



Mental Health and Workplace Analysis Project Report

By Jlassi Maram
& Ktari Wiem

IDS4

2024-2025

1. Context and Problem Framing.....	3
2. Data Source(s) and Preparation.....	3
Data Sources.....	3
Data Preparation Steps.....	4
1.Standardization:.....	4
2.Missing Values:.....	4
3.Age Cleaning:.....	4
4.Gender Normalization:.....	4
5.Country Normalization:.....	4
6.Feature Engineering:.....	4
3. Engineering Workflow (Tools, Architecture, Challenges).....	5
ETL Architecture.....	5
Key Challenges and Solutions.....	6
4. Analytical approach and insights.....	6
4.1 Methodology.....	6
4.2 Analytical Process.....	7
5. Discoveries, Conclusions and Recommendations.....	7
5.1 General Demographics and Treatment Patterns.....	7
5.2 Factors Associated with Seeking Treatment.....	8
5.3 Mental health and support.....	10
5.4 Mental Health vs Physical Health Analysis.....	13
6. Reflections on the Value and Impact of the Work.....	15

1. Context and Problem Framing

The decision to focus on mental health in the workplace stems from its increasing significance in global well-being and sustainable development. Mental health is not only a personal concern—it is a systemic issue that affects organizational productivity, employee retention, and overall societal health. This project directly contributes to United Nations Sustainable Development Goal 3: Good Health and Well-being, which emphasizes the importance of ensuring healthy lives and promoting well-being for all at all ages. Within this framework, mental health is recognized as a vital component of health, yet it often remains overlooked in professional environments.

By leveraging data from multiple mental health surveys conducted over the past decade, this project seeks to provide evidence-based insights into how workplace mental health has evolved. Through data engineering and analysis, it supports informed decision-making for employers, HR professionals, and policymakers aiming to create mentally healthier and more inclusive workspaces.

The work is divided into two primary components:

- **Data Engineering:** Construction of a robust ETL pipeline.
- **Data Analysis:** Exploration and visualization of trends and patterns.

2. Data Source(s) and Preparation

Data Sources

Sources:

- 2025 Survey: Loaded from Google Sheets.
- 2014 & 2016 Surveys: Loaded from local CSV files.

Key Functions:

- `load_google_form_survey()`: Downloads and parses 2025 survey.
- `load_datasets()`: Aggregates all raw datasets.

Data Preparation Steps

1. Standardization:

- Lowercased column names.
- Harmonized column headers (e.g., `horodateur` → `timestamp`).

2. Missing Values:

- Imputed with “Unknown” or median values.

3. Age Cleaning:

- Replaced out-of-bound values (outside 18–100) with the median.

4. Gender Normalization:

- Applied regex-based mapping to standard categories: "Male", "Female", and "Other".

5. Country Normalization:

- Unified country names (e.g., "US", "United States" → "USA").

6. Feature Engineering:

- Created `mh_impact_score` to convert textual mental health impact into a numeric scale.
- Created `has_benefits` as a binary indicator of organizational mental health support (available in 2016)

3. Engineering Workflow (Tools, Architecture, Challenges)

ETL Architecture

- Extraction:
 - `load_google_form_survey()` retrieves data from Google Sheets (2025).
 - `load_datasets()` loads and aggregates all raw surveys.
- Transformation:
 - `transform_surveys()` handles standardization and feature creation.
- Integration:
 - `merge_all_surveys()` unifies all cleaned datasets into a single file with a `survey_year` tag.
- Validation:
 - `validate_data()` ensures no nulls in key fields, handles outliers, and verifies binary indicators.
- Output:
 - Cleaned individual surveys and an integrated dataset:
 - `data/processed/cleaned_survey_2014.csv`
 - `data/processed/cleaned_survey_2016.csv`
 - `data/processed/cleaned_survey_2025.csv`
 - `data/outputs/integrated.csv`
 - `data/outputs/metadata.json`

Key Challenges and Solutions

Challenge	Solution
Schema Variability	Manual column mapping and alignment logic
High Missingness	Imputation with “Unknown” or calculated medians
Gender Inconsistency	Regex-based normalization (e.g., “Cis Male” → “Male”)
Language Differences	Applied translation dictionary for French-to-English mapping

4. Analytical approach and insights

4.1 Methodology

The primary objective of this project was to explore mental health treatment patterns among employees by developing questions that are **specific, actionable, and measurable**, ultimately **leading to meaningful insights**. The following key questions guided the analysis:

- What personal and workplace factors are associated with seeking mental health treatment?
- How do employees perceive employer support for mental health?
- Can we predict who might need mental health support/treatment in the future?
- What practical solutions or recommendations can companies adopt?

These questions enable an analytics framework that leverages historical data to **understand past trends, assesses their current impact, and predicts future needs**. This comprehensive approach ensures that the project’s outputs are built on solid empirical bases and remain relevant and usable for future decision-making.

4.2 Analytical Process

To answer these questions, **“treatment”** (which is the column related to the following question: Have you sought treatment for a mental health condition?) was defined as the target variable for prediction and structured the analysis in several parts:

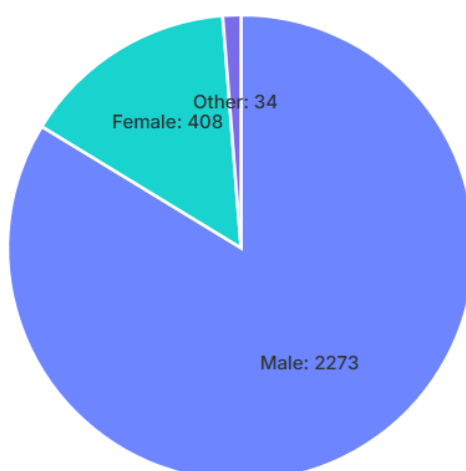
- **General demographics:** Understand the basic profile of individuals.
- **Factors influencing treatment-seeking:** Analyze personal and workplace-related variables associated with treatment uptake.
- **Employer support analysis:** Evaluate how mental health support is offered and perceived within companies.
- **Mental vs. physical health:** Compare how seriously mental health concerns are taken relatively to physical health.

This process was conducted both on the **global dataset** and focused specifically on **Tunisia**, providing localized insights relevant to the country of residence.

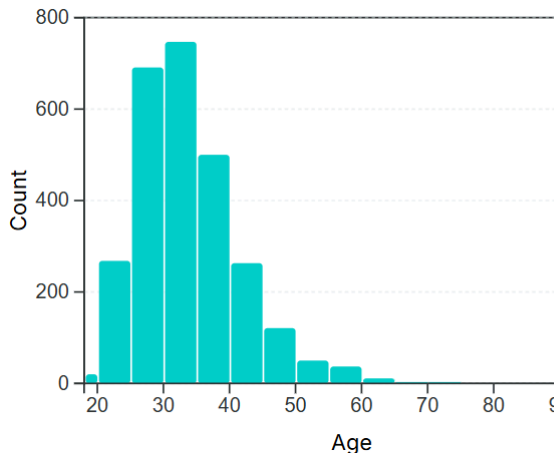
For the **predictive modeling phase**, multiple classification algorithms were experimented and, based on evaluation metrics, the Random Forest classifier was selected as the best-performing model to predict who might need mental health treatment. After training the model, the top features influencing the prediction were extracted, which informed the development of practical recommendations.

5. Discoveries, Conclusions and Recommendations

5.1 General Demographics and Treatment Patterns



The number of males in the dataset are 5.5 times the number of females. Thus, we must keep this in mind and avoid making any faulty assumptions that males are more susceptible to mental health issues etc.



Most respondents are between 20 and 40 years old, indicating the majority are working-age adults — the primary target for workplace mental health programs.



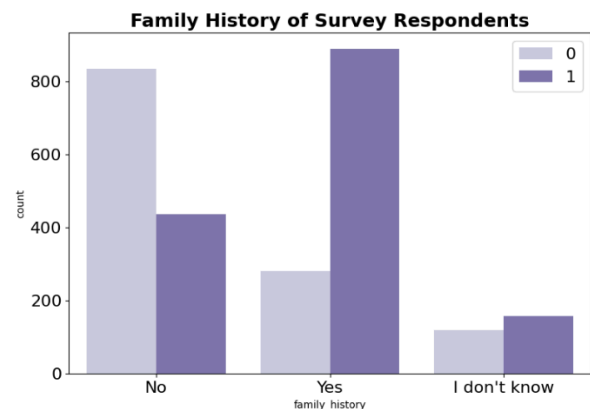
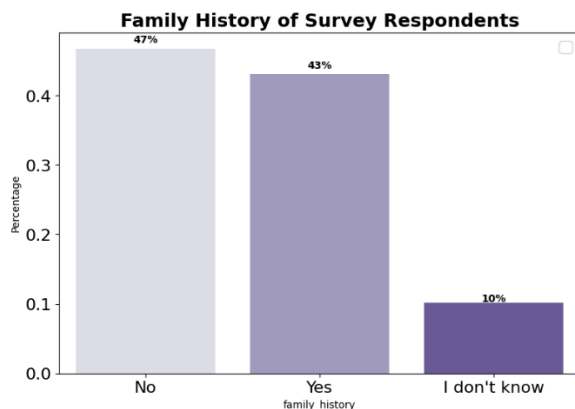
Treatment Rate

54.6%

A significant portion (more than a half) has sought mental health treatment, highlighting the prevalence of mental health challenges among workers.

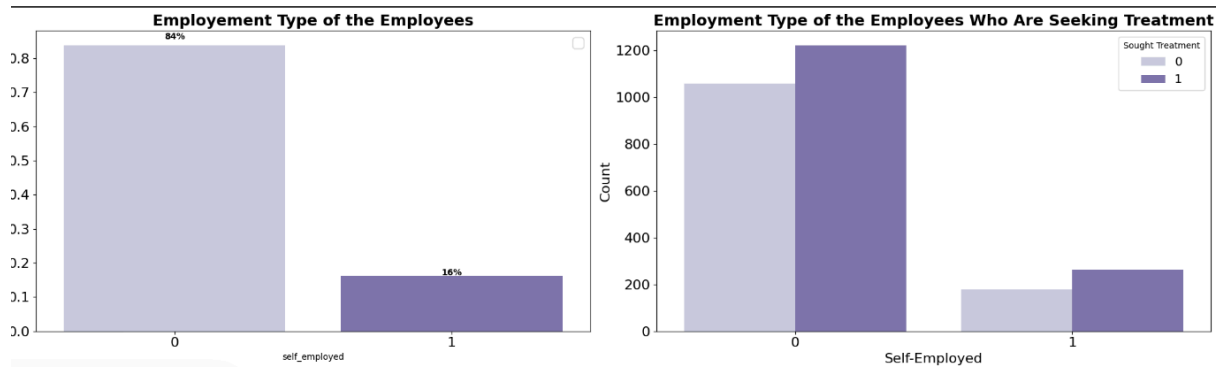
5.2 Factors Associated with Seeking Treatment

****Family History (Do you have a family history of mental illness?)**



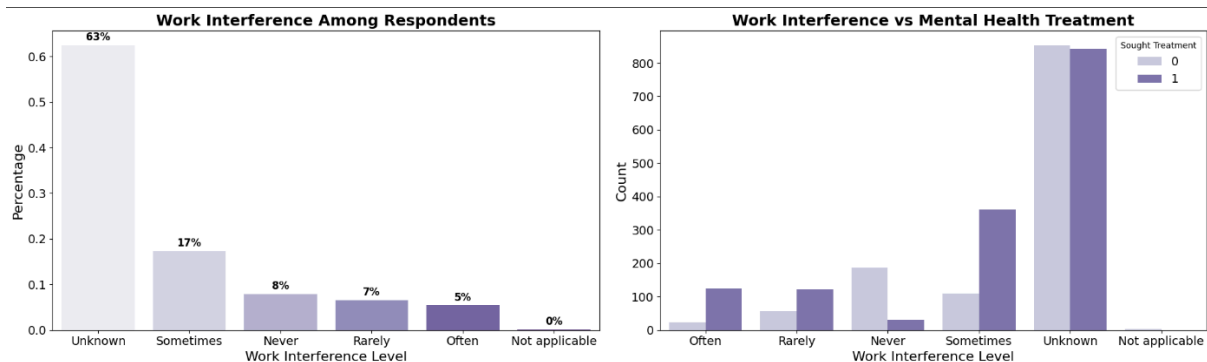
People with a family history of mental illness are much more likely to seek treatment, indicating a strong familial influence the fact that people with a family history pay more attention to mental illness. Thus, this is an important factor that has to be taken under consideration as it influences the behaviour of the employees to a significant extent.

****Self-employed (Are you self-employed?)**



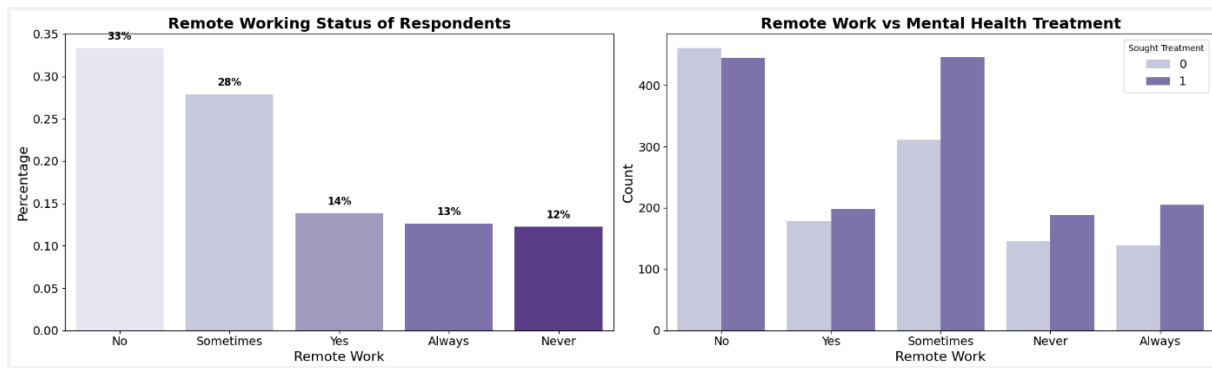
We see that the number of people who are self employed are around 16%. We also see that though there is a vast difference between people who are self employed or not, the number of people who seek treatment in both the categories is more or less similar. Thus, we may conclude that whether a person is self employed or not, does not largely affect whether he may be seeking mental treatment or not.

****Work interference level (If you have a mental health condition, do you feel that it interferes with your work?)**



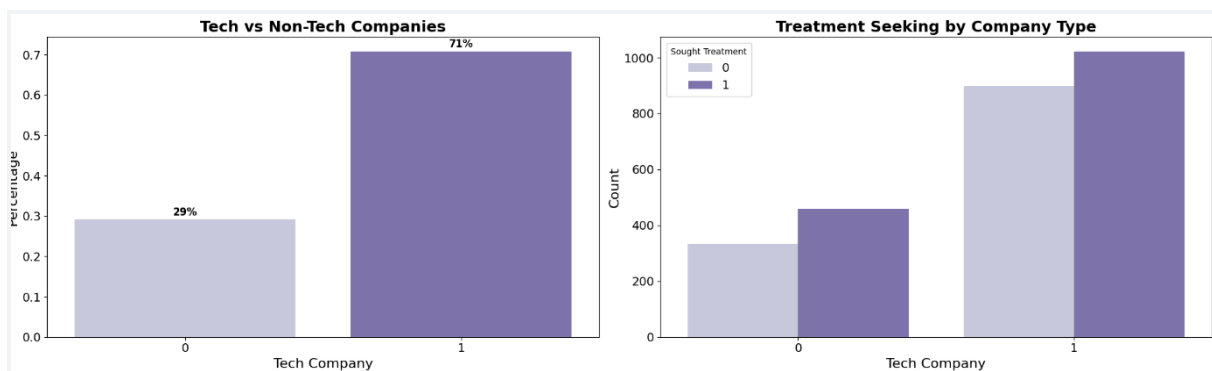
- On seeing the first graph we conclude that around 37% of people say that sometimes work interefers with their mental health. Now 'Sometimes' is a really vague response to a question, and more often than not these are the people who actually face a condition but are too shy/reluctant to choose the extreme category.
- Coming to our second graph, we see that the people who chose 'Sometimes' had the highest number of people who actually had a mental condition. Similar pattern was shown for the people who belonged to the 'Often' category'. But what is more surprising to know is that even for people whose mental health 'Never' has interfered at work, there is a little group that still want to get treatment before it become a job stress. It can be triggered a variety of reasons like the requirements of the job do not match the capabilities, resources or needs of the worker.

****Remote (Do you work remotely (outside of an office) at least 50% of the time ?)**



Around 45% of respondents don't work remotely, which means one factor of mental health disorder came up triggered on the workplace.

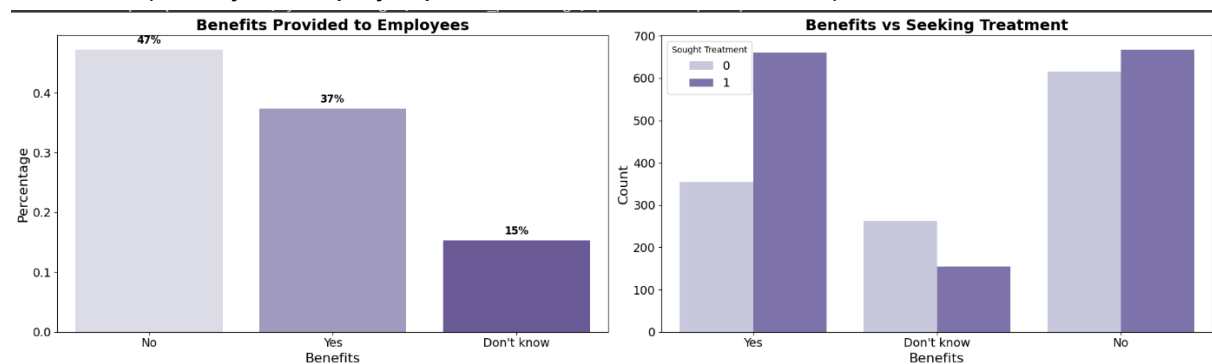
****Company type (Is your employer primarily a tech company/organization?)**



29% of the companies belong to the non-tech field. However, looking at the second graph, one may conclude that whether a person belongs to the tech field or not, mental health still becomes a big problem.

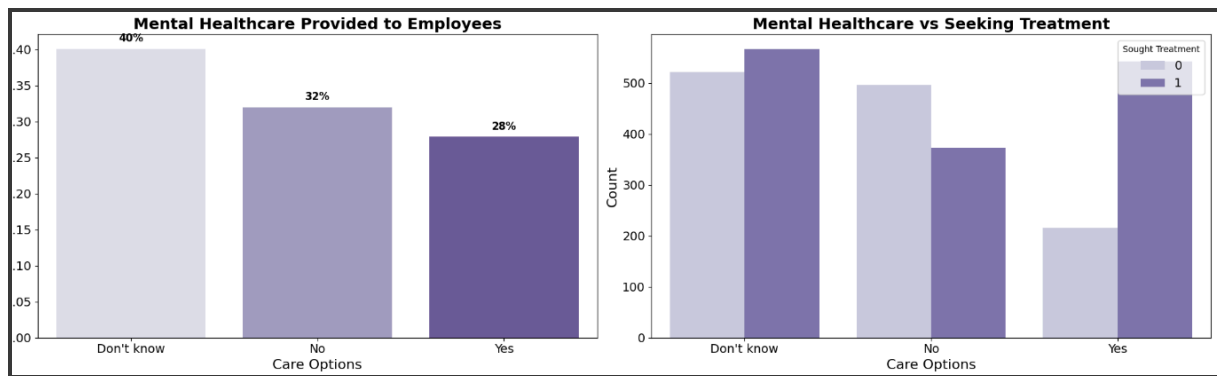
5.3 Mental health and support

****Benefits (Does your employer provide mental health benefits?)**



Only 37% of the respondents said that they were provided with mental health benefits, whereas a significant number (47%) of them didn't even know whether they were provided this benefit. Coming to the second graph, we see that for the people who said YES to mental health benefits, around 63% of them said that they were seeking medical help. Even the people who said NO, close to 45% of them said that they were seeking medical help.

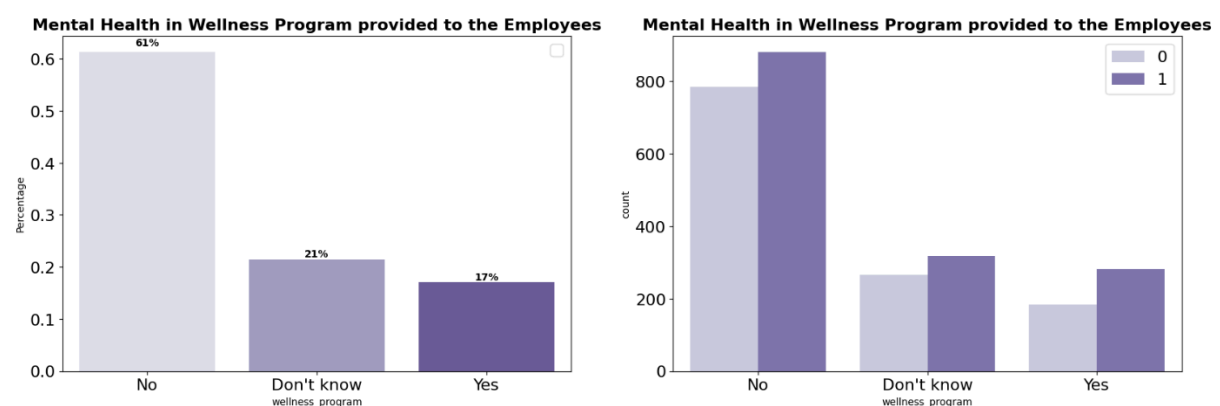
****Care options ('Do you know the options for mental health care your employer provides?')**



40% of respondents answered "I don't know" and 32% answered "No", which highlights a significant lack of awareness and education on the mental health resources available in the workplace.

Interestingly, those who responded "Yes" showed a high tendency to seek treatment, but a notable portion of those who answered "I don't know" also reported seeking treatment. This suggests that awareness may not always be a prerequisite for seeking help, but increasing transparency and communication about available resources could further encourage more individuals to access care.

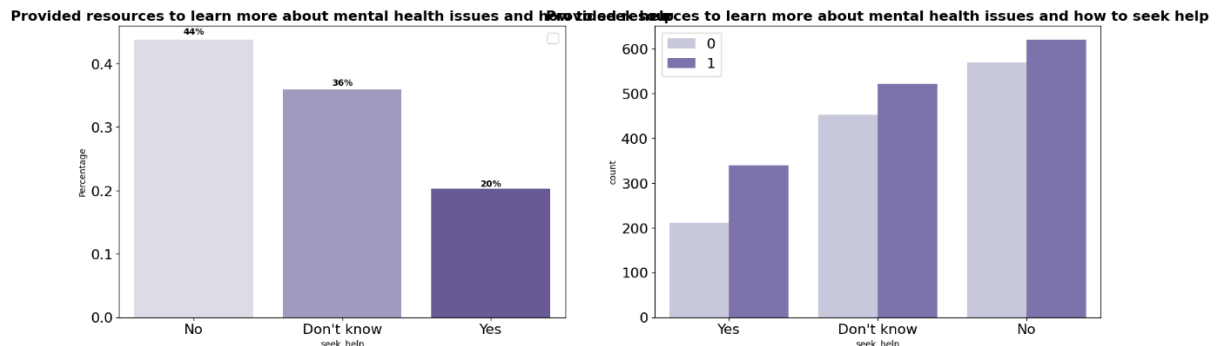
****Wellness program ('Has your employer ever discussed mental health as part of an employee wellness program?')**



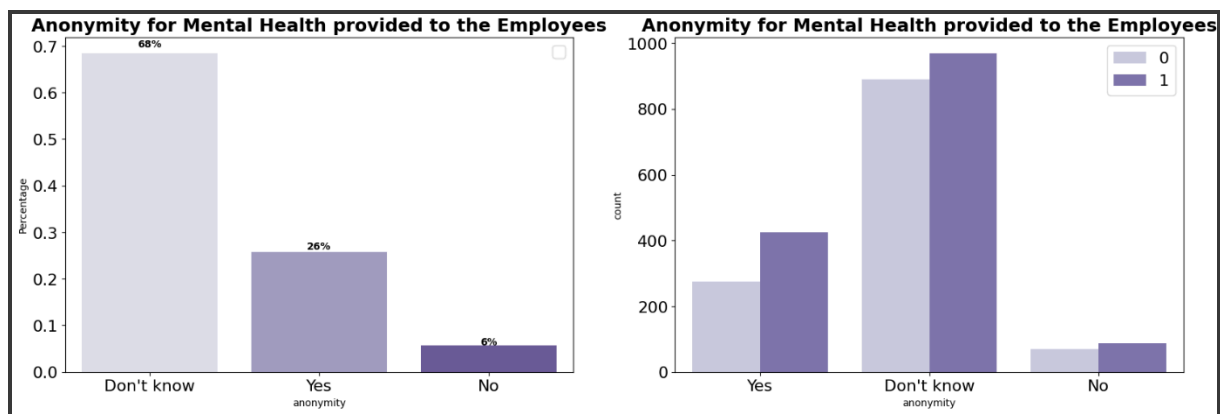
About 17% said YES and out of those, 60% of employees want to get treatment. One shocking revelation is that more than 65% of respondents say that there aren't any wellness programs provided by their company. But close to half of those

respondents want to get treatment, which means the company needs to fulfil its duty and provide it soon.

****Seek help (Does your employer provide resources to learn more about mental health issues and how to seek help?)**

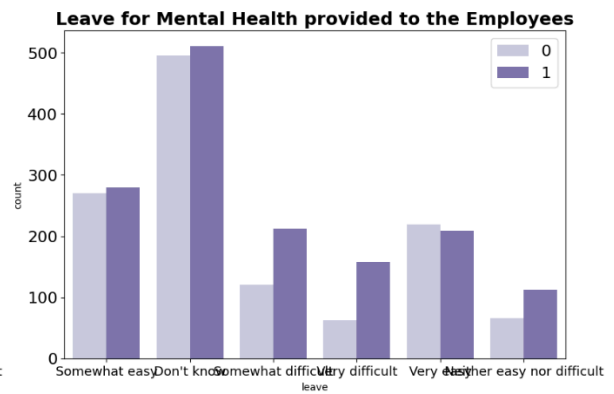
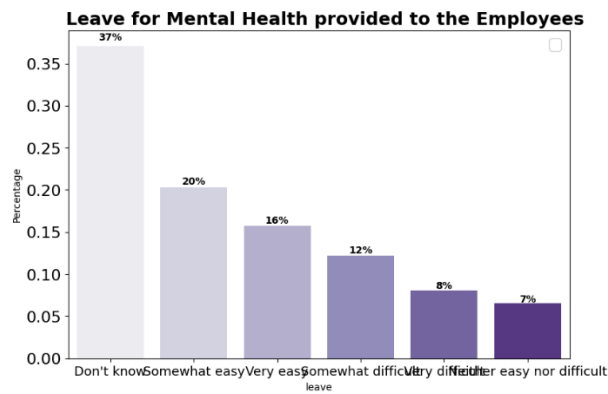


****Anonymity ('Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources?')**



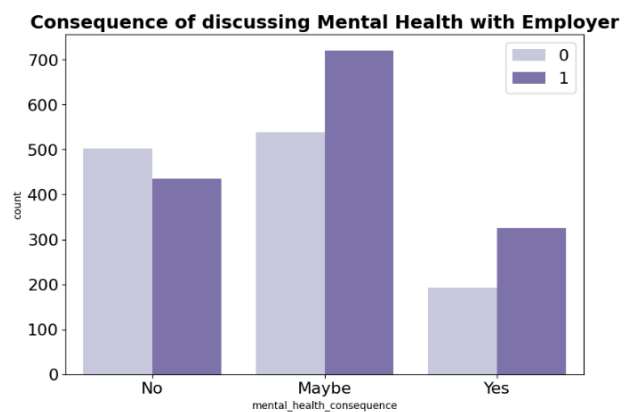
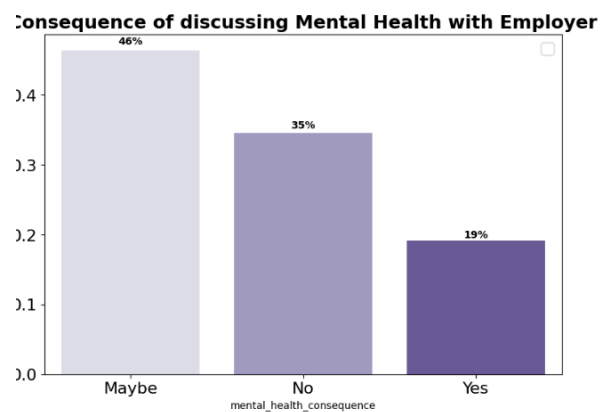
Only 26% said yes to the provision of anonymity by the company and around 65% of the people were not aware whether anonymity was provided to them. Looking at the second graph, we see that out of the people who answered yes to the provision of anonymity, around 60% of them were seeking help regarding their mental condition. Possible reasoning for this may be that the employee feels that the company has protected his/her privacy and can be trusted with knowing the mental health condition of its workers. The most basic reason behind hiding this from fellow workers can be the social stigma attached to mental health.

****Medical leave (How easy is it for you to take medical leave for a mental health condition?)**

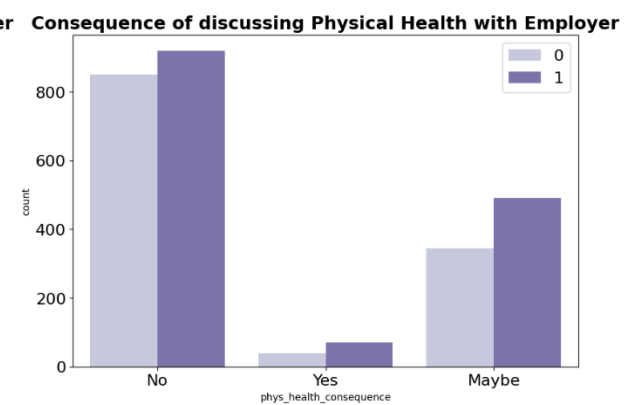
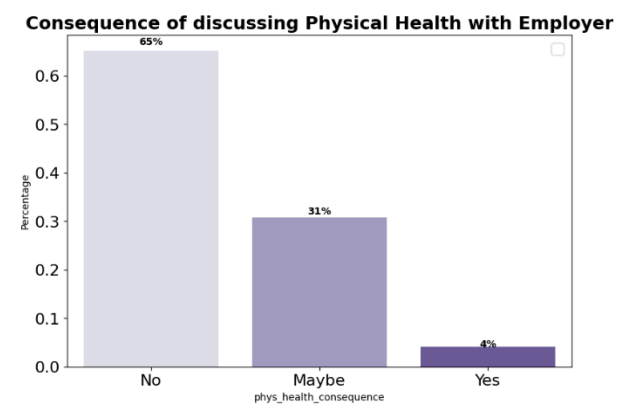


5.4 Mental Health vs Physical Health Analysis

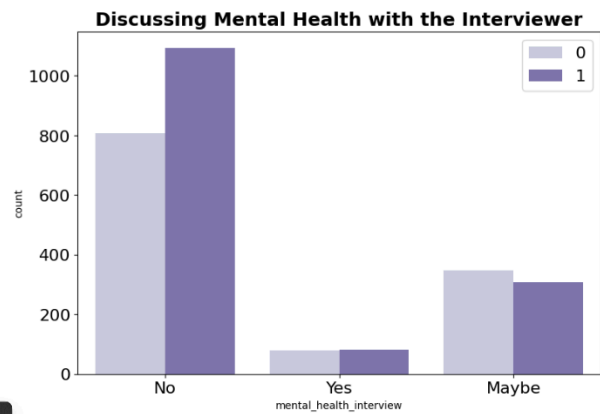
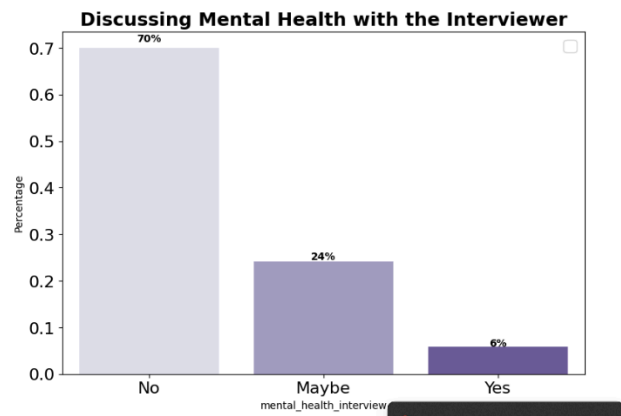
Mental health consequences



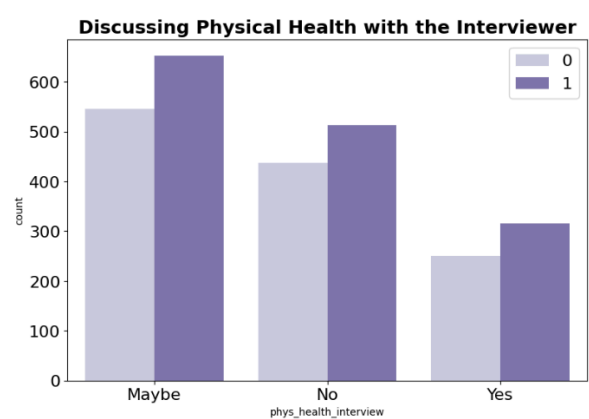
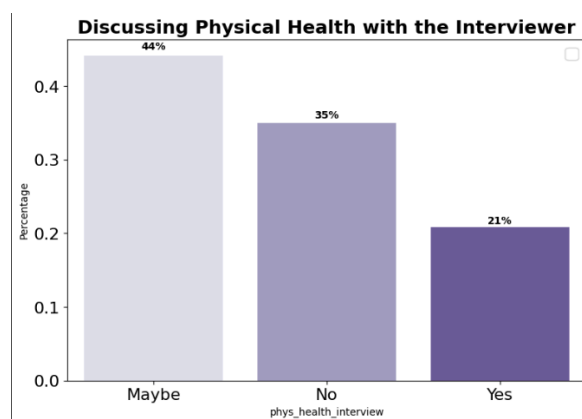
Physical health consequences



Mental_health_interview



physical health interview



Recommendations for Companies

Based on the identified key factors influencing mental health treatment uptake and model insights, companies can consider adopting the following practical solutions:

- Enhance mental health awareness and education programs tailored to demographic groups at higher risk.
- Implement or improve employer-provided mental health support, such as counseling services, flexible work policies, and peer support groups.
- Develop targeted interventions for vulnerable employee segments identified by predictive features (e.g., self-employed, family history of mental illness).
- Foster an organizational culture that reduces stigma around mental health discussions, encouraging employees to seek help early.

- Leverage predictive analytics for proactive support, identifying employees who may need assistance before critical issues arise.

6. Reflections on the Value and Impact of the Work

This project bridges data analytics and mental health by not only exploring historical and current patterns but also by enabling **predictive insights** that can empower companies to act proactively. The ability to anticipate mental health needs supports more **effective resource allocation** and can improve employee well-being, productivity, and retention.

Moreover, focusing analysis on Tunisia adds **localized value**, helping stakeholders understand cultural and contextual factors affecting mental health treatment in the region. This localized insight is crucial for tailoring interventions and policies that resonate with the specific workforce.

Ultimately, the work contributes to a **data-driven foundation** for improving mental health support in workplaces, reinforcing the importance of mental well-being as a strategic priority.

