Mental Health in the Technology Industry

Sameer Ladha

501208249

The Raymond Chang School of Continuing Education

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Dr. Ceni Babaoglu & Dr. Tamer Abdou

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Abstract, Literature Review, Data Description, & Approach

Ryerson University

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Abstract

Mental health is a topic that has garnered a lot of attention. Specifically, companies and organizations have been working to implement organization level interventions while simultaneously aiming to provide a healthy working environment (Leka & Nicholson, 2019). These interventions seek to prevent mental health related issues but often have many implementation issues (Leka & Nicholson, 2019). Research has shown that, in recent years, approximately 20% of the adult population has a mental health problem (International Labour Organization, 2000). Consequently, the COVID-19 Pandemic has exacerbated mental health problems (Hossain et. al., 2020). Mental health can also affect an individual's performance within the workplace (International Labour Organization, 2000). This can result in negative workplace behaviours such as absenteeism, greater sick leave requirements, and reduced productivity (International Labour Organization, 2000). However, this is not a problem that employees need to solve on their own. Workplace stress is one of the major sources of workplace related mental health issues globally (Wang et. al., 2020). A study conducted showed that a toxic work environment has a negative correlation with project success (Wang et. al., 2020). This study also showed that organizational support can help overcome the many issues that employees may face in a toxic work environment (Wang et. al., 2020). In other words, although many workplaces are stressful and expect high output from employees providing adequate and thorough support for their employees can effectively negate a large amount of the workplace stress that may arise. The purpose of this paper is to explore how an organization, specifically in the technology sector, response to mental health affects their employees. This paper will explore the relationship between mental health/illnesses and employee performance in the workplace, whether treatment of mental health issues and/or remote work influences employee performance.

Additionally, it will explore if the size or location, within the USA, of a company/organization correlates with how comfortable employees are about speaking about their mental health. For example, disclosing it in interviews, talking to co-workers or supervisors, taking time off, and utilizing company benefits. The data used is part of an annual survey conducted by the Open Sourcing Mental Illness. This non-profit organization is dedicated to raising awareness, educating, and providing resources surrounding mental health/wellness in the tech communities (OSMI, 2015). The survey has been conducted yearly since 2014; the data used in this research paper will be from 2016. This year was chosen as it had the greatest number of responses. This paper will use data mining and knowledge discovery techniques, such as decision trees, Bayesian classification and more, to extract patterns and predict outcomes using the survey data.

Literature Review

Research has shown that the combination of increasing demands on the job and decreased control that results in this stress (Rao & Chandraiah, 2012). Additionally, Rao and Chandraiah (2012), showed that "the pressure to perform" can increase stress and thus result in negative workplace behaviours. Mental health is just as vital as physical health, but often organizations do not take this into account when creating policies and programs. Therefore, creating unnecessary and redundant programming; it is for this reason that analyzing the response from employees, regarding mental health, is vital.

The impact of mental health is well known. Research has shown that the proportion of the population that does not experience a mental disorder is small (Schafer et. al., 2017). In other words, the experience of a mental health disorder or mental health concern has become the norm, rather than an exception (Schafer et. al., 2017). Workplace stress, toxic work environments and a lack of organizational support can be a major source of these mental health problems (Wang et. al., 2020). Increased stressed levels result in employees being more likely to engage in negative coping behaviours, such as drinking, smoking, poor eating habits and avoiding physical activity, all leading to greater mental health issues arising (Wang et. al., 2020). Mental health can also affect an individual's performance within the workplace (International Labour Organization, 2000). Research has shown that the combination of increasing demands on the job and decreased control that results in this stress (Rao & Chandraiah, 2012). Additionally, Rao and Chandraiah (2012), showed that "the pressure to perform" can increase stress and thus result in negative workplace behaviours. Mental health is just as vital as physical health, but often organizations do not take this into account when creating policies and programs. Therefore, creating unnecessary and redundant programming.

However, a study conducted by Wang et. al. (2020), revealed that an organization that provides more support and actively tries to mitigate a toxic work environment can actively reduce stress. Thus, resulting in more efficient and productive employees (Wang et. al., 2020). The purpose of this paper is to explore how an organizations', specifically in the technology sector, response to mental health affects their employees. This paper will critique what is already known about the topic, examine other research with a similar goal, explore where this paper fits in with other works and conclude by justifying the need for this research.

To begin, employers often utilize employee assistance programs (EAP) as they are designed to help individuals resolve modifiable behavioural issues (Attridge, 2019). However, these EAP's have, in recent years started to become a barebones version of the original idea, thus resulting in little usage (Attridge, 2019). Although, these EAP's provide some support to employees, they are often tied to the organization and can cause some hesitation with using them. Additionally, even with these programs in place, there is still a large stigma around mental health and addiction that continues to remain a hinderance to significant change in the workplace (Attridge, 2019). It is vital to acknowledge that this stigma also exists outside of the workplace. This stigma can only truly be alleviated, when change begins from the top down. In other words, senior leadership recognizing, understanding, and actively making a change to support those with mental illnesses (Attridge, 2019).

Next, these programs are sometimes found to be based in research surrounding western culture and thus do not account for the impact that culture has within mental health (Lee et. al., 2017). Similarly, in mental health research, there is a lack of representation of transgender individuals, resulting in them feeling inadequately represented (Ghorbanian et. al., 2022). One can speculate that there is a lack of representation for a variety of people such as women, visible minorities, individuals with disabilities, and indigenous populations to name a few. In short, although employers attempt to aid employees with mental health issues, the lack of research and continued stigma around mental health will continue to hinder the progress that needs to be made.

The Open Sourcing Mental Health/Illness (OSMH/I) is a very popular resource that is used amongst researchers to gather data surrounding mental health and mental disorders. OSMH/I is a corporation that is dedicated to advocating for mental wellness, raising awareness, and providing resources (OMSI, 2015). Thus, the OMSI dataset has become a popular dataset and featured in numerous studies.

The first of which, conducted by BH et. al. (2022), utilizes the dataset to analyze the cause of mental health disorders and the severity of mental illnesses, based on several factors and attributes. Their objective was to educate the public on mental health issues in working environments with the hopes of mitigating them from occurring (BH et. al., 2022). In their paper, they utilized machine learning algorithms such as KNN, decision trees, random forest, naïve bayes and more, along with logistic regression to determine a potential cause of mental health disorders (BH et. al., 2022). They used their findings to provide recommendations to employers to help reduce mental health issues for employees (BH et. al., 2022). Like the research in this paper, the study utilized the OMSI dataset to analyze mental health in the workplace and similar machine learning algorithms, unlike this paper, the study focused on determining the causes of mental illness in the workplace.

Likewise, Singer & Golan (2021), conducted an analysis of the OMSI dataset to help develop a methodology that can predict an employee’s willingness to disclose and develop a tool to design intervention programs that encourage employees to disclose their mental illness with their supervisor. Using several machine learning algorithms such as C4.5, random tree, PART, naïve bayes, and JRIP rule learner, the researchers aimed to utilize these methods in both an organizational and healthcare context to analyze mental health disclosure. (Singer & Golan, 2021). After implementing these algorithms, the researchers determined the one with the best classification performance and used that to identify sub-groups in which programs can be targeted (Singer & Golan, 2021). This research allowed for practical use cases for managers identify employees who could be at risk for non-disclosure and implement programming to rectify that (Singer & Golan, 2021). Like the research in this paper, the study, once again, utilized the OMSI dataset and similar machine learning algorithms, but centered their analysis on disclosure.

Like this paper, Havaei et. al., (2021), conducted a study on nurses to determine the more important workplace factors in predicting mental health. The study's focus was a nurses' work environment, and instead of focusing on a few factors to determine the most important (Havaei et. al., 2021). This study did not use the OMSI dataset, but instead utilized several questionnaires, that measure depression, anxiety, PTSD, burnout, and life satisfaction (Havaei et. al., 2021). The researchers used random forest, comparative fit index, Tucker Lewis index, and standardized root mean squared residual to conduct their analysis (Havaei et. al., 2021). Unlike this paper, Havaei et. al., (2021), focused on the mental health of nurses and determining factors that contributed to mental health, whereas this paper will focus on the relationship between mental health and the workplace in areas such as performance, organizational response, and descriptive attributes about the organization.

Finally, Uddin et. al., (2022), conducted an analysis of mental health, using the OSMI dataset, in the tech workplace, with the goal of determining the frequency of mental health disorders versus those without mental health disorders. The researchers used the OSMI dataset and conducted some basic descriptive statistics to examine the data and extrapolate findings from different categories such as age, current mental health status, physical location, family history, knowledge of company care options, and anonymity (Uddin et. al., 2022). The study then goes on to give recommendations to organizations to aid in managing employees with mental health issues, such as offering more robust benefits, having posters advocating for mental health, and training for supervisors (Uddin et. al., 2022). The study conducted by Uddin et. al., (2022), is very similar to the analysis conducted in this paper, with a few key differences. The first being the focus on performance, this paper will examine the relationship between performance and mental health, and the factors that influence performance. Likewise, this study does not use machine learning techniques to extrapolate their data, but rather basic data visualization.

Although, the above four studies are like the purpose of this paper, each provide a unique perspective on mental health within the workplace, as does this paper. Similarly, three of the four studies utilize the OSMI dataset for their analysis and can provide a unique analysis to suggest recommendations for different aspects of mental health in the workplace. This paper can be another tool that employers can utilize when developing mental health programming for their employees, whether that be workshops on managing stress or a hollistic benefits package that incorporates robust mental health coverage. This paper can examine the relationships that employers have with their employees with regards to anonymity and their responses to mental health/illness, fitting in to the existing research surrounding mental health. Finally, the study conducted by Uddin et. al., (2022), is the only study mentioned that focuses on the technological sector showing that there is still much room for analysis and growth in this area of research.

Mental health is a health problem that affects people globally without any bias. One in two individuals will experience a mental disorder in their lifetime (Singer & Golan, 2021). Research has shown considerable evidence connecting work design/conditions and workplace culture to employee mental health and job performance (Attridge, 2019). Similarly, it has shown that poor quality jobs, work culture, psychological demand, socio-economic status, culture, and more can all affect mental health of employee’s (Attridge, 2019). Leka & Nicholson, (2019), stated that “there is a need for mental health and wellbeing to be integrated into the planning and control cycle of an enterprise.” In other words, mental health needs to be considered from the beginning of policy making within organizations rather than as an afterthought. The researchers also noted that to promote mental health in the workplace holistically and see progress, there needs to be “synergy from various perspectives,” and that these perspectives must be rooted in current knowledge and existing needs (Leka & Nicholson, 2019). The purpose of this paper, to examine the relationship between employee performance and mental health in the tech workplace, aligns with the research previous and helps break down the stigma surrounding mental health.

Descriptive Statistics

The dataset, upon completing a basic review, had 1433 responses and 63 variables. Upon removing unnecessary variables 31 remained. Conducting a basic descriptive analysis of the age variable revealed that the mean age of participants is 34.09, with 33 being the most frequent age. The youngest participant was 19 and the oldest 74. In the gender variable, the responses had more variety as this category was a text box rather than a dropdown to remain inclusive. Therefore, the categories were broken down into male, female, non-binary, and other gender identity to keep inclusivity at the forefront, (Figure 2). This revealed that the participants mostly consisted of males. Likewise, this dataset had mostly tech employees, (Figure 3), and approximate equal distribution of employees that worked remotely, (Figure 4). One must consider that this data was collected in 2016, before the COVID-19 Pandemic, therefore, one can speculate that looking at this data from 2020-2021 would reveal a much larger number of employees that work remotely. Similarly, the dataset had an approximate equal distribution of employees diagnosed with a mental illness, (Figure 6). Finally, most participants worked at organizations that had between 26 and 100 employees, (Figure 5).

Methodology

Selection

- Selecting the appropriate dataset for the purposes of this study

Preprocessing

- Prepare the data for analysis (Recode variables, data normalization, NA values, changing variable types, etc.)
- Conduct a descriptive statistics analysis on the now cleaned data to garner an overview and summarize the data

Data Mining

- Apply the selected Machine Learning Algorithms to the now processed data
- Extract information from this process to utilize in the next stage

Interpretation/Evaluation

- Interpret the results of the mining and extract knowledge from the data
- Evaluate the Machine Learning methods to determine their reliability and validity

Appendix

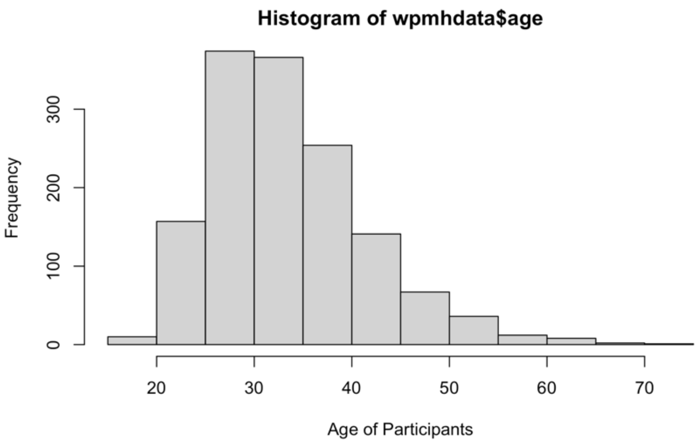


Figure 1

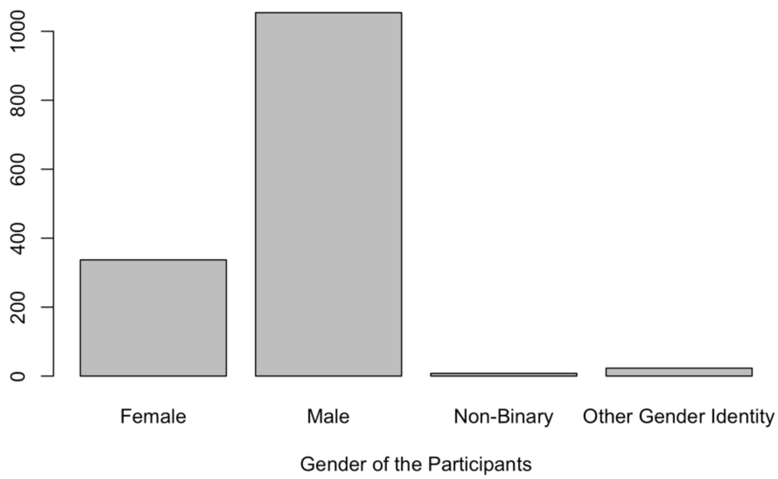
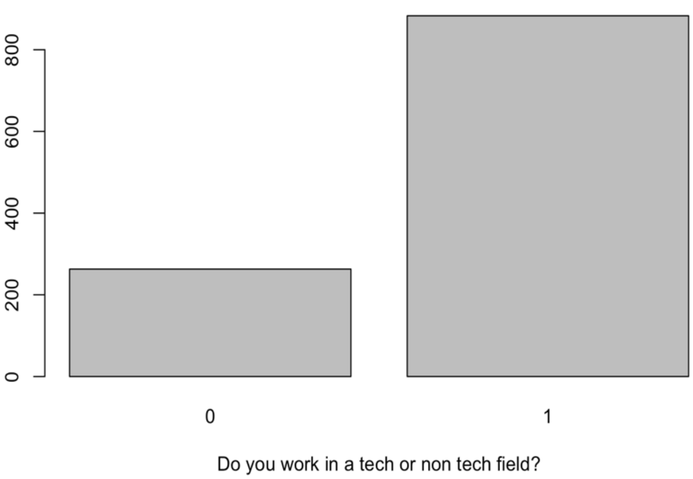


Figure 2



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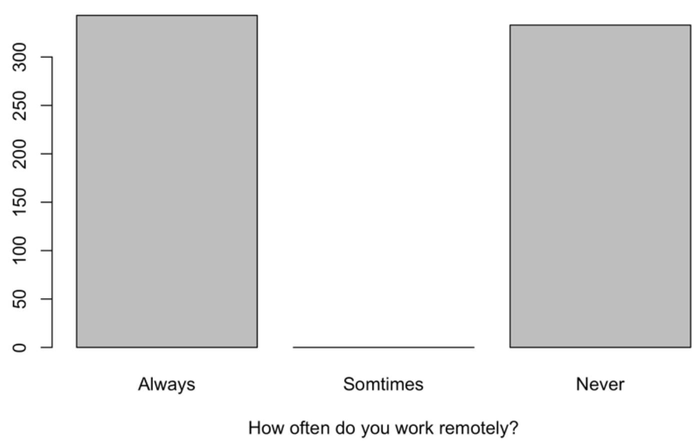

Figure 4

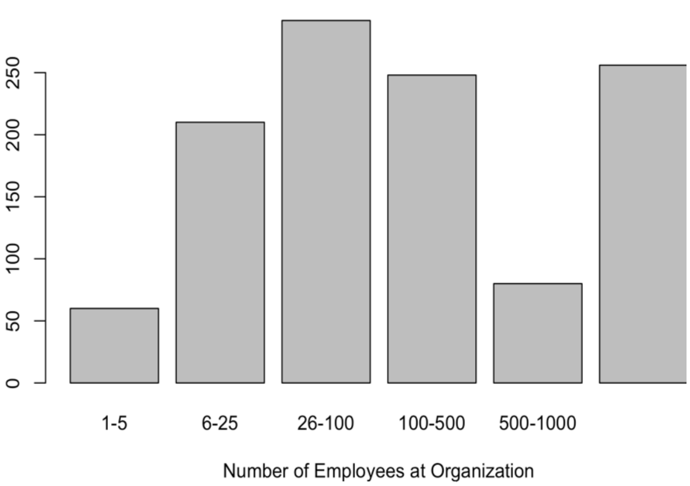

Figure 5

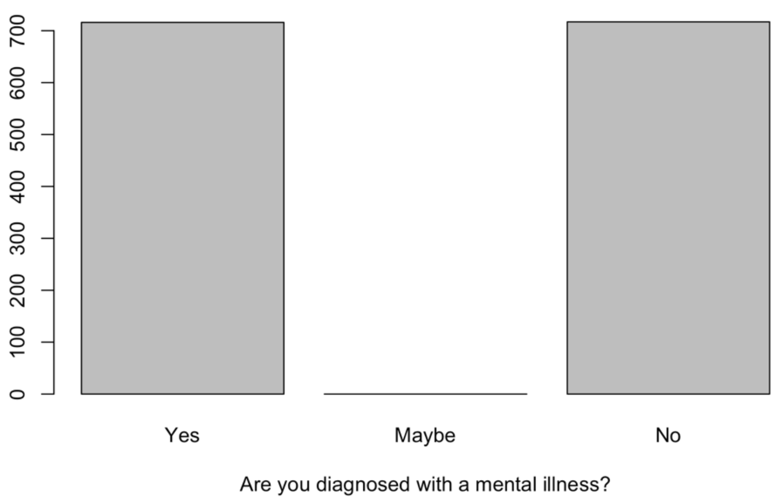

Figure 6

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Dataset Link: https://www.kaggle.com/datasets/osmi/mental-health-in-tech-2016

GitHub Link: https://github.com/sameerladha/Big-Data-Project.git