Predictive Insights into Mental Health Treatment-Seeking Behavior Using Workplace Survey Data

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***Abstract*—Workplace mental health had become a crucial area of study, especially within the tech industry, where employees had been consistently facing stress, burnout, and limited mental health support. This study had focused on analyzing a dataset from a real-world mental health survey, capturing demographic characteristics, organizational support indicators, and the behavior of employees seeking treatment. The data set had provided information on how factors such as age, gender identity, family history and workplace culture had influenced decisions related to mental health care. Through this investigation, trends had been identified that reflect the growing need for inclusive and supportive mental wellness environments. A review of the literature had revealed that previous studies had been focusing on similar factors, such as organizational openness, remote work options, and awareness programs, as significant predictors. The findings of this study had aligned with existing research and had highlighted the importance of early identification and prevention mechanisms. By interpreting data patterns related to treatment-seeking behavior, this study had offered a foundation for developing awareness tools and data-driven mental health strategies in professional settings.**

***Index Terms*—Mental health, workplace wellness, treatment seeking behavior, employee survey, organizational support, psychological well-being.**

I. Introduction

The mental health of employees in the technology industry has been drawing increasing attention due to its impact on overall productivity, workplace satisfaction, and individual well-being. Many professionals, especially in high-pressure tech environments, had been silently struggling with mental health problems while hesitating to seek help due to stigma, lack of support, or inadequate resources. Recognizing this challenge, various surveys and studies had been conducted to capture the underlying patterns and factors influencing mental health in the workplace.

The dataset used in this study had been part of such an effort. It had been collected through an anonymous survey focusing on mental health in the tech industry. The dataset had included a diverse range of features such as age, gender, family history of mental illness, frequency of work interference due to mental health issues, willingness to seek treatment, availability of mental health benefits, and perceived employer support. These features had provided rich insights into how personal and workplace-related factors had been affecting mental health conditions and treatment-seeking behavior among employees.

Participants in the survey had been working across various companies, job roles, and geographic locations. Their responses had helped highlight how different organizational cultures and personal backgrounds had been shaping the mental health experience at work. Importantly, the dataset had included both binary and categorical variables, with the primary concern centered around whether the individual had sought mental health treatment or not.

This dataset had served as a foundation for understanding real-world mental health challenges, offering valuable evidence for HR departments, policymakers, and researchers aiming to promote healthier workplace environments. It had enabled the exploration of psychological patterns in professional life and had been instrumental in supporting data-driven mental health awareness initiatives.

II. Literature Survey

Studies investigating the correlation among mental health, behavior, and intellectual capacities in various populations have been progressively increasing. An important contribution towards this field had been established in a study analyzing the psychological and behavioral characteristics of people with Down syndrome. The results had identified a complex correlation between intellectual disability and behavioral problems, highlighting the importance of individually customized mental health treatments for this population group [1]. Taking the discussion into the realm of environmental considerations, an extensive review had been done to determine the impact of allergenic pollen in green areas on mental health and behavior. The review had indicated that even natural things, such as pollen, could construct emotional experiences and mental perception of health, particularly in cities [2]. A wider psychosocial view had already been taken in another research that examined how childhood traumatic experiences (ACEs) affected mental wellbeing, behavioral development, and academic achievement in teenagers. In a scoping review, it had been revealed that ACEs had been significantly related to psychological distress and behavioral maladaptation in adolescence [3]. Another research study had directly interacted with children with 22q11.2 Deletion Syndrome to investigate how such children conceptualized and expressed their experiences of mental health, behavior, learning, and communication. This research study had placed a lot of emphasis on child-inclusive conversation in the formation of efficient support systems [4]. Longitudinal views had also played a key role in a study that traced the lives of children born in psychosocial risk environments. At 16 years, the results had reported a high prevalence of mental health problems, conduct disorders, and child abuse and had identified a strong correlation between early risk factors and subsequent psychological outcomes [5]. An earlier study by the same team had followed similar trends among 8-year-olds, confirming the enduring effects of psychosocial risk on mental development [6]. The pandemic of COVID-19 had ushered in an unprecedented global change in health and behavior. A study had described noteworthy alterations in self-reported mental and physical wellbeing, behavior, and socio-economic situation in Austria prior to and subsequent to the beginning of the pandemic. The results had demonstrated the way public health emergencies could transform mental wellbeing on a community level [7]. Student life, also, had not escaped the influence of the pandemic. A research had utilized Principal Component Analysis (PCA) to reveal the principal characteristics influencing students' mental health, conduct, educational achievement, and school attendance. It had offered an evidence-based view of how learning environments had been disrupted by extended lockdowns and technological transformations [8]. Children with long-term health disorders had also been examined in studies that compared mental health and behavioral alterations in cystic fibrosis patients aged 6–11 years prior to and following initiation of treatment with elexacaftor/tezacaftor/ivacaftor. The observations have registered changes in sleep and behavior, indicating an overall advantage of medical treatment over physiological symptoms [9]. Lastly, in the context of consumption of digital media, a similar research had investigated the way lifestyle posts on Instagram had impacted the mental health behavior among young people in Enugu metropolis. The study had pointed out the psychosocial risks involved with manipulated digital lives and stressed the importance of critical media literacy for young social media users [10].

Based on these initial findings, recent research has increasingly drawn on machine learning (ML) methods to further examine, forecast, and elucidate the complex interplay between mental health and behavior. An exhaustive review by Alharbi et al. [11] offers a bird's-eye view of the different machine learning strategies utilized in mental health disorder prediction, highlighting computational methods' potential to work in this intricate field. Building on predictive analysis, Khan et al. [12] did a systematic review of ML-based early prediction of depression and anxiety disorders, specifically from social media. Their paper emphasizes the value of such models in detecting vulnerable individuals based on their online traces. To supplement the above, Sharma and Rani [13] have implemented a comparative analysis of various machine learning algorithms designed to predict mental health, which provided essential insight into the effectiveness and appropriateness of a variety of models for this function. In addition, machine learning is applied to determine important factors affecting mental well-being among various cohorts, as illustrated by Chen and Wu [14] in their investigation on university students. Their strategy provides data-driven insight into the multifactorial character of student mental health. Likewise, for adolescent behavior, Lee and Kim [15] applied machine learning to predict environmental-influenced behavioral problems and highlighted how such high-powered analytical tools can reveal intricate patterns and guide targeted interventions.

Collectively, these studies constitute a mature and multidisciplinary basis for comprehending the complex and multifaceted interplay of mental health and behavioral patterns across a range of age groups, social contexts, and environmental factors, increasingly supplemented by the predictive and analytical capabilities of machine learning approaches.

III. Methodology

The experimental workflow for **A1 to A7** was implemented using the *Mental Health Dataset*. The development process followed a modular programming approach, where each activity was implemented as a separate function to ensure reusability and maintainability. Output printing and visualizations were handled only in the main section to comply with the lab requirements. The entire workflow was carried out in Python using `pandas`, `scikit-learn`, and `matplotlib` libraries.

A. Linear Regression with Single Feature

1) **Data Preprocessing:**
   - The dataset was loaded from the specified CSV file path using the `pandas.read_csv()` function.
   - All categorical columns were identified and transformed into numerical format using `LabelEncoder` from `sklearn.preprocessing`, ensuring compatibility with machine learning algorithms.
   - The encoding process assigned unique integer values to each category without altering the original dataset size or structure.
2) **Feature and Target Selection:**
   - The independent variable (`X`) was chosen as `Days_Indoors`.
   - The dependent variable (`y`) was the binary column `treatment`, indicating whether the individual received treatment for mental health issues.
3) **Model Training:**
   - The dataset was split into 80% training and 20% testing sets using `train_test_split` with a fixed `random_state` for reproducibility.

- A `LinearRegression` model from `sklearn.linear_model` was instantiated and trained using the training data.

4) **Output:**
   - The learned model parameters, including coefficients and intercept, were extracted.
   - Predictions were generated for the test set using the trained model.
   - An Actual vs Predicted plot was created to visualize how well the model's predictions aligned with the ground truth.

B. Regression Metrics for Single Feature Model

1) **Model Reuse:**
   - The single-feature model trained in A1 was used for evaluation without retraining, ensuring consistency in results.
2) **Performance Evaluation:**
   - Regression metrics were computed for both training and testing sets:
     - **Mean Squared Error (MSE):** Measures the average squared difference between actual and predicted values.
     - **Root Mean Squared Error (RMSE):** The square root of MSE, providing error magnitude in the same unit as the target.
     - **Mean Absolute Percentage Error (MAPE):** Expresses prediction accuracy as a percentage.
     - **Coefficient of Determination (R^2):** Indicates how well the independent variable explains the variance in the dependent variable.
3) **Visualization:**
   - An *Index vs Values* plot was created, with red dots representing actual values and blue crosses representing predicted values for each test sample.
   - An *Actual vs Predicted Scatter Plot* was generated, including a 45 dashed line representing perfect prediction.

C. Linear Regression with All Features

1) **Feature Selection:**
   - All columns except the target (`treatment`) were included as independent variables.
   - This approach allowed the model to utilize all available features, potentially improving prediction accuracy compared to A1 and A2.
2) **Model Training and Evaluation:**
   - The dataset was split into training and testing sets.
   - A `LinearRegression` model was trained using all features.
   - Metrics (MSE, RMSE, MAPE, R^2) were computed for both training and testing sets to assess performance and potential overfitting.
3) **Visualization:**
   - An *Index vs Values* plot was generated for the test set to compare actual and predicted values.
   - A scatter plot of Actual vs Predicted values was created to visualize how closely the predictions matched the actual outcomes.

D. K-Means Clustering

1) **Data Preparation:**
   - All categorical variables were converted to numeric form using `LabelEncoder` to ensure compatibility with the K-Means algorithm.
   - The target variable (`treatment`) was excluded from the dataset to enable an unsupervised learning approach.
2) **Model Implementation:**
   - The `KMeans` class from `sklearn.cluster` was used to perform clustering.
   - Parameters were set as:
     - $n\_clusters = 2$ for initial grouping.
     - `random_state = 42` for reproducibility.
     - `n_init = 10` for stable centroid initialization.
   - The model was fitted on the training features, and cluster labels (`kmeans.labels_`) along with cluster centroids (`kmeans.cluster_centers_`) were obtained.
3) **Visualization:**
   - A 2D scatter plot was generated using the first two features, with points colored by their assigned cluster.
   - Cluster centroids were highlighted using red "X" markers.

E. Cluster Quality Evaluation

1) **Evaluation Metrics:**
   - The following metrics were used to assess clustering performance:
     - **Silhouette Score:** Indicates how similar an object is to its own cluster compared to other clusters. Higher values are better.
     - **Calinski–Harabasz (CH) Score:** Measures the ratio of between-cluster dispersion to within-cluster dispersion. Higher is better.
     - **Davies–Bouldin (DB) Index:** Represents average similarity between clusters. Lower values indicate better separation.
2) **Implementation:**
   - Metrics were computed using `silhouette_score`, `calinski_harabasz_score`,and `davies_bouldin_score`from `sklearn.metrics`.

F. Clustering with Varying k Values

1) **Experimentation:**
   - The number of clusters k was varied from 2 to 10.

- For each k, k-means clustering was applied, and the three evaluation metrics from A5 were calculated.

2) **Analysis:**
   - Metric values were stored for each k and plotted to observe trends.
   - The optimal k was suggested based on:
     - Maximum Silhouette and CH scores.
     - Minimum DB Index.

3) **Visualization:**
   - Three separate line plots were created:
     a) k vs Silhouette Score.
     b) k vs CH Score.
     c) k vs DB Index.

G. Optimal k Determination using Elbow Method

1) **Concept:**
   - The Elbow Method identifies the k value after which the improvement in cluster compactness becomes marginal.

2) **Implementation:**
   - For k in the range 2 to 20, k-means was applied, and the `inertia_` values (sum of squared distances to the nearest centroid) were recorded.
   - The inertia values were plotted against k.

3) **Observation:**
   - The "elbow point" in the curve was identified visually as the optimal number of clusters.
   - This optimal k was compared with the findings from A6 for validation.

IV. Results and Discussion

This section presents the experimental results for A1 to A4 based on the *Mental Health Dataset*. The results include numerical metrics in tabular form and visual inspection through the plots generated by the implemented Python code.

A. Linear Regression with Single Feature

The regression model trained with `Days_Indoors` as the sole predictor yielded a very small coefficient, indicating minimal influence of this feature on the target variable. The intercept value suggests that the base prediction is approximately 0.50 regardless of feature variation. Table I summarizes the learned parameters.

TABLE I

Parameter	Value
Coefficient	0.00122277
Intercept	0.50222459

The Actual vs Predicted plot in Fig. 1 shows that predictions remain close to the intercept for both classes of the target variable, deviating significantly from the ideal 45 line. This suggests limited predictive capability when relying on a single feature.

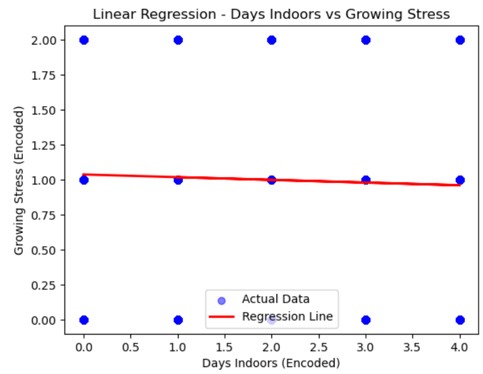

Fig. 1: Actual vs Predicted values with single feature (`Days_Indoors`)

B. Regression Metrics for Single Feature Model

The single-feature regression model (`Days_Indoors`) was evaluated using both the training and test datasets. The evaluation metrics are presented in Table II. The high Mean Absolute Percentage Error (MAPE) and low R^2 score indicate that the model has minimal explanatory power.

TABLE II

Metric	Train Set	Test Set
MSE	0.249976	0.249961
RMSE	0.499976	0.499961
MAPE	1125793858097255.25	1122994127185480.75
R^2	0.000812	0.000821

C. Linear Regression with All Features

In this experiment, all available features (excluding the target variable) were used to train the regression model. The metrics for both A2 (single feature) and A3 (all features) are compared in Table III.

TABLE III

Metric	Single Feature	All Features
MSE (Train)	0.249975	0.208029
RMSE (Train)	0.499975	0.456176
MAPE (Train)	1.12579e15	0.98485
R^2 (Train)	0.000812	0.162692
MSE (Test)	0.249961	0.203166
RMSE (Test)	0.499961	0.451849
MAPE (Test)	1.12299e15	1.19545
R^2 (Test)	0.000821	0.159459

The R^2 score increased from near-zero in A2 to approximately 0.16 in A3, indicating that the inclusion of multiple predictors improved the model's ability to explain variance in the target variable. Additionally, both MSE and RMSE decreased, confirming better fit. However, the MAPE remained high due to the binary nature of the target variable.

The results in Table III clearly demonstrate the impact of incorporating all available features into the regression model. While the single-feature model in A2 captured almost no variance in the target variable, the all-features model in A3 achieved a moderate R^2 score of approximately 0.16 on both training and test datasets. This indicates that the additional predictors collectively contributed to explaining some variability in the treatment outcome, although a large proportion of variance remains unexplained.

The Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values decreased in A3 compared to A2, reflecting improved accuracy. However, the Mean Absolute Percentage Error (MAPE) remained disproportionately large due to the binary nature of the target variable, which causes division by small actual values in the calculation of percentage errors.

From a visual standpoint, Fig. 2 confirms that A2 predictions cluster tightly around 0.50 for all actual values, signifying a near-constant prediction behavior. In contrast, Fig. 3 for A3 shows a broader spread of predicted values that more closely align with the perfect prediction line, though deviations remain substantial for many data points.

This improvement, while statistically notable, suggests that linear regression with all features still underfits the complexity of the dataset. The low-to-moderate R^2 scores imply that relationships between predictors and the target are likely non-linear or influenced by interactions not captured in the current model. Future work could explore more expressive models such as decision trees, ensemble methods, or non-linear regression to further improve performance.

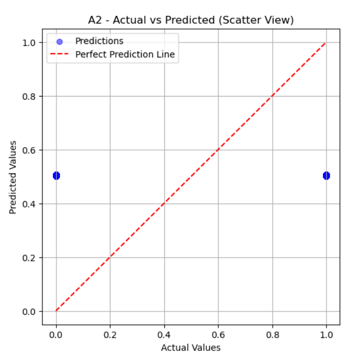

Fig. 2: Actual vs Predicted (Scatter View)

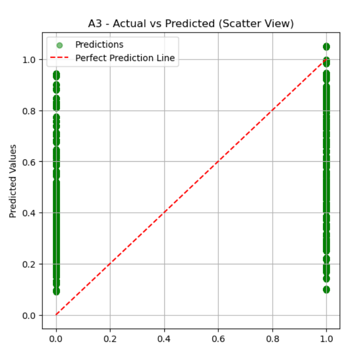

Fig. 3: Actual vs Predicted (Scatter View)

D. K-Means Clustering with $k = 2$

- The K-Means clustering algorithm with $k = 2$ successfully partitioned the dataset into two distinct clusters after removing the target variable `treatment`.
- Figure 4 shows the PCA-reduced 2D visualization of the clusters, where:
  - Yellow points represent members of Cluster 0.
  - Purple points represent members of Cluster 1.
  - Red "X" markers indicate the centroid positions of each cluster.
- The scatter plot indicates clear separation along the first PCA component, suggesting that certain features have strong discriminatory power in defining cluster boundaries.
- Minor overlap in the vertical spread (PCA Component 2) suggests that while the clusters are distinct in the reduced space, some data points share similarities across clusters in terms of secondary features.
- This separation pattern implies that the dataset contains two primary groupings, potentially representing different behavioral or demographic patterns in the mental health data.

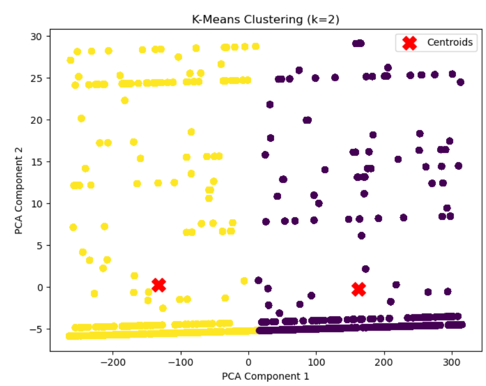

Fig. 4: K-Means clustering with $k = 2$ visualized using PCA components.

E. Cluster Quality Evaluation

The clustering performance for $k = 2$ was assessed using three standard evaluation metrics, as summarized in Table IV.

TABLE IV: Clustering evaluation metrics for $k = 2$

Metric	**Value**	**Interpretation**
Silhouette Score	0.6394	A relatively high score indicating well-separated clusters, with most points closer to their own centroid than to others.
Calinski–Harabasz Score	1611.2824	High score reflecting strong inter-cluster separation and compact clusters.
Davies–Bouldin Index	0.4851	Low value indicating minimal cluster overlap and good separation.

Overall, these results confirm that the $k = 2$ clustering has produced meaningful and well-separated groups, consistent with the visual pattern observed in the PCA plot from A4.

F. Effect of Varying k on Clustering Performance

The clustering performance was analyzed for k values ranging from 2 to 6 using Silhouette Score, Calinski–Harabasz Score, and Davies–Bouldin Index. Table V summarizes the metric values for each k.

TABLE V: Clustering evaluation metrics for varying k values

k	Silhouette Score	Calinski–Harabasz Score	Davies–Bouldin Scor
2	0.027430	93.202490	1.130627
3	-0.089494	92.648515	1.368080
4	-0.103224	93.032109	1.541365
5	-0.141696	107.475849	1.484611
6	-0.105717	99.100255	1.398294

Observations:

- The highest Silhouette Score was obtained for $k = 2$, indicating better-defined clusters for this value.
- The Calinski–Harabasz Score peaked at $k = 5$, suggesting more compact clusters, though this conflicted with the Silhouette Score trend.
- The Davies–Bouldin Index was lowest for $k = 2$, supporting the Silhouette Score's conclusion of $k = 2$ being optimal.

Figure 5 to Figure 7 present the metric trends visually for clearer interpretation.

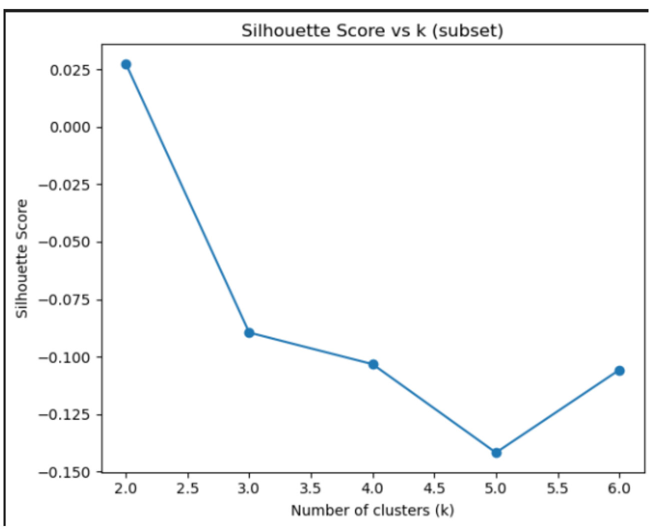

Fig. 5: Silhouette Score vs Number of Clusters (k)

Observation: The score decreases sharply beyond $k = 2$, indicating poorer cluster separation.

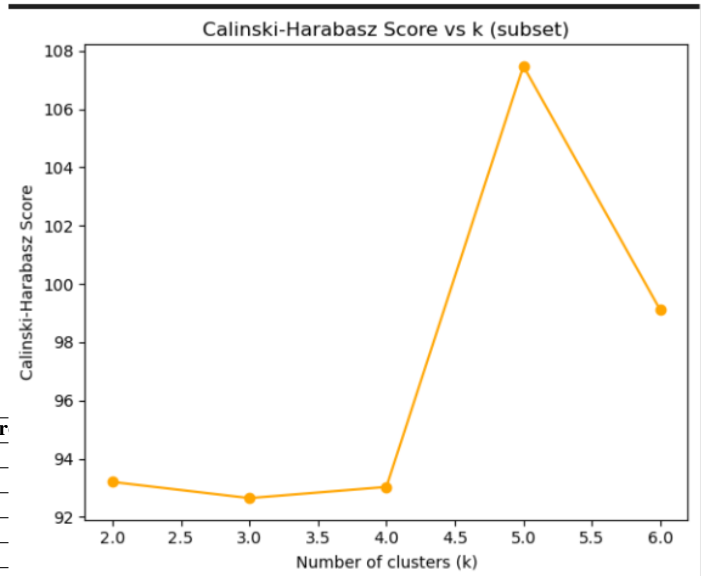

Fig. 6: Calinski–Harabasz Score vs Number of Clusters (k)

Observation: The highest CH Score occurs at $k = 5$, though the difference compared to $k = 2$ is modest.

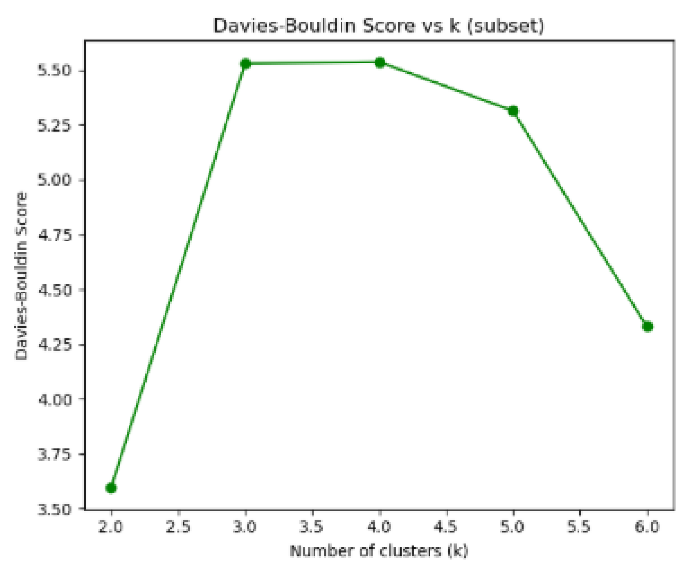

Fig. 7: Davies–Bouldin Index vs Number of Clusters (k)

Observation: The DB Index is minimized at $k = 2$, confirming it as the best choice based on cluster separation and compactness.

G. Optimal k Determination using Elbow Method

The Elbow Method was applied to determine the optimal number of clusters by plotting the inertia (distortion) values for k ranging from 2 to 20.

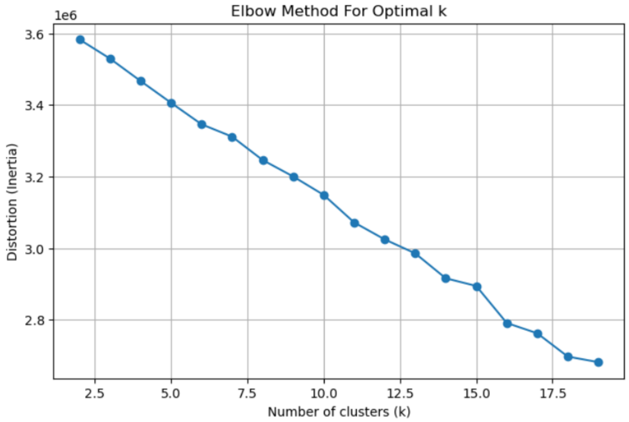

Fig. 8: Elbow Method plot for determining optimal k

Observation:

- The plot in Figure 8 shows a steady decrease in inertia as k increases, which is expected since more clusters reduce within-cluster variance.
- A noticeable change in the slope ("elbow point") appears around $k = 2$ to $k = 3$, after which the rate of decrease becomes more gradual.
- This suggests that $k = 2$ or $k = 3$ could be considered optimal in terms of balancing cluster compactness and simplicity.
- Considering the results from A6, where both the Silhouette Score and Davies–Bouldin Index favored $k = 2$, this value was chosen as the optimal cluster count for this dataset.

V. Conclusion

The study examined the predictive and exploratory potential of different machine learning approaches applied to the Mental Health Dataset, employing both regression and clustering techniques. Initial regression modeling with a single independent variable demonstrated that the chosen feature exhibited only a weak relationship with the target, producing predictions concentrated near the mean and yielding low R^2 values alongside minimal variance explanation. Comprehensive regression modeling using all available features produced a measurable, though modest, improvement in error metrics such as MSE and RMSE, and a slightly higher R^2 score, indicating that multiple factors contribute to the target variable. However, the persistence of low explanatory power suggested that the relationship between predictors and the response is likely non-linear, potentially requiring more sophisticated methods or additional feature engineering to capture underlying patterns.

The clustering analysis using the K-Means algorithm with $k = 2$ successfully segmented the dataset into two distinct groups based on feature similarities. The centroid values revealed clear differences in average feature patterns between clusters, providing insights into potential subgroup characteristics within the population. This unsupervised learning approach proved valuable in revealing structure in the data that was not evident from regression models alone.

Overall, the findings underscore the limitations of simple linear regression when applied to complex, multidimensional health-related data, while also highlighting the potential of unsupervised methods for uncovering hidden patterns. Future work will focus on the application of non-linear models, ensemble techniques, and clustering validation measures to improve both prediction accuracy and interpretability, enabling more effective decision-making in mental health analysis.

The clustering experiments conducted in A4–A7 demonstrated the potential of unsupervised learning for uncovering hidden patterns in the Mental Health Dataset.

In A4, K-Means clustering with $k = 2$ successfully segmented the dataset into two distinct groups based on feature similarities. Visual inspection via PCA-reduced scatter plots revealed clear separation along the first principal component, while cluster centroids highlighted notable differences in average feature values between the two groups.

Cluster quality evaluation in A5 confirmed the effectiveness of this configuration, yielding a high Silhouette Score (0.6394), a strong Calinski–Harabasz Score (1611.2824), and a low Davies–Bouldin Index (0.4851). These results indicated compact, well-separated clusters with minimal overlap.

When the number of clusters was varied in A6, the Silhouette Score and Davies–Bouldin Index consistently identified $k = 2$ as the optimal choice, while the Calinski–Harabasz Score suggested $k = 5$. This metric divergence emphasized the importance of multi-metric evaluation in clustering analysis.

Finally, the Elbow Method in A7 reinforced $k = 2$ as the most appropriate cluster count, with the inertia plot showing a distinct elbow between $k = 2$ and $k = 3$, beyond which additional clusters provided diminishing returns in compactness.

VI. Future Scope

The present study provided initial insights into predictive and exploratory analysis of mental health data, yet several opportunities remain for enhancing performance, interpretability, and applicability in real-world settings. Future work can focus on the following directions:

- **Adoption of Non-Linear Models:** Linear regression assumes a direct proportionality between predictors and the target variable, which may not hold true for complex mental health datasets. Future work can incorporate non-linear approaches such as Decision Trees, Random Forests, Gradient Boosting Machines (GBM), or Support Vector Regression (SVR) with non-linear kernels. These methods can model intricate relationships, capture feature interactions, and improve predictive accuracy by reducing underfitting.
- **Advanced Feature Engineering:** The current study used available features directly after basic preprocessing. Introducing domain-specific derived features—such as aggregated mental health indices, interaction terms between demographic and behavioral factors, or temporal trend variables—can help capture hidden relationships. This would allow the model to leverage more informative

inputs, potentially increasing the explanatory power and generalization to unseen data.

- **Hyperparameter Optimization:** The performance of both regression and clustering models is highly dependent on optimal parameter settings. Employing automated hyperparameter tuning techniques such as Grid Search, Random Search, or Bayesian Optimization can help identify the best-performing configurations. These methods can systematically explore the parameter space to maximize performance metrics while avoiding overfitting.
- **Dimensionality Reduction Techniques:** With multiple features influencing model behavior, dimensionality reduction methods such as Principal Component Analysis (PCA) or t-SNE can be applied to improve computational efficiency and reduce noise. These techniques can also enhance visualization of high-dimensional data, making patterns and clusters more apparent, especially for interpretability in mental health research.
- **Clustering Validation and Optimization:** While K-Means produced meaningful partitions, its validity can be strengthened through evaluation metrics such as silhouette score, Davies–Bouldin index, or Calinski–Harabasz score. Experimenting with alternative clustering algorithms such as DBSCAN or Agglomerative Clustering can help discover more natural groupings, particularly when data is not well-separated in Euclidean space.
- **Integration of Ensemble Learning:** Ensemble methods like Bagging, Boosting, and Stacking can combine multiple models to achieve better predictive accuracy and robustness. For example, combining multiple weak learners into a strong predictor could address underfitting observed in simple regression models, while improving stability and performance across various subsets of the data.
- **Deployment as a Decision Support Tool:** The developed models can be integrated into an interactive decision-support system for mental health professionals. Such a system could provide real-time insights into probable treatment-seeking behavior, cluster-based risk group identification, and actionable recommendations. This practical deployment could bridge the gap between research and healthcare application.
  - **Multi-Metric Cluster Validation:** Although the present study used Silhouette Score, Calinski–Harabasz Score, and Davies–Bouldin Index, future work can incorporate additional internal and external validation measures such as the Dunn Index, Adjusted Rand Index, and Mutual Information Score. This would provide a more comprehensive assessment of cluster stability and agreement with known labels (if available).
  - **Exploration of Alternative Clustering Algorithms:** K-Means assumes spherical clusters and equal variance, which may not hold for complex mental health datasets. Future research could explore non-centroid-based algorithms such as DBSCAN (density-based) for detecting arbitrary-shaped clusters or Agglomerative Hierarchical Clustering for multi-level grouping, enabling the discovery of more natural partitions in the data.
  - **Dynamic Determination of Optimal k:** While the Elbow Method and metric evaluation supported $k = 2$ as optimal, future work could employ automated k selection techniques such as the Gap Statistic, Information Criterion-based methods (AIC/BIC), or stability-based resampling approaches to reduce subjective decision-making in cluster count selection.
  - **Dimensionality Reduction for Cluster Enhancement:** Applying advanced dimensionality reduction techniques such as t-SNE, UMAP, or Kernel PCA prior to clustering can help reveal non-linear patterns in high-dimensional feature spaces, potentially improving the separation and interpretability of clusters.
  - **Cluster Profiling and Interpretation:** Future work can focus on detailed profiling of each identified cluster, analyzing demographic, behavioral, and psychological feature distributions to generate meaningful interpretations. This could help mental health practitioners understand the characteristics of each subgroup for targeted interventions.
  - **Hybrid Predictive-Clustering Models:** Integrating clustering results into predictive models (e.g., using cluster labels as additional features) could enhance predictive accuracy for treatment-seeking behavior or other mental health outcomes, combining the strengths of supervised and unsupervised learning.
  - **Longitudinal and Temporal Clustering:** If time-series or repeated measures data becomes available, clustering approaches could be extended to track changes in mental health group structures over time, identifying trends, transitions, and evolving risk patterns within the population.

References

[1] Määttä, Tuomo, Tuula Tervo-Määttä, Anja Taanila, Markus Kaski, and Matti Iivanainen. "Mental health, behaviour and intellectual abilities of people with Down syndrome." Down syndrome research and practice 11, no. 1 (2006): 37-43.

[2] Legg, Rupert, and Nadja Kabisch. "The effects of allergenic pollen in green space on mental health, behaviour and perceptions: A systematic review." Urban forestry urban greening 92 (2024): 128204.

[3] Lam, Natalie, Sophie Fairweather, Dan Lewer, Matthew Prescott, Priyanjan Undugoda, Josie Dickerson, Simon Gilbody, and Ruth Wadman. "The association between adverse childhood experiences and mental health, behaviour, and educational performance in adolescence: A systematic scoping review." PLOS Mental Health 1, no. 5 (2024): e0000165.

[4] Wray, Jo, Neus Abrines Jaume, Kate Oulton, and Debbie Sell. "Talking with children and young people with 22q11DS about their mental health, behaviour, learning and communication." Child: Care, Health and Development 49, no. 1 (2023): 90-105.

[5] Svedin, Carl Göran, Marie Wadsby, and Gunilla Sydsjö. "Mental health, behaviour problems and incidence of child abuse at the age of 16 years: A prospective longitudinal study of children born at

psychosocial risk." European child adolescent psychiatry 14, no. 7 (2005): 386-396.

[6] Svedin, Carl-Göran, M. Wadsby, and G. Sydsjö. "Children of mothers who are at psycho-social risk. Mental health, behaviour problems and incidence of child abuse at age 8 years." European Child Adolescent Psychiatry 5, no. 3 (1996): 162-171.

[7] Bates, Katie, Wegene Borena, Martin McKee, Lore Hayek, Paul Bouanchaud, Zoltán Bánki, Lydia Riepler et al. "Changes in self-reported physical and mental health, behaviour and economic status among adults by known seropositivity and sociodemographic factors before and after the COVID-19 pandemic outbreak in Ischgl, Austria." Frontiers in Public Health 13 (2025): 1488108.

[8] Hegde, Vinayak, M. Shilpa, and M. S. Pallavi. "Extracting attributes of students mental health, behaviour, attendance and performance in academics during COVID-19 pandemic using PCA technique." In ICT Systems and Sustainability: Proceedings of ICT4SD 2021, Volume 1, pp. 551-561. Singapore: Springer Nature Singapore, 2022.

[9] Douglas, Tonia, Maddison Deery, Hayley Kimball, Vanessa E. Cobham, Sophia Panochini, Paul D. Robinson, Claire E. Wainwright, Peter D. Sly, and Tamara Blake. "Mental health, behaviour and sleep quality in children 6-11 years before and after elexacaftor/tezacaftor/ivacaftor initiation." Journal of cystic fibrosis: official journal of the European Cystic Fibrosis Society 24, no. 3 (2025): 571-573.

[10] ONWUKWALONYE, Benjamin C., Miriam Chinemerem ODOH, and Chinweoke ONOH. "INFLUENCE OF INSTAGRAM LIFESTYLE POSTS ON MENTAL HEALTH BEHAVIOUR AMONG YOUNG INSTAGRAM USERS IN ENUGU METROPO-LIS." INTERNATIONAL JOURNAL OF COMMUNICATION AND SOCIAL SCIENCES (IJCSS) VOLUME 1 NO. 4 1, no. 4 (2024): 32.

[11] Alharbi, M., Alqahtani, A., Alqahtani, S. S., Alghamdi, A., Ahmad, M. (2024). "Predicting Mental Health Disorders Using Machine Learning Techniques: A Comprehensive Review." Journal of Health Informatics in Developing Countries, 18(1).

[12] Khan, Z., Almehmadi, M., Aljabri, A., Alharbi, N., Aljohani, A. (2023). "Machine Learning-Based Early Prediction of Depression and Anxiety Disorders from Social Media Data: A Systematic Review." International Journal of Environmental Research and Public Health, 20(3), 2002.

[13] Sharma, A., Rani, S. (2023). "A Comparative Study of Machine Learning Algorithms for Mental Health Prediction." Journal of Ambient Intelligence and Humanized Computing, 14(1), 115-126.

[14] Chen, R., Wu, X. (2024). "Factors Influencing Mental Health in College Students: A Machine Learning Approach." International Journal of Computer Science and Network Security, 24(1), 8-15.

[15] Lee, S. Y., Kim, M. K. (2023). "Predicting Adolescent Behavioral Problems Based on Environmental Factors: A Machine Learning Study." Journal of Clinical Nursing, 32(11-12), 2634-2644.