

# Mental Health in Tech



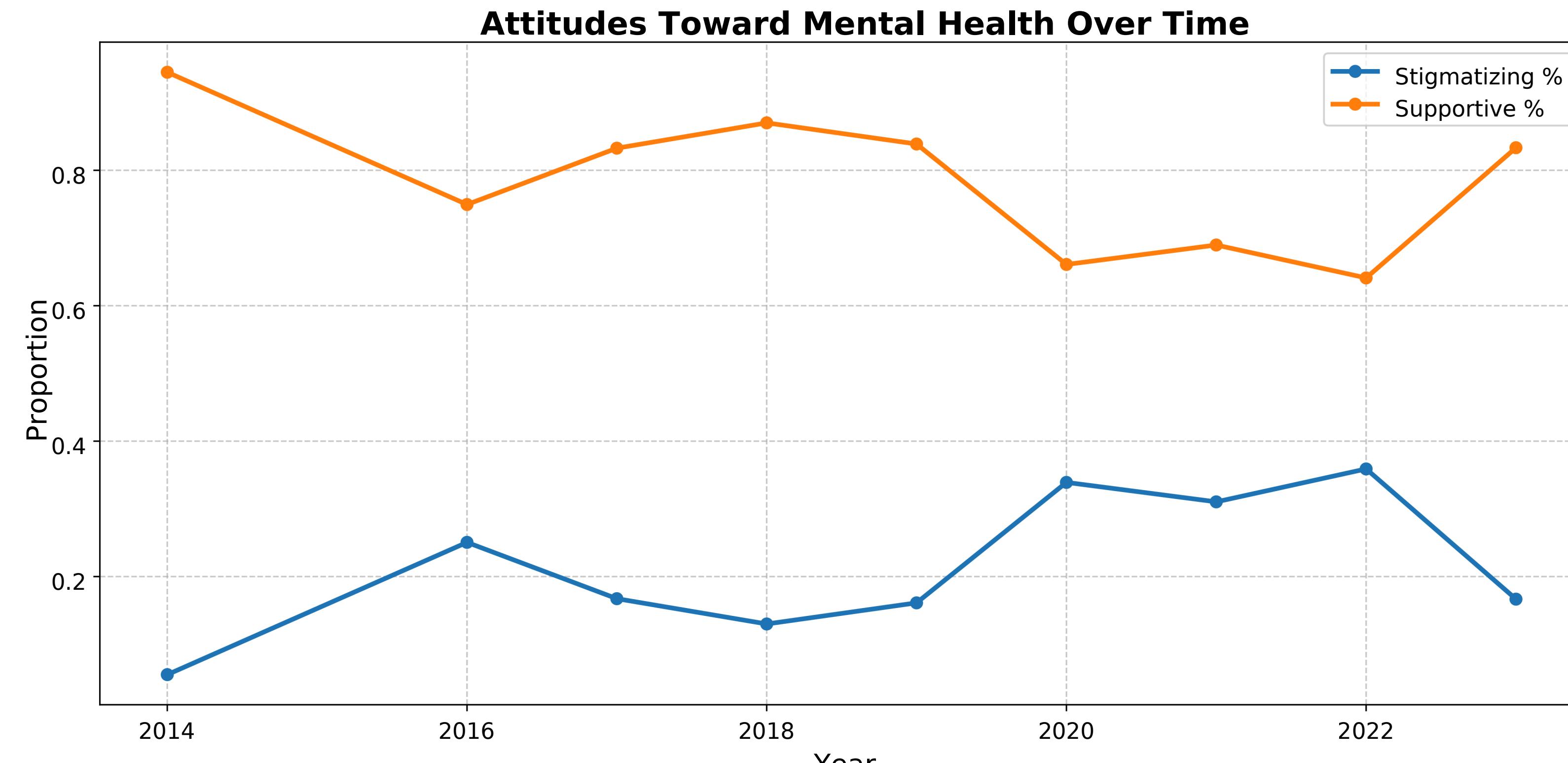
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## Approach

- Acquired and aligned the core 2014, 2016-2019 OSMI survey dataset with newly collected responses from 2020-2023.
- Built a supervised classifier using open-text embeddings, predicting the presence of a mental health disorder.
- Implemented a transformer-based NLP model (RoBERTa) to build a classifier detecting stigmatizing versus supportive language in open-ended text for annual tracking

## Methodology

- Followed CRISP-DM process.
- Preprocessing: missing value imputation, text normalization and One-Hot Encoding. Generated Sentence-BERT embeddings. Developed a manual + LLM-assisted labeling pipeline for stigma classification, followed by tokenization and sequence preparation using RoBERTa.
- Modeling: Comparison of Random Forest, LightGBM, Kernel SVM, MLP with hyperparameter tuning. Fine-tuned RoBERTa transformer to classify open-ended responses
- Evaluation: AUC and ROC curves, confusion matrices, and longitudinal trend plots. Accuracy, precision, recall to detect stigmatization.



## Introduction

- The demanding nature of the tech industry, characterized by high cognitive load and remote work, makes understanding and supporting workforce mental health critical to mitigating risks like burnout and anxiety.
- Our objectives:
  - Raise awareness and reduce stigma surrounding mental health in the tech sector.
  - Identify key risk factors and track long-term mental health trends within the industry.

## Data

- Our dataset was the Kaggle combined survey [1] merged with OSMI Research Surveys [2].
- Total size was ~5000 rows.
- Key features were demographics (age, gender), workplace environment, past treatment and current disorder status.
- Main challenges were combining inconsistent survey questions across years, and mitigating missing data and leakages.

## Results

- Best prediction model was Random Forest, AUC 0.927.
- Embeddings didn't improve performance.
- Top predictors were past disorders, age, family and workplace attitude.
- RoBERTa-based classifier successfully distinguished supportive vs stigmatizing text
- The model enabled year-by-year analysis of public attitudes in tech.
- Supportive language consistently dominated (~70-90% across years).
- Identified words associated with stigmatizing language.

