Impact Of Technology Usage on Mental Health: A Data-Driven Analysis

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***Abstract*—This study analyzes a dataset of 10,000 users with 14 features, covering demographics (age and gender) and key factors affecting mental health, including technology usage (technology usage hours, social media use, gaming activity, and screen time), health factors (sleep duration and physical activity), and the work environment. To identify patterns and relationships, the study applies data visualization and statistical methods. The findings indicate that higher technology usage and screen time are positively correlated with increased mental health problems. On average, people spend 5.4 hours per day using technology, reflecting high digital engagement. Social media is used for 2.8 hours daily, gamers spend about 1.5 hours, and total screen time averages 8.7 hours per day, indicating very high screen exposure. Short sleep duration and low physical activity are strongly associated with higher stress levels. People sleep an average of 6.9 hours per night, slightly below the recommended 7–9 hours, and exercise only 1.2 hours per week. The average mental health score is 3.4 out of 5 (5 being the best and 1 the worst), indicating fair mental well-being. The average stress level is also 3.4. Although 78% of users have support options available, 45% are negatively affected by their workplace environment.**

***Index Terms*—Technology Usage, Mental Health, Screen Time, Social Media Usage, Stress Levels, Exploratory Data Analysis (EDA).**

I. INTRODUCTION

The fast progress of digital technology has changed drastically how people communicate, work, and spend their free time. During the last 10 years, the spread of mobile phones, social media sites, and digital entertainment has significantly raised the time spent in front of screens, as well as the dependence on technology, among all age groups [19][25]. Still, apart from the many benefits brought by these technological changes such as better communication, a great variety of information, and working from home possibilities a new wave of concerns has been raised about the psychological impact of these changes [23]. Nowadays, mental health is one of the most important public health issues [8]. Scientists and health professionals have greatly increased their reporting of the link between heavy use of technology and mental health problems such as high levels of stress, anxiety, depression, disturbed sleep, and a general decline in the sense of well-being [5][13]. Social media is the one that has been studied the most by researchers as it is so much part of our lives and can lead to negative emotions through social comparison, exposure to cyberbullying, and even patterns of addictive use [6][10].

II. OBJECTIVE OF THE STUDY

Analysis relationship between technology usage and mental health. To Identify key factors affecting mental health (sleep, stress, activity). Using visualization techniques to detect patterns in the dataset Providing insights for improving digital lifestyle habits.

III. METHODOLOGY

A. Dataset Description

The dataset comprised of 10,000 user records gathered from Kaggle [1] was employed in this paper. It included 14 features reflecting different aspects of individual behavior and well-being. Among these features, there were demographic characteristics (age, gender), technology-related aspects (total number of hours of technology usage, social media usage, gaming hours, screen time), health characteristics (sleep duration, physical activity level), mental health parameters (mental health status score, stress level), and environmental features (work environment impact, availability of support systems, and online support utilization). Having such lots of features allows for a quantum and multi-faceted analysis of digital lifestyle habits and their association with psychological outcomes. Data manipulation was done through the Pandas library [21] while numerical computations were performed using NumPy [22].

B. Data Preprocessing and Cleaning

A detailed data preprocessing workflow was applied to the dataset before any data analysis step to maintain the quality and integrity of the data. Initially, missing values were detected and imputation methods most suitable for each variable's characteristics were used to fill in the gaps. And, categorical variables like gender, mental health status, and stress level were transformed into a format that is compatible with analytics. Various statistical approaches were implemented for the identification of outliers, one of which was the Interquartile Range (IQR) method, and the outliers were dealt with So to avoid distortion of the results. Apart from eliminating duplication of records, all feature data types were made consistent.

To make different numerical variables (that might have been measured using different units) comparable, feature scaling or normalization was also performed.

C. Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) was undertaken to dive deep into the dataset, understand its structure thoroughly, figure out potential patterns, and get to know how the variables relate to each other on a primary level. Descriptive statistics were calculated for the entire set of numerical features, focusing on measures of central tendency, dispersion, and the overall shape of the distribution.

The degree of association between variables, in particular the ones related to screen time, sleep duration, physical activity, and mental health scores, was determined using a correlation matrix. The effort was directed toward revealing clusters of behavior, tracing demographic trajectories, and finding patterns of joint appearances among lifestyle variables. Besides, identifying which groups are the most vulnerable to overuse of technology has been made possible by subgroup comparison analysis based on gender, age bracket, and stress level [15].

D. Data Visualization

Many different visualization methods were implemented with the help of Python libraries-Seaborn [3] and Matplotlib [2]-for visually analyzing the relationships in the dataset [4]. Grouped box plots allowed us to look at how screen time varies among different categories of mental health states. Violin plots were used to visualize and compare the distributions of sleep hours among stress-level and gender groups. This method gives the reader a good understanding of the shape of the distributions and the density of the data. Grouped bar charts were used to show the patterns of social media usage related to mental health and stress indicators. Scatter plots were made with different gender markers to explore the connection between gaming hours and mental health status. Pair plots were used to give an entire multi-variable correlation picture by visualizing pairwise relationships among all continuous features simultaneously and uncovering interaction effects that aren't visible in individual charts.

IV. RESULTS AND ANALYSIS

Screen Time and Mental Health Status-Figure 1 present a grouped box plot depicting the distribution of daily screen time among different mental health status groups (rated 15). In particular, screen time is high and more or less similar across all mental health groups, with the lowest value of about 7.5 hours and the highest about 8.4 hours. Individuals with a mental health score of 1-2 result in a slightly higher median value of screen time than those with a score of 4-5. Yet, the overlapping interquartile ranges show that the differences between groups are not statistically significant. Besides, the high level of screen time in all groups indicates that it is not the only factor responsible for mental health differences. It is quite possible that other behavioral variables, such as sleep duration and physical activity, collectively influence and may predispose, mediate, and moderate the relationship between screen time and mental health outcomes, making these factors important contributors to overall psychological well-being [9][19].

Sleep Hours and Stress Levels-The violin plot of Figure (2) visually compares the sleep hours distribution for the three stress levels (High Low Medium) split by gender (Female Male Other).

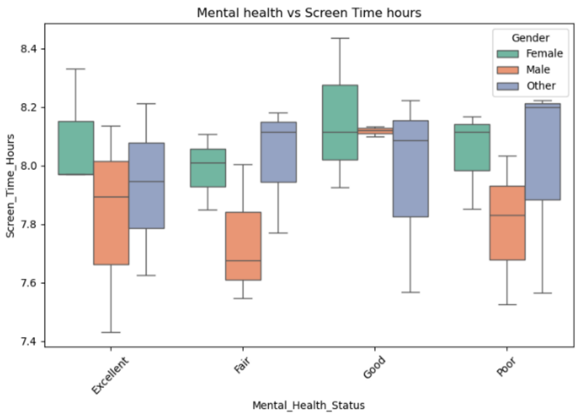

Figure 1 Grouped box plot effect of screen time on mental health.

It shows that stressed people tend to sleep less, that this is true for all gender groups, and that the differences between the stress - sleep patterns are visually bigger in the stressed groups. Women under stress seem to be the most affected group, showing both a more reduced and a more variable sleep distribution which points to the disruption of sleep due to stress.

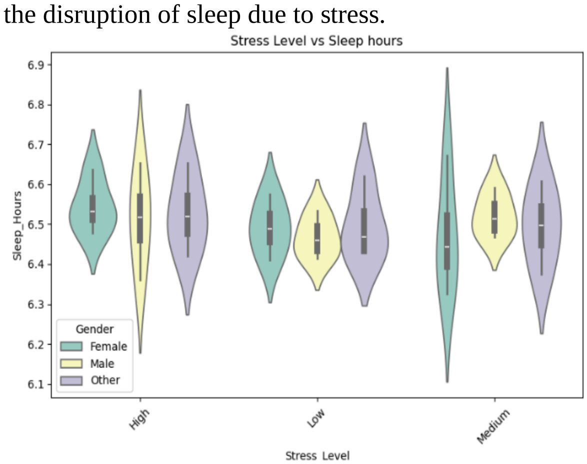

Figure 2 Violin plot effect of sleeping hours on stress level.

The uniformity of the violin shapes for the low-stress group suggests more stable and regular sleep patterns for all genders. The result support the well-documented two-way relation between lack of sleep and high psychological stress [13][26], and indicate that gender is a factor that influences how stress is expressed through sleeping behavior. Mental Health and Social Media Usage Hours-The amount of time people spend on social media is more or less the same as shown in Figure 3; so, it doesn't really look like one of the really good signs of their mental health or stress level.

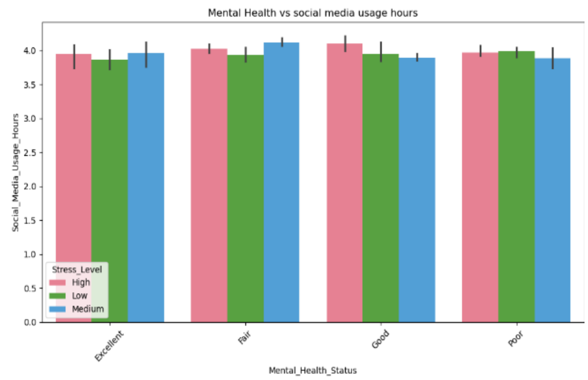

Figure 3 Grouped bar chart effect of social media on mental health.

Gaming Hours and Mental Health-Figure 4 illustrates with a scatter plot the correlation of daily gaming duration and mental health condition, with diverse shapes of markers signifying gender identities. The data points display a scattered, non-linear pattern, showing that gaming hours by themselves hardly lead to a linear effect on mental health status. But, groups of low mental health score can be seen in the users with long gaming sessions (over 2 hours per day). Besides, gender differences can be seen, male players show a greater variety of gaming time than female ones.

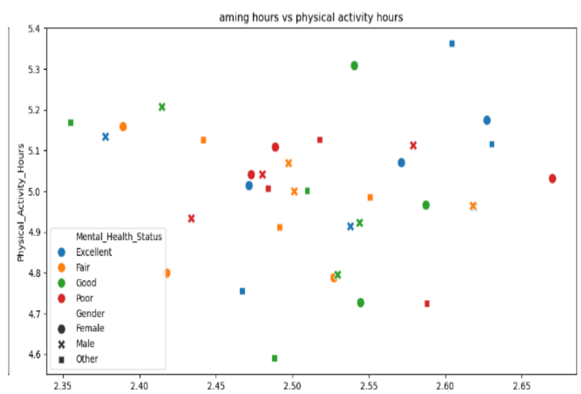

Figure 4 Scatter Plot depicting Gaming hours vs Mental Health.

Such tendencies point to Really gaming is not harmful in a general way, yet overdoing it might be linked to worse mental health conditions, mainly for males [14]. The connection proved to be influenced by other lifestyle factors as well, that means gaming habits should be viewed as part of the entire digital behavior profile of an individual.

V. KEY FINDINGS

A. Different levels of mental health may not significantly change the average daily technology usage a lot. On the high side, it might range from 6. 35 to 6. 57 hours in each mental health group. In general, using technology is quite normal for each mental health group, even if they have different levels of mental health. Sleep duration is somewhat connected to mental health status. Those who are mentally healthier may have a bit the habit of sleeping well, whereas the groups with poor mental health may be the ones who experience sleep disturbance or irregular sleep schedules. Finally, sleep quality is one of the most important lifestyle indicators that affect psychology besides sleep schedules.

B. The amount of sleep may be, to some degree, related to mental health status. Usually, people with good mental health go for somewhat healthier sleeping habits, whereas people with poor mental health are almost certainly the ones who face sleep problems and the likelihood of irregular sleep schedules. In conclusion, sleep-related changes are among the most important things that influence psychology and one can look at sleep schedules as a way of trying to determine how good or bad a person is actually doing.

VI. STATISTICAL SUMMARY

Age Distribution: Most users are in their early 30s, with a relatively normal distribution around this age.
Technology Usage: Users spend an average of 5.4 hours per day using technology, indicating high engagement with digital devices. Social Media Usage: Social media usage is moderate, averaging 2.8 hours per day [18][25]. Gaming and Screen Time: On average, users spend 1.5 hours on gaming and 8.7 hours in front of screens daily, highlighting a significant amount of screen time [9]. Mental Health Status: The average mental health status score is 3.4 on a scale from 1 (poor) to 5 (excellent), suggesting moderate mental well-being among users. Stress Levels: The average stress level is 3.4, indicating that users experience a moderate level of stress. Sleep Patterns: Users get an average of 6.9 hours of sleep, which is slightly below the recommended 7-9 hours.
Physical Activity: Users engage in an average of 1.2 hours of physical activity per week, which is relatively low [11]. Support Systems and Work Environment: A significant percentage of users have access to support systems (78%), but nearly half are affected by their work environment (45%). Online Support: Over half of the users (53%) utilize online support resources, indicating a trend towards seeking digital assistance.

VII. CONCLUSION

This research shows that there is a strong link between using technology and one's mental health. Spending a lot of time on a computer or a mobile, especially on social media, may lead to stress, less sleep, and inactivity. All these things together lead to mental health problems [9]. Also, changes in one's working environment, along with the availability of support, are important factors impacting mental health, as per the report. People who live a healthy life, with limited time in front of screens, enough sleep, and consistent exercise, generally have better mental health [11]. In essence, the research stresses the need to encourage good digital habits and inform people about the negative psychological impacts of too much technology use. Continuing studies could look into the cause and effect as well as the ways to help in this new digital era.

VIII. FUTURE SCOPE

This study aims to use Machine Learning models to predict mental health status by analyzing user behavior and psychological patterns. It also focuses on performing an in-depth analysis of the impact of social media on mental health and emotional well-being. The research incorporates real-time behavioral data to improve the accuracy of assessment and continuous monitoring. Additionally, the study seeks to develop intelligent mental health recommendation systems that provide personalized support, early intervention, and suitable coping strategies for individuals.

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