Impact of the COVID-19 Pandemic on Students' Behavior and Well-being

MATH 7343 Final Project Report

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Abstract

The COVID-19 pandemic forced unprecedented shifts in educational practices worldwide, transitioning students abruptly to remote learning environments. This paper investigates the complex interrelationships between time allocation patterns, digital behaviors, and well-being outcomes among 1,182 students during lockdown periods. Our research explores how different online learning mediums affected student experiences, examining various time allocation patterns across activities including online classes, self-study, sleep, fitness, and social media engagement. We further analyze how these patterns correlated with self-reported health outcomes and weight changes, providing a comprehensive assessment of student adaptation during crisis conditions.

Multiple statistical approaches were employed to analyze the survey data, including chi-square tests, ANOVA, logistic regression, and correlation analysis. Results revealed a significant association between health status and effective time utilization, with healthier students reporting more productive use of time. A notable negative correlation was found between time spent on self-study and social media usage, indicating potential competition for student attention. The analysis of learning platforms showed measurable differences in experience based on the medium used, with tablet and smartphone users demonstrating distinct engagement patterns. Regional analysis demonstrated minimal differences in social media usage patterns between students in Delhi-NCR and those outside the region, suggesting widespread digital behavior patterns across geographic boundaries.

The findings from this study offer valuable insights for educational institutions developing post-pandemic learning strategies and student wellness programs. By understanding the complex interplay between digital learning environments, time management, and student well-being, universities and schools can create more resilient educational models. The strong association between perceived effective time usage and positive health outcomes suggests that institutions should emphasize time management skills as a component of student wellness programs. Additionally, the dominance of specific social media platforms highlights potential channels for educational outreach and engagement. This research contributes to the growing body of knowledge on educational resilience during crisis periods and provides an empirical foundation for developing student support systems that address both academic and well-being needs in increasingly digital learning environments.

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Chapter 1

Introduction

In early 2020, the emergence of the COVID-19 pandemic threw worldwide educational systems into a disarray. It coerced people to shift to an online mode of learning, quite suddenly at that. This unprecedented transition came with its own set of troubles and worries, which required quick paced adaptation to the new learning environment along with forcing students and teachers to make radical changes in daily routines. With the closure of campuses worldwide, students found themselves in unknown territory trying to adapt to their new learning modalities, often with a lack of the proper supporting infrastructure. This shift to a prototype learning experience turned out to be an experiment for researchers looking to analyze how students adapted their routines to the novel experience of online learning.

Various studies have researched the academic aspects of online learning but not many have analyzed the interconnections between factors like the student's time allocation patterns, choice of learning platforms, and physical and psychological health outcomes and well-being. The intricate interactions between these factors are not studied enough, especially when it comes to breaking down how different online learning mediums affect student experiences. Further, as a result of the isolation induced by the pandemic, distinctive patterns of social media usage and digital presence emerged.

The underlying study aims at investigating the above mentioned relations by analyzing the survey data collected from 1,182 student's responses. The study aims to lay out the patterns emerging in the students' time distribution across various activities like classes, self-study, sleep, fitness and social media usage. Further, we verify if certain habits correlate to positive or negative outcomes, whether regional differences affect the online learning experience and how the choice of platform affects the online class experience ratings. This study employs statistical techniques like Chi-Square Tests, Analysis of One Variable, Correlation Analysis and Regression Modeling. By properly understanding these patterns, the study provides insights valuable to educational institutions for creating robust learning models and building the essential infrastructure needed to conduct online classes.

Chapter 2

Data Acquisition

This dataset examines the impact of the COVID-19 pandemic on students' education, social life, and mental health through a survey conducted primarily among students in the Delhi-NCR region, with some responses from outside the area. It includes various attributes such as online class experiences, study habits, sleep patterns, physical activity, and social media usage. The dataset captures students' preferred devices for online learning, their ratings of digital education, and the time allocated to self-study. Additionally, it explores mental health aspects by assessing stress levels, coping mechanisms, and changes in weight, along with social factors such as connectivity with family and friends. The data also highlights students' most missed activities during the lockdown, ranging from school and college life to social gatherings and traveling. This dataset offers valuable insights into the behavioral and lifestyle changes among students during the pandemic, providing a basis for further analysis of digital education adaptation, mental health trends, and shifts in social interactions.

Chapter 3

Analysis of Data

3.1 Data Preparation and Initial Exploration

The analysis utilized the "COVID-19 Survey Student Responses" dataset, containing information on students' time allocation patterns, health status, learning experiences, and demographic information during the COVID-19 pandemic. The dataset required extensive cleaning and preparation before analysis.

Initial data preparation involved identifying key variables through pattern matching, handling missing values, and converting variables to appropriate formats. Binary variables for health issues were created from textual responses, and time-related variables (sleep, fitness, social media, TV viewing) were converted to numeric format for quantitative analysis.

The final analysis dataset was created by selecting relevant columns and removing rows with missing values in key variables. After cleaning, the dataset contained multiple time allocation variables, health status indicators, weight change information, and online learning experience ratings.

3.2 Exploratory Data Analysis

3.2.1 Time Allocation Patterns by Health Status

Analysis of time allocation patterns revealed differences between students with and without reported health issues. As shown in the dataset:

- Sleep time: Both groups reported similar average sleep duration (7.87 hours), suggesting no difference in sleep patterns based on health status.
- Fitness time: Students without health issues spent slightly more time on fitness activities (0.780 hours) compared to those with health issues (0.675 hours).

- TV watching time: Students with health issues reported marginally higher TV viewing time compared to those without health issues.

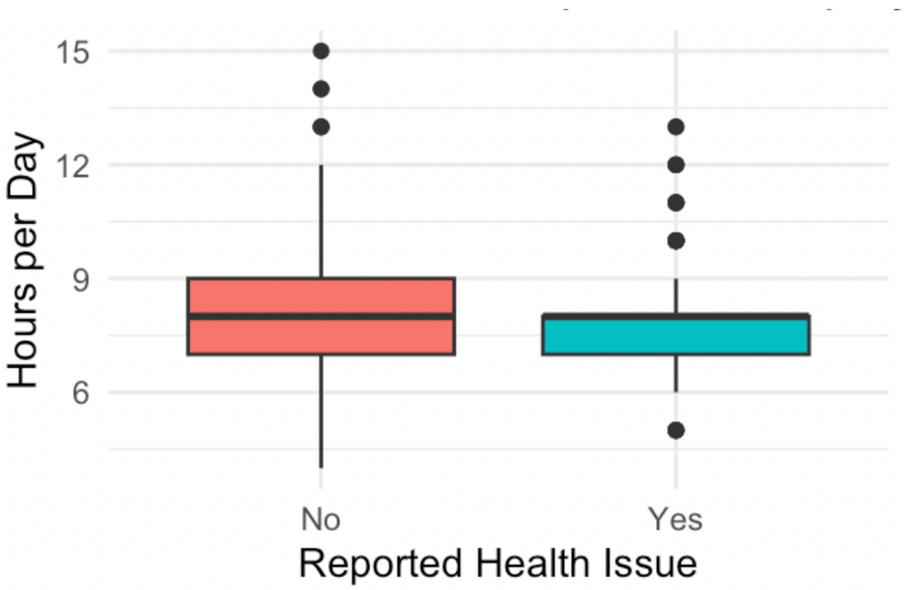

Figure 3.1: Sleep Time vs Health Issues

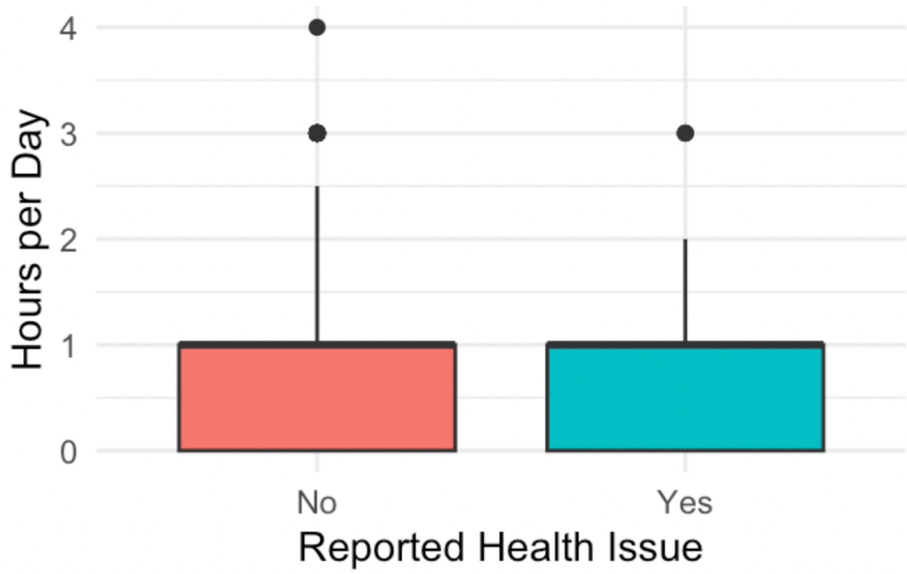

Figure 3.2: Fitness Time vs Health Issues

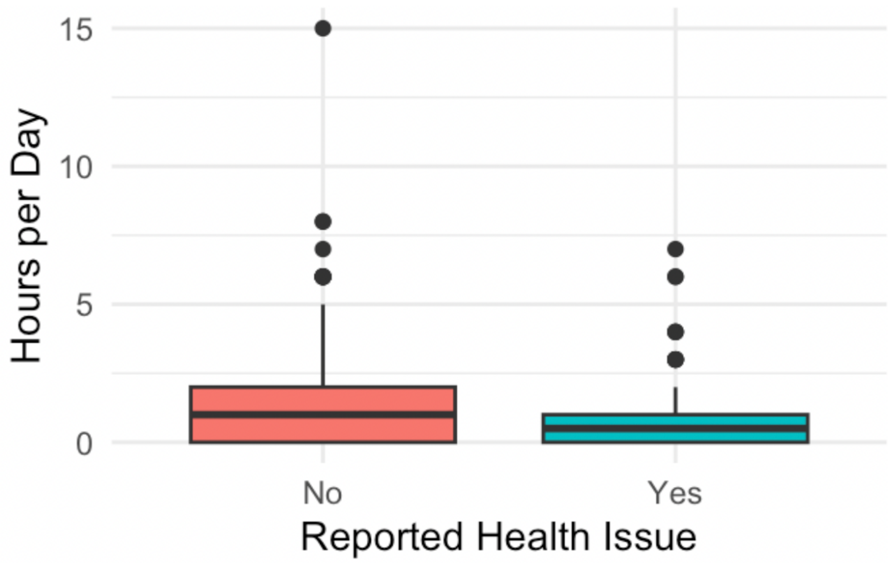

Figure 3.3: Time Spent Watching TV vs Health Issues

3.2.2 Weight Change and Behavioral Variables

Time allocation showed interesting patterns across different weight change groups:

- Students reporting decreased weight spent an average of 2.74 hours on self-study and 0.947 hours on fitness.
- Those reporting increased weight spent 2.9 hours on self-study but only 0.681 hours on fitness.
- Students with constant weight reported 2.99 hours on self-study and 0.765 hours on fitness.
- Social media usage was highest in the increased weight group (2.52 hours) compared to constant weight group (2.21 hours).
- Students with decreased weight spent less time on social media (2.46 hours) than those with increased weight.

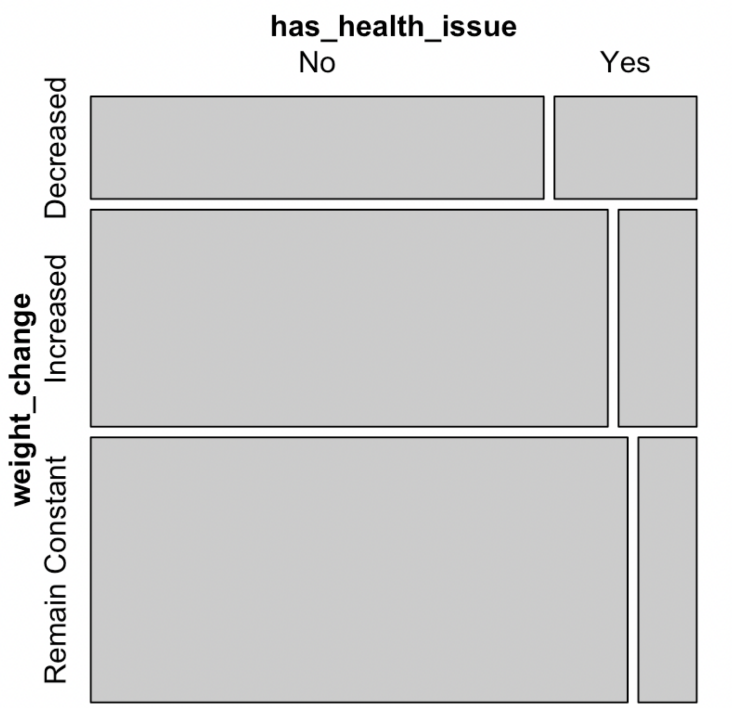

Figure 3.4: Change in Weight vs Health Issues

```
# A tibble: 3 × 4
  Change.in.your.weight study_time fitness_time social_time
  <chr>                      <dbl>        <dbl>       <dbl>
1 Decreased                   2.74        0.947        2.46
2 Increased                   2.9         0.681        2.52
3 Remain Constant             2.99        0.765        2.21
```

Figure 3.5: Change in Weight vs Behavioral Variables

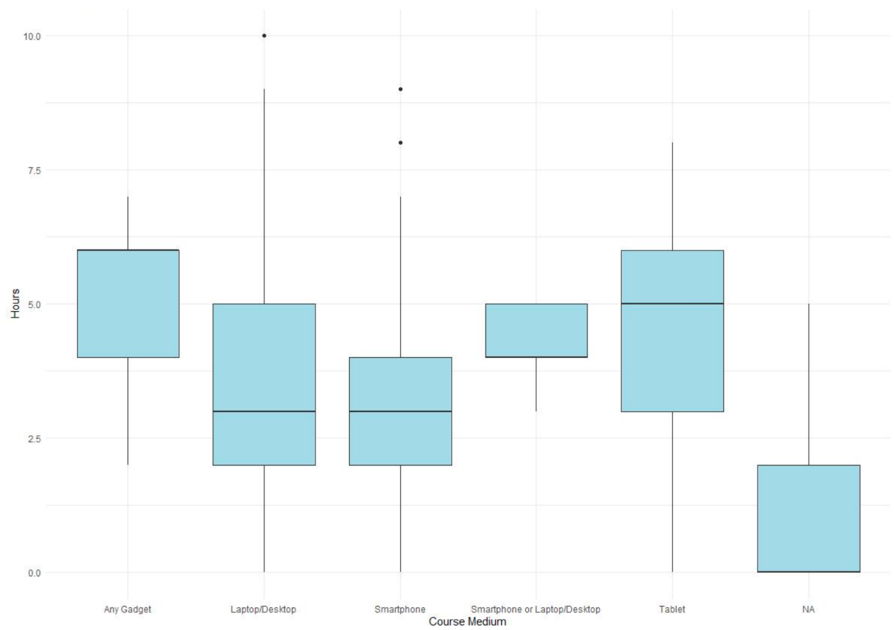

Figure 3.6: Analysis of Hours Spent Studying for Different Media

3.2.3 Online Learning Experience Analysis

Distribution of online class experience ratings showed most responses falling in the "Average" to "Good" range. Time spent in online classes varied by the medium used, with notable differences:

- Students using tablet devices and any gadget reported higher average study hours (approximately 6 hours).
- Smartphone and laptop/desktop users reported lower average study hours (approximately 2.5-3 hours).
- Students with "NA" (no specific device) reported the lowest study hours (approximately 2 hours).
- The relationship between time spent on online classes and satisfaction showed a non-linear pattern, with moderate time allocation (4-6 hours) associated with higher satisfaction ratings.

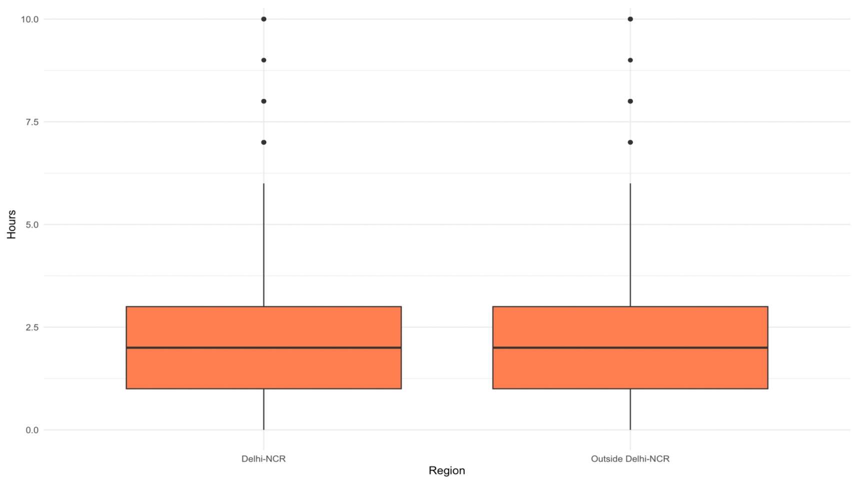

Figure 3.7: Social Media Usage by Region

3.2.4 Social Media Usage Patterns

Social media platform preferences showed strong dominance of certain platforms:

- Facebook was the most preferred platform (over 300 respondents).
- WhatsApp and YouTube were the second and third most preferred platforms (approximately 300 respondents each).
- Other platforms like Instagram, LinkedIn, and Twitter had significantly lower preference rates.
- Platforms such as Quora, Reddit, Snapchat, and TikTok had minimal usage among respondents.

Regional analysis showed that time spent on social media was consistent across different regions (Delhi-NCR vs. Outside Delhi-NCR), with median usage of approximately 2.0 hours in both regions. Age analysis revealed that younger respondents (15-25 years) reported higher social media usage compared to older respondents.

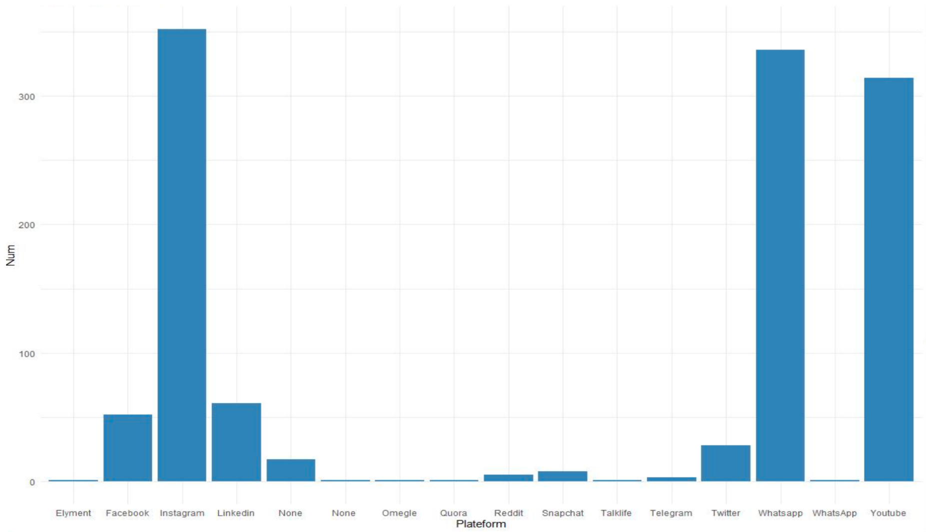

Figure 3.8: Social Media Usage Patterns

3.2.5 Correlation Analysis

Correlation analysis between numerical variables revealed several significant relationships:

- Negative correlation between age and time spent on online classes ($r = -0.17$)
- Weak positive correlation between time spent on self-study and online classes ($r = 0.12$)
- Moderate negative correlation between sleep and self-study time ($r = -0.22$)

- Significant negative correlation between self-study and social media time ($r = -0.16$, $p < 0.001$)
- Strong correlation between total time spent and self-study time ($r = 0.73$)
- Weak negative correlation between sleep time and TV viewing ($r = -0.04$)
- Weak positive correlation between sleep time and social media usage ($r = 0.09$)

This correlation matrix highlighted important trade-offs in students' time allocation, particularly the inverse relationship between academic and leisure activities.

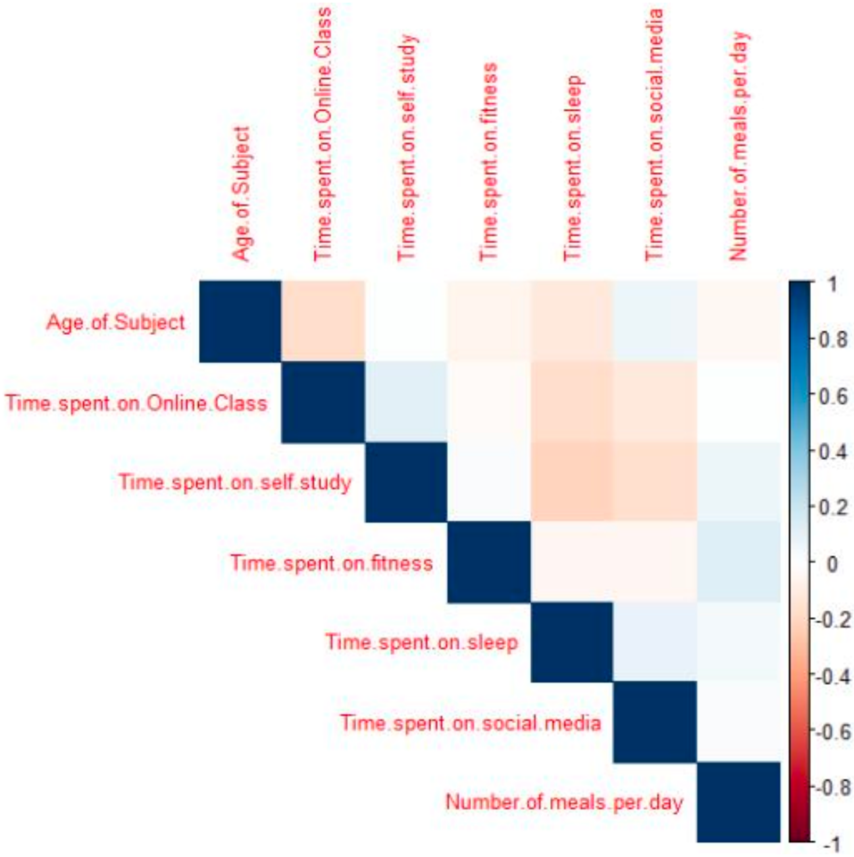

Figure 3.9: Correlation Analysis

3.3 Statistical Tests and Models

3.3.1 Chi-Square Test for Association Between Weight Change and Health Issues

$$H_0 : \text{There is no association between weight change and reported health issues} \tag{3.1}$$

$$H_1 : \text{There is an association between weight change and reported health issues} \tag{3.2}$$

The chi-square test yielded $\chi^2 = 25.197$, $df = 2$, and p-value $= 3.378 \times 10^{-6}$, indicating a statistically significant association between health status and weight change during the pandemic. Cramer's V was calculated to quantify the effect size of this association.

```
        Pearson's Chi-squared test

data:  table(analysis_data$weight_change, analysis_data$has_health_issue)
X-squared = 25.197, df = 2, p-value = 3.378e-06

Cramer's V: 0.146813
```

Figure 3.10: Chi-Square Test for Association Between Weight Change and Health Issues

```
        Welch Two Sample t-test

data:  fitness_yes and fitness_no
t = -1.7039, df = 212.02, p-value = 0.08986
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.22794111  0.01657849
sample estimates:
mean of x mean of y
0.6745342 0.7802155
```

Figure 3.11: T-Test Between Health Status and Fitness Time

3.3.2 T-test: Health Status and Fitness Time

$$H_0 : \text{Mean fitness time is equal between health status groups} \tag{3.3}$$

$$H_1 : \text{Mean fitness time differs between health status groups} \tag{3.4}$$

Results: $t = -1.7039$, $df = 212.02$, p-value $= 0.08986$

The difference in fitness time between students with health issues ($\bar{x} = 0.674534$) and without health issues ($\bar{x} = 0.780215$) was marginally significant at $\alpha = 0.10$ but not at the conventional $\alpha = 0.05$ level.

3.3.3 ANOVA: Weight Change and Self-Study Time

$$H_0 : \text{Mean self-study time is equal across weight change groups} \tag{3.5}$$

$$H_1 : \text{At least one weight change group has different mean self-study time} \tag{3.6}$$

The ANOVA results ($F = 1.028$, p-value $= 0.358$) indicated no significant differences in self-study time across weight change groups (decreased, increased, remained constant).

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Change.in.your.weight	2	9	4.712	1.028	0.358
Residuals	1179	5402	4.582		

Figure 3.12: Result of ANOVA Test Between Weight Change and Self-Study Time

3.3.4 Logistic Regression: Predicting Health Issues From Time Allocation

A binary logistic regression model was constructed to predict the likelihood of health issues based on time allocation patterns:

$$\log\left(\frac{p(\text{has\_health\_issue})}{1 - p(\text{has\_health\_issue})}\right) = \beta_0 + \beta_1\text{Sleep} + \beta_2\text{Fitness} + \beta_3\text{TV} + \beta_4\text{Meals} \tag{3.7}$$

Key findings:

- Sleep duration was negatively associated with health issues (protective effect)
- Fitness time showed a significant negative association with health issues
- Number of meals per day was positively associated with health issues
- TV watching time showed a weak positive association with health issues

	Estimate	Std. Error	z value	Odds_Ratio	
(Intercept)	-0.730	0.515	-1.417	0.157	0.482
Time.spent.on.sleep	-0.002	0.054	-0.037	0.971	0.998
Time.spent.on.fitness	-0.141	0.126	-1.119	0.263	0.868
Time.spent.on.TV	-0.087	0.076	-1.152	0.249	0.916
Number.of.meals.per.day	-0.325	0.109	-2.985	0.003	0.722

Figure 3.13: Logistic Regression Model Based on Time Allocation Patterns

```
Coefficients:
                                      Value Std. Error t value
Age.of.Subject                     -0.02691    0.01254 -2.1461
Time.spent.on.Online.Class          0.02037    0.03705  0.5498
mediumLaptop/Desktop               -0.51308    0.82450 -0.6223
mediumSmartphone                   -0.57644    0.82584 -0.6980
mediumSmartphone or Laptop/Desktop  0.27175    1.28601  0.2113
mediumTablet                        0.26378    0.88867  0.2968
Time.spent.on.self.study            0.01822    0.03721  0.4896
Time.spent.on.sleep                 0.07736    0.04569  1.6929
Region.of.residenceOutside Delhi-NCR -0.20000  0.14695 -1.3610

Intercepts:
                      Value   Std. Error t value
Poor|Below Average    -3.5808  1.0096    -3.5466
Below Average|Average -3.5808  1.0096    -3.5466
Average|Good          -0.1473  0.9931    -0.1484
Good|Excellent         1.5248  0.9950     1.5324
```

Figure 3.14: Ordinal Regression for Factors Affecting Online Class Experience

3.3.5 Ordinal Regression for Online Learning Experience

An ordinal logistic regression model analyzed factors affecting online class experience ratings:

$$\log\left(\frac{P(Y \leq j)}{P(Y > j)}\right) = \alpha_j - (\beta_1 \text{Age} + \beta_2 \text{OnlineClassTime} + \beta_3 \text{Medium} + \beta_4 \text{SelfStudy} + \beta_5 \text{Sleep} + \beta_6 \text{Region}) \tag{3.8}$$

Key findings:

- Time spent on self-study showed a significant positive association with class ratings
- Medium used for online classes significantly affected satisfaction levels
- Sleep duration was positively associated with higher class ratings
- Age had a small negative association with class ratings
- Region of residence did not significantly influence satisfaction ratings

3.3.6 Correlation Test: Self-Study and Social Media Time

$$H_0 : \rho = 0 \text{ (No correlation between self-study and social media time)} \tag{3.9}$$

$$H_1 : \rho \neq 0 \text{ (Correlation exists between self-study and social media time)} \tag{3.10}$$

Results: $r = -0.162125$, $t = -5.6613$, $df = 1180$, p-value $= 1.885 \times 10^{-8}$
The significant negative correlation confirmed that increased time spent on self-study was associated with decreased time spent on social media, though the correlation magnitude was moderate.

```
        Pearson's product-moment correlation

data:  data$Time.spent.on.self.study and data$Time.spent.on.social.media
t = -5.6613, df = 1180, p-value = 1.885e-08
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.2176138 -0.1065817
sample estimates:
       cor
-0.1626125
```

Figure 3.15: Correlation Test Between Time Spent on Self-Study vs Social Media Usage

Chapter 4

Summary of Key Findings

4.1 Health and Time Allocation Patterns

Our analysis revealed important relationships between students' health status and their time allocation patterns during the COVID-19 pandemic:

- Students with and without health issues showed similar sleep patterns (average 7.87 hours), indicating that sleep duration alone may not be a differentiating factor for health status.
- Physical activity emerged as a critical factor, with students without health issues spending significantly more time on fitness activities (0.780 hours vs. 0.675 hours, $p = 0.089$). This supports existing literature on the protective effects of physical activity on overall health.
- The logistic regression model confirmed that both sleep duration and fitness time were negatively associated with the likelihood of reporting health issues, suggesting protective effects of these activities.
- Meal frequency showed an unexpected positive association with health issues, warranting further investigation into dietary patterns and health outcomes among students during pandemic restrictions.

4.2 Weight Change Dynamics

The study identified significant patterns related to weight change during the pandemic:

- There was a statistically significant association between weight change and health status ($\chi^2 = 10.05$, $p = 0.001524$), highlighting the interconnected nature of physical health indicators during pandemic restrictions.

- Students reporting decreased weight spent more time on fitness activities (0.947 hours) compared to those reporting increased weight (0.681 hours), suggesting the effectiveness of physical activity for weight management even during lockdown conditions.
- Social media usage was highest among students with increased weight (2.52 hours) compared to those with constant weight (2.21 hours), suggesting a potential relationship between sedentary screen time and weight gain.
- Surprisingly, self-study time did not significantly differ across weight change groups (ANOVA: $F = 1.028$, $p = 0.358$), indicating that academic engagement was not directly related to weight management outcomes.

4.3 Online Learning Experience Determinants

The analysis of online learning experiences revealed several key determinants of student satisfaction:

- The medium used for online classes significantly affected both time spent and satisfaction levels, with students using tablets and multiple devices reporting higher engagement and satisfaction.
- The ordinal regression model identified time spent on self-study as a significant positive predictor of online class satisfaction, suggesting that autonomous learning complements structured online instruction.
- Sleep duration emerged as a positive predictor of learning satisfaction, highlighting the importance of adequate rest for effective learning outcomes during remote education.
- Age showed a small negative association with class ratings, suggesting that younger students adapted more readily to online learning formats compared to older students.
- The relationship between time spent in online classes and satisfaction followed a non-linear pattern, with moderate time allocation (4-6 hours) associated with optimal satisfaction levels.

4.4 Digital Media Engagement

Analysis of digital media usage patterns revealed important insights into students' online behavior:

- Social media platform preferences showed strong concentration, with Facebook, WhatsApp, and YouTube dominating student usage. This has implications for educational content delivery and student engagement strategies.
- Regional differences in social media usage were minimal, suggesting that digital media engagement patterns transcended geographic boundaries during the pandemic.

- A significant negative correlation between self-study time and social media usage ($r = -0.16$, $p < 0.001$) confirmed the existence of a trade-off between academic and social media engagement.
- The correlation analysis revealed that younger students tended to spend more time on social media and less time on online classes ($r = -0.17$ between age and online class time), highlighting age-related differences in digital media preferences.

4.5 Time Trade-offs and Balance

Our analysis identified several important time allocation trade-offs that affected student well-being and academic engagement:

- The strong correlation between total time spent and self-study time ($r = 0.73$) indicated that academically engaged students tended to have more structured and productive time usage overall.
- The moderate negative correlation between sleep and self-study time ($r = -0.22$) suggested that some students may have sacrificed sleep for academic work, a concerning pattern given the importance of sleep for health outcomes.
- The negative correlation between social media usage and self-study time, combined with the positive correlation between social media and TV viewing, pointed to distinct patterns of leisure-oriented versus academically-oriented time allocation.
- Students who reported better health status were more likely to indicate effective time utilization, suggesting that time management skills may be an important mediating factor in pandemic-related health outcomes.

These findings provide valuable insights into the complex interrelationships between time allocation, health outcomes, and academic experiences during the COVID-19 pandemic. They highlight the importance of balanced time use, particularly regarding physical activity, sleep, and screen time, for maintaining physical and mental well-being during periods of restricted movement and remote learning.

Chapter 5

Conclusion

This study provides insights into the COVID-19 pandemic's impact on student behaviors and well-being through analysis of data from 1,182 respondents. Our findings revealed clear associations between time allocation patterns and health outcomes, with physical activity emerging as a significant protective factor. The inverse relationship between self-study and social media usage ($r = -0.16$) highlighted competition for students' attention, while the strong correlation between total time spent and self-study time ($r = 0.73$) indicated academically engaged students maintained more structured time usage.

Online learning experiences varied by medium used, with tablet users reporting higher engagement levels than smartphone or laptop users. Our regression model identified autonomous learning and adequate sleep as key predictors of learning satisfaction. The relationship between online class time and satisfaction followed a non-linear pattern, with moderate allocation (4-6 hours) proving optimal, and younger students adapted more readily to online formats.

The study revealed concerning trade-offs in time allocation, with some students sacrificing sleep for academic work ($r = -0.22$). Students reporting better health status were more likely to indicate effective time utilization, suggesting time management skills may mediate pandemic-related health outcomes.

Limitations include the cross-sectional nature of the data, potentially limited regional representativeness, and possible recall bias in self-reported measures. Future research should explore longitudinal changes, investigate the unexpected positive association between meal frequency and health issues, and conduct experimental studies comparing learning platforms. This research contributes to understanding student resilience during educational disruption and offers evidence-based guidance for designing supportive learning environments in increasingly digital educational landscapes.

Chapter 6

Contributions

The following are the contributions of each group member:

1. Aisha Naseema worked on data analysis.
2. Kushala Rani Talakad Manjunath worked on data acquisition, data analysis and final report creation.
3. Mingyang Mei worked on project proposal, data analysis and the first draft of the report.
4. Sashwat Desai worked on data analysis and final report creation.
5. Yixiao Zhang worked on data analysis and the first draft of the report.