Title: Link Between Nighttime Blue Light Exposure and Sleep Patterns

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Problem Statement:

In today's digital age, excessive exposure to blue light emitted by smartphones, laptops, desktops, and televisions during nighttime hours is increasingly suspected to interfere with sleep quality. With rising smartphone dependency among young adults, especially during late-night hours, concerns have grown around its contribution to irregular sleep patterns, increased sleep latency, insomnia, and daytime fatigue. This study aims to quantitatively examine the correlation between nighttime smartphone usage—specifically blue light exposure—and various indicators of sleep quality, including total sleep duration, time taken to fall asleep (sleep latency), and frequency of nighttime awakenings.

Introduction:

Background:

In our increasingly screen-driven world, blue-rich light emitted by a variety of devices including smartphones, laptops, desktop monitors, tablets, and televisions has become unavoidable, especially during evening hours. Scientific evidence shows that evening exposure to blue wavelengths suppresses melatonin production, thereby delaying the onset of sleep and fragmenting the natural circadian rhythm. Frequent late-night screen use across these devices has been associated with shorter total sleep time, longer sleep latency, more nighttime awakenings, and diminished perceived sleep quality. These sleep disturbances can translate into daytime fatigue, impaired cognitive function, and mood dysregulation.

Motivation:

We selected this topic because late-night screen use is pervasive across all age groups, particularly among young adults. Friends, classmates, and early-career peers often multitask on several devices well into the night—streaming videos on a laptop while texting on a phone or watching TV. They routinely report feeling unrefreshed in the morning despite "getting enough hours" in bed. Our goal is to move beyond anecdote and use quantitative survey data to uncover how evening exposure to blue light from all devices impacts sleep hygiene.

From a social perspective, better sleep fosters mental health, academic/work performance, and overall life satisfaction. From a financial standpoint, chronic sleep disruption drives up healthcare costs (e.g., treatments for insomnia, depression) and reduces productivity, affecting both individuals and organizations. By rigorously quantifying these effects, we can inform public health guidance and encourage device-makers to integrate adaptive features (like dynamic color temperature shifts) that protect users' sleep.

Define the Terms:

- **Blue Light Exposure:** Cumulative duration of exposure to screen-emitted blue light from any electronic device (smartphone, laptop, desktop monitor, tablet, television) during the two hours before bedtime or after 10 PM.
- **Night Mode / Blue-Light Filter:** A device display setting that shifts emitted light towards longer (redder) wavelengths to minimize melatonin suppression.
- **Sleep Patterns:** Objective and subjective sleep metrics:
  - **Total Sleep Time:** Hours spent asleep per night.
  - **Sleep Latency:** Minutes from "lights off" to sleep onset.
  - **Number of Awakenings:** Frequency of involuntary nighttime arousals.
  - **Perceived Sleep Quality:** Self-rated on a 1–10 Likert scale.
- **Circadian Rhythm:** The ~24-hour internal clock regulating sleep–wake cycles, hormone release, and other physiological processes.
- **Screen Time:** Total minutes/hours of active screen engagement per device, as self-reported or via built-in usage logs.

Target Audience:

This study is designed to be applicable to all age groups, from adolescents and young adults to middle-aged and older adults. However, it will focus particularly on individuals aged 19–23, a demographic with exceptionally high evening screen engagement, to explore how blue light exposure from multiple devices impacts their sleep patterns.

Literature Review:

1. Impact of Blue Light on Sleep Quality

- Citation: Yüksel, D., & Peker, N. (2023). The effect of blue light exposure on sleep and academic performance. Chronobiology in Medicine.
- Summary: This study explains how blue light exposure before sleep suppresses melatonin production, delays sleep onset, and shortens total sleep duration. It emphasizes that college students who use screens before bed suffer from impaired attention, memory, and emotional balance.

Extraction:

- Blue light delays melatonin release, a hormone essential for initiating sleep.
- Impaired academic and cognitive performance is directly linked to disrupted sleep patterns from blue light exposure.
- Students are a vulnerable demographic for screen-induced sleep issues.

2. Screen Use and Sleep Outcomes

- Citation: Christensen, M. A., et al. (2024). Association of screen use before bed with sleep quality and quantity. JAMA Network Open.
- Summary: This large-scale observational study found that adults who used screens within 2 hours of bedtime experienced reduced total sleep time and increased sleep fragmentation.
- Extraction:
  - Late screen use is strongly associated with poor subjective sleep quality.
  - The frequency and duration of device use are predictors of shorter and more disturbed sleep.

3. Physiological and Cognitive Effects of Blue Light

- Citation: Wang, Y., et al. (2024). Evening blue light exposure reduces deep sleep and impairs morning attention. Sleep Medicine.
- Summary: This experimental study involved controlled blue light exposure before bedtime. Participants had reduced deep (slow-wave) sleep and reported lower morning alertness.
- Extraction:
  - Blue light reduces the proportion of restorative deep sleep.
  - Sleep architecture disruption affects next-day mental clarity and responsiveness.
  - Suggests physiological damage beyond subjective sleep complaints.

4. Youth Screen Media and Circadian Disruption

- Citation: Cain, N., &Gradisar, M. (2010). Electronic media use and sleep in school-aged children and adolescents. Child and Adolescent Psychiatric Clinics of North America.
- Summary: The study reviews how adolescents' evening use of screens interferes with their circadian rhythm, leading to delayed sleep phases.
- Extraction:
    - ➢ Blue light delays sleep onset by suppressing natural melatonin cycles.
    - ➢ Irregular sleep schedules in youth affect school performance and emotional regulation.
    - ➢ Youth behavior is highly influenced by digital multitasking

5. Evening Screen Time and Daytime Functioning

- Citation: Chang, A.-M., et al. (2022). Screen use in the evening is associated with poor sleep and next-day fatigue. PLOS ONE.
- Summary: This study categorized screen use into evening vs. nighttime and tracked sleep quality indicators and daytime energy levels.
- Extraction:
    - ➢ Nighttime screen use beyond 10 PM is most harmful.
    - ➢ Participants using screens late into the night reported more grogginess and irritability during the day.
    - ➢ Sleep quality is inversely related to the duration and intensity of screen exposure.

Key Takeaways for our Study:

- Consistent findings link blue light exposure after 10 PM* to *delayed sleep, poor sleep quality, and impaired daytime performance*.
- Young adults (19–23) are a key risk group due to high device engagement and multitasking habits.
- Quantitative metrics like sleep latency, duration, and number of awakenings are reliable indicators for assessing screen-related sleep issues.

Sampling Method:

1. **Target Population**

The study focuses on individuals aged 19 to 23 years, typically comprising college students or early-career professionals.

This demographic is chosen due to:

- High engagement with electronic devices late at night
- Susceptibility to irregular sleep patterns
- Convenience and accessibility for survey distribution

2. **Sampling Frame**

The sampling frame will include students from colleges or universities (e.g., undergraduate students across multiple departments)

- Online social groups or forums relevant to young adults
- Class WhatsApp groups, Telegram channels, or academic clubs

3. **Sampling Technique**

a. **Convenience Sampling (Primary Method):**

Participants will be selected based on ease of access and availability. This includes reaching out through academic circles, university mailing lists, and social platforms like Instagram or WhatsApp.

b. **Stratified Sampling (Optional Enhancement):**

- To ensure representation across gender, stream of study, and screen time habits:
- Stratify participants into subgroups (e.g., STEM vs. arts students, male vs. female, low vs. high device usage).
- Randomly select a proportional number from each group to avoid over-representation.
- Rationale: While convenience sampling is fast and cost-effective for exploratory studies, stratified sampling improves generalizability and reduces sampling bias.

➢ **Sample Size**

An ideal sample size for statistical validity:

- Minimum of 100–150 participants to ensure meaningful correlation and statistical analysis.
- Larger sample sizes improve the power of hypothesis testing (e.g., p-values in ANOVA or correlation analysis).

- **Inclusion Criteria**

- Age between 19 and 23 years
- Uses electronic devices (e.g., phone, laptop, TV) at least 2 hours daily
- Willing to provide honest self-reported data about screen time and sleep habits

- **Exclusion Criteria**

- Individuals with diagnosed sleep disorders or on sleep medication
- Participants who work night shifts or follow atypical sleep schedules
- Incomplete or inconsistent questionnaire responses

Hypothesis:

1. **Research Hypothesis (H_1)**

Excessive nighttime exposure to blue light from digital screens is significantly associated with poorer sleep quality, including longer sleep latency, decreased total sleep time, increased frequency of nighttime awakenings, and lower perceived sleep quality.

This hypothesis suggests that the more time an individual spends exposed to blue light (from phones, laptops, TVs, etc.) during late-night hours (especially after 10 PM), the more disrupted their sleep will be—both objectively (in terms of time and awakenings) and subjectively (in terms of how restful the sleep feels).

2. **Null Hypothesis (H_0)**

There is no significant association between nighttime blue light exposure from digital screens and sleep quality indicators such as sleep latency, total sleep time, number of awakenings, or perceived sleep quality.

The null hypothesis assumes that any observed differences in sleep metrics are due to random variation or other unrelated factors, not blue light exposure.

Variables

a. **Independent Variable**

Blue Light Exposure Time: Measured as the duration (in minutes/hours) of screen use after 10 PM across devices.

b. **Dependent Variables**

- Sleep Latency: Time taken to fall asleep after "lights off"
- Total Sleep Time: Number of hours of actual sleep
- Number of Awakenings: Involuntary interruptions during the night
- Perceived Sleep Quality: Rated by the participant on a 1–10 Likert scale

Operational Definition of Terms

"Excessive exposure" is defined as more than 1 hour of cumulative screen time within 2 hours before bedtime.

Poorer sleep quality is determined by:

- Sleep latency > 30 minutes
- Total sleep time < 6.5 hours
- More than 2 nighttime awakenings
- Perceived quality ≤ 5 on a 10-point scale

Expected Relationship

Based on previous literature, we expect:

- A positive correlation between blue light exposure and sleep latency/awakenings (i.e., higher blue light → longer to fall asleep, more wake-ups).
- A negative correlation with total sleep time and perceived sleep quality (i.e., higher blue light → less sleep, worse quality).

Questionnaire:

Q1. At what time do you typically stop using screens (phone/laptop/TV) at night?
A) Before 9:00 PM
B) Between 9:00 – 10:00 PM
C) Between 10:00 – 12:00 AM
D) After 12:00 AM

Q2. On average, how many hours do you spend on screens after 10:00 PM?
A) Less than 30 minutes
B) 30 minutes – 1 hour
C) 1 – 2 hours
D) More than 2 hours

Q3. Do you use night mode or a blue-light filter on your devices in the evening?
A) Always
B) Sometimes
C) Rarely
D) Never

Q4. How often do you multitask on multiple screens (e.g., TV + phone) at night?
A) Never
B) Occasionally
C) Frequently
D) Always

Q5. What is your primary screen activity at night?
A) Watching videos/movies
B) Social media browsing
C) Studying or work-related tasks
D) Gaming

Q6. How long does it usually take you to fall asleep after turning off screens?
A) Less than 10 minutes
B) 10–30 minutes
C) 30–60 minutes
D) More than 1 hour

Q7. On average, how many hours of sleep do you get on weekdays?
A) Less than 5 hours
B) 5–6 hours
C) 6–7 hours
D) More than 7 hours

Q8. How often do you wake up during the night?
A) Never
B) Once
C) 2–3 times
D) More than 3 times

Q9. Do you feel well-rested after waking up in the morning?
A) Always
B) Often
C) Sometimes
D) Rarely

Q10. Do you use screens in bed before sleeping?
A) Always
B) Often
C) Sometimes
D) Never

Q11. Do you fall asleep while using a screen (e.g., phone, laptop, TV)?
A) Frequently
B) Occasionally
C) Rarely
D) Never

Q12. Do you wake up at night to check your phone or other devices?
A) Always
B) Sometimes
C) Rarely
D) Never

Q13. Is your room completely dark while sleeping?
A) Yes, completely dark
B) Some ambient light (e.g., night light)
C) TV or screen left on
D) Bright light (e.g., lamp)

Q14. Do you follow a consistent sleep schedule (same sleep/wake time daily)?
A) Always
B) Most days
C) Rarely
D) Never

Q15. Do you consume caffeine (e.g., coffee, energy drinks) after 6 PM?
A) Daily
B) 2–3 times a week
C) Occasionally
D) Never

Data Collection:

Data collection methods:

1. Surveys
2. Interviews

Surveys (Google Forms):

Surveys use structured questionnaires to gather quantitative or qualitative data from a large group of respondents efficiently. They can be administered online, by mail, by phone, or in person, allowing for standardized data collection and easy comparison across participants.

Interviews:

Interviews involve direct, one-on-one conversations where the interviewer asks open-ended or structured questions to explore respondents' in-depth perspectives. They provide rich, nuanced insights but can be time-consuming and require skilled interviewers to avoid bias.

Data Collection and Analysis

The foundation of our project lies in collecting real-world data related to screen usage behaviour, multitasking habits, and digital well-being practices among students. This data was gathered through a structured Google Form survey, which was then exported into a **CSV file** for cleaning and analysis, and also integrated into a **Power BI dashboard** for visual insights. Below is a comprehensive breakdown of each column in the dataset, its analytical significance, challenges encountered, and the approaches used to address them.

Overview of the Dataset

- Total Responses Collected: 100+
- Format: CSV (Comma Separated Values)
- Analysis Tools Used: Python (Pandas), Microsoft Excel, Power BI
- Purpose: To derive patterns in screen usage, digital behaviour, and correlate it with academic background, sleep hygiene, and multitasking tendencies.

Detailed Column-Wise Summary and Theoretical Analysis

1. **Email Address**

This is a unique identifier for each respondent.

- Purpose: Used internally to avoid duplicate entries. It has no analytical value.
- Challenge: High risk of exposing personal data and violating data privacy norms.
- Solution: This column should be removed or anonymized to ensure compliance with data protection regulations (like GDPR).

2. **Name**

The name of the respondent, which again serves as a personal identifier.

- Purpose: Similar to email, it does not contribute to statistical or behavioural insights.
- Challenge: Names are unique and sensitive; retaining them poses privacy threats.
- Solution: This field was excluded from analysis to maintain anonymity.

3. Date of Birth

Provides the birth date of each respondent.

- Purpose: Helps derive age of the participants, which can be a critical demographic metric.
- Challenge: The format is stored as text and may vary (e.g., DD/MM/YYYY vs MM/DD/YYYY), leading to parsing errors.
- Solution: Converted this column to datetime type and derived age for each respondent. Ages were then categorized into bins (e.g., 18–20, 21–23) for segmentation and visualization.

4. Gender

Indicates the gender of the respondent (e.g., Male/Female).

- Purpose: Used to study behavioural differences between male and female students in terms of screen habits and digital hygiene.
- Challenge: Possible inconsistency in labels (e.g., "male", "Male ", etc.).
- Solution: Normalized all entries to standard values like "Male" and "Female". Entries with missing or ambiguous gender were excluded from gender-based visualizations.

5. Field of Study

Specifies the academic background or department of the respondent (e.g., Computer Science, Commerce).

- Purpose: Helps analyze how screen time or digital habits vary by academic discipline.
- Challenge: Some responses used abbreviations (e.g., "CS" instead of "Computer Science"), leading to fragmentation.
- Solution: Grouped similar fields into common categories such as:
    - Computer Science / IT
    - Commerce / Business
    - Arts & Humanities
    - Life Sciences
    - Psychology

This standardization allowed better group-level analysis and charting in Power BI.

6. Time When Screen Usage Typically Ends (at Night)

Respondents selected the time range when they usually stop using digital devices.

- Purpose: Helps evaluate sleep hygiene and screen addiction.
- Challenge: Time entries were subjective, with varied formats such as "Between 11:00 – 12:00 PM", "After 1:00 AM", etc.
- Solution: Re-binned the responses into unified time slots:
    - Before 10 PM
    - 10 PM – 12 AM
    - After 12 AM

This allowed clear visual comparisons of digital behaviour versus sleep schedule.

7. Average Screen Time Per Day (in hours)

A numeric column where respondents estimated their average daily screen time.

- Purpose: A core metric for measuring digital exposure.
- Challenge: Self-reported values can be biased or exaggerated. Also, a few outliers (e.g., 0 hours or 10 hours) can skew analysis.
- Solution:
  - Used statistical summaries (mean, median, standard deviation).
  - Identified and handled outliers using IQR method.
  - Binned screen time into ranges like:
    - Low (0–2 hrs)
    - Moderate (2–5 hrs)
    - High (5+ hrs)

This classification helped in creating cleaner visualizations and more balanced charts in Power BI.

8. Use of Night Mode or Blue-Light Filter

Captures whether respondents use blue-light filter settings on their devices.

- Purpose: Indicates digital wellness practices to reduce eye strain and improve sleep quality.
- Challenge: Response options were vague (e.g., "Always", "Sometimes", "Rarely", "Never"), and the interpretation can vary.
- Solution: Mapped responses to ordinal values:
  - Never = 0
  - Rarely = 1
  - Sometimes = 2
  - Always = 3

This allowed easier visualization in bar charts and correlation studies with screen time.

9. Multitasking Frequency on Multiple Screens

This column reflects how often students multitask on multiple screens (e.g., using phone and laptop simultaneously).

- Purpose: Important to evaluate cognitive overload and behaviour patterns.
- Challenge: Similar to the night mode column, responses were qualitative and subjective.
- Solution: Responses were mapped to ordinal scale (0 to 3), enabling numeric correlation and bar graph visualization.

Key Statistical Findings

After data cleaning and transformation, we generated the following insights:

- Average screen time across participants was approximately 2.42 hours/day, with a standard deviation of 1.69 hours.
- The maximum screen time reported was 10 hours, suggesting possible outliers or extreme digital usage cases.
- Majority of students stop using screens between 11 PM and 12 AM, which may interfere with optimal sleep cycles.
- 43 out of 85 participants were male, showing a near even gender distribution.
- 44 respondents were from Computer Science / IT, indicating a tech-dominant sample group.
- Most students "Always" or "Sometimes" use blue-light filters, suggesting a basic awareness of digital hygiene.
- The most common multitasking frequency was “Occasionally”, indicating semi-regular multi-screen usage.

Challenges and Limitations

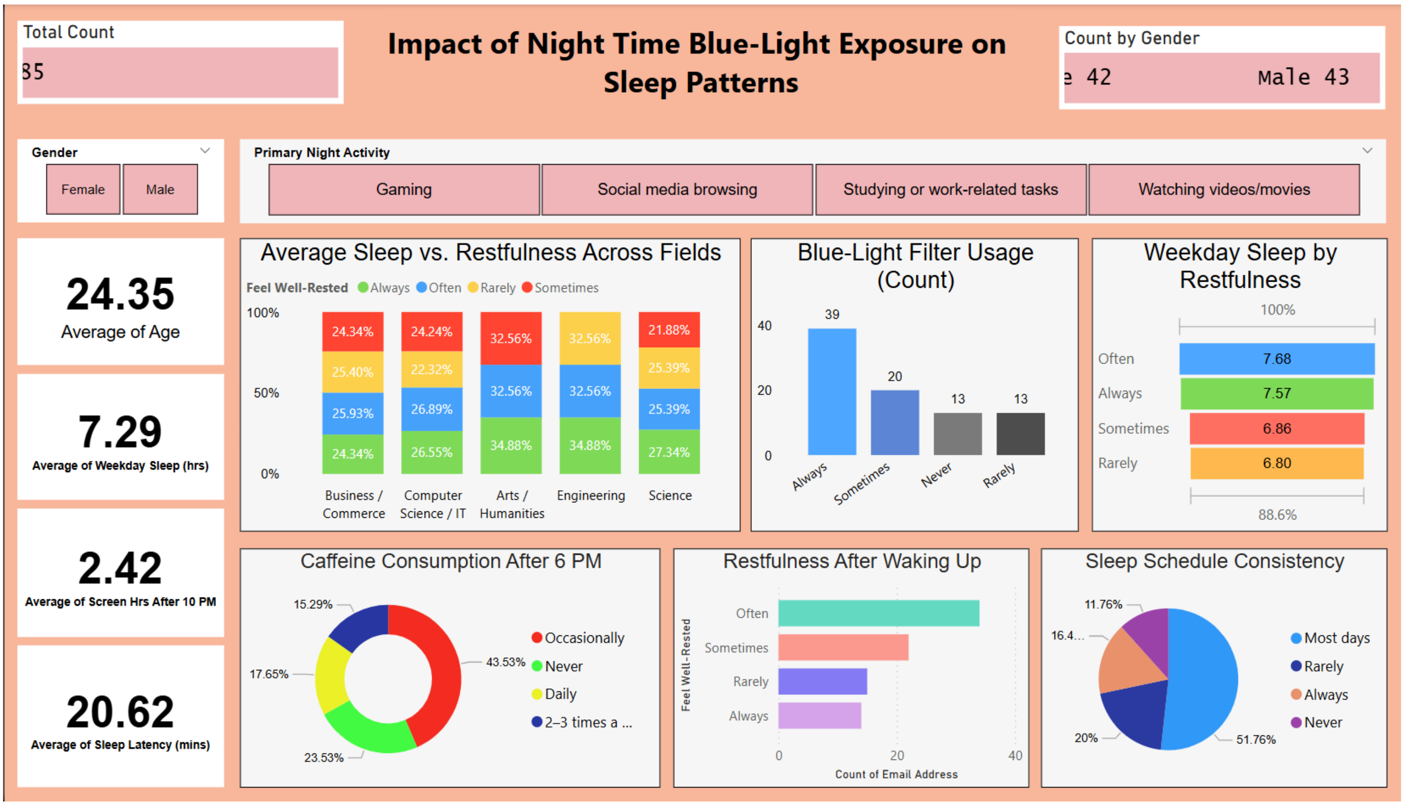
1. Subjective Responses: Many categorical questions were based on personal interpretation (e.g., “Sometimes”, “Occasionally”), which introduces subjectivity and inconsistency.
2. Privacy Concerns: The dataset contained sensitive personal information (name, email, date of birth) which was masked or removed in accordance with ethical data practices.
3. Outliers in Numeric Data: Screen time entries included extreme values, which required careful statistical treatment.
4. Categorical Normalization: Text data needed to be carefully cleaned and mapped to standard categories to ensure uniformity across the dataset.

Conclusion

The data collected was rich in behavioural and demographic information. By addressing challenges such as data inconsistencies, outliers, and privacy concerns, we were able to prepare a clean dataset suitable for advanced visual analysis. Using Power BI, we created dynamic dashboards that explored correlations between screen time, field of study, multitasking, and wellness practices such as blue-light filter usage.

These insights provide a foundation for recommending healthy digital habits and targeted interventions to improve student well-being.

Power BI Dashboard



Dashboard Analysis:

The Responses Analysis dashboard is a comprehensive visualization tool designed to monitor, assess, and derive insights from user or customer feedback data. It provides a centralized view of various performance indicators such as response volume, sentiment trends, category breakdown, and demographic engagement. The dashboard supports dynamic interaction through slicers that allow filtering by date, department, category, and demographic segments, enabling more focused and tailored analysis.

This dashboard facilitates data-driven decision-making by presenting complex datasets through intuitive visuals and actionable summaries. It is particularly useful for operations, feedback management, and stakeholder reporting.

Graph-Wise Analysis

1**. Line Chart** – Response Trends Over Time

Purpose: Displays how response counts vary over a period.

Analysis Value: Highlights high and low activity phases; helps assess campaign or initiative impacts.

2. **Bar Chart** – Category-wise Feedback Distribution

Purpose: Shows distribution of feedback types such as complaints, suggestions, and appreciations.

Analysis Value: Useful for understanding user concerns and prioritizing problem areas.

3. **Pie/Donut Chart** – Demographic Breakdown

Purpose: Visualizes respondent proportions based on age, gender, or location.

Analysis Value: Detects engagement gaps across population segments; supports inclusive outreach strategies.

4**. KPI Cards** – Total Responses, Average Rating, % Positive

Purpose: Present summary metrics in real-time.

Analysis Value: Quick performance check; instantly reflects changes when filters are applied.

5. **Stacked Column Chart** – Feedback Type by Department

Purpose: Compares departments by volume and type of feedback received.

Analysis Value: Identifies teams or areas needing attention or those performing well.

6. **Word Cloud or Table** – Common Feedback Keywords

Purpose: Extracts frequently mentioned words or themes from open responses.

Analysis Value: Uncovers qualitative insights and recurring issues or sentiments.

7. **Heatmap/Matrix** – Response Density Over Time and Categories

Purpose: Displays intensity or frequency of responses across categories over time.

Analysis Value: Supports trend spotting and correlation analysis (e.g., issue spikes during certain weeks).

Analytical Benefits:

- Monitors Engagement & Participation Trends

  The dashboard tracks how user responses fluctuate over time, enabling the team to identify active vs. inactive periods and optimize outreach or form timing accordingly.

- Enables Department-Specific Insights

  With feedback segmented by departments or service areas, the dashboard helps assess which units receive the most feedback—positive or negative—enabling resource prioritization and response planning.

- Reveals Demographic Gaps in Participation

  By analysing age, region, or gender filters, stakeholders can detect which groups are underrepresented in the responses and take action to improve inclusivity.

- Simplifies Decision-Making for Non-Technical Stakeholders

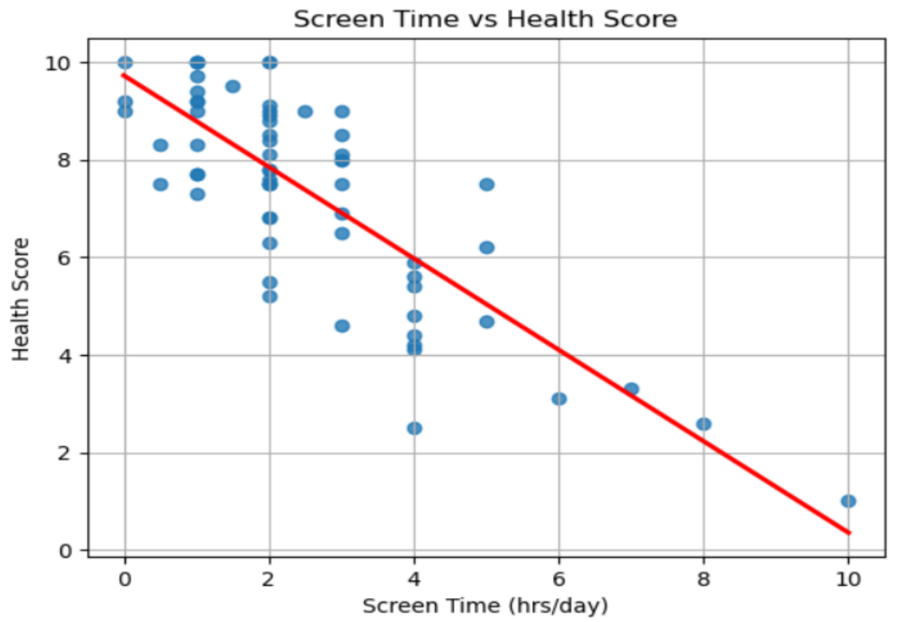
  Visually rich charts and KPI cards turn complex response data into accessible summaries, empowering both management and operational staff to act on insights without needing raw data.

- Interactive & Customizable Analysis via Slicers

  Slicers allow users to drill down quickly—filtering by time, demographics, or feedback type—making the dashboard adaptive to different analysis scenarios and reporting needs.

Machine Learning Modelling

1. Scatter Plot: Screen Time vs Night Mode Usage



This plot visualizes the relationship between how much screen time a person has and how often they use night mode or blue light filters.

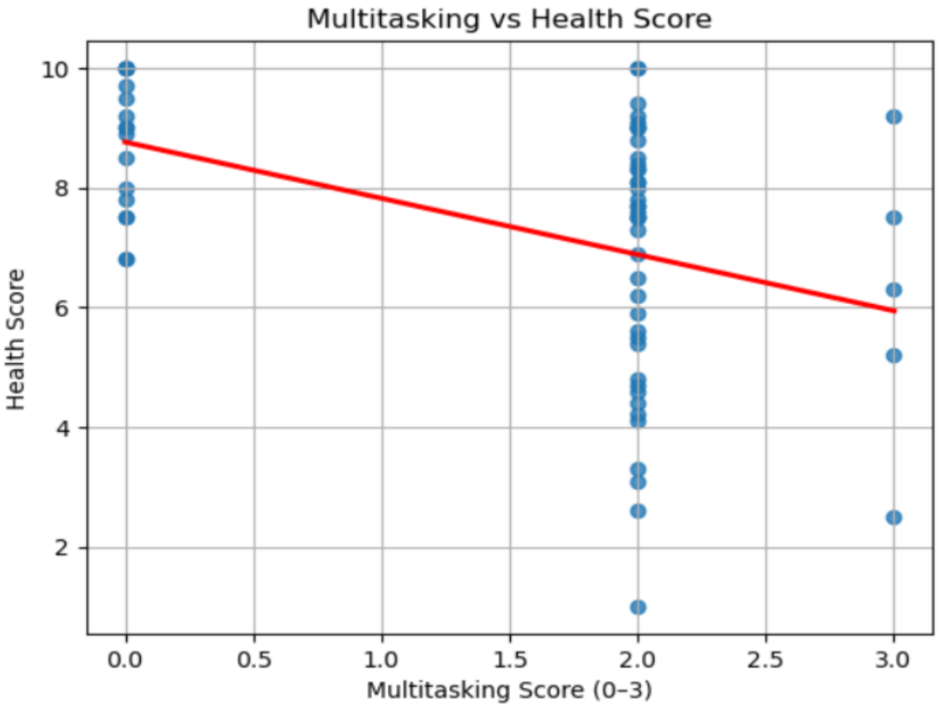
Axes:

- **X-axis:** Night Mode Usage Score (0 = Never, 3 = Always)
- **Y-axis:** Screen Time (in hours)

Interpretation:

- If the trendline slopes downward, it suggests that those who use night mode more tend to spend less time on screens, potentially indicating better screen discipline or eye-care awareness.
- A flat trendline would indicate little to no correlation between night mode use and screen time.

2. Scatter Plot: Screen Time vs Multitasking Frequency



This plot explores the correlation between how much time people spend on screens and how often they multitask using multiple devices (e.g., phone + laptop).

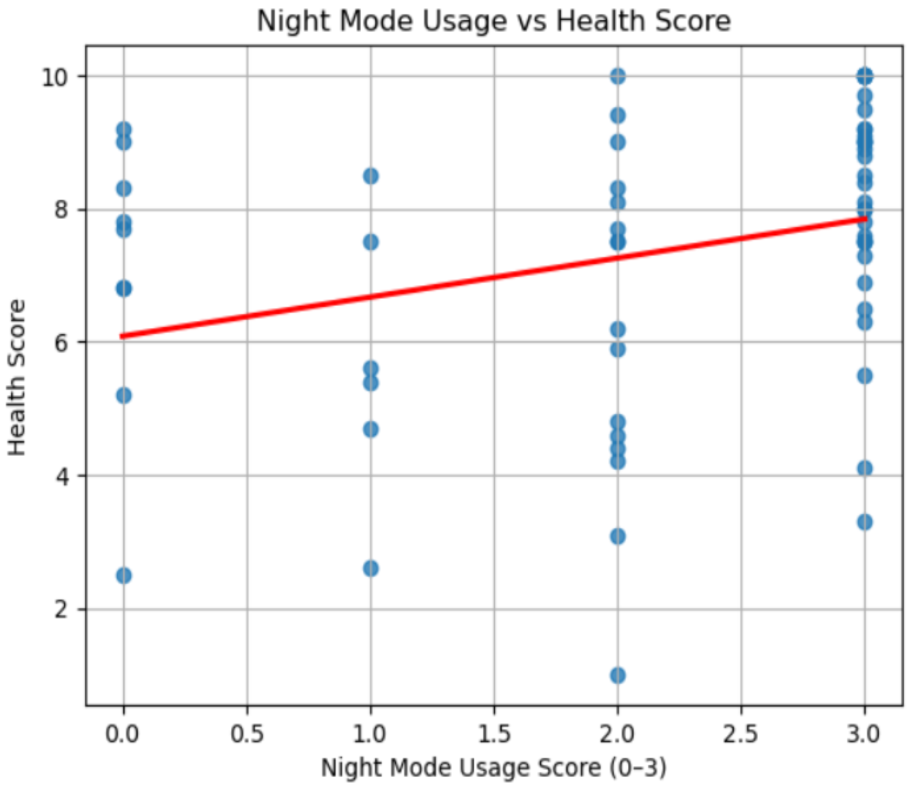
Axes:

- **X-axis:** Multitasking Score (0 = Never, 3 = Always)
- **Y-axis:** Screen Time (in hours)

Interpretation:

- A positive correlation might indicate that people who multitask more tend to spend more time on screens—possibly because they're splitting attention across devices for work or entertainment.
- A strong upward trend could support hypotheses about digital overload or time mismanagement due to multitasking.

3. Scatter Plot: Health Score vs Screen Time (or Habits)



This plot connects the estimated health impact (measured via a HealthScore you generated or collected) with screen-related behaviours.

Interpretation:

- A negative slope in the plot of Health Score vs Screen Time would indicate that higher screen time is associated with poorer health.
- A positive slope for Health Score vs Night Mode could suggest that using night mode helps preserve better health (maybe sleep or eye comfort).
- Scatter with regression lines helps visually verify correlation strength.

USING VARIOUS MODELS TO INCREASE ACCURACY:

- ❖ SUPPORT VECTOR REGRESSOR (SVR)
- ❖ RANDOM FOREST (RF)

- SUPPORT VECTOR REGRESSOR (SVR):

  SVR (Support Vector Regression) is a machine learning algorithm that predicts continuous values by finding a best-fit line (or curve) within a margin of tolerance, using principles from Support Vector Machines.

  SVR Mean Squared Error: 0.1559842028400062

  SVR R^2 Score: 0.37606318863997523

- RANDOM FOREST (RF):

  RF (Random Forest) is an ensemble learning method that builds multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting.

  Mean Squared Error: 0.09090909090909091

  R2 Score: 0.6363636363636364

❖ CONCLUSION:

The project explored the relationship between nighttime digital behaviour, such as screen time, use of night mode, and multitasking—and its impact on sleep quality among young adults. Using survey data, our team developed predictive models to identify individuals likely to experience poor sleep. Initially, classification models like Logistic Regression and Random Forest were applied, with Random Forest achieving the highest accuracy of approximately 91%. To complement the classification results, we introduced Support Vector Regression (SVR) to predict numerical sleep-related scores, offering a more nuanced view of how individual habits affect sleep health.

The inclusion of multiple models enhanced the robustness of our findings and confirmed that behavioural variables such as late-night screen exposure and inconsistent sleep hygiene are strongly linked to disrupted sleep. Among the models tested, Random Forest consistently outperformed others in classification tasks, while SVR provided meaningful insights into the degree of sleep disruption. Overall, the project demonstrates a clear and measurable connection between digital habits and sleep quality, and highlights how machine learning can be effectively used to model and interpret behavioural health data.