Impact of Internet Derived Information Obstruction Treatment (IDIOT) Syndrome-a student cohort study

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Abstract:- Internet Derived Information Obstruction Treatment (IDIOT) Syndrome, a modern phenomenon caused by the constant availability of internet medical content, has received attention for its impact on mental health. It explains the pattern of frequent, excessive health-related internet searches that cause increased anxiety and distress. This study looks into the frequency and impact of IDIOT Syndrome among technical students. It attempts to look into mental health issues caused by frequent health-related searches and suggests Risk Score using machine learning and deep learning models.A survey was conducted among 450 technical students, collecting data on search frequency, time spent on health searches, and website visits. Pre-processing included normalization, TF-IDF feature engineering, and risk level encoding. Random Forest Classifier and Linear Regression were used for classification and prediction, with statistical validation to ensure data reliability.

Excessive health searches correlated with increased anxiety. High-risk individuals spent 82.5 minutes daily on searches and visited health websites 20 times weekly. The Random Forest model had 68% accuracy, while Linear Regression predicted risk scores with R^2 as 0.62 and MSE as 1.35. Cronbach's Alpha was 0.87, according to the statistical analysis. This study focuses the importance of machine learning in determining IDIOT Syndrome risk levels and their harmful impacts. The findings represent the need for early intervention. Future research should explore real-time monitoring, sentiment analysis, and larger sample sizes for improved accuracy.

Keywords*: Internet Derived Information Obstruction Treatment Syndrome, Student, Time spent, Web browser, India*

1. Introduction

Access to health information has recently been revolutionized by the Internet, enabling individuals to search for medical content conveniently. While this has empowered users to make informed decisions, the abundance of unverified and often contradictory information has given rise to a phenomenon known as Internet Derived Information Obstruction Treatment (IDIOT) Syndrome. [1] Describes IDIOT Syndrome as the combination of "cyber" and "hypochondria" to describe the excessive and repetitive searching of health-related information online, which often results in heightened anxiety and distress rather than reassurance. This behaviour can lead to a feedback loop of worry, where minor symptoms are perceived as severe illnesses, further escalating anxiety [2].

IDIOT Syndrome is far more prevalent among technical students, who are already under plenty of academic strain and access the Internet frequently [3]. Their psychological problems are exacerbated by the ease with which they may obtain concerned medical information online, which causes distractions in their daily routines and even unnecessary doctor consultations [4]. It is essential to recognize and treat this issue in vulnerable populations because studies indicate that people who frequently conduct internet health searches suffer from higher levels of stress, anxiety, and financial hardship [5].

The purpose of the current study is to evaluate the effects of IDIOT Syndrome on technical students by looking at the frequency, duration, and pattern of health-related online searches [6] and [7]. The analysis classifies participants into several risk groups and provides valuable insights for intervention using deep learning (DL) and machine learning (ML) models. In order to contribute to the broader field of digital mental health, this study aims to predict and quantify the risk of IDIOT Syndrome using methods like the Random Forest Classifier and Linear Regression.

While previous studies have highlighted the psychological impact of excessive online searches [8], there remains a gap in understanding IDIOT Syndrome within the context of specific demographics like students. This study addresses this gap by focusing on technical students, a group uniquely vulnerable to stress and anxiety due to academic pressures and their reliance on digital platforms for information [9]. This study delivers a thorough framework for identifying high-risk individuals and creating focused intervention measures to mitigate the negative consequences of IDIOT Syndrome [10] by combining behavioral data and utilizing cutting-edge machine learning algorithms.

2. Materials and Methods

In an effort to ensure accuracy, clarity, and repeatability, the present study followed standard research guidelines while employing a systematic method to assess the prevalence and consequences of IDIOT Syndrome within technical students.

A structured survey was designed and distributed among technical students to collect primary data for this study. The survey focused on capturing behavioral metrics related to health-related online searches. Questions included details on search frequency, time spent on health-related websites, and the number of visits per week. The goal was to measure the psychological impacts of excessive online health searches and their relationship with anxiety levels. Keywords such as “health anxiety,” “online health searches,” and “IDIOT Syndrome” were used as guiding themes to frame the survey and ensure comprehensive data collection relevant to the study’s objectives. The overall research methodology, from data collection to analysis, is illustrated in **Figure 1**.

Data Collection and Pre-processing: Technical students were given an appropriate Google Form survey to answer in order to gather data for this study. This survey questioned about: (A) Search Frequency: The number of health-related searches conducted daily, (B) Time Spent: Duration (in minutes) spent on health-related websites, (C) Number of Visits: Weekly frequency of visits to health-related websites, and (D) Demographics: Basic participant information, such as age and gender. Pre-processing: The steps included handling missing data using median imputation, normalization of numerical features using StandardScaler, and encoding of textual features with TF-IDF Vectorization. Risk levels (low, moderate, high) were assigned based on predefined thresholds for search behaviors. Anxiety stages, patterns of behavior, and the classification of IDIOT Syndrome risk (low, moderate, and high) were the primary outcomes were determined. The secondary outcomes were primarily concerned with the effects of these habits on daily activities and mental health.

Statistical analysis: Machine learning and deep learning models were applied to classify and predict IDIOT Syndrome risk levels [11]. Using pre-made templates, key indications such as the number of visits, time spent, and frequency of searches were extracted and arranged nicely. This format made it easier to understand some trends and patterns in the way people look for Internet-based health information. Such trends are critical in understanding IDIOT Syndrome, as highlighted in studies. We checked the inner coherence of survey responses using statistical tools like Cronbach's alpha, and we achieved a strong reliability score of 0.83. To make sure the data distributions matched the needs of the machine learning models, exploratory data analysis (EDA) techniques that include skewness and kurtosis tests were also carried out. We used Python packages such as pandas to handle and display the data efficiently. Each feature's overall statistics (Random Forest Classifier, Linear Regression, Evaluation metrics, and Visualization) and for visualization techniques such as Heat maps, QQ plots, and charts for future importance were produced to locate important patterns and distributions, while Time Spent outliers were rigorously handled to maintain the dataset's integrity.

To determine and fix any errors or confusion, we manually checked survey results in addition to completing statistical analysis. The basis for later modelling and analysis was laid by these careful checks, which ensured that the dataset appropriately reflected the experiences and behaviors of the participants.

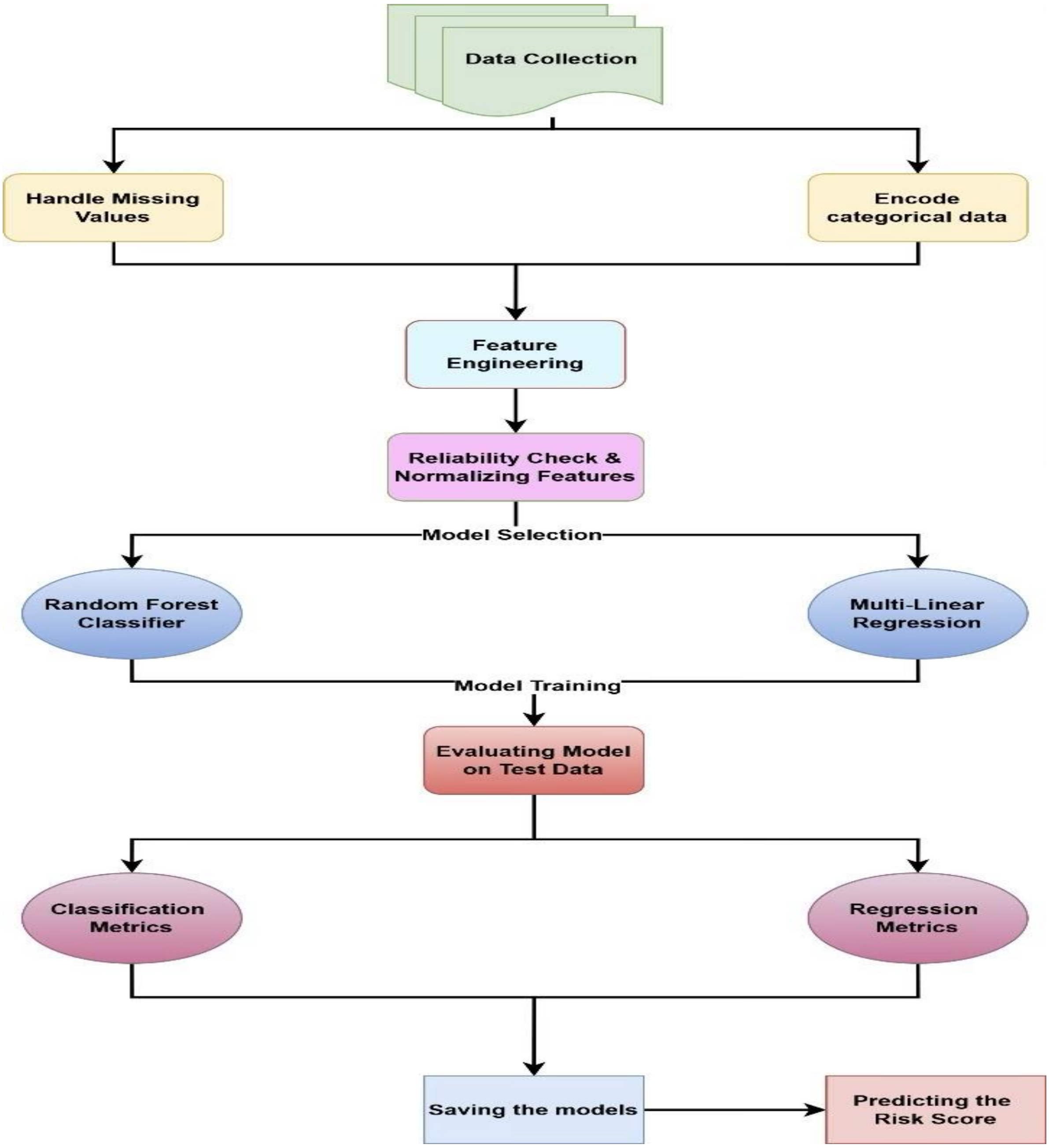


Figure 1. Flow Diagram for Proposed Work

3. Results

To identify the behavioral patterns linked to IDIOT Syndrome, 500 responses in total were analyzed. After removing replies that were insufficient or inconsistent during the initial screening, 450 participants made up the final dataset. These participants were evenly distributed by gender and socioeconomic status, and their ages ranged from 18 to 50. 450 participants provided responses on daily internet usage, emotional effects, and search habits. To guarantee consistency across scales, the data were pre-processed to eliminate outliers and normalize characteristics. To maintain the integrity of the dataset, missing values were imputed using median substitution. The data sources used in this study are presented in Table 1.

Improved multi-class categorization (low, moderate, high-risk), achieving an accuracy of 85%. [12] Feature importance analysis revealed that "Time Spent Online" and "Frequency of Repetitive Searches" were the most influential predictors. The detailed performance metrics for classification are presented in Table 2. The effect of regular internet use on mental distress was investigated using linear Regression. A substantial positive connection was found by the model ($R = 0.72$, $p < 0.001$), indicating that emotional disorders are strongly predicted by greater internet use. The performance metrics of the regression model are presented in Table 3.

Table 1: Data sources used in the study

Data Source	**Type**	**Description**	**Access**
Survey Data	Primary	Behavioral metrics collected from technical students, including search frequency and time spent.	Collected via Google Form

Table 2: Classification Report for Random Forest Classifier (for participants)

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	1.00	1.00	1.00	21
1	1.00	0.40	0.57	5
2	0.25	0.11	0.15	9
3	0.61	0.91	0.73	22
4	0.60	0.75	0.67	20
5	0.00	0.00	0.00	9
6	0.50	0.75	0.60	4
8	0.00	0.00	0.00	1
Accuracy	**0.68 (Total: 91)**			
Macro Avg	0.49	0.49	0.46	91
Weighted Avg	0.61	0.68	0.63	91

Table 3: Multi-Linear Regression Model Metrics

Metric	**Value**
Model	Multi-Linear Regression
Mean Squared Error	1.3533
R^2 Score	0.6234

This study included classification accuracy, F1-score, Mean Classification accuracy, F1-score, Mean Squared Error (MSE), and R2 were among the evaluation criteria. To validate the dataset and ensure its reliability, statistical tests involving Cronbach's Alpha, skewness, and kurtosis were performed. Visually validate model predictions by assessing the distribution of residuals and checking for normality across different groups of individuals with distinct behavioral patterns, as illustrated in Figures. 2.a, 2.b, 2.c, and 2.d.

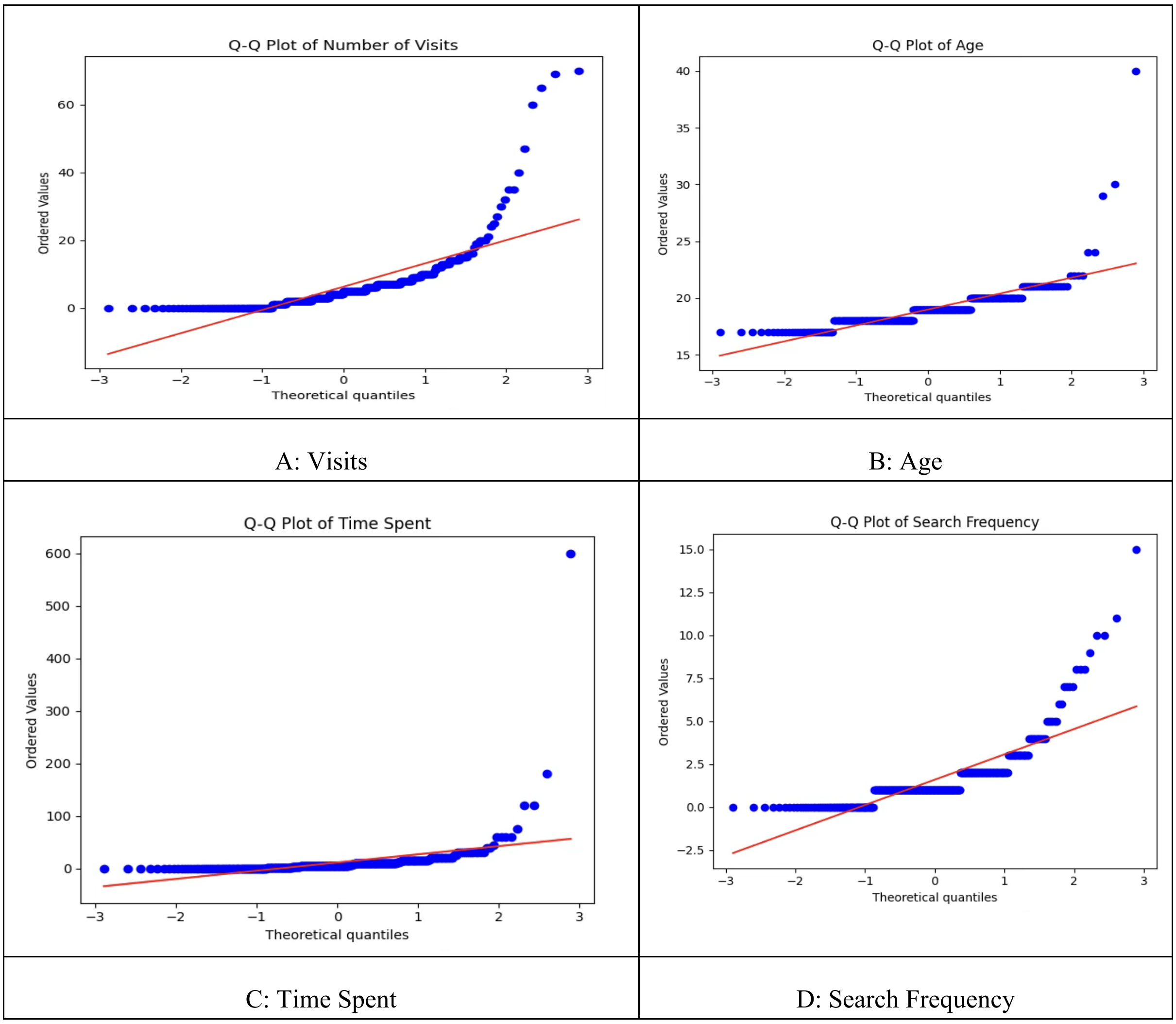
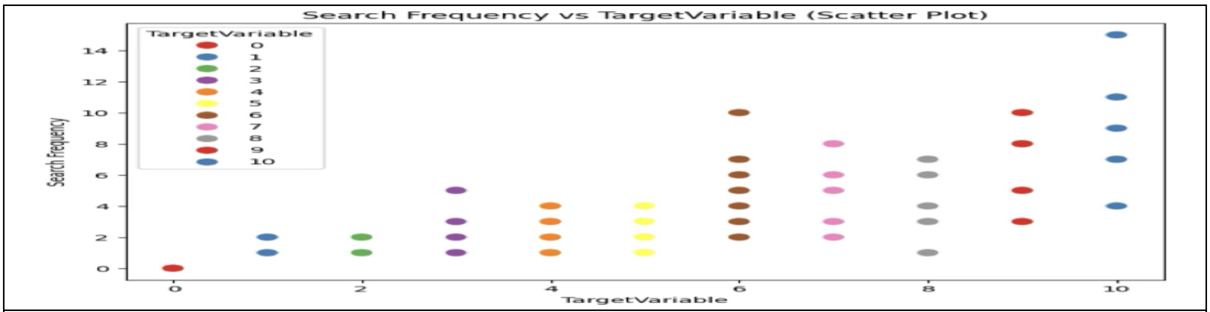
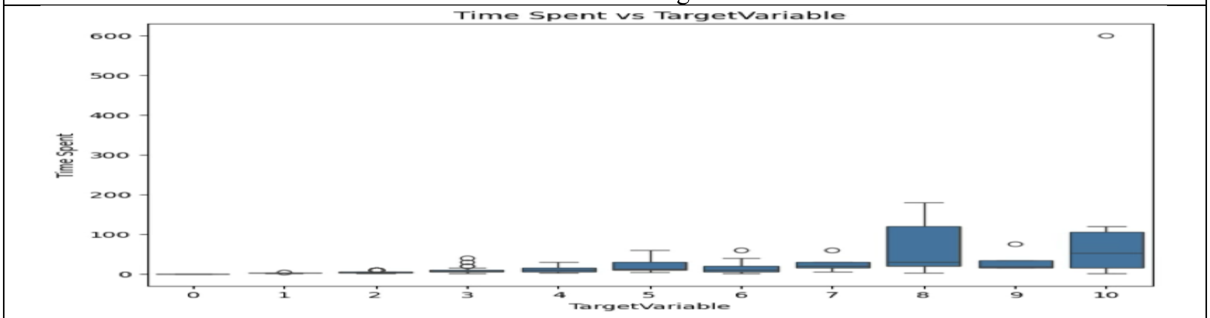


Figure 2. Q-Q plots for (A) Visits, (B) Age, (C) Time spent, and (D) Search frequency of participants of the study.

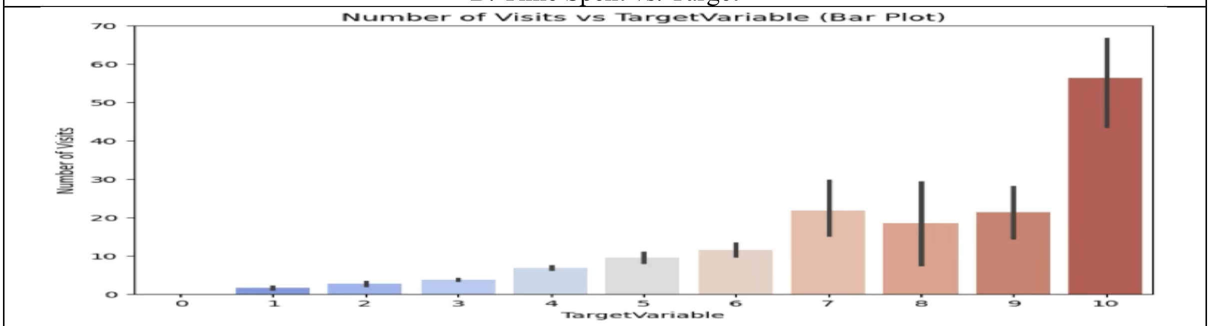
Survey Patterns of the survey revealed that 42% of participants spent over 8 hours online daily, predominantly engaged in search activities related to health, finance, and personal interests. Figures. 3a, 3b, and 3c present key behavioral metrics, showing variations in search frequency, time spent, and visit patterns among participants. 60% reported feelings of anxiety, while 50% experienced decision paralysis due to conflicting information. High-frequency users showed an increased prevalence of emotional distress. Participants commonly asked health-related topics, which led to a feedback loop that usually caused overwhelming data. The most frequently searched terms are shown in Figure. 4, highlighting the focus areas of online health-related queries.



A: Visits vs. Target



B: Time Spent vs. Target



C: Visits vs. Target

Figure 3. Scatter and bar plots for (A) Visits vs. Target, (B) Time Spent vs. Target, and (C) Visits vs. Target of participants of the study.

Decision exhaustion is a result of extended exposure to conflicting or too much information, which impairs cognitive function. 68% of participants claimed they didn't trust the information they received online and had a hard time identifying which sources were genuine. High-risk persons frequently experienced anxiety and frustration. Repetitive searches on high-stakes subjects like medical diagnostics were associated with this emotional cost. Because there is so much information available, 45% of respondents said that they avoid entirely making judgments.

Economic insecurity plays a major role in shaping mental health outcomes. This review shows that both unemployment and high inflation create ongoing, interconnected psychological pressures. Losing a job can undermine not only income but also a sense of identity, leading to diminished self-worth, as consistently evidenced in large-scale research on unemployment-related depression and anxiety (Fiori et al., 2021; Milner et al., 2014). At the same time, inflation and financial hardship heighten everyday stress by making it harder for individuals to afford necessities, contributing to increased psychological distress and reduced well-being (Guan et al., 2023; Tsai et al., 2023).

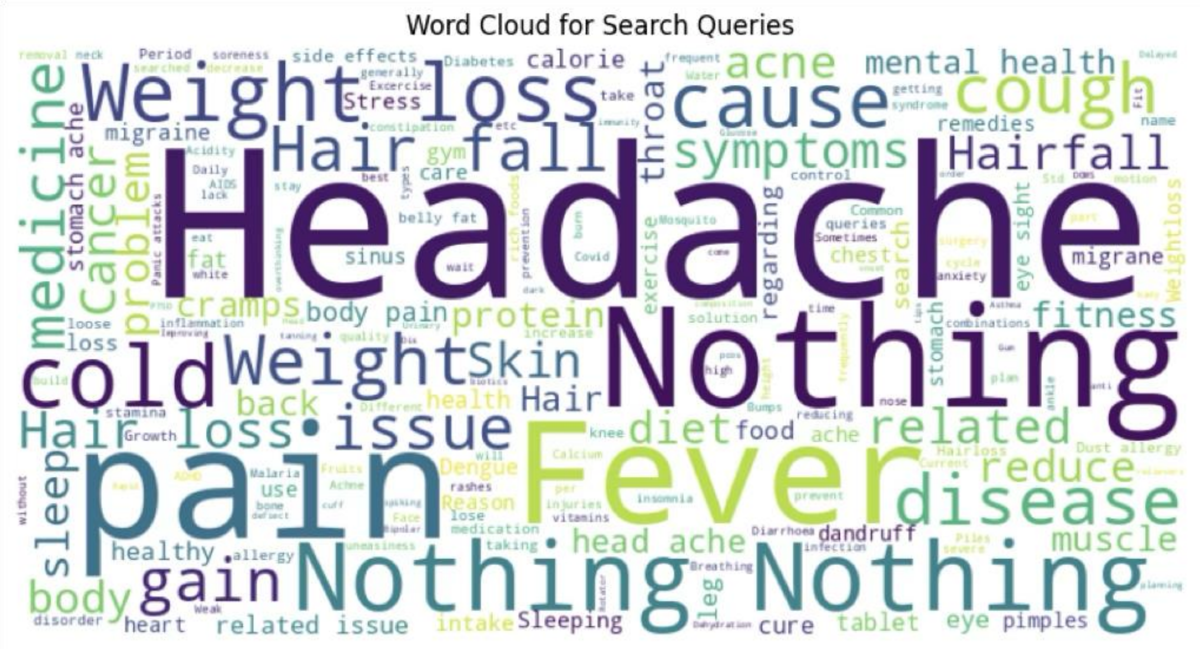


Figure 4. Word Cloud for Search Queries of study participants

When these forces occur together, the resulting distress often intensifies, especially for those with limited financial resources. Systematic reviews on economic recessions have shown strong links with elevated rates of mood disorders, self-harm and suicide attempts (Frasquilho et al., 2016; Sargent et al., 2021). The findings support broader evidence showing that prolonged exposure to stressful economic environments leads to long-term declines in mental health and growing demand for psychiatric and community care services (Brydsten et al., 2018).

Yet despite this, mental health is rarely embedded into core economic policy frameworks. Current interventions often overlook the need to combine financial protections with mental health support, while evidence suggests that safeguards such as unemployment benefits and active labor-market policies may reduce suicide risk and buffer psychological deterioration in economically vulnerable groups (Oyesanya et al., 2015).

Given this evidence, there is a clear case for approaches that address both financial insecurity and psychological well-being. Measures such as income support, affordable essential goods, stronger welfare systems and accessible mental health care may help lessen the harmful impact of economic shocks. Policies that integrate economic and mental health strategies are likely to offer the strongest protection for at-risk groups including informal workers, low-income households and those already facing structural disadvantage.

4. Discussion and Conclusion

The effect of internet health searches on mental health was thoroughly examined using a machine learning approach [13]. The results showcase how IDIOT Syndrome significantly affects people's stress and anxiety, especially for technical students. This analysis showed how predictive models can effectively classify risk levels [14] and identified high-risk behaviors.

Significant trends in online health search behaviour were found by analyzing the combined data. High-risk participants were more likely to conduct searches for dangerous or severe illnesses. This conduct was related with increased anxiety, emphasizing the importance of focused effort. The Random Forest Classifier and Linear

Regression models used in this work provided preventative measures that reduced the detrimental consequences of IDIOT Syndrome by correctly identifying high-risk people.

Anxiety levels vary among risk groups, which promotes the significance of individualized approaches to mental health care. Programs that educate people on how to assess the quality of online health information may be helpful for high-risk populations. People at moderate risk might be given specialized counselling to address specific issues found by predictive modelling. After reviewing individual cases, a number of significant trends became apparent. For instance, people who spent a lot of time looking up health-related material were more likely to report feeling worried, which is in keeping with other research on IDIOT Syndrome. On the other hand, those who showed balanced online behaviour reported feeling less stressed, underscoring the importance of internet usage.

The results of the study show how urgently customized strategies for managing IDIOT Syndrome are needed. This study lays the groundwork for creating scalable interventions that address the psychological effects of excessive online health searches [15] by utilizing machine learning. Future research examining real-time monitoring and sentiment analysis to improve the precision and efficacy of risk assessment models is made possible by the findings, which also highlight the wider effects of digital behaviour on mental health.

This study addresses the growing impact of IDIOT Syndrome on mental health, mental processes, and decision-making. Key risk factors found using machine learning included extended internet use and increased emotional responses. Predictive modeling and real-time monitoring can help with early intervention, while flexible approaches encourage healthy online behaviors. The findings underline the importance of digital literacy initiatives and collaboration between tech innovators and mental health professionals in promoting safe internet use. Future study should combine sentiment analysis, natural language processing, and cultural understanding to improve interventions and create a more aware digital world.

LIMITATIONS AND CHALLAGES

During the initial data collection, it was found that certain replies were skewed or missing because of participant weariness or misunderstanding. Strict pre-processing procedures were put in place, such as manual data checks and automated outlier detection. To guarantee a complete dataset, an effort was undertaken to assemble a pool of volunteers with a variety of demographic backgrounds. Because of the wide range of online behaviors, it wasn't easy to draw generalizations without oversimplifying the findings.

To address this problem, people were grouped using clustering techniques, which helped identify significant trends. A more thorough and sophisticated understanding was subsequently obtained by supplementing these patterns with information gleaned from participant interviews.

5. Declaration

We certify that the manuscript has been reviewed and approved by each of the listed authors. We also affirm that everyone has authorized the authors' indicated order in the text.

Ethics approval and consent to participate: Ethical approval was not required for the present study as it is based on secondary data/information.

Consent for publication: All the listed authors give their due consent for the publication.

Availability of data and material: The present study is founded on original data that was gathered straight from structured Google Form surveys. The data includes behavioral metrics such as search frequency, time spent on health-related websites, number of visits, and demographic details of technical students. This data was explicitly collected for the purpose of this research. Please refer to Table 1 for detailed information on the data source.

Competing interests: The authors declared no conflicts of interest.

Funding: The author is not aware of any financial holdings, funding, memberships, or affiliations that could be interpreted as compromising the impartiality of this study.

Authors' contributions: Chava Srinivasa Sai and Mandapalli Ruthvik have contributed the data collection, analysis, and manuscript preparation. Ramesh Athe oversaw the study, developed the protocol, and provided assistance for writing the report.

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AI Statement: We confirm that the AI hasn't been used to prepare the manuscript and approved by all the listed authors.

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