International Journal of Social Science and Human Research

ISSN (print): 2644-0679, ISSN (online): 2644-0695

Volume 07 Issue 06 June 2024

DOI: 10.47191/ijsshr/v7-i06-76, Impact factor- 7.876

Page No: 4166-4172

Investigation of the Unemployment Based on Poor Mental Conditions

Himali Loku Pathiranage

Department of Statistics, School of Mathematics, Northwest University, Xi'an, Shaanxi, China.

ABSTRACT: Psychological wellness is essential for everyone in society since it fosters personal growth andsuccess. In a variety of ways, people's work status is linked to their psychological well-being. Individuals who become unemployed are more likely than those who stay employed to suffer from poor psychological health. Unemployed people who have poor psychological conditions are less inclined to look for jobs.As a result, while work has a noteworthy impression on one's mental security, one's mental health determines whether or not one finds work. To minimize this burning issue, it's necessary to find out the practical solutions through developed techniques. This study focus to address this issue through secondary data. This data was collected from 334 individuals by Michael Corley in 2019. The logistic regression model is used as a baseline model. In contrast, the Support Vector Machine, Decision Tree, and Random Forest models were chosen to check their performance in the study field. The study focuses on five mental health explanatory factors: namely, sadness, tiredness, obsessive thinking, panic attacks, and anxiety. The Support Vector Machine model outperforms logistic regression, Decision Tree, and Random Forest when predicting unemployment based on poor mental health. The Support Vector Machine produced a 71% predictive accuracy, and anxiety significantly influenced unemployment prediction. Future research should focus on detecting destructive mental health issues early on is critical to avoid undesirable actions. These conditions can be lessened with technology, and we can prevent individuals from adopting drastic measures that further safeguard their future.

KEYWORDS: Anxiety, Destructive mental health issues, Poor mental conditions, Unemployment

INTRODUCTION

The problem of unemployment and its profound impact on mental health has emerged as a critical issue in contemporary society, particularly not only for developing countries. While unemployment is traditionally viewed as an economic challenge, its repercussions extend far beyond financial instability to encompass significant implications for mental well-being. Unemployment not only contributes to heightened levels of stress, anxiety, and depression among individuals but also exacerbates existing mental health conditions, creating a vicious cycle of economic hardship and psychological distress.

The nexus between unemployment and mental health is complex and multifaceted, influenced by various individual, societal, and systemic factors. Individuals who experience unemployment often face feelings of worthlessness, hopelessness, and social isolation, as they grapple with the loss of financial security and social identity. The uncertainty surrounding future employment prospects, coupled with the stigma and discrimination associated with unemployment, further compounds the psychological burden experienced by individuals, leading to a deterioration in mental health outcomes.

Moreover, unemployment disproportionately impacts vulnerable populations, including youth, women, and persons with disabilities, exacerbating existing social inequalities and widening the gap in access to mental health support services. Discrimination in the labor market, lack of employment opportunities, and structural barriers to workforce participation perpetuate cycles of poverty and marginalization, amplifying the mental health disparities faced by these marginalized groups.

The COVID-19 pandemic has further exacerbated the unemployment-mental health nexus, as widespread job losses, economic instability, and social distancing measures have heightened levels of stress, anxiety, and depression across populations. The pandemic-induced economic recession has led to unprecedented levels of unemployment, exacerbating pre-existing mental health challenges and straining mental health services and resources.

Despite the growing recognition of the link between unemployment and mental health, significant gaps remain in our understanding of this complex relationship. Existing research often fails to capture the nuanced interplay between individual characteristics, socio-economic factors, and mental health outcomes, limiting the development of targeted interventions and policy responses. Moreover, the majority of studies focus on the negative consequences of unemployment on mental health, overlooking potential protective factors and resilience-building strategies that may mitigate the adverse effects of unemployment on psychological well-being.

Addressing the problem of unemployment and its impact on mental health requires a multifaceted and interdisciplinary approach that encompasses economic, social, and psychological perspectives. Efforts to reduce unemployment rates must be accompanied by targeted interventions to support individuals' mental health and well-being, including access to affordable mental health care, psychosocial support services, and skills training programs. Moreover, addressing systemic inequalities and structural barriers to workforce participation is essential for promoting social inclusion and reducing disparities in mental health outcomes.

In conclusion, the problem of unemployment and its repercussions on mental health represent a pressing societal challenge that requires urgent attention and concerted action. By understanding the complex interplay between unemployment, mental health, and socio-economic factors, policymakers, practitioners, and researchers can develop holistic strategies to promote mental well-being, foster social inclusion, and create more equitable and resilient societies.

The complexity of the unemployment problem extends beyond the superficial examination of labour market supply and demand dynamics. This intricacy is particularly pronounced in transition countries that have shifted from pre-transition economic systems to market-oriented economies. The notion of disparity is employed to characterize imbalances in the supply and demand for labour. More precisely, mismatch denotes the challenge in aligning actual unemployment with opportunities at a disaggregated level. The contemporary labour landscape, marked by heightened global competitiveness and rapid technological advancements, complicates the response to shifting labour demands.

To minimize this burning issue, it’s necessary to find out the practical solutions through developed techniques. Number of researchers pay their attention to create such tools and approaches since more than 20 years. This research article represent a diverse array of topics related to unemployment and its impact on psychological wellbeing of affected individuals. By exploring this topic in depth, the research aims to provide a comprehensive understanding of the complexities of the psychological impact of unemployment and offer insights into potential policy responses.

LITERATURE REVIEW

Mental health is critical to the population, stimulating human growth and development. Mental health has different definitions because so much research has been done on human mental health. According to the World Health Organization, mental health is “a state of well-being in which the individual realizes his or her abilities, can cope with the normal stresses of life, can work productively and fruitfully, and contribute to his or her community” (WHO, 2002).

A significant investigation has been done into why people become unemployed, and each person has different problems. However, one of the most important causes of unemployment is poor mental conditions (NIP, 2017).

Ham and Rea's study delves into the psychological implications of unemployment, focusing specifically on its impact on individual happiness. Through an analysis of the case of South Korea, the researchers explore how unemployment serves as a significant source of personal unhappiness.

Unemployment is not merely an economic phenomenon but also a deeply personal experience that can profoundly affect an individual's well-being. Ham and Rea highlight the emotional toll of unemployment, comparing it to other distressing life events such as breakups or grief. By examining the case of South Korea, the study provides empirical evidence of the detrimental effects of unemployment on individual happiness.

The findings of Ham and Rea's research underscore the importance of addressing unemployment not only from an economic perspective but also from a social and psychological standpoint. Policies aimed at reducing unemployment should consider the broader impact on individuals' quality of life and well-being. By understanding the emotional consequences of unemployment, policymakers can design interventions that provide support and mitigate the negative effects on individuals and communities.

Goncalves et al. (2020) conducted research based on Corley’s (2019) entire dataset to investigate whether mental illnesses and associations concerning unemployment can be predicted. They used four machine learning classification models: Random Forest, Gradient Boosted Trees, K-Nearest Neighbor, and Decision Tree. Their findings revolved that Random Forest achieved the highest accuracy at 94.14% (Goncalves et al., 2020).

The work status of people is closely related to their mental health in different ways. Research by Paul and Moser (2008) has shown that people who become unemployed have a greater chance of developing poor mental health than those employed. Taris (2002) showed that people with poor mental health and who are unemployed exhibit less job-seeking behavior. Therefore, work significantly impacts mental health, but mental health affects whether someone finds work.

The present research endeavours to bridge empirical and theoretical gaps in the existing literature by elucidating various facets of unemployment, particularly focusing on the impact of unemployment on mental well-being. This investigation adopts a comprehensive approach, utilizing machine learning techniques to scrutinize the factors influencing on the psychological repercussions stemming from unemployment.

In essence, this research not only adds depth to the understanding of unemployment but also contributes to the broader discourse on the nexus between mental health and unemployment. By employing advanced analytical methods, the study strives to enhance predictive accuracy and offer insights that may inform targeted interventions and policies addressing the multifaceted challenges posed by unemployment, particularly in relation to mental security.

METHODS

• Introduction to Preprocessing:

Preprocessing is a critical step in data analysis that involves cleaning, transforming, and preparing raw data for further analysis. It encompasses a range of techniques aimed at addressing issues such as missing values, outliers, and inconsistencies in the data, ensuring that the data is suitable for analysis. Common preprocessing techniques include data cleaning, feature scaling, dimensionality reduction, and feature engineering.

In the context of our research, preprocessing plays a crucial role in ensuring the quality and integrity of the data used for analysis. By systematically addressing data quality issues and standardizing the format and structure of the data, we can minimize the risk of bias and error in our analysis. Moreover, preprocessing allows us to extract relevant features and patterns from the data, enhancing the accuracy and interpretability of our results.

• Introduction to Descriptive Analysis:

Descriptive analysis involves summarizing and visualizing key characteristics of the data to gain insights into its underlying patterns and distributions. It provides a comprehensive overview of the data, including measures of central tendency, variability, and distribution, as well as graphical representations such as histograms, box plots, and scatter plots.

In our research, descriptive analysis serves as the foundation for understanding the basic properties of the data and identifying potential trends and relationships. By systematically analyzing the distribution of key variables and exploring their relationships with one another, we can gain valuable insights into the underlying structure of the data. This information not only informs subsequent analyses but also provides important context for interpreting the results.

• Introduction to Machine Learning Algorithms:

Machine learning algorithms are computational techniques that enable computers to learn from data and make predictions or decisions without being explicitly programmed. They encompass a broad range of methods, including supervised learning, unsupervised learning, and reinforcement learning, each of which is suited to different types of tasks and data.

In our research, machine learning algorithms play a central role in analyzing and modeling the data to predict unemployment based on mental health conditions. Supervised learning algorithms, such as logistic regression, decision trees, and support vector machines, are employed to build predictive models that identify patterns and relationships between predictor variables (mental health conditions) and the target variable (unemployment status). By leveraging the power of machine learning, we can uncover complex patterns in the data and generate actionable insights for addressing unemployment-related mental health challenges.

• Adjusting Research Methods for Clarity and Depth:

To enhance the clarity and depth of the research methods section, several adjustments can be made. Firstly, provide a more detailed explanation of the preprocessing techniques used, including specific steps and algorithms employed. This will help readers understand how the raw data was transformed and prepared for analysis.

Secondly, expand on the descriptive analysis by including a more comprehensive overview of the key characteristics of the data, such as summary statistics, distributional plots, and correlation matrices. This will provide readers with a clearer understanding of the data's underlying structure and patterns.

Finally, delve deeper into the machine learning algorithms used, including a discussion of their theoretical foundations, practical applications, and advantages and limitations. This will enable readers to appreciate the complexity of the modeling process and understand how machine learning techniques are leveraged to address the research objectives.

By making these adjustments, we can ensure that the research methods section provides a clear and comprehensive overview of the preprocessing, descriptive analysis, and machine learning techniques employed in the study, facilitating a deeper understanding of the research approach and findings.

DATA

This research depends on a single dataset. Secondary data was collected from 334 individuals by Michael Corley in 2019 to predict unemployment based on poor mental conditions. Enumerators compensated Survey Monkey respondents in an overall sampling of populations without emphasizing any particular population group. Survey Monkey categorizes the sample depending on factors like income and region. Even though individuals who did not have a mental disorder were rejected, they were nonetheless given the entire survey. That is, the data includes a sample of people with and without a psychological disorder, as well as a yes/no indication. The questionnaire asked about respondents' characteristics (marriage status, level of education,how long they were unemployed in months), their physical and mental health, attitudes about employment and unemployment, and expectations for the future. Furthermore, respondents arequestioned if they have sought medical treatment for conditions (heart attack, stroke, headache,and mental complaint) in the previous 12 months to determine whether the individual who responded has been diagnosed with a psychological disorder.

This inquiry did not require the integration of many datasets as it employed just one. The initialstage is to grasp the information being collected. It entailed examining the total number of unemployed participants as well as how many suffered psychological issues as stated in the dataset. This displayed the number of missing values. In all, 42 values were missing from the dataset. Because they did not have any significance in this investigation, these variables were eliminated.

The dataset describes all relevant variables with "yes" and "No." These have to be converted first into a 1 for "Yes" and a 0 for "No." This is required so that the data may be used for featureselection and classification methods. To transform the category data into numeric binary variables, the one-hot-encoding approach was used.

TECHNIQUES

The study focuses on five mental health explanatory factors: namely, sadness, tiredness, obsessive thinking, panic attacks, and anxiety. The primary objective is to scrutinize the impact of each explanatory factor on the dependent variable—unemployment.

To establish a baseline model, a logistic regression model is employed, chosen for its suitability as a foundational predictive framework. Additionally, the study incorporates more advanced machine learning models, namely Random Forest, Support Vector Machine, and Decision Tree models. These models are selected based on their recognized efficacy within the domain of mental health studies, ensuring a comprehensive evaluation of predictive capabilities.

The adoption of diverse models enhances the robustness of the study, providing a multifaceted analysis of the relationship between mental health factors and unemployment. By leveraging both conventional and advanced methodologies, this research aims to contribute nuanced insights into the intricate dynamics linking mental health indicators and the risk of unemployment.

This research relies on a singular dataset, initially imported into Python from an Excel file for comprehension and cleaning. An initial examination of the dataset involved assessing the count of unemployed respondents, identifying those with mental health issues, and categorizing the represented age groups. Forty-two instances with missing values were identified and subsequently excluded from the study.

All variables pertinent to the research were dichotomized as "yes" or "no," necessitating transformation into binary format (1 for "yes" and 0 for "no"). The categorical inputs were further converted into numeric binary variables through the one-hot-encoding method. Upon closer scrutiny of the dataset, it was observed to be unbalanced, with 25.75% of respondents categorized as unemployed and 74.25% as employed. The inherent imbalance in the dataset poses challenges, particularly in classification systems with a predictive objective, leading to skewed class distributions.

To address this imbalance, an oversampling technique was employed for the minority group, thereby achieving a more balanced dataset. The study aims to investigate the potential association between mental health problems and unemployment. The dataset was partitioned into two subsets, one containing five predictor variables and the other encompassing the variable under examination. Additionally, a distribution of 20% testing data and 80% training data was implemented for each classification algorithm

RESULTS

The outcome and discussion are separated into two sections: data visualization and Ensemble Model implementation to get the desired results.

Table 1: Characteristics of the Sample

Variable	*Employed %*	*Unemployed %*
Age		
18-29	69	31
30-44	75	25
45-60	82	18
>60	67	33

Gender		
Male	77	23
Female	72	28
Suffering from mental illness	64	36
Lack of concentration	65	35
Anxiety	63	37
Depression	62	38
Obsessive Thinking	57	43
Tiredness	70	30
Compulsive behaviour	69	31

Table 1 presents a comprehensive overview of employment and mental health dynamics, revealing that over 70% of both male and female respondents are employed. Notably, more than half of the participants are cognizant of having one or more psychological illnesses. Among the employed population, a substantial proportion reports experiencing tiredness and obsessive thinking.

In the context of employing an Ensemble Model, the initial step involves utilizing the Random Forest feature selection technique to discern the extent to which adverse psychological health impacts the target variable. Subsequently, the study outlines both baseline and classification models designed to assess unemployment based on poor mental health.

The feature selection process, employing the random forest algorithm, unveils the percentage of association between each poor mental condition and unemployment. Remarkably, the dataset underscores anxiety as the most significant negative psychological determinant predicting unemployment, constituting 29% of the total impact according to the findings. This pivotal insight emphasizes the critical role of anxiety in influencing unemployment within the studied population, providing valuable focus for further analysis and intervention strategies.

Table 2: Impact of Poor Mental Conditions on Unemployment

Poor Mental Conditions	***Score***
Anxiety	29%
Lack of concentration	21%
Depression	16%
Obsessive thinking	13%
Compulsive behaviour	11%
Tiredness	10%

Table 2 provides valuable insights into the factors influencing the prediction of unemployment due to poor mental health. A comprehensive analysis of the table suggests that anxiety and a lack of concentration emerge as the most influential variables in forecasting unemployment in the context of poor mental health. Conversely, compulsive behavior and tiredness are identified as comparatively less critical factors in poor mental circumstances.

Building upon these findings, the researcher proceeded to implement a baseline model alongside three distinct classification algorithms, namely Random Forest, Support Vector Machine, and Decision Tree. The objective of this application was to evaluate the effectiveness of each classification model in predicting unemployment stemming from poor mental health. This methodological approach enhances the study's analytical rigor, offering a multifaceted examination of the predictive capacities of various models in the context of mental health-related unemployment.

Table 3: Performance of the Fitted Models

ML Model	***Precision***	***Recall***	***F1-score***	***Accuracy***
Logistic Model	66%	64%	62%	64%
Support Vector Machine	71%	70%	70%	71%
Decision Tree	74%	69%	67%	69%
Random Forest	73%	68%	66%	68%

Table 3 presents the baseline model and three distinct classification representations, with the logistic regression model serving as the baseline for evaluating the capabilities and expectations of the other machine learning models. This baseline model not only provides a comparative benchmark but also offers insights into the anticipated performance levels that machine learning models may achieve.

Contrary to expectations, the results reveal that logistic regression does not outperform machine learning models and demonstrates the weakest performance on this dataset. It is essential to note that the literature suggests that logistic regression models do not necessarily surpass machine learning models, a phenomenon attributed, in part, to the fact that logistic regression has fewer parameters available for tuning compared to machine learning models.

Among the machine learning models assessed, the support vector machine model emerges with the highest accuracy, reaching 71%. This finding indicates that the support vector machine model excels in predicting whether a respondent with poor mental health is likely to become unemployed. This analytical insight underscores the significance of selecting appropriate models tailored to the dataset characteristics, thereby enhancing the predictive accuracy in the context of mental health-related unemployment.

DISCUSSIONS

The exploration of reasons for unemployment reveals a multitude of factors, each individualized and distinctive. However, psychological concerns emerge as a predominant cause, as noted by the National Institute of Psychology (NIP, 2017). Despite the acknowledged significance of mental health in unemployment, limited studies have specifically investigated the nexus between poor mental health and unemployment. Therefore, the primary aim of this study is to address this research gap and deepen the understanding of this intricate relationship.

The predictive influence of various negative psychological states on unemployment is examined. Anxiety and a lack of concentration emerge as significant factors influencing the prediction of unemployment due to poor mental health. Conversely, compulsive behavior and tiredness exert less impact on forecasting unemployment, signifying their relatively lower significance in this predictive context. These insights contribute to a nuanced understanding of the interplay between mental health indicators and unemployment prediction, highlighting the pivotal role of specific psychological states, particularly anxiety and lack of concentration, in shaping employment outcomes in individuals with poor mental health.

In the realm of predicting unemployment based on poor mental health, the support vector machine (SVM) model exhibits superior performance compared to the random forest model, logistic regression model, and decision tree. This finding aligns with Srividya et al.'s (2018) exploration of predicting psychological well-being, where decision trees, a Naive Bayes classifier, a support vector machine, a K-nearest neighbor classifier, and logistic regression were employed. In this investigation, SVM, random decision trees, and K-nearest neighbors demonstrated comparable levels of accuracy. However, Cho et al.'s (2019) study identified the support vector machine as having the most remarkable accuracy in the context of mental health.

At the heart of this research lies the recognition that unemployment is not solely an economic phenomenon but has far-reaching consequences for individuals' mental well-being. Unemployment can lead to feelings of loss, inadequacy, and despair, contributing to heightened levels of stress, anxiety, and depression. Moreover, the psychosocial impacts of unemployment extend beyond individual experiences to encompass broader societal implications, including increased healthcare costs, reduced productivity, and social disintegration. By elucidating the mechanisms through which unemployment affects mental health, this research underscores the urgency of addressing this pressing societal challenge.

CONCLUSIONS

The culmination of extensive research efforts has led to profound insights into the intricate relationship between unemployment and mental health. As we conclude this comprehensive study, it becomes evident that unemployment does not merely represent an economic phenomenon but rather a multifaceted societal challenge with profound implications for individuals, communities, and societies at large. Through a synthesis of empirical evidence, theoretical frameworks, and methodological advancements, this research has contributed to a deeper understanding of the complex interplay between unemployment and mental health and offers actionable insights for addressing this pressing issue.

The integration of advanced predictive modelling techniques, such as machine learning algorithms, represents a significant methodological innovation in this research. By harnessing the power of data-driven approaches, researchers can develop more accurate and nuanced models for predicting mental health outcomes during unemployment. These models not only enhance our understanding of the dynamics of mental health but also provide valuable tools for identifying at-risk individuals, tailoring interventions, and allocating resources effectively.

A critical takeaway from this research is the importance of adopting a holistic and multi-dimensional approach to addressing the mental health implications of unemployment. Rather than viewing unemployment and mental health in isolation, policymakers and practitioners must recognize the interconnectedness of these issues and develop comprehensive strategies that address the underlying social, economic, and psychological determinants. This requires collaboration across sectors, disciplines, and stakeholders to implement integrated interventions that promote mental well-being, enhance resilience, and foster social inclusion.

Furthermore, this research underscores the need for targeted interventions that are tailored to the unique needs and circumstances of diverse populations. Vulnerable groups, such as youth, women, and individuals from marginalized communities, may face disproportionate challenges in accessing mental health support services during unemployment. Therefore, efforts to promote equity and social justice must be central to the design and implementation of interventions aimed at addressing mental health disparities. By prioritizing inclusivity and accessibility, policymakers can ensure that all individuals have access to the resources and support they need to thrive.

One of the key findings of the research is the significant psychological impact of unemployment on individuals' mental health. The experience of job loss can trigger a range of emotional responses, including feelings of stress, anxiety, depression, and low self-esteem. For many individuals, unemployment represents a loss of identity and purpose, leading to a sense of hopelessness and despair. Moreover, the stigma associated with unemployment can exacerbate these feelings, further isolating individuals and hindering their ability to seek support.

It is essential to recognize that the psychological impact of unemployment is not uniform and can vary depending on individual circumstances and coping mechanisms. Some individuals may exhibit resilience and adaptability in the face of adversity, while others may struggle to cope with the challenges of unemployment. By understanding the diverse range of psychological responses to unemployment, policymakers and practitioners can develop targeted interventions that address the unique needs and vulnerabilities of different populations.

REFERENCES

1. Corley, M. (2019). Exploring the causation on high unemployment among the mental ill. Unemployment and mental illness survey, Version 2. https://www.kaggle.com/michaelacorley/unemployment-and-mental-illness-survey
2. Goncalves, C., Ferreira, D., Neto, C., Abelha, A., & Machado, J. (2020). Prediction of Mental Illness Associated with Unemployment Using Data Mining. Procedia Computer Science, 177, 556-561. https://doi.org/10.1016/j.procs.2020.10.078
3. NIP, (2017, January). Hoeveel mensen raken arbeidsongeschikt door psychische klachten? Cijfers en trends. http://psynip.nl/actueel/themas/toolbox-werk-en-psychischeklachten/cijfers-en-trends/
4. Paul, K. I., & Moser, K. (2008). Unemployment impairs mental health: Meta-analyses. Journal of Vocational Behavior, 74(3), 264-282. https://doi.org/10.1016/j.jvb.2009.01.001
5. Srividya, M., Mohanavalli, S., & Bhalaji, N. (2018). Behavioral Modeling for Mental Health using Machine Learning Algorithms. Journal of Medical Systems, 42(5), 1-15.
6. Taris, T. W. (2002). Unemployment and mental health: A longitudinal perspective. International Journal of Stress Management, 9, 43-57. Doi:1072-5245/02/0100-0043/0. (Corley, 2019)
7. World Health Organization. (2002). World Health Report. Mental health - new conception, new hope.