Impact of Remote Working on Mental Health Condition

Marta Betti, *Computer Science Student, Università di Bologna*

Abstract—The abstract goes here.

Index Terms—Mental Health, Remote Working

1 Introduction

THREE years ago, due to the outbreak of COVID-19, many companies were forced to either close definitively or to shift the execution of their activities from the material world to a digital world, also by updating their technological infrastructure and by granting more flexibility to their employees.

This society update was dictated by the necessity of not stopping the economy but, even though the pandemic is just a vague and blurred memory, remote work is still a reality.

The main goal of this research is to understand how remote working affects mental health, stress levels and sleep quality.

Indeed, technological devices play an important role in our lives and they can cause technostress, detachment from reality, burn-out and the sensation of never being disconnected.

Furthermore, given that the dataset that is going to be used contains also data about demographics and working-related data such as satisfaction or productivity, this research will also try to find patterns between the economic sectors, the satisfaction of employees or other aspects of the employees' lives and remote working.

However, remote work can be preferred to the traditional way of doing your job due to factors, such as personality traits, household needs, commuting time, and many others that have not been taken into consideration in the data set.

This can be seen as a limitation concerning other case studies that have been carried out on the same topic.

All the phases that are illustrated in the following image of the CRISP-DM from the data understanding to the evaluation were performed except the first one and the last one.

It is dutiful to admit that not much time was dedicated to the first phase of the CRISP-DM model but we must all be aware of the importance of having a business understanding and the only reason why this phase was not covered was just a matter of lack of time in obtaining some professionals' opinion about this topic and this data set.

Some of the attributes of the data set were chosen to understand if a person is likely to have a problematic mental condition because, even though similar data sets have been used in other research papers as we will see later, none of the other research papers considered the same attributes and, for the sole reason that they were already in a data set, this was already sufficient to consider them interesting attributes to have more insights on.

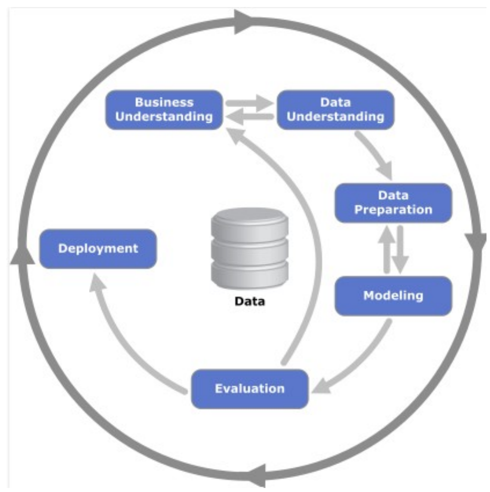

Fig. 1. CRISP-DM

Finally, the deployment part was not performed because the work that has been done must undergo through a stricter evaluation process performed by people who are more experienced than the only member of the team.

That being said, let's take a glance at similar studies that have been carried out about the topic.

2 Connected Papers

The first paper found about the topic is a discussion paper written by 4 professors teaching in the universities of Padua and Venice. (Bertoni-RemoteWorkingMental-2021)

The reason why this paper was chosen is that it brings a different way to understand the impact of remote work on mental health using the clustering approach and by applying Bayesian models during the first wave of the COVID-19 outbreak by collecting qualitative data via telephone interviews in Europe and Israel.

The people interviewed were clustered according to 3 different parameters: gender, number of children and region.

E-mail: marta.betti5@studio.unibo.it

The survey analysis pointed out that mental health was not compromised for those who see it as a necessity, especially in regions where the mortality rate was high; however, women with children were more prone to developing mental health problems because of the overload of both professional and household responsibilities.

Even though this analysis was performed in a different context than the one this paper is about, it is interesting to see how attributes that seem to be unrelated to the topic lead to the discovery of social differences.

But now let's move to another analysis that has much more in common with the one we are going to talk about in the end.

Indeed, this research has been conducted on the same data source used for this assignment paper by some professors coming from many different universities in the USA (Impact of Remote Work Dynamics on Mental Health and Productivity).

The data was processed and analyzed using statistical software such as R programming Language and SPSS software which were well-equipped to handle large datasets and conduct a variety of statistical tests.

The outcomes were very different and offered a more complete picture of the situation and possible solutions with respect to the ones analyzed in the paper that were previously discussed. These differences are mainly due to the different periods during which the study has been conducted but also because of the difference in the parameters considered.

The most stunning discovery was that 75% of employees report anxiety, burnout, or depression, affecting all genders equally, even though qualitative differences exist. Women face more domestic responsibilities, while men experience stress from performance expectations.

The second important finding was that hybrid work models are the ones offering the best balance, improving satisfaction and productivity compared to fully onsite or fully remote work.

Finally, not many differences concerning the openness to remote working were found among different industries or regions but most of the employees agreed on is that what makes their job a source of mental problems is not determined by how much they work but by how the work is organized. Frequent meetings and lack of focus time contribute to burnout and stress.

To conclude, a well-structured remote work model boosting employee well-being and organizational success must prioritize hybrid work, mental health support, and strategies tailored to genders and industries. Now it is time to focus on the core of the assignment paper by explaining how the ML model has been developed.

3 Methodology

The first phase of the project is related to data cleaning.

The first step consisted of eliminating all the records containing bad-quality data by eliminating all the records where the distance between the age and the years of experience was less than 16.

Later, since there was some missing data in the attribute mental health condition and physical activity, two assumptions have been made to solve this problem:

1) When there was a missing value in the Mental Health Condition attribute, it had been assumed that the person was not falling into the categories of Anxiety, Burnout or Depression.
2) When physical activity was not specified, it had been taken for granted that the person interviewed had unknown physical activity habits.

For this reason, the null values of both attributes have been replaced by the label "Other".

After deciding, all the non-numerical attributes were turned into ordinal attributes when sorting logic was applicable (e.g., sleep quality from 0 = poor to 2 = good) or underwent a one-hot encoding process (e.g., industry, region, or age group).

Finally, to diminish the impact of attributes having a big variance, a normalization process has been performed by using the MaxAbsScaler.

Once the data were normalized, it was time to understand the impact of each attribute in determining the corresponding class. For doing this, the RFE was used, and an unexpected discovery was made.

What was not expected was the scarce contribution that each attribute brings to the overall process of classification. Indeed, the most impactful attribute has less than 10% impact in determining the class.

This characteristic of the dataset made the classification process challenging. The initial idea was to build a classifier able to spot the depressed, the anxious, the burned-out and the people not falling in the former three categories but guaranteeing a decent level of accuracy was impossible.

More than 1 classification approach has been tried out to achieve this goal but none of them worked; so, to create a more effective model, the way of classifying mental conditions has been changed.

Instead of spotting the exact mental health condition, the classifier now had the task of understanding if one of the records was likely to be classified in one of the mental conditions present in the dataset (anxiety, burnout and depression) or not.

So, in the end, the possible classes that could be predicted have been turned into numbers by the use of a Label Encoder going from the less severe mental health condition to the worst one: Other=0 and mental Illness=1.

To do it, the first 4 most value-carrying attributes with an impact of more than 5% were the ones chosen together to build the classifier.

To tune the model, a Grid Search method has been used to understand both the optimal depth and entropy Index to set.

The model has been trained by using 80% of the dataset while the rest of it was used as the test set.

It is dutiful to mention that accuracy has not been the only indicator that has been considered to build the decision tree.

As has been said at the beginning of this paper, mental conditions related to work are a hot topic nowadays, and if neglected they can lead to serious consequences this means, in data mining terms that false negatives cost more than false positives.

This is the reason why also precision and recall have been considered while building the decision tree model.

Finally, for what concerns the visualization of the model, some ready-made Matplotlib was used for visualizing the decision tree.

4 Discoveries

To comment on the discoveries made through the model, it is necessary to admit that it has not been easy to find patterns since this dataset was homogeneous regarding attributes distribution.

The following link contains a descriptive analysis of the data made by a professional Kaggle user (Remote Work & Mental Health EDA) and as you can see there is a uniform distribution of employees based on gender, industry, region and in general many other attributes including the ordinal ones. This feature made the decision tree's life much more difficult while trying to find patterns and it sometimes looks like the splitting criterion is unclear or not good enough to perform a correct classification.

But now let's use the paper written by the American professors as a benchmark.

Given that the dataset was the same, most of the interviewed employees were likely to have one of the 3 reported mental conditions.

It has been confirmed by both analyses that industry, the region of provenance and gender do not impact much on mental health conditions as they affect subjects independently from these factors.

Talking about the differences between the 2 studies, it is necessary to remember that different starting parameters have been taken into consideration to perform the classification process.

The American model focused more on companies' attitudes and opinions towards remote working, in other words, factors that do not depend on the employees, while the model created for this project focused more on features related to them and their working conditions, particularly the age, the years of experience, the number of virtual meetings and the number of hours worked per week, where the first bifurcation of the tree occurs.

Individuals working less than 20.5 hours per week have a higher likelihood of developing mental illness. This could imply that job insecurity or underemployment is associated with psychological distress. Conversely, long working hours (more than 39.5 hours/week) also appear to have a positive association with the risk of mental illness, likely due to stress, burnout, and work-life interference.

Age is also a significant factor that determines mental health. The decision tree has shown that young workers (under 31.8 years) are likely to suffer from mental illness. This is due to initial career difficulties, instability, and adjustment pressures. Anyhow, among older workers, mental illness persists when combined with overwork and long tenure.

Years of experience is the third attribute considered by the decision tree and is a multifaceted determinant of mental health outcomes since on one hand, the least experienced employees may suffer from anxiety due to job uncertainty, while employees with over 36.8 years of experience who work very long working hours are also at greater risk of mental illness. This suggests that both career and prolonged occupational exposure can lead to mental health risks.

Finally, the frequency of virtual meetings is also an important consideration. Employees who have over 9.5 virtual meetings per week seem less likely to be experiencing mental illness, possibly due to heightened communication and interaction with peers. A very low or intermediate level of virtual meetings, particularly when combined with other variables, is more likely to result in mental distress. This suggests that isolation in the workplace or poor communication pathways contribute to deteriorated mental health.

5 Conclusions

With machine learning algorithms, we have always been trying to label, create an order and find the probability of some events that we do not expect but reality is not just so simple, and it is not either black or white so let's think about this project just as another perspective on such a complicated and delicate topic.

We can never know from this dataset if the parameters we chose are the most effective ones because they are associated with other factors such as hope for the future or appreciation of being alone.

Many researches have been performed but most of them were strongly influenced by the pandemic context while now in more "normal" times we lack research of this kind and it would be interesting to know more also about the relationship between mental conditions and attributes that are more intertwined with the personal lifestyle, household condition or personality of the workers even though these aspects can be challenging to deal with, to collect and to process.

I think that this project helped me a lot in understanding the importance of data preparation and most importantly the way ML algorithms reason by actively interacting, experimenting and tuning them.

However, the hardest pill to swallow was that it doesn't matter how much effort you put into building the model; if the data are poor, you are going to end up with unsatisfying results.

In the future, I hope I will have the chance to experiment more and to reach a conclusion that is more representative of reality also by using better-quality data.