Research of Finding a Correlation Between Phone Screen Time and Previous Grade Point Semester (GPS) from Computer Science and Data Science Majors in BINUS University

Group 2

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BINUS UNIVERSITY
Survey Sampling Method

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EXECUTIVE SUMMARY

This report presents the findings of a survey conducted to explore the relationship between students' screen time and their academic performance, measured by their Grade Point Semester (GPS). In an era of rapidly increasing digital device usage among university students for both academic and leisure purposes, understanding its potential impact on academic success is particularly relevant. The insights from this survey aim to help students make more informed decisions about managing their screen time effectively. By analyzing both the quantity and quality of screen use, this study provides a clearer picture of how different screen time habits may support or hinder academic outcomes.

Main Objectives

1. Measure the average daily screen time of university students and identify the most frequently used types of applications (e.g., social media, games, videos).
2. Understand how often students feel distracted by non-academic smartphone use.
3. Explore whether students have made efforts to reduce their smartphone use in the past semester.
4. To analyze the relationship between screen time habits and academic performance based on students' Grade Point Semester (GPS) and self-assessment.
5. Provide insights into the relationship between digital behavior and academic performance.

Summary of Key Findings

1. No strong correlation found between phone screen time and Grade Point Semester (GPS).
2. High screen time is common since the majority of students spend more than 8 hours daily on their smartphones across all GPA levels.
3. Smartphone distraction does not directly lead to a lower academic performance, so we suggest that every student should focus on guiding distraction management rather than restricting phone access.
4. The type of applications used may be more relevant to academic performance rather than screen time duration.
5. There may a potential disconnect between screen time perceived impact with the actual impact, so we encourage students to develop more accurate self-awareness about their technology use patterns.

Implications and Recommendations

The survey findings suggest that students need to be focused on prioritizing their apps rather than limiting their usage only, guiding distraction management rather than restricting phone access, and developing more accurate self-awareness about their technology use pattern. For the next research, we recommend finding more on the correlation between type of application or distraction management with the academic rather than screen time duration only.

CHAPTER I: INTRODUCTION

1.1 Topic Background

The massive integration of digital technology into daily life has significantly changed human behavior (Sapci et al., 2021), especially among students. For example, smartphones can be used for different purposes such as communication, entertainment, and navigation (Auer, 2025). Understanding the implications of students' digital habits, including screen time and application usage has gained significant academic interest. Screen time, a commonly discussed metric in studies of digital behavior, reflects the total time individuals spend on electronic devices like smartphones or tablets.

1.2 Problem Statement

As smartphone usage continues to grow among university students, many are spending a significant portion of their day engaged in screen-based activities, often without realizing how it affects their learning outcomes. This pattern of excessive screen time raises concerns about reduced student performance, poor time management, and lower academic motivation among students. A research done in University of Toledo, United States of America (2021) found that one additional hour of phone use per day lowered the current term GPA by 0.152 on average. While smartphones can support academic tasks, their use for non-academic purposes like social media, video streaming, and gaming may interfere with concentration and time management. These distractions can lead to procrastination, fragmented study sessions, and decreased academic efficiency, which may contribute to lower academic performance over time.

Furthermore, the constant accessibility of digital content can make it difficult for students to establish boundaries between study time and leisure activities. This blurred line may result in habitual multitasking or frequent task-switching, which are known to reduce cognitive focus and academic productivity. As these digital habits become deeply embedded in students' daily routines, it becomes increasingly important to understand their potential consequences on academic achievement, particularly in relation to measurable outcomes like the Grade Point Semester (GPS).

Computer Science and Data Science students at BINUS University should be able to manage their digital habits effectively to maintain high academic performance measured in GPS. There is a high, yet unquantified level of phone screen time among these students. However, the specific relationship between the amount of screen time and their actual academic performance (GPS) at BINUS is unknown. There is a lack of empirical data and a clear understanding of whether a correlation (positive, negative, or none) exists between daily phone screen time and the previous semester's GPS for Computer Science students and Data Science students at BINUS University. Without this crucial knowledge, neither the university nor the students can make informed decisions. For instance, the university cannot develop targeted digital wellness programs, and students lack concrete data to improve their study habits effectively. It remains an assumption rather than an evidence-based issue. Therefore, this study aims to investigate the correlation between daily phone screen time and the previous semester's GPS among Computer Science and Data Science students at BINUS University to fill this knowledge gap.

1.3 Research Question

a. Is there a statistically significant correlation between the average daily phone screen time and the previous semester's Grade Point Semester (GPS) among Computer Science and Data Science students at BINUS University?
b. If such correlation exists, which aspect within digital habits that strengthens the correlation?

1.4 Main Objectives

1. Analyze the potential correlation between phone screen time and GPS.
2. Examine students' average daily screen time.
3. Identify the most frequently used application types.
4. Explore patterns and associations between digital habits and academic outcomes.
5. Provide insights into the relationship between digital behavior and academic performance.

1.5 Importance of Study

This research is significant because it moves beyond general assumptions about screen time to provide specific, data-driven insights within an academic context. The findings of this study are expected to be important for several key stakeholders:

1. **For Computer Science and Data Science students at BINUS University**
   This study will provide students with concrete data of how they should improve their studying and digital habits. For example, if a negative correlation between daily average screen time and GPS is found, it empowers them to make informed decisions about their digital habits to potentially improve their academic performance. Students also often worry about their phone usage. This research will provide evidence to either validate those concerns, or if no significant correlation is found, this may alleviate unnecessary anxiety.
2. **For BINUS University and its faculties**
   This research's findings can help BINUS University to equip academic advisors, counselors, and faculty members with data to better support students who are struggling in their academic performance. It allows them to have more nuanced conversations that include digital habits as a potential factor in academic performance. If a correlation is found, the institution can design evidence-based workshops to help students manage their digital distractions. This research provides BINUS University with a deeper and data-driven understanding of its students in the digital age, specifically within its high-demand technology programs. This can be valuable for curriculum planning and program initiatives.
3. **For Academic and Research Community**
   While much research has discussed the correlation screen time and academic performance, this study fills a specific gap by focusing on a distinct population,

which is university students in Indonesia, specifically BINUS University, within the Computer Science and Data Science field. This research allows for comparative analysis in the future for other studies in the same topic. This study also potentially raises new questions. For instance, if a correlation is found, future research could investigate the causes, or explore whether the type of screen time (social media, productivity apps, gaming, etc) has a more significant impact, leading to a deeper and more actionable understanding of the issue.

CHAPTER II: METHODOLOGY

2.1 Survey Design

Description of the Questionnaire

The primary data collection instrument was a self-administered online questionnaire, created using Google Forms. This tool was selected for its ease of access for respondents and its efficient data compilation capabilities.

The final questionnaire was structured to be concise and logical, ensuring clarity for the participants. It was divided into four main parts with seven sections in the Google Forms:

- **Informed Consent**: The survey began with a clear statement outlining the research purpose, the voluntary nature of participation, and the assurance of data confidentiality and anonymity. Participants who proceed are those who agreed on participating in this questionnaire.
- **Demographic Data**: This section collected the major of the participants, whether they are from Computer Science or Data Science.
- **Screen Time**: This core section gathered data on smartphone habits, such as the daily average screen time (in hours), the most used applications, and their digital habits.
- **Academic Performance**: This section collected the GPS data of the participants and their thoughts on how their screen time affected their academic performance.

Types of Questions Used and Rationale

- **Multiple Choice Questions**: Used for demographic data (Major), screen time ranges, binary question asking whether the participant has voluntarily decreased their smartphone usage or not, and academic performance (GPS)
- Rationale: This format simplifies the response process and facilitates straightforward data categorization. For screen time and GPS questions, ranges were used instead of asking for an exact value. This was done to protect data sensitivity and privacy concerns, encouraging more accurate and complete responses.
- **Checkbox (Multiple Selection Questions)**: Used to identify the top three application categories
- Rationale: This allowed for the collection of categorical data that adds important context to the quantitative screen time metric, helping to understand the nature of smartphone usage.
- **Likert Scale Questions**: A 5-point Likert scale was used to measure students' perceived level of distraction from their smartphones.
- Rationale: This question type effectively quantifies a subjective experience, allowing for the measurement of attitudes and perceptions. The Likert scale was described in detail (of what 0 to 5 mean) so participants can have the same understanding as researchers.
- **Open Ended Questions**: Used to ask the participants to convey their opinions on how their screen time affected their academic performance in the past semester.

- Rationale: The purpose of this question was to gather rich, qualitative data that cannot be captured by predefined formats. It provided the participants an opportunity to offer context for their answers. This qualitative feedback serves as a valuable supplement for interpreting the quantitative results.

Pre-test Process and Revisions

Before deploying the main survey, a pilot test was conducted with a sample of 20 respondents from the target population. The purpose of this pilot test was to identify any ambiguities, assess the clarity of the questions, and refine the overall instrument. Based on the feedback and analysis of the pilot test, several key revisions were made:

- **Enhanced Clarity and Specificity**: The question "How much is your daily screen time?" was revised to "How much is your daily smartphone screen time (in hours)?" and a note was added instructing respondents to check their weekly average to ensure standardized and more accurate measurements.
- **Removing Redundant Question**: An initial question about screen time dedicated to academic purposes was removed as it was deemed redundant with other questions and unnecessarily lengthened the survey.
- **Improved Details and Guidance for Participants**: For the question regarding the top three application categories and screen time checking, clear instructions were added to guide respondents on how to find this information on their specific devices, thereby improving the reliability of the data collected.
- **Enriched Data Collection**: A 5-point Likert scale question was added to capture the crucial perceptual dimension of how distracted students feel by their smartphones, adding depth to the quantitative screen time data.
- **General Wording Refinements**: Minor changes to the wording of several questions were made to prevent misinterpretation and ensure all items were as clear as possible.

Following these revisions, the final version of the questionnaire was distributed for the main data collection effort, which gathered responses from 86 participants.

2.2 Population and Sampling

Target Population

B27 students majoring in Computer Science and Data Science at BINUS University, Kemanggisan campus, with an estimated total of 785 students.

Sampling Frame

The potential respondents for this survey include students from the following B27 classes at BINUS University:

- Computer Science: LA01, LB01, LC01, LD01, LE01, LF01, LG01, LH01, LI01
- Data Science: LA09, LB09, LC09

Sampling Method

To collect responses effectively, this survey will use a **Simple Random Sampling** method within a non-probability sampling framework. Respondents will be selected by approaching students randomly through WhatsApp groups and inviting them to participate via personal messages. This approach ensures that every student in the target classes has an equal chance of being selected, which helps minimize selection bias and improve the representativeness of the sample within the available population. Using simple random sampling is suitable for this context because it is easy to implement, especially when using digital platforms, and allows for fair participation from different student groups.

Sample Size

The sample size for finite populations (small to moderate), the following formula will be used:

$$n = \frac{N \cdot Z^2 \cdot p \cdot (1-p)}{(N-1) \cdot e^2 + Z^2 \cdot p(1-p)}$$

Where:

- n = Required sample size
- N = The total population size (785)
- Z = The Z-score corresponding to the chosen confidence level
- p = The estimated proportion of the population
- e = The desired margin of error

The following parameters were applied for the calculation:

- Confidence level = 95%, which corresponds to a Z-score of 1.96.
- Estimated proportion = 0.5, this is used because it is the most conservative estimate.
- Margin of error = 10%, indicating that the findings from the sample are expected to be within 10% of the actual population values.

$$n = \frac{785\ (1.96)^2 \cdot 0.5 \cdot (1-0.5)}{(785-1) \cdot 0.1^2 + (1.96)^2 \cdot 0.5 \cdot (1-0.5)}$$

$$n = 85.6681 \approx 86\ people$$

The calculation yielded a required sample size of approximately 85.67. This figure was rounded up to the nearest whole number. Therefore, the target sample size for this research was set at 86 respondents.

Actual Sample Obtained

The data collection effort successfully achieved the target sample size determined by the calculation. A total of 86 valid responses were collected from students. The composition of the final sample reflects the two programs targeted by this research. The demographic breakdown of the respondents by major is as follows:

- Computer Science: 44 respondents (51.2%)
- Data Science: 42 respondents (48.8%)

This collected sample of 86 students forms the basis for the data analysis and the results presented in the subsequent chapters of this paper.

2.3 Data Collection Process

The data collection was conducted systematically to ensure that the target sample size was reached and that the data gathered was of high quality. The process involved defining the survey mode, a specific timeframe for the data collection, and actively managing challenges as they arose.

2.3.1 Survey mode (e.g., online, in-person)

The survey was administered entirely online using Google Forms. This mode was chosen for its accessibility, cost effectiveness, and ease of distribution among the university student population. Due to the unavailability of an official student database, a Simple Random Sampling method was applied to the most comprehensive available sampling frame, accessed through the list of members of official student groups for Computer Science and Data Science groups. Each selected student was then approached individually via a personal chat message. This message introduced the objective, assured confidentiality, and provided link to the online questionnaire. This method ensured that every student within the sampling frame had an equal and independent chance of being selected to participate, thereby minimizing selection bias.

2.3.2 Duration of Data Collection

The data collection period was active for approximately three weeks from Tuesday, 21st May 2025 to Tuesday, 10th June 2025.

2.3.3 Challenges encountered and how they were addressed

The primary challenge on this survey was participant non-response. A significant portion of the initially selected students did not respond to the invitation message. To address this and ensure the target sample size was met, a systematic follow-up was conducted. For each selected student who did not respond, a polite follow-up message was sent after days. This was often sufficient to result in a response and secure participation. If a student remained unresponsive after two follow-up attempts, a replacement was done. To maintain the integrity of the sample size and the randomization process, a new student was then randomly selected from the sampling frame as a replacement until the target of 86 responses were achieved.

CHAPTER III: DATA ANALYSIS

3.1 Data Cleaning

In the data cleaning stage, missing values were handled by converting null values to 0. This was done because all questions in the survey were mandatory, so no *null* values should exist. Null values only appeared in the question regarding the reasons for reducing screen time (open ended question), which was only answered by respondents who had previously indicated that they had reduced their screen time. Therefore, *null* in this column was treated as equivalent to having no reason.

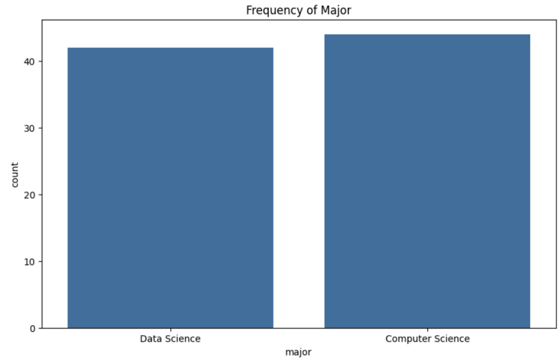
In addition, for open-ended questions, several typos or spelling errors were identified in respondents' answers. These were manually corrected to ensure consistency and to facilitate subsequent analysis. No outliers or inconsistent responses were found in this dataset, so no further cleaning steps were required.

3.2 Descriptive Statistics

To facilitate data visualization and make the analysis process more efficient, several column names were renamed to shorter and clearer labels. This step was taken to improve readability and simplify references during the visualization process. The changes made were as follows:

- Jurusan → *major*
- Berapa rata-rata waktu penggunaan layar smartphone (screen time) harian kamu (dalam satuan jam)? → *screentime_spend*
- Dari total screen time smartphone kamu, jenis aplikasi apa yang paling banyak menghabiskan waktumu? → *screentime_app*
- Seberapa sering kamu merasa terganggu oleh penggunaan smartphone untuk hal non-akademik (e.g. sosial media, game, streaming video) saat sedang belajar? → *phone_distraction_freq*
- Apakah kamu pernah secara sadar mengurangi penggunaan smartphone pada semester kemarin? → *reduced_phone_use*
- Apa alasan utama kamu mengurangi penggunaan smartphone pada semester kemarin? → *reduction_reason*
- Berapa range Grade Point Semester (GPS) kamu pada semester ganjil 2024/2025? → *GPS*
- Menurut kamu, bagaimana efek dari screen time terhadap performa akademik pada semester kemarin (semester ganjil 2024/2025)? → *screentime_impact*
- Bagaimana kebiasaan screen time memengaruhi performamu dalam belajar di semester ganjil 2024/2025. → *screentime_on_learning*

3.2.1 Sample Distribution



Based on the barplot, we obtained data from two majors: Computer Science and Data Science. The number of respondents from Computer Science is slightly higher than from Data Science. Although the sample appears relatively balanced with 44 Computer Science and 42 Data Science students, in reality, the population size of Computer Science students is much larger than that of Data Science. This imbalance means that treating each response equally could misrepresent the actual proportion of students from each major in the broader population.

3.2.2 Weighting

To address this, we conduct all statistical calculations using weighted analysis, ensuring that each major is proportionally represented based on its actual population size.

The weight for each major is calculated as:

$$Weight_{major} = \frac{Sample\ Size\ Actual}{Sample\ Size\ Obtained}$$

Computer Science:

$$Weight_{CS} = \frac{600}{44} = 13.636363636363637$$

Data Science:

$$Weight_{DS} = \frac{185}{42} = 4.404761904761905$$

	screentime_impact	phone_distraction_freq
count	86.000000	86.000000
mean	2.863889	3.777273
std	0.964736	1.088920
min	1.000000	1.000000
25%	2.000000	3.000000
50%	3.000000	4.000000
75%	4.000000	5.000000
max	5.000000	5.000000

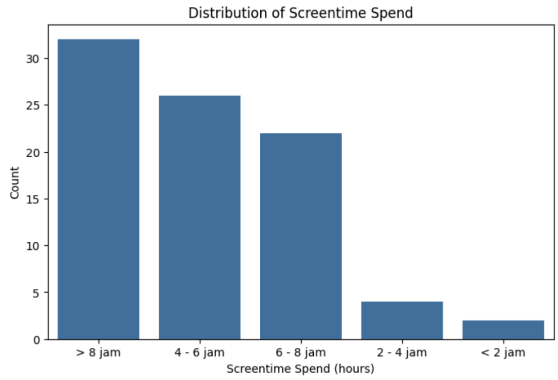
Although the variables analyzed are based on ordinal-scale responses (e.g., Likert-type scales from 1 to 5), we conducted an experimental weighted analysis to observe general trends while accounting for the disproportionate number of students from different majors. This weighting adjusts the influence of each major in proportion to its actual representation in the population.

The results show a mean screentime impact score of 2.86, which suggests that students generally perceive screen time as having a neutral to slightly negative effect on their academic performance. The standard deviation of 0.96 indicates a moderate level of variability, meaning opinions differ but tend to cluster around the middle of the scale.

Similarly, the mean phone distraction score is 3.78, pointing to frequent distractions caused by phone use while studying. The standard deviation of 1.09 shows that while many students feel frequently distracted, there is still a notable spread in responses.

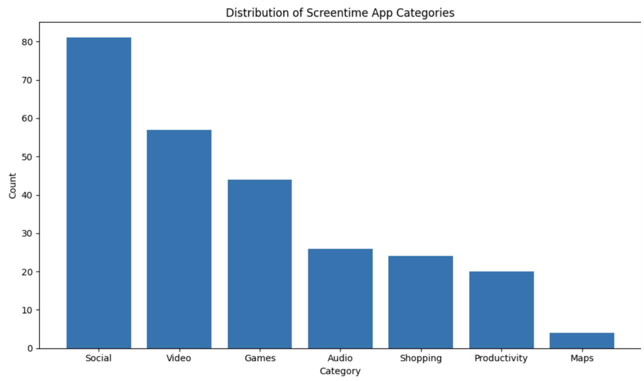
However, it's important to note that this weighted approach is exploratory. Since our main objective is not to compare differences across majors, we will not use this weighting in further analysis. This experiment simply aimed to test how weighting might shift aggregate insights, but future steps will treat the dataset without major-based weighting to maintain focus on overall student experiences.

3.2.3 Screen Time Distribution



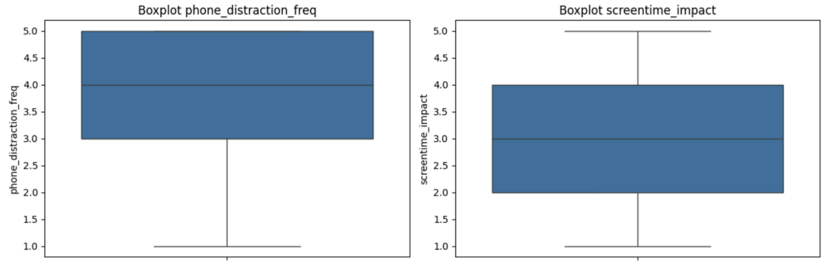
The barplot of screentime_spend shows that the majority of respondents reported spending a significant amount of time on their smartphones daily. The most common category was more than 8 hours per day, followed by 4-6 hours and 6-8 hours. Only a small proportion reported lower screen time, with very few spending 2-4 hours or less than 2 hours per day. This indicates that high daily screen time is typical among respondents, highlighting a potential concern regarding excessive smartphone usage in the student population.

3.2.4 Screen Time Categories Distribution

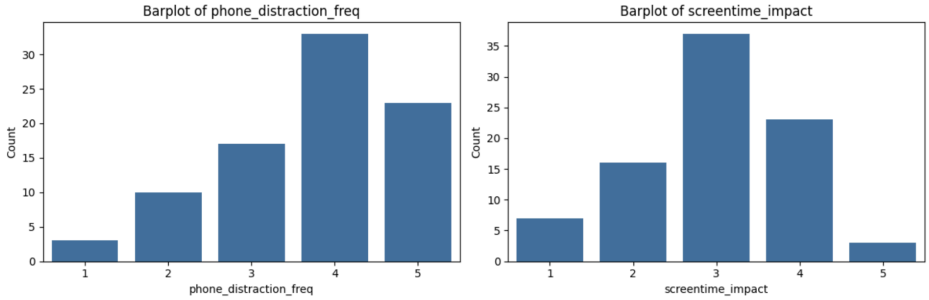


From the screentime_app data, most respondents reported using social media, video, and gaming applications. This shows that screen time is largely spent on entertainment and social interaction, reflecting common digital behavior patterns among students today.

3.2.5 Variation in Screen Time Impact and Distraction Levels

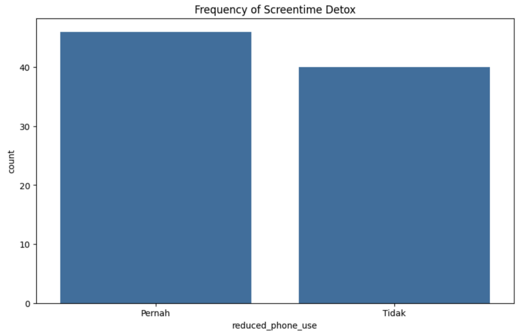


The boxplots revealed considerable variation in the perceived impact of screen time, making it clear that we cannot directly conclude that screen time always has a significant effect. Meanwhile, phone_distraction_freq tends to skew toward higher levels, with most respondents reporting frequent distractions (level 4 or 5). This is reasonable and does not require preprocessing, as distraction levels naturally vary among individuals.

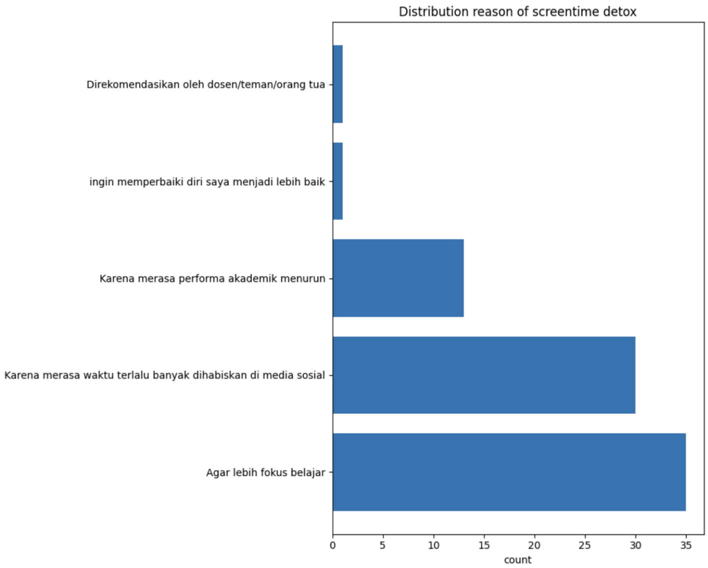


Barplots exploring phone_distraction_freq and screentime_impact further confirmed these trends. Most respondents reported high levels of distraction during study sessions, with level 4 being the most common, followed by level 5. In contrast, perceptions of screen time's academic impact were more balanced. The most frequent response was level 3 (neutral or moderate impact), followed by level 4 (somewhat negative impact) and level 2 (slightly positive or minor impact). Only a few perceived an extreme impact (either very negative at level 5 or very positive at level 1). This suggests that while many see screen time as disruptive, its effect on academic performance is perceived as moderate or mixed.

3.2.5 Screen Time Detox Effect

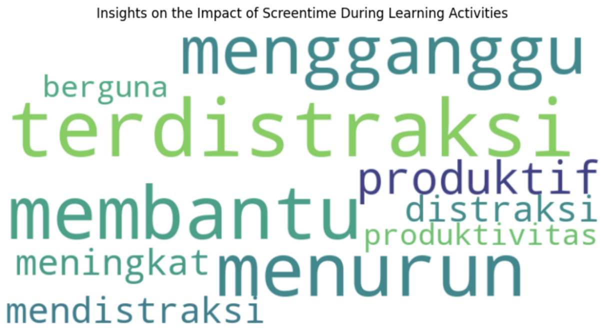


The bar plot of reduced_phone_use shows that slightly more respondents reported having consciously reduced their smartphone usage ("Pernah") compared to those who had not ("Tidak"). This suggests that a significant portion of students are aware of their smartphone habits and have made efforts to limit their usage, although many have not attempted screen time reduction.



Based on the bar chart, the most common reason students reduced smartphone usage was "*Agar lebih fokus belajar*" (to focus more on studying), followed by "*Karena merasa waktu terlalu banyak dihabiskan di media sosial*". This indicates that academic focus and awareness of excessive social media use are key motivators for screen time reduction. Fewer students reported reducing screen time due to declining academic performance, while very few did so based on self-improvement or recommendations from others (e.g., friends, lecturers, or parents). This suggests that most students reduce their usage based on internal academic motivations rather than external pressure.

3.2.6 Student Perceptions Toward Screen Time in Learning



The top 10 most frequent words reveal mixed perceptions of screentime during learning. Negative terms like *terdistraksi*, *mengganggu*, *menurun*, and *distraksi* suggest that many students feel easily distracted and experience reduced focus. However, positive words such as *membantu*, *produktif*, *meningkat*, *produktivitas*, and *berguna* show that others find screen time helpful and supportive of their learning process. This contrast indicates that the impact of screen time largely depends on individual habits and how it is used.

3.3 Inferential Analysis

Cross Tabulation

app_list GPS	Audio	Games	Maps	Productivity	Shopping	Social	Video
2.00 - 2.99	3	3	0	2	1	4	2
3.00 - 3.49	10	17	3	3	8	27	16
3.5 - 3.89	10	19	0	11	11	36	27
< 2.00	1	0	1	0	1	0	0
> 3.90	2	5	0	4	3	14	12

The crosstab shows that social media and video apps are widely used across all GPA levels, especially among mid (3.00-3.49) and high GPA students (≥3.5). Productivity apps are more common in higher GPA groups, suggesting more balanced digital habits. While games are popular in mid-range GPAs, they also appear among top performers. Low GPA students (<3.00) show limited app use, but still use social and video apps. Overall, higher-GPA students combine entertainment with more purposeful app usage.

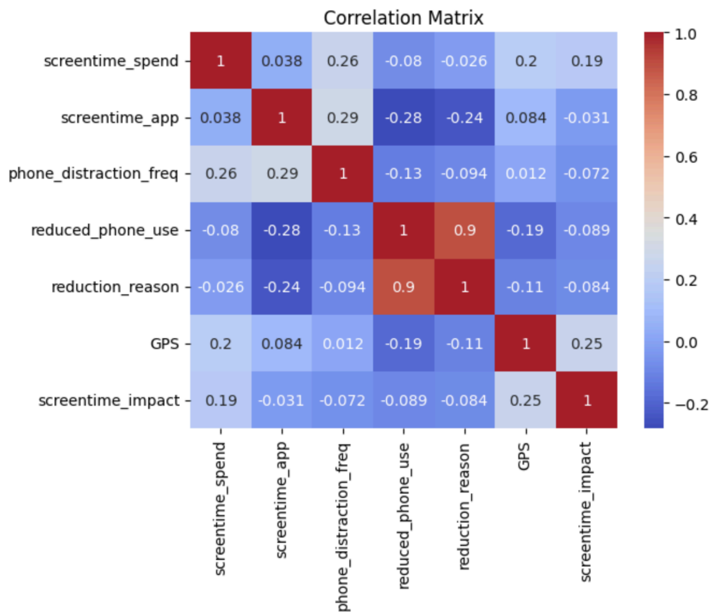
phone_distraction_freq GPS	1	2	3	4	5
2.00 - 2.99	0	0	2	2	1
3.00 - 3.49	0	4	4	11	9
3.5 - 3.89	2	5	7	16	8
< 2.00	1	0	0	0	0
> 3.90	0	1	4	4	5

The crosstab shows that moderate to high phone distraction (levels 3-5) is common across all GPA groups. Mid (3.00-3.49) and high GPA students (3.5-3.89) report the most frequent distraction, especially at level 4. Even top GPA students (>3.90) report high distraction levels. This suggests that frequent phone distraction is common regardless of GPA, and doesn't directly reflect poor academic performance.

screentime_impact GPS	1	2	3	4	5
2.00 - 2.99	1	3	1	0	0
3.00 - 3.49	4	4	13	7	0
3.5 - 3.89	1	6	17	12	2
< 2.00	0	1	0	0	0
> 3.90	1	2	6	4	1

The crosstab shows that most students across all GPA levels perceive a moderate impact (level 3) of screen time on academic performance, especially those in the 3.00-3.49 and 3.5-3.89 GPA ranges. Even high GPA students (>3.90) report some impact, with responses spread across levels 3 to 5. Meanwhile, lower GPA students (<3.00) mostly report low impact (levels 1-2). Overall, screen time is generally seen as having a moderate effect, regardless of GPA.

Correlation Test



We conducted a Spearman correlation test to explore the relationships between the variables. The correlation matrix, as visualized in the heatmap, shows that most of the variables have weak or very weak correlations with each other. This indicates that there is no strong linear or monotonic relationship between most of the features in this dataset.

The only strong correlation observed is between reduced_phone_use and reduction_reason. This is expected, as the *reduction_reason* column is only filled in by respondents who had indicated that they had reduced their smartphone usage. This naturally leads to a high correlation between these two variables.

Additionally, we can observe some weak positive correlations, such as:

- GPS and screentime_impact ($\rho \approx 0.25$) suggesting that students who perceived screen time as impacting their academic performance slightly tended to have corresponding GPS ranges.

- screentime_spend and phone_distraction_freq ($\rho \approx 0.26$) indicating that higher daily screen time is mildly associated with more frequent feelings of distraction.

Overall, these findings suggest that no single factor strongly predicts academic performance (GPS) or screen time impact in this dataset, except for logical dependencies between related columns.

3.4 Reliability and Quality Check

The target for this survey was 86 respondents, and we successfully obtained responses from all 86 individuals, resulting in a 100% response rate.

To evaluate the quality of the data collected, we first assessed internal consistency through a reliability check using Cronbach's Alpha. We focused on the variables screentime_spend, phone_distraction_freq, and screentime_impact. The analysis produced a Cronbach's Alpha value of 0.238, indicating very low internal consistency. This suggests that these variables do not correlate strongly with one another and are not measuring a single underlying construct.

Such a result is reasonable, as each variable captures a distinct aspect of smartphone use: screentime_spend reflects total daily usage, phone_distraction_freq measures how often respondents feel distracted by their smartphones while studying, and screentime_impact indicates their perception of how screen time affects academic performance. Given these differences in focus, a low Cronbach's Alpha is expected and does not undermine the validity of the data.

```
KMO Score: 0.434
Bartlett's Test p-value: 0.03889

Eigenvalues:
Factor 1: 1.25
Factor 2: 1.08
Factor 3: 0.67

Factor Loadings:
               Question  Distraction Level  Usage Behavior
      screentime_impact          -0.005787        0.494589
phone_distraction_freq           0.556259       -0.203433
       screentime_spend           0.544455        0.266115
```

Further, to assess construct validity, we conducted a factor analysis using the Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity. The KMO score was 0.434, indicating low sampling adequacy and suggesting that the dataset may not be ideal for factor analysis. Nonetheless, Bartlett's Test yielded a p-value of 0.03889, showing that the variables are sufficiently correlated to justify the analysis. The factor analysis extracted two main factors based on eigenvalues greater than 1 (Factor 1: 1.25, Factor 2: 1.08).

The loadings revealed that phone_distraction_freq and screentime_spend were more strongly associated with one factor, interpreted as representing *Distraction Level*, while screentime_impact was more aligned with the second factor, interpreted as *Usage Behavior*. Some overlap was observed, as screentime_spend showed loadings on both factors. Overall, these findings, combined with the low KMO score and the limited number of items, suggest that the construct validity is weak, and interpretations of the factor structure should be approached with caution.

CHAPTER IV: KEY FINDINGS AND DISCUSSION

4.1. Most Important Insights and Discussion

Based on previous data analysis, here are the most important insights to examine the correlation between phone screen time and academic performance (GPS) among Computer Science and Data Science students in BINUS University:

a. No Strong Correlation Found

Regarding our main objective of finding a correlation between phone screen time and GPS, our analysis revealed that there is no strong correlation between phone screen time and Grade Point Semester (GPS). The Spearman correlation analysis showed only weak correlations between most variables, indicating that screen time alone does not have a strong association with academic outcomes (Jiawei H. et al, 2012).

b. High Screen Time is Common

Based on the question of how much screen time that the students spent (*screentime_spend*), this survey showed a consistent pattern that the majority of students spend more than 8 hours daily on their smartphones across all GPA levels. This result indicates that smartphone integration has become a baseline behavior in modern student life regardless of academic outcome. In context, this result supports the finding by Sapci et al., 2021, who noted that digital technology has significantly transformed human behavior, suggesting that high screen time on smartphones may be characteristics of modern university students in technology-related fields. This result also challenges that high screen time would lead to poor academic performance from a research done in University of Toledo, United States of America (2021) that stated one additional hour of phone use per day lowered the current term GPA by 0.152 on average.

c. Frequently Distracted Does Not Mean Low Academic Performance

Based on the question of how frequent students get distracted with their smartphone (*phone_distraction_freq)*, the high levels of phone distraction (levels 4 to 5) while studying is reported across all GPA ranges, even with high-GPA students (GPA >3.90). This result indicates that a smartphone distraction does not directly lead to a lower academic performance. Instead, how students manage their distraction may be a more important factor rather than the duration of smartphone screen time. This result also suggests that every student should focus on guiding distraction management rather than restricting phone access.

d. The Balance of Application Usage May be More Relevant

Based on the question of which application (apps) that each student spent the most (*screentime_app*), higher GPA students show more balanced digital habits, combining entertainment apps (social media, videos) with productivity apps, while lower GPA students primarily use entertainment apps. This result indicates that the type of applications used may be more relevant to academic performance rather than screen time duration. The integration of productivity apps alongside entertainment suggests that high-GPA students have developed strategies to balance entertainment with academic tools may suggest a stronger relationship between smartphone use and academic outcomes. Thus, we encourage students to prioritize their apps rather than limiting their usage only.

e. Perception of Screen Time Impact Does Not Reflect Actual Performance
From the question of how screen time is affecting their performance (*screentime_impact*), regardless of their actual GPA, most of the students perceive screen time as having a moderate impact (level 3) on their academic performance. Interestingly, lower GPA students reported perceiving less impact from screen time than higher GPA students. This result suggests a potential disconnect between perceived and actual impact so we encourage students to develop more accurate self-awareness about their technology use patterns.

CHAPTER V: CONCLUSION AND RECOMMENDATION

5.1 Main Takeaways

This project concludes that there is no strong correlation between daily smartphone screen time and students' academic performance (measured by GPS) among BINUS University's Computer Science and Data Science students. Although high screen time and frequent distractions were commonly reported, these behaviors did not show a significant direct impact on academic achievement. Instead, the type of apps used (e.g., productive vs. entertainment) and how students manage their distractions seem to play a more meaningful role. This insight shifts the focus from reducing screen time alone to encouraging more intentional and balanced digital habits.

5.2 Areas for Improvement

The project could be improved by refining the sampling process to better reflect the actual distribution of students across majors and extending the data collection period for more robust responses. Additionally, incorporating more objective behavioral data (e.g., app usage logs) could enhance the accuracy of self-reported screen time. Designing the questionnaire to minimize potential interpretation bias and adding more diverse variables, such as mental health, motivation, or time management, would also provide a more holistic view of the issue.

5.3 Limitations of the Study

This study has several limitations that should be acknowledged. First, the data is based entirely on self-reported responses, which may be subject to recall bias or social desirability bias, students may underestimate or overestimate their screen time or GPA. Second, the cross-sectional design only captures a snapshot of student behavior at one point in time, making it difficult to infer causality between screen time and academic performance. Third, while the sample size met statistical requirements, it may not fully represent the broader population of BINUS University students, especially given the disproportion between the actual number of Computer Science and Data Science students. Finally, the use of categorical ranges for key variables (e.g., screen time and GPS) limits the precision of the analysis and restricts deeper statistical modeling.

5.4 Future Analysis Plan

To address the research problem more thoroughly, future analysis may include applying regression models to identify interaction effects between multiple factors such as app category usage, distraction levels, and GPS. Further, cluster analysis could help uncover behavioral profiles among students with similar screen time patterns and academic outcomes. Lastly, conducting a longitudinal study would help assess changes over time, revealing potential causal relationships rather than relying solely on correlation-based insights. This follow-up analysis would provide a deeper, more actionable understanding for both students and university stakeholders.

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APPENDICES

Link Final Questionnaire, Dataset, and Presentation:
https://drive.google.com/drive/folders/15z9bSreYl_Z9KiMUi9oA5kSLZk6UV9r7