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ORIGINAL RESEARCH

Mental Health in Tech: Analysis of Workplace Risk Factors and Impact of COVID-19

K. M. Mitravinda[1] · Devika S. Nair[1] · Gowri Srinivasa[1]

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Abstract
The psychological, emotional and social well-being of an individual determines their ability to contribute and function as a social member. Several studies over the years have proven that an alarming number of people live with mental illnesses, of which only a fraction is documented. Studies conducted by Open Sourcing Mental Illness (OSMI) organization have indicated that these figures are much higher in the tech industry. We present an analysis of patterns and infer contributory factors for mental illness in the tech industry, to aid in the early detection and assess employees' risk of diagnosis. Towards this end, the study comprises a detailed analysis, models for prediction of diagnosis, risk-based clustering and investigation into existing literature on factors contributing to mental illness. In addition to this, we have attempted to understand the impact of Covid-19 through analyzing trends of the factors influencing mental health, pre- and post-pandemic. We conclude with an insight to the impact of the COVID-19 pandemic on global mental health and the actions taken in the workplace to mitigate this.

Keywords Mental health · Risk · Clustering · Prediction · COVID-19

Introduction

WHO estimated that globally, nearly 264 million people suffer from depression and anxiety [1]. The consequent loss of productivity due to employees suffering from depression and anxiety related disorders is estimated to have cost the global economy nearly USD 1 trillion per year [2]. In 2019, over 53.2 million full-time employees were employed in the information and communication technology sector and the number is forecasted to reach 62 million by 2023 [3]. Given the increasing number of employees in the tech sector, it is crucial to consider the workplace-factors affecting the mental health of employees, for a negative working environment can result in physical and mental health problems.

Despite the massive number of people diagnosed with mental health issues, the estimated median delay after the onset of mental health issues, until the first contact with a general medical doctor is 10 years and 11 years until the first contact with a psychiatrist. Even for the most severe disorders, the average delay between the onset and first treatment contact is 5 years [4]. According to studies, untreated mental health disorders can progress in frequency, severity, and spontaneity [5]. Diagnosis and early intervention in the initial stages of a mental health issue can have consequential effects on a person's mental health as it allows for timely and effective treatment [6].

From Prediction to Prevention Using Analytics

Predictive analytics in mental health is an emerging field with significant capabilities to revolutionize the clinical practice in psychiatry, further prompting improvements in personalized and precision medicine [7]. Further, the use of

K. M. Mitravinda and Devika S. Nair have contributed equally to this work.

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✉ Gowri Srinivasa
gsrinivasa@pes.edu

K. M. Mitravinda
mitravinda462@gmail.com

Devika S. Nair
devika.dsn@gmail.com

1 PES Center for Pattern Recognition, Department of Computer Science and Engineering, PES University, Bengaluru, Karnataka, India

machine learning to develop risk models to determine an individual's risk of progressing to a mental health condition can greatly aid the processes of early detection and diagnosis of mental health issues [8]. This, in turn, allows for early preventive interventions.

What is the present study about? This study presents a machine learning workflow to not only predict employees' disposition of progressing to a mental health issue, but also to identify and understand the factors that influence employees' mental health in their workplaces. Further, we investigate the impact that the COVID-19 pandemic and its attendant challenges, such as quarantine and lockdown that limited social contact with friends and family, had on mental health.

Related Work

Research to detect mental health issues. Detection and diagnosis of mental health issues in individuals is one of the major applications of machine learning in the mental health domain. It also involves modelling risk frameworks to predict the individuals' susceptibility to mental health issues which can help in providing early interventions [8–10].

Another recent study asserted that care for mental health is based mostly on self-assessment as mental issues are the consequences of patients' behaviour. The study also demonstrated that predictive models could be used to identify a patient who requires relatively higher care and concern [11].

Models have also been used to predict mental health disorders in employees of technical and non-technical companies [12, 13]. Among other observations, these studies have reported employees' past mental health issues and their family history of mental illness as the most-contributing features for predicting mental health disorders.

Patterns of stress in employees and factors contributing most to stress-levels have been analyzed in the context of the tech industry [14]. However, these studies conducted during the pre-pandemic years, do not factor the impact of COVID-19 and the attendant changes to lifestyle, the work culture and general psychological distress that the pandemic had on people's mental health. This paper aims to provide predictions on the employees' mental health and employee risk-levels to help organisations understand their employees' mental health and identify any workplace contributory factors. We hope these insights would raise the awareness of employers and thereby effect workplace mental health interventions to improve their mental well-being.

Dataset

The data used in this study are the Open Sourcing Mental Illness (OSMI)—Mental Health in Tech Survey for the years 2016–2021 [15]. The 2016 survey aims to gauge the attitudes towards mental health of employees in tech and examines the frequency of mental health issues among them); this comprises over 1400 responses collected for 63 questions related to mental health of the employees, their view towards mental health in the workplace, awareness of mental health, demographics, etc. Similarly, the data sets of OSMI Mental Health in Tech Survey 2017–2021 comprise 756 respondents in 2017, 417 in 2018, 352 in 2019, 180 in 2020 and 131 in 2021. The data sets were used to analyse the trends in the workplace culture, mental health scenario of employees and understand the impact of COVID-19 on the same.

Proposed Methodology

A schematic diagram of the analytics pipeline used in this study is presented in Fig. 1.

Pre-processing and Exploratory Data Analysis

The first step in the analytics pipeline is pre-processing the OSMI Mental Health in Tech Survey 2016 data set. It included cleaning the data (columns with over 50% missing values were dropped) and column names were changed for consistency and facilitate easy referencing. This was

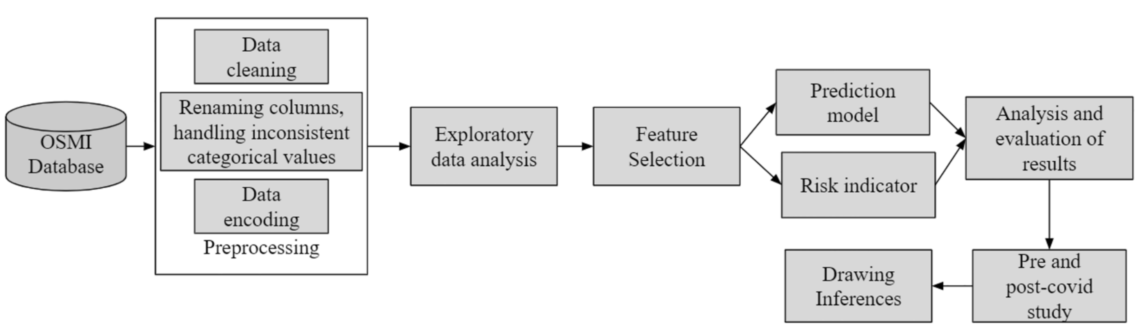

Fig. 1 System level design of the major phases of the project

followed by replacing outliers in a category with the column average. Finally, we resorted to encoding categorical and ordinal variables to be amenable to apply various exploratory data analysis (EDA) techniques for feature selection and build predictive models.

Data Visualization

Data visualization was performed on the OSMI Mental Health in Tech Survey 2016 to understand and study the mental health scenario in workplaces and its impact on the employees' mental wellness. *Effect of company-size on provision of mental health benefits:* The variations in the percentage of employees provided with mental health benefits as a part of health coverage in companies of different sizes was explored. It was found that the fraction of employees who received mental health benefits as a part of health coverage increases with increase in the company-size. The highest percentage of employees (74.8%) provided with mental health benefits was seen in the companies with more than 1000 employees and the lowest percentage (21.1%) was seen in the companies with 1–5 employees.

Employees' awareness of available mental health care options: The employees' awareness on the mental health care options available to them showed that only 37.1% of the employees were aware of the mental health care options available to them, while 31.2% of the employees were not aware and 31.7% of them were not sure of the options available. Thus, employers must put efforts towards promoting awareness about mental health among their employees and the mental health benefits available to them. Such awareness can not only better equip the employees to manage their mental well-being, but also encourage them to support and empower other employees in improving their mental wellness.

Gender diversity (across geographic regions) in tech: The proportions of employees of different genders in different geographic regions were explored. It can be seen from Fig. 2 that a majority of the employees were male in all the 3 geographic regions considered, with the Asia and Africa region reporting the highest percentage (87.5%) of male employees. The representation of female employees and employees of other gender minorities like: bigender, transgender, non-binary, transfeminine, etc., was minimal in all the three regions considered. The highest percentage of female employees seen was only 29.7%, seen in North, South and Central America, whereas the highest percentage of employees of other gender minorities was merely, 2.6% in the Europe and Australia.

Employees' openness (across geographic regions) to share mental illness: The willingness of employees to share their mental illness with their friends and family was studied across different geographic regions. Figure 3 shows that the majority (over 40%) of employees in all three regions considered were somewhat open to share their mental illness with friends and family. The highest percentage (18.5%) of employees who were very open share was found in the Europe & Australia region and the lowest percentage (10%) was seen in the Asia & Africa region. Interestingly, the lowest percentage (2.5%) of employees who were not open to share was also seen in the Asia & Africa region. This could be due to the Asia & Africa region comprising of the highest percentage (25%) of employees who had a neutral stance regarding sharing their mental illness.

Fear (in men and women) to discuss mental health issues with employer: The fear of negative consequences in male and female employees on discussing mental health issues with their employers was studied. Figure 4 shows that a higher percentage (25.3%) of female employees were afraid of the negative impact of disclosing their mental health issues with their employers compared to the percentage (16.3%) of male employees who bore the same fear. Similarly, a lower percentage (33.3%) of female employees felt that discussing their mental health issues with their employers will not have any negative consequences.

Employees' level of comfort to discuss mental health issues with supervisors: Figure 5 depicts the level of comfort of employees whose employers (a) have discussed mental

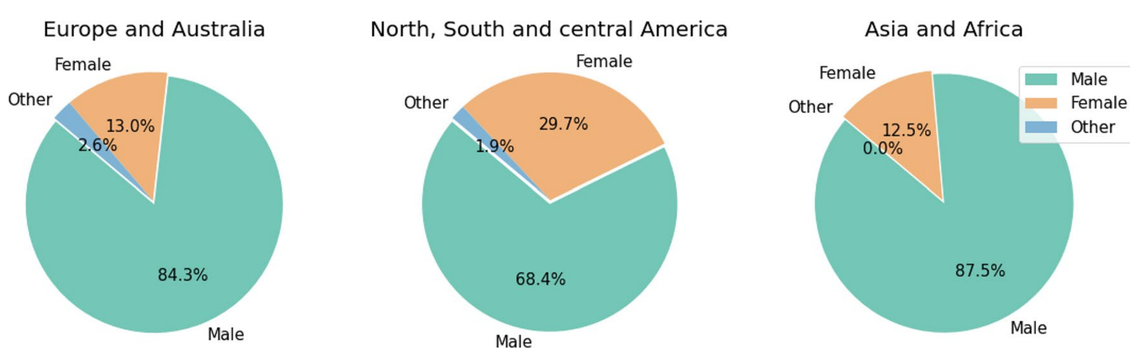

Fig. 2 Gender proportions of employees in different regions

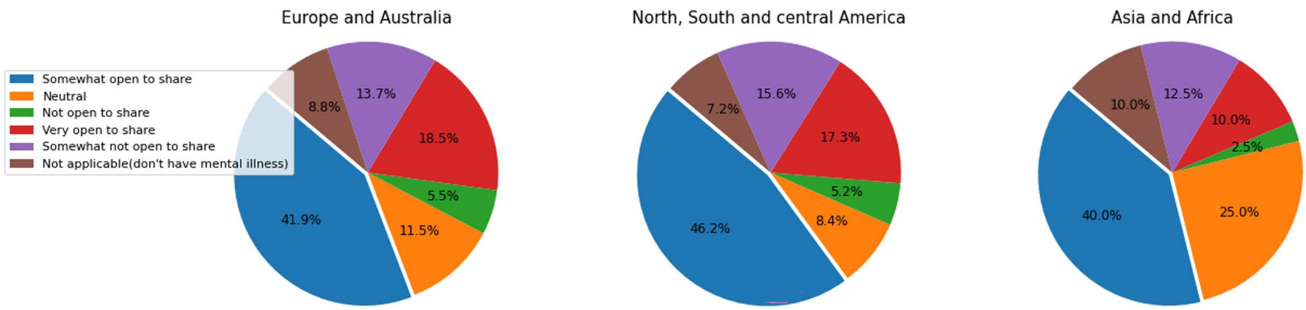

Fig. 3 Willingness of employees to share mental illness with friends and family in different regions

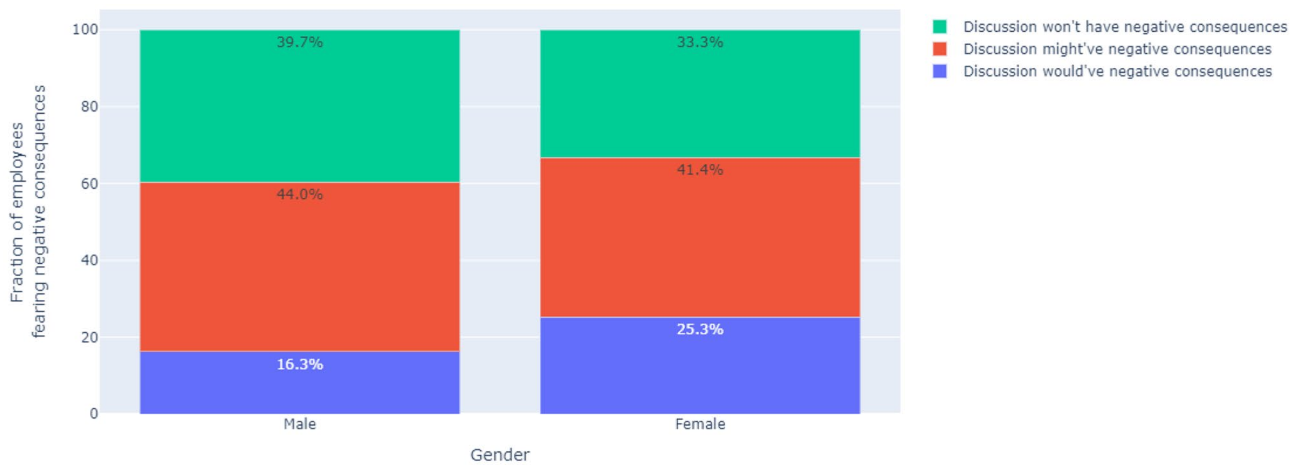

Fig. 4 Fear of negative consequences in male and female employees on discussing mental health issues with their employers

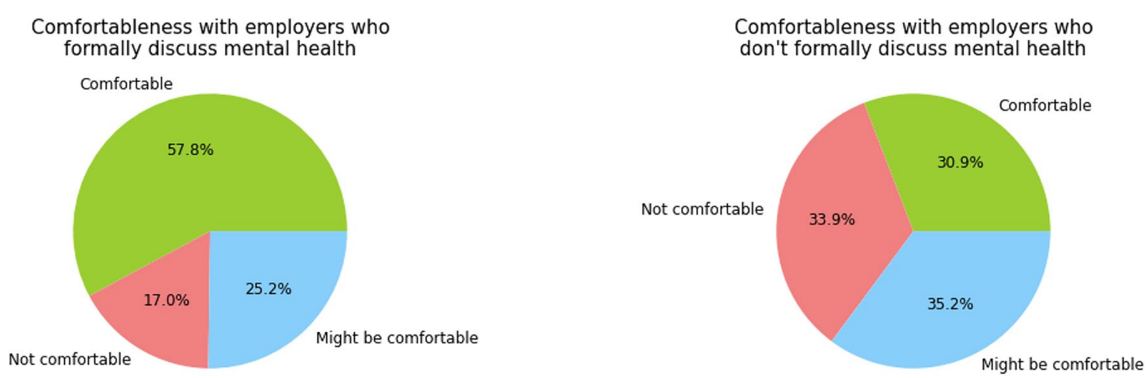

Fig. 5 Effect of formal discussion of mental health by employers on the employees' comfortableness in discussing mental health issues with their supervisors

health as part of their wellness campaigns or other official communications and (b) have not formally discussed mental health. We observe that a majority of employees (57.8%) whose employers have formally discussed mental health were seen to be comfortable in discussing mental health issues with their direct supervisors and a comparatively lesser percentage of employees (17%) were not comfortable. Whereas in the case of no formal discussion of mental health by employers, only 30.9% of employees were seen to be comfortable in discussing mental health issues with their direct supervisors vis-à-vis a relatively larger percentage of employees (33.9%) reported not being comfortable.

Predicting Mental Health Diagnosis

To predict the employees' possibility of being diagnosed with a mental health issue, different prediction models were implemented. The predictions were obtained by classifying the employees into two classes namely: 'diagnosed for mental health issue by a medical professional' and 'not diagnosed for mental health issue by a medical professional'. The classification was done based on the target variable, 'Have you been diagnosed with a mental health condition by a medical professional?'. 70% of the data set was used for training and 30% for testing.

Models tested include the k-nearest neighbor (kNN) classifier, logistic regression, decision tree classifier, random forest, ADABoost, XGBoost and Gradient Boosting classifiers. These classifiers were selected based on their suitability as small-data machine learning models in a supervised learning setting and the success seen with predecessor effort for similar understanding of some of the older OSMI data [12–14].

Risk Indicator

We endeavored to build a risk indicator to understand an employee's risk of progressing to a mental health issue The risk indicator was modelled using various clustering techniques where the employees were separated into three clusters representing different levels of risk of the employees. We used k-means, kmeans++, partition around medoids, (PMM), spectral clustering, agglomerative hierarchical and BIRCH clustering techniques to segment employees based on risk and gain insight to the data.

In particular, we considered three risk levels: high, medium and low. Once the employees were clustered to three different clusters, a risk-score is assigned based on two parameters: (i) whether or not the employees had a mental health issue at the time of the survey and (ii) whether or not the employees had been diagnosed with a mental health condition by a medical professional by the time of the survey. Once a risk-score is assigned to each employee in the cluster, the average risk-score of all the employees in a cluster became the risk-score of that cluster. The cluster with the highest score was labelled as the high-risk cluster, the cluster with the next highest score became the medium-risk cluster and the one with the lowest score became the low-risk cluster.

Results and Discussion

Predicting Mental Health Diagnosis

The performances of the classification models were evaluated using the metrics: Accuracy, Recall, Precision, F1 score and Root Mean Squared Error as shown in Table 1.

We observe the XGBoost and Gradient Boosting classifiers have nearly comparable results and yield the highest predictive accuracies among the methods tested. These methods also yield among the highest recall and precision scores. Given that false positives may be better in the present application (more support provided to an employee perceived at-risk of a mental health issue) than missing out on detecting the presence of a mental health issue, we favor a higher recall and consider the Gradient Boosting Classifier the best models for prediction.

Risk Indicator

The performances of the clustering models used to build the risk indicator were evaluated on the basis of three different metrics- Silhouette score, Calinski Harabasz Index and Davies–Bouldin Index. (i) *Silhouette score:* It is used to measure the goodness of clustering algorithms and the quality of the clusters obtained. If *'b'* is the average distance between a data point *'X'* and all the samples in the nearest cluster of which *'X'* is not a part and *'a'* is the average distance between the data point *'X'* and other samples in the same cluster, the Silhouette score of *'X'* is represented as:

Table 1 Performance of classification models

Model	Accuracy (%)	Precision	Recall	F1 score	Root mean squared error
Logistic regression	91.414	0.926	0.903	0.91	0.293
Decision tree	85.353	0.861	0.841	0.847	0.383
Random forest	91.414	0.934	0.9	0.909	0.293
KNN	89.898	0.924	0.882	0.892	0.318
AdaBoost	88.383	0.881	0.882	0.881	0.34
XGBoost	93.434	0.944	0.924	0.931	0.256
Gradient boost classifier	93.939	0.948	0.930	0.937	0.246

$$S(X) = (b - a)/max(b, a) \tag{1}$$

(ii) *Calinski–Harabasz Index:* It is also called as the Variance Ratio Criterion (VRC). It is used to evaluate the quality of the clusters obtained by calculating the cohesion and separation of the clusters. The higher the value of the index, the better is the quality of the clusters. The index CH can be calculated as:

$$CH = \left[\frac{\sum_{k=1}^{K} n_k \|c_k - c\|^2}{K - 1}\right] \Bigg/ \left[\frac{\sum_{k=1}^{K}\sum_{i=1}^{n_k} \|d_i - c_i\|^2}{N - K}\right], \tag{2}$$

where N refers to the total no. of data points,

d_i refers to the i^{th} data point in the data set $D = [d_1, d_2, ...d_N]$,

K refers to the number of clusters in the data set D,

c_k refers to the centroid of the k th cluster,

c is the global centroid and

n_k refers to the number of points in the k^{th} cluster

(iii) *Davies–Bouldin Index:* Its value ranges between [0,1]. The index is calculated as the mean similarity of each cluster with a cluster that is most similar to it. The lower the value of Davies–Bouldin Index, the more distinguishable the clusters are. The index DB can be calculated as:

$$DB = \frac{1}{n}\sum_{i=1}^{n} max_{j \neq i}\left(\frac{S_i + S_j}{M_{ij}}\right), \tag{3}$$

where n refers to the total number of clusters,

S_i and S_j refer to the within-cluster scatter of cluster i and j, respectively, and

M_{ij} refers to the distance between clusters i and j

The values of the performance metrics were obtained for each clustering technique as shown in Table 2.

On computing the performance metrics, the Spectral Clustering model was seen to have the highest Silhouette score which indicates that the data points are more similar to the clusters they are associated with and the lowest Davies–Bouldin Index which indicates that the clusters are more distinguishable. A high Calinski–Harabasz Index is also seen which indicates that the clusters are dense and are well separated. Thus, the clusters provided by the Spectral Clustering model were selected to build the risk indicator.

Employees in each of the three clusters were assigned a risk-score based on their response to questions on whether (i) they currently suffer from a mental health disorder and (ii) have been diagnosed with a mental health condition by a professional.

The employees who had a mental health issue at the time of the survey and had been diagnosed with a mental health condition by a medical professional by the time of the survey were assigned the highest risk-score. The employees who neither had a mental health issue at the time of the survey nor had been diagnosed with a mental health condition by a medical professional by the time of the survey were assigned the lowest risk-score. The risk-score of a cluster is equal to the average of the risk-scores of all the employees in that cluster.

Inferences

Risk Analysis

Susceptibility to mental illness of an individual is influenced by various factors like: environmental factors, biological factors, their lifestyle etc.

Impact of family history: For some mental health issues, family history of mental illness is said to be one of the indicators of possible risk. A correlation between the risk level and family history was explored. It was found that the highest number of employees with a family history of mental illness was found in the high-risk cluster. With the decrease in the risk level, the number of employees with a family history of mental illness decreases. This is corroborated by multiple studies that report a family history of mental illness impacts the risk of developing certain mental health conditions, such as anxiety and depression [16–18].

Table 2 Performance of clustering models

Model	Silhouette score	Calinski–Harabasz Index	Davies–Bouldin Index
K-Means clustering	0.221	334.545	1.417
K-Means++ clustering	0.22	334.65	1.416
Partition around medoids clustering	0.194	321.36	1.525
Agglomerative hierarchical clustering	0.210	321.727	1.439
Gaussian mixture model clustering	0.025	118.254	2.278
BIRCH clustering	0.209	324.456	1.454
Spectral clustering	0.244	316.759	1.252

Impact of past history of mental health disorder: The presence of mental health issues in the past instils in individuals fear of recurrence along with anxiety and worry. The percentage of employees with a mental health disorder in the past was studied across the 3 risk clusters. It was found that majority of employees (76.8%) with a mental health disorder in the past belonged to the high-risk cluster. This is in agreement with predecessor research that the risk of relapse or developing another mental illness after a first diagnosis is higher than the chance of a first diagnosis [19, 20].

Impact of age: We know that as one ages, changes in one's body and mind are inevitable. Similarly, age can impact one's mental health. It was seen that 45.71% of employees in the age group 26–45 belonged to the high-risk cluster and 54.29% of them were in the medium-risk cluster. Majority of the employees (74.07%) in the age group 46–65 belonged to the low-risk cluster while the remaining 25.93% of them belonged to the medium-risk cluster. A 100% of employees in the age group 66–75 were seen to be in the low-risk cluster. This is in line with results reported on anxiety, substance abuse and mood disorders for various age groups [21, 22].

Impact of gender: In the tech industry, it is known that women are a minority. Research conducted by AnitaB.org Institute in 2020 measured 51 companies and over 500 thousand technologists and found that only 28.8% of women were a part of the tech workforce [23]. Being the minority, women suffer more from the negative consequences of the gender differences and are seen to have higher rates of mental health concerns. The fractions of female employees in each of the three risk clusters were studied. We observed that a majority of the female employees (62.9%) belonged to the high-risk cluster, 33.1% of them belonged to the medium-risk cluster and only 4% of them were in the low-risk cluster. This is consistent with the findings in the literature on higher rate of 12 months and lifetime diagnosis of any mental health condition in women over men [21, 24].

Impact of workplace social support: The risk levels of employees experiencing lack of support towards mental health in workplace was studied. It was that majority of the employees (52.9%) whose employers do not offer resources to learn about mental health concerns and options for seeking help belonged to the high-risk cluster, 41.2% of them belonged to the medium-risk cluster and only 5.9% of them belonged to the low-risk cluster. 49.2% of employees who observed or experienced lack of support or badly handled response to mental health issues in their workplaces were in the high-risk cluster and majority of employees (49.2%) whose employers do not formally discuss mental health were in the high-risk cluster. Research by Peter et al. found low perceived social support to be significantly associated with lower subjective work ability as well as lower mental health [25]. Study by Graveling et al. examined the impact of various workplace interventions on mental well-being in workplace. The organisational interventions or practices adopted to improve mental wellness was seen to increase mental well-being (Fig. 6).

An Analysis of Mental Health Pre- and Post-COVID-19

Resources offered by employers to learn more about mental health disorders and options for seeking help: Employees' expectations from their work, employers and workplace have undergone significant changes. According to the American Psychological Association 2022 Work and Well-being Survey, 81% of respondents expressed that when looking for work in the future, they shall seek workplaces that provide support for mental health [26]. The proportions of employers offering their employees resources to learn more about mental health disorders and options for seeking help was studied across the years 2017–2021 using the OSMI Mental Health in Tech Survey (see Fig. 7).

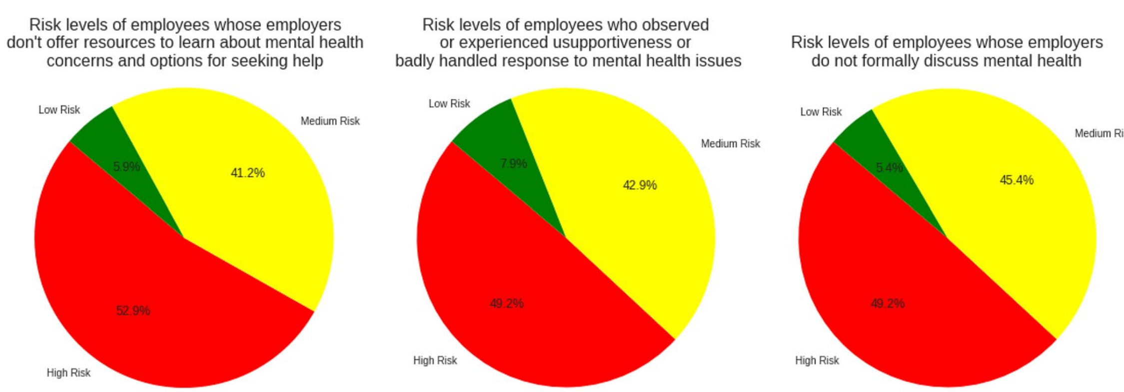

Fig. 6 Effect of lack of social support towards mental health by employers

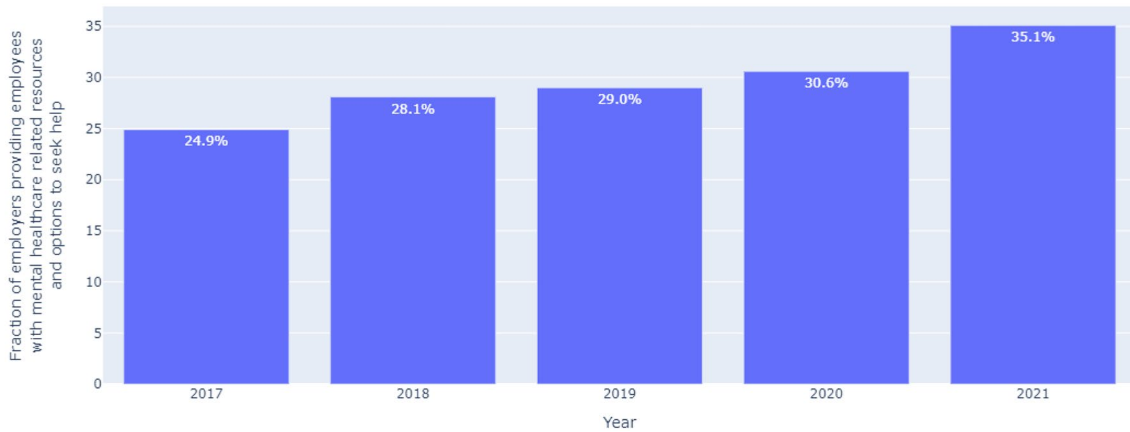

Fig. 7 Fraction of employers offering their employees resources to learn more about mental health disorders and options for seeking help

Formal discussion on mental health by employers: The fractions of employers who have formally discussed mental health as part of any official communication or a wellness campaign was explored across the years 2017–2021. It was found that the percentage of employers who have formally discussed mental health in workplace has increased post-pandemic in comparison to the pre-pandemic era. In 2017, only 21.4% of employers were seen to have formally discussed mental health with employees, which is seen to have increased to 36.7% in 2020 and 35.1% in 2021. In the recent years, companies and employers are indulging in discussions about mental health in workplace to a greater degree and encouraging their employees to open up about their mental health concerns. Managers are being given training to approach conversations related to mental health and 18% of employees stated that hosting events for mental health awareness and education is one of the types of mental health benefits provided by employers [27]. Does this increased support meet the needs of the employees?

Support towards mental health issues in workplace: A study of the fraction employees who observed or experienced lack of support or poorly handled response to a mental health issue at their workplace during 2017–2021 has reduced post-pandemic. The percentage of such employees is seen to decrease steadily from the year 2019 with 2021 comprising of 30.8% of them, a dip of 9% when compared to the year 2017. COVID-19 has given impetus to raise awareness about mental health issues and improve the accessibility of mental health support. It has also not only led to more open discussions about mental health, but also normalized seeking mental health help and reduced the stigma around mental health issues [28].

Employees' openness to discuss mental health issues in workplace: The fractions of employees who discussed their mental health with their co-workers is consistently greater than the fraction of employees who discussed with employers is consistently greater through the years 2017–2021 (see Fig. 8). It is also, noteworthy that the overall discussion (whether with employers or coworkers) has reduced

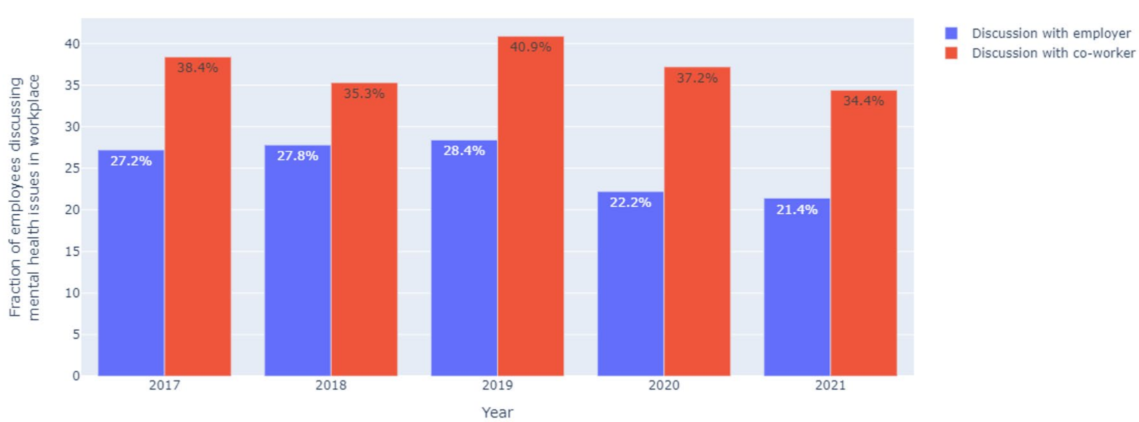

Fig. 8 Fraction of employees who have discussed their mental health with their employer and/or co-workers

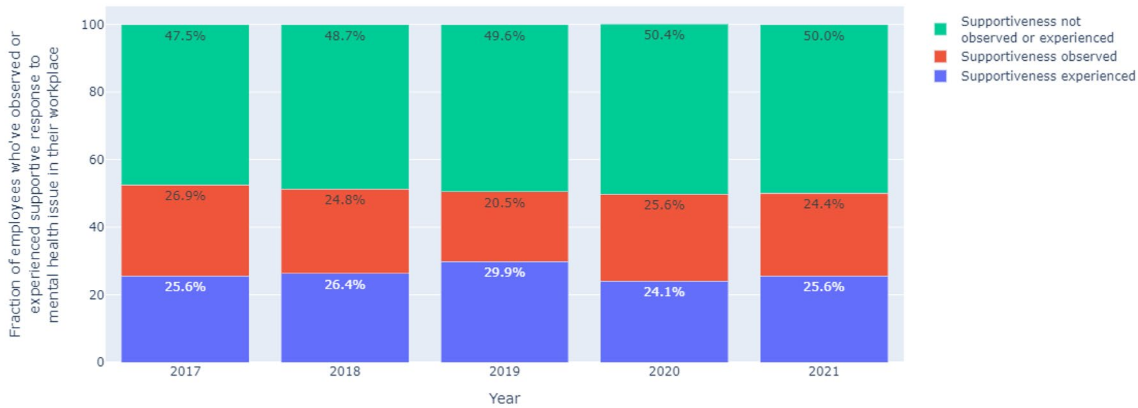

Fig. 9 Fraction of employees who have observed or experienced a supportive or well-handled response to a mental health issue their workplace

post-pandemic. This is consistent with the Paychex's survey of 1075 full-time employees, in which 54% of employees reported to have felt uncomfortable discussing about mental health with their supervisors or managers [29]. It was also found that 29% of employees feared that discussion about their mental health issues might affect their promotion. Further, amongst the employees who talked about their mental health issues, 35% of them seen to have discussed with their co-workers and 21% of them discussed with their supervisor and merely 5% of them discussed with an HR representative.

Requesting a mental health leave of absence: It was found that the fraction of employees who feel it is an easy feat to request a mental health leave has decreased post-pandemic (50.3% in 2019, 47.8% in 2020 and 45.6% in 2021). According to Mind Share Partners' 2021 Mental Health at Work Report, despite the growth (from the year 2019) in the availability of Mental Health Days and extra paid time off, the rates of utilization of such resources has not seen any growth from 2019 [30]. Another study found that 48% of employees who had taken Mental Health Days in the previous year stated that they have taken lesser Mental Health Days in the present year than in the previous years due to the increase in hybrid or remote work [31]. Further, 58% of employees stated that taking Mental Health Days has become more difficult to justify due to the increase in remote work and 39% of employees who had taken at least a single Mental Health Day were afraid of a negative reaction from employers.

Handling of mental health issues in workplace: Across the years 2017–2021, a majority of employees (approximately 47–50%) have neither observed nor experienced support to a mental health issue at their workplace (see Fig. 9). The percentage of employees who observed supportiveness and those who have experienced support, sum to an approximate percentage of only 50%. Thus, despite mental health being increasingly talked about and employers taking up different mental health-related initiatives, it does not suffice the employees' requirements. Workplaces that are mentally healthy and sustainable are what the employees need and expect [30]. For most companies, the mental health of employees has not been a priority; only 32% of HR professionals stated that mental health was a main concern at their company [32]. According to the Harris Survey, 41% of employees stated that no counselling, therapy and other mental health-related benefits are given by their company, despite the good progress made in the mental health domain by corporate America [27].

Conclusions

The goal of this study was to use systematic, nuanced and rounded approaches to study the mental health scenario in the tech industry. The results and inferences obtained from the present study on the mental health scenario in the tech industry are consistent with the social, psychological and professional implications reported in literature. We find that there is a greater awareness of mental health issues at the workplace and employers are making an increased effort to provide support to employees. However, these efforts may not be having the desired impact, particularly post pandemic with options for working remotely. Thus, it is hoped that insight from studies such as the present one will facilitate employers in identifying any workplace factors affecting their employees' mental health, and in implementation of workplace mental health interventions that benefit the employees meaningfully.

Reproducible research: To facilitate reproducing the results reported in this work, the entire data and code used in this study is available online.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability All the data and code used in this study has been made available online https://bitbucket.org/GowriSrinivasa/mental-health-in-tech/src/main/.

Declarations

Conflict of interest The authors declare that there is no conflict of interest.

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