress



Number of closed Tasks/Bugs over time against stress management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Closed Tasks/bugs (sum)	26	23	28	21	18	13	17	19	23	16	25	26	27	25	33	19	15	16	19	15	18	14	24	28	23	22	31	20	14	19	17	14	15	13	19	31
Average SMS	67	51	70	63	57	51	61	56	59	53	69	67	65	70	72	57	56	58	61	53	50	52	54	70	63	52	73	64	57	60	50	64	64	61	54	72

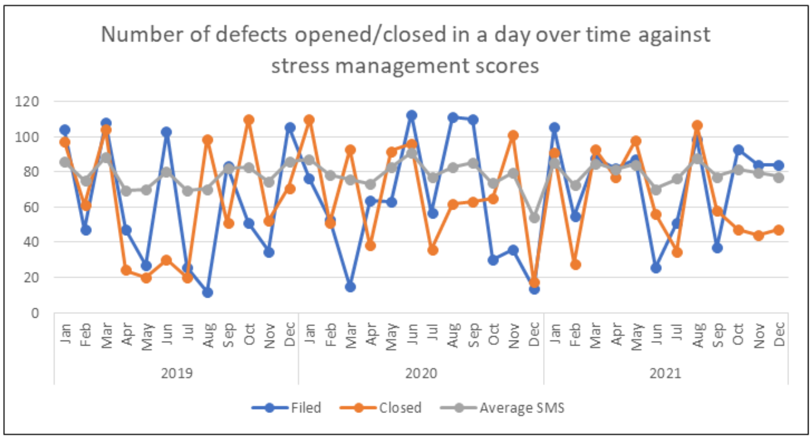
Graph 2.4: Developers: How reliably and consistently resolving problems affects the ability to handle stress



Number of Tasks/bugs opened (assigned) in a day over time against stress management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Open Tasks/bugs (sum)	22	24	19	26	21	21	17	23	19	23	11	19	23	24	20	21	18	21	18	19	21	27	11	16	24	26	24	25	21	24	16	17	17	26	12	18
Average SMS	80	79	83	74	78	77	83	76	85	80	89	80	79	79	85	75	83	79	85	85	79	75	88	83	78	71	80	78	78	79	82	85	81	75	90	85

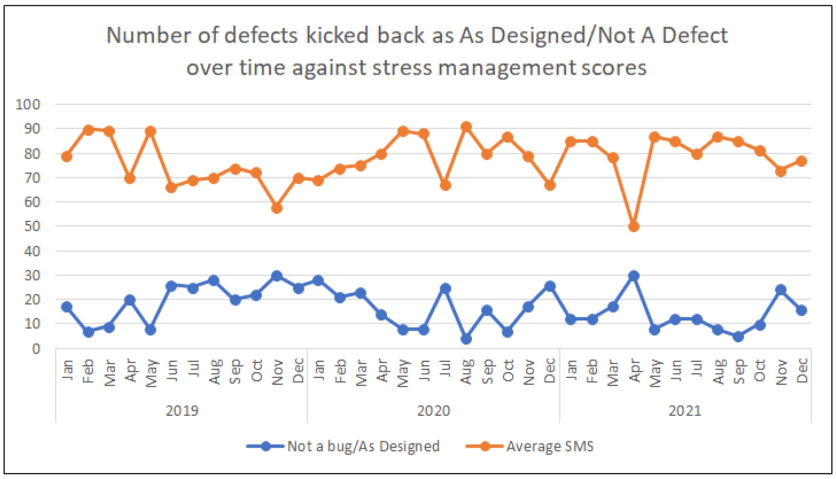
Graph 2.5: Developers: How a sudden influx of problems to resolve affects the ability to handle stress



Number of defects filed/closed in a day over time against stress management scores

Year	2019												2020												2021											
Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Filed	104	47	108	47	27	103	26	12	83	51	35	106	76	53	15	64	63	113	57	111	110	30	36	14	105	55	88	82	87	26	51	99	37	93	84	84
Closed	97	61	104	24	20	30	20	99	51	110	52	71	110	51	93	38	92	96	36	62	63	65	101	17	91	28	93	77	98	56	35	107	58	47	44	47
Average SMS	86	75	89	70	70	80	70	71	82	83	75	86	87	79	76	73	83	91	77	83	86	74	80	55	86	73	85	82	85	71	76	88	78	82	80	78

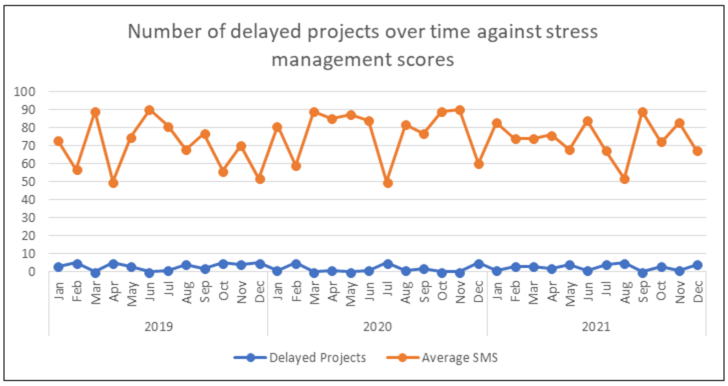
Graph 3.0: QA: How reliably and consistently reporting problems and successfully verifying solutions affects the ability to handle stress



Number of defects kicked back as As Designed/Not A Defect over time against stress management scores

Year	2019												2020												2021											
Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Not a bug/As Designed	17	7	9	20	8	26	25	28	20	22	30	25	28	21	23	14	8	8	25	4	16	7	17	26	12	12	17	30	8	12	12	8	5	10	24	16
Average SMS	79	90	89	70	89	66	69	70	74	72	58	70	69	74	75	80	89	88	67	91	80	87	79	67	85	85	78	50	87	85	80	87	85	81	73	77

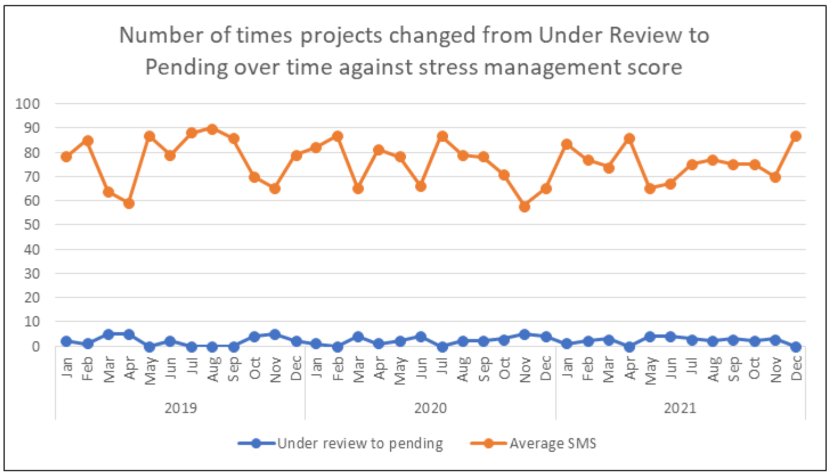
Graph 3.1: QA: How system updates resulting from unfocused execution of tasks can affect ability to handle stress



Number of delayed projects over time against stress management scores

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Delayed Projects	3	5	0	5	3	0	1	4	2	5	4	5	1	5	0	1	0	1	5	1	2	0	0	5	1	3	3	2	4	1	4	5	0	3	1	4
Average SMS	73	57	89	50	75	90	81	68	77	56	70	52	81	59	89	85	87	84	50	82	77	89	90	60	83	74	74	76	68	84	67	52	89	72	83	67

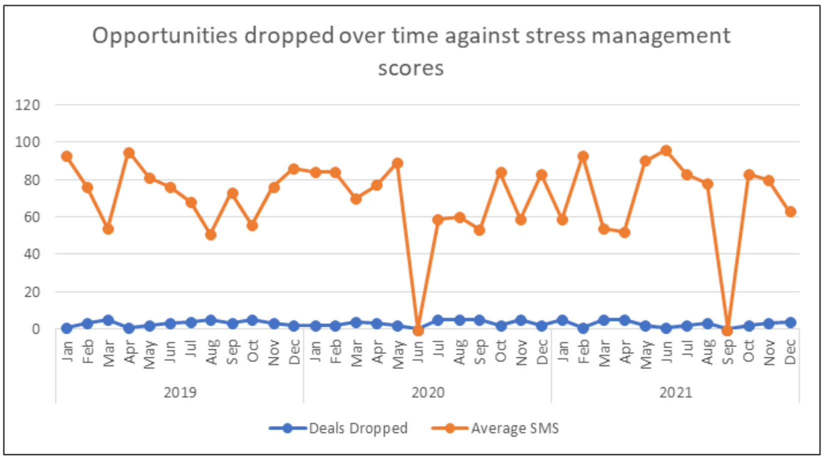
Graph 4.0: PM: How an influx of delayed projects affects the ability to handle stress



Number of times projects changed from Under Review to Pending over time against stress management score

Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Under review to pending	2	1	5	5	0	2	0	0	0	4	5	2	1	0	4	1	2	4	0	2	2	3	5	4	1	2	3	0	4	4	3	2	3	2	3	0
Average SMS	78	85	64	59	87	79	88	90	86	70	65	79	82	87	65	81	78	66	87	79	78	71	58	65	84	77	74	86	65	67	75	77	75	75	70	87

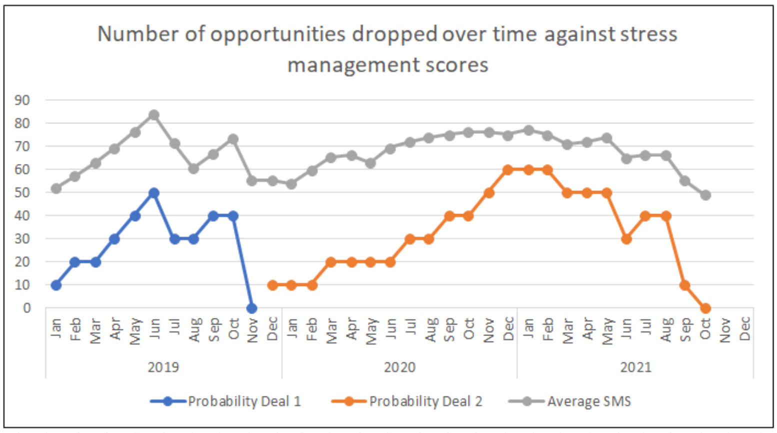
Graph 4.1: PM: How an increase in unsuccessful projects can affect the ability to handle stress



Opportunities dropped over time against stress management scores

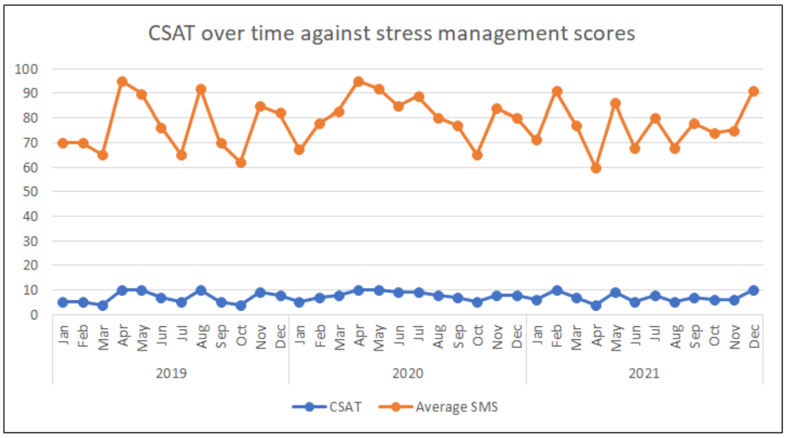
Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Deals Dropped	1	3	5	1	2	3	4	5	3	5	3	2	2	2	4	3	2	0	5	5	5	2	5	2	5	1	5	5	2	1	2	3	0	2	3	4
Average SMS	93	76	54	95	81	76	68	51	73	56	76	86	84	84	70	77	89	0	59	60	53	84	59	83	59	93	54	52	90	96	83	78	0	83	80	63

Graph 5.0: Sales: Number of sales opportunities dropped over time against stress management scores



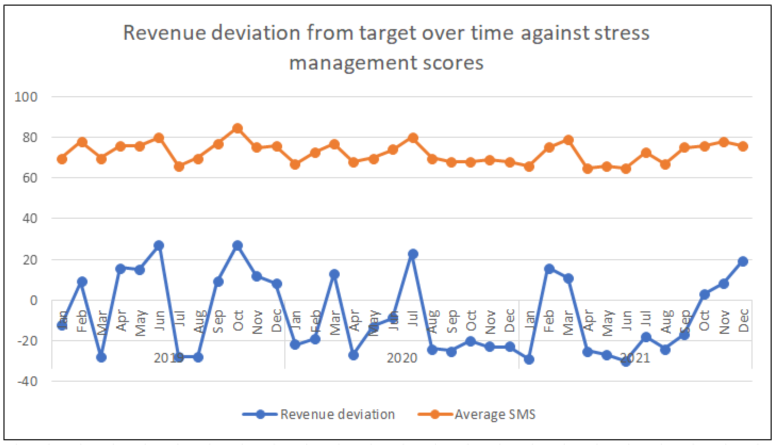
Number of opportunities dropped over time against stress management scores																																				
Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Probability Deal 1	10	20	20	30	40	50	30	30	40	40	0																									
Probability Deal 2												10	10	10	20	20	20	20	30	30	40	40	50	60	60	60	50	50	50	30	40	40	10	0		
Average SMS	52	57	63	69	76	84	71	61	67	73	55	55	54	59	65	66	63	69	72	74	75	76	76	75	77	75	71	72	74	65	66	66	55	49		

Graph 5.1: Sales: How outcomes of pursued sales deals can affect the ability to handle stress



CSAT over time against stress management scores																																				
Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CSAT	5	5	4	10	10	7	5	10	5	4	9	8	5	7	8	10	10	9	9	8	7	5	8	8	6	10	7	4	9	5	8	5	7	6	6	10
Average SMS	70	70	65	95	90	76	65	92	70	62	85	82	67	78	83	95	92	85	89	80	77	65	84	80	71	91	77	60	86	68	80	68	78	74	75	91

Graph 6.0: Product Management: How dipping/increasing customer satisfaction stores can affect the ability to handle stress



Revenue deviation from target over time against stress management scores																																				
Year	2019												2020												2021											
Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Revenue deviation	-12	9	-28	16	15	27	-28	-28	9	27	12	8	-22	-19	13	-27	-13	-9	23	-24	-25	-20	-23	-23	-29	16	11	-25	-27	-30	-18	-24	-17	3	8	19
Average SMS	70	78	70	76	76	80	66	70	77	85	75	76	67	73	77	68	70	74	80	70	68	68	69	68	66	75	79	65	66	65	73	67	75	76	78	76

Graph 6.1: Product Management: How struggling to meet revenue targets can affect your ability to handle stress

DETAILED ANALYSIS

In this section we discuss conclusions that can be drawn from collected information and graphs derived from information collected.

In *Graph 1.0*, we plotted the total number of incidents that were marked to Closed state (implying that the observed support engineer subjects successfully resolved the associated incident and closed it in the system) over a period of 3 years. During this observation period, we calculated the average of generated Stress Management scores across days in each month. We observed a consistent trend where an increase in number of closed incidents was accompanied by an increase in Stress Management scores (note: an increased Stress Management score indicates increased resilience and well-being). Conversely, a dip in number of closed incidents roughly precipitated a drop in average Stress Management scores (with a *p-value* < 0.04).

In *Graph 1.1*, we plotted the total number of incidents that were in Open state (implying that the observed support engineer was dealing with incidents that were taking time to resolve and presumably causing negative outcomes in terms of stress, urgency, etc.) over a period of 3 years. During this observation period, we calculated the average of generated Stress Management scores across days in each month. We observed a consistent trend where an increased number of Open incidents was accompanied by a decrease in Stress Management scores. Conversely, a dip in number of Open incidents was accompanied by an increase in Stress Management scores (with a *p-value* < 0.04).

In Graph 1.2, we plotted the total time taken to close incidents over a period of 3 years, selectively filtering out a maximum of 3 incidents daily. The criteria for selection of the incidents were by sorting in descending order based on total time taken to close incidents (longest to shortest) and selecting up to 3 incidents on given day. During this observation period, we calculated the average of generated Stress Management scores across days in each month. We observed a consistent trend where increased time taken to close incidents was accompanied by a decrease in Stress Management scores. Conversely, a decrease in time taken to close incidents was accompanied by an increase in Stress Management scores (with a *p-value* < 0.04).

In Graph 1.3, we plotted the total number of newly opened incidents over time over a period of 3 years. During this observation period, we calculated the average of generated Stress Management scores across days in each month. We observed a consistent trend where many opened incidents in each interval was accompanied by a decrease in Stress Management score; conversely, a lesser number of opened incidents in each interval would be accompanied by a noticeable increase in Stress Management scores (with a *p-value* < 0.04).

In Graph 2.3, we concentrated on specific characteristics of work done by software developers, particularly referencing aspects of their day where they work with a source code management (SCM) system. Any changes made by developers usually results in a *code check in*, which results in changes to source files. Every code check-in can affect one or more files. In software engineering, it is usually a good practice to check in changes to source code after thoroughly establishing the validity of the change (which could involve some forms of testing, review of the proposed change, etc.). For this reason, having an unusually large number of code check-ins in the *same source file* is considered by experts to be an indicator that the desired outcome is not being met despite repeated events. When we plotted this metric across the average of generated Stress Management scores across days in each month for 3 years, we observed a consistent trend where many check-ins in the same source file coincided with a decrease in Stress Management scores, and a smaller number of check-ins in the same source file would result in higher Stress Management scores (with a *p-value* < 0.04).

In Graph 2.4, we took cognizance of the fact that developers (who are working on addressing issues in code) are frequently required to update the status of filed bugs in some sort of bug tracking/defect management system. When a developer finish addressing of an issue in code, the developer will usually mark the bug in said system as Closed (in some systems, the state of the bug will change to In QA and the assigned QA engineer will verify the defect fix and mark it as Closed). Similarly, any enhancements/new functionality added by a developer will usually require the developer to update the associated *task* in a Task Management system (like Jira) to Closed (to indicate completion of the task). When we plotted the total number of closed Tasks/Bugs by a developer daily over a time period of 3 years against the average of Stress Management scores across each month of the time period, we observed a noticeable decrease in Stress Management Scores coinciding with a decrease in closed tasks/bugs (with a *p-value* < 0.04).

In Graph 2.5, we looked at data with respect to Open bugs/tasks assigned to developers. These are usually an indicator of “unfinished” work for the developer, more-over the *priority* of the Task/Bug can indicate its urgency to the filer (i.e., Critical bugs opened for a developer usually indicate the need to *fix this right now!*). When we plotted the total number of bugs opened in a day over a period of 3 years against the average of Stress Management scores monthly across the same time period, we observed that an increase in number of open bugs filed would coincide with a decrease in Stress Management Scores and vice versa (with a *p-value* < 0.04).

In Graph 3.0, we approached data gathered from QA engineers. QA engineers primarily evaluate software to look for issues; when issues are found, they usually file open bugs in associated systems. When a developer finish addressing the bug, QA engineers are required to *verify* that the Bug was addressed correctly by the change done by the developer, and mark the bug as closed. There are certain situations, however, where a developer can find that the QA engineer has incorrectly reported an issue; these can occur for various reasons. We looked at two reasons in particular; if a developer finds that the QA engineer reported an issue because of misunderstanding that the observed behaviour was part of the feature design, the developer can *kick back* the defect as "As Designed", in a related scenario, if the developer thinks that a reported issue either does not exist or is not really an issue, the developer can kick back the defect as Not A Defect. These two indicators are usually considered to be negative consequences for a QA engineer (as they imply a lack of understanding of the feature being tested). When we plotted the total number of defects kicked back as "As Designed" or "Not A Defect" over a period of 3 years against the average Stress Management Score across months in the same period, we observed that as the total number of such kicked back defects increased, this would coincide with a decrease in Stress Management scores, and vice versa (with a *p-value* < 0.04).

In Graph 3.1, filing of Open defects is usually considered an indicator that a QA engineer is performing an adequate job; similarly, successful closure of defects by the QA engineer is perceived the same way. When we plotted the total number of defects opened/closed across 3 years against the average Stress Management Score across months in the same period, we observed that as the total number of defects opened/closed increased, this would coincide with an increase in Stress Management scores, and vice versa (with a *p-value* < 0.04).

In Graph 4.0, we looked at project managers. When we plotted the total number of delayed projects over a period of 3 years against average Stress Management Score across months in the same time period, we observed that as the total number of delayed projects increased, this would coincide with a drop in Stress Management scores, and vice versa (with a *p-value* < 0.04).

In Graph 4.1, for project managers, when we plotted the total number of times a project changed from Under Review to pending (which would indicate that projects were not getting completed successfully and were continuously being reworked upon) against average Stress Management Score across months in the same time period, we observed that as the total number of times this occurred, it would coincide with a drop in Stress Management scores, and vice versa (with a *p-value* < 0.04).

In Graph 5.0, for sales professionals, we relied on their usage of CRM tools (like Salesforce) to track relevant attributes. In this graph, we plotted the number of sales opportunities that were dropped (indicating that revenue could not be realized) over a time period of 3 years against average Stress Management Score across months in the same time period, we observed that as the total number of times this occurred, it would coincide with a drop in Stress Management scores, and vice versa (with a *p-value* < 0.04).

In Graph 5.1, we exploited the feature in CRM systems to track changes (over time) in the probability of a deal. The *probability* of a deal is the likelihood that it will result in a sale (and gain in revenue). We observed an increase in Stress Management scores for opportunities where probability trended *upwards*, on opportunities where probability decreased (i.e., deal becoming more and more unlikely to materialize), we would see a corresponding decrease in Stress Management scores (with a *p-value* < 0.04).

In Graph 6.0, we concentrated on *product managers*, who are responsible for managing the lifecycle of a product in various ways. We picked two methods of evaluating workplace activities for product managers, a measure called a CSAT (Customer Satisfaction) score that evaluates how satisfied customers are with the product (this information usually comes in through surveys of said customers); the other measure being assessing the percentage by which the actual revenue brought in by a product deviated from the set *targets* for revenue of the product. In 6.0, we observed that as CSAT values increased, there was a corresponding increase in Stress Management scores, and vice versa (with a *p-value* < 0.04).

In Graph 6.1, as the deviation trended towards a positive value (indicating a product *beating* revenue estimates), this would coincide with an increase in Stress Management scores, and vice versa (with a *p-value* < 0.04).

IDEAS FOR STRESS MITIGATION

While the focus of this article is to investigate if a co-relation exists between workplace stress and wellness and productivity, the authors would also like to offer some ideas and strategies for mitigation of stress based on our research:

- When dealing with repetitive tasks, a certain degree of automation can significantly reduce stress. For example, a support engineer who is required by

Service Level Agreements (SLAs) to respond to customer complaint emails within minutes can greatly benefit from employing tools that provide an automated acknowledgement of the complaint, leaving the engineer to concentrate on actual problem resolution.

- Time slicing potential stressful activities so that they are restricted to specific periods of the day (i.e. handling urgent requests for updating tasks in system, etc.) can result in significant drop in stress levels, and increase the perceived "value" of work completed due to active prioritization and time management.
- Utilizing tools that enable a professional to monitor current progress and which thereby provides *actionable* suggestions/guideposts for achieving short term goals can greatly reduce the uncertainty of performance self-assessment; by enabling professionals to accordingly prioritize what has to be done in *limited time available* allows them to maximize productivity, and also has the effect of reducing stress from uncertainty and lack of awareness of goals.
- Using time reclaimed from strategies for optimizing work in order to pursue health and fitness goals is a hugely successful strategy for reducing stress, and improving health outcomes in general.

CONCLUSIONS

Based on our results, p values generated lead us to *reject* our null hypothesis (i.e. increase in undesirable work outcomes has no effect on Stress Management score), and thereby indicate that our alternate hypothesis was more likely.

The results we obtained from our research did go some way towards confirming the link between work stress and wellness along with productivity. The research made clear that the effects of work stress are not momentary; a consistent pattern of work stress causes widespread changes in mental/physical health as measured through key metrics, and results in a significant loss of productivity, which can hamper entire teams and organizations at critical junctures in the long run.

It also became apparent that with sufficiently advanced analytics and diligent data capture, we can both recognize patterns of work stress and actively *change conditions* so that work stress is mitigated (if not eliminated completely). It is not necessary to merely pause at a method of diagnosis in other words; the need of the hour is active mitigation by recognition of beneficial patterns of work to productivity and wellness (which may well be the subject of further research articles).

REFERENCES

- Demerouti, Mostert: Burnout and Work Engagement: A Thorough Investigation of the Independency of Both Constructs.
- Csikszentmihalyi, LeFevre: Optimal Experience in Work and Leisure.
- Brightbill, C. K. (1960). The challenge of leisure. Englewood Cliffs, NJ: Prentice-Hall.
- Dumazedier, J. (1974). Sociology of leisure. New York: Elsevier.
- Neulinger, J. (1974). The psychology of leisure. Springfield, IL: Charles C Thomas
- Csikszentmihalyi, M. (1975). Beyond boredom and anxiety. San Francisco, CA: Jossey-Bass.
- Csikszentmihalyi, M. (1982). Toward a psychology of optimal experience. In L. Wheeler (Ed.), Review of personality and social psychology (pp. 13-36). Beverly Hills, CA: Sage.
- Spira, J. B., & Feintuch, J. B. (2005). "The Cost of Not Paying Attention: How Interruptions Impact Knowledge Worker Productivity", Basex.
- Bureau of Labor Statistics, http://www.bls.gov/
- Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, 52, 397-422.
- Bakker, A. B., Demerouti, E., & Verbeke, W. (2004). Using the job demands-resources model to predict burnout and performance. *Human Resource Management*, 43, 83-104.
- Hurtz, G. M., & Donovan, J. J. (2000). Personality and job performance: The big five revisited. *Journal of Applied Psychology*, 85, 869-879.
- Duru, C. E., & Shimawua, D. (2017). The effect of work environment on employee productivity: A case study of edo city transport services benin city, edo state Nigeria. *European Journal of Business and Innovation Research*, *5*(5), 23-39.
- Anjum, A., Ming, X., Siddiqi, A. F., & Rasool, S. F. (2018). An empirical study analyzing job productivity in toxic workplace environments. *International journal of environmental research and public health*, *15*(5), 1035.