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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CHAPTER I: INTRODUCTION

1.1 Background

The massive integration of digital technology into daily life has significantly changed human behavior, particularly among university students. Smartphones have become ubiquitous tools used for communication, entertainment, and navigation, making screen time a critical metric in understanding digital behavior patterns. This research addresses the growing concern about smartphone usage among university students and its potential impact on academic performance.

1.2 Problem Statement

The problem statement centers on the observation that Computer Science and Data Science students at BINUS University spend significant portions of their day engaged in screen-based activities, often without realizing the effects on their learning outcomes. Research from the University of Toledo found that one additional hour of phone use per day lowered current term GPA by 0.152 on average. However, the specific relationship between screen time and academic performance at BINUS University remains unknown, creating a knowledge gap that prevents both the university and students from making informed decisions about digital wellness programs and study habits.

1.3 Measurements

The primary measurement variables include respondent field of study, daily phone screen time (measured in hours), Grade Point Semester (GPS) from the previous semester, frequency of phone distraction during study sessions (using a 5-point Likert scale), types of applications most frequently used, and students' perceived impact of screen time on their academic performance. The research questions focus on determining whether there is a statistically significant correlation between average daily phone screen time and GPS among Computer Science and Data Science students, and if such correlation exists, measuring its strength.

CHAPTER II: DESIGN SAMPLING

2.1 Sampling Method

The study employed a Simple Random Sampling method within a non-probability sampling framework. This approach was selected to ensure that every student in the target classes had an equal chance of being selected, thereby minimizing selection bias and improving sample representativeness. It was especially effective in a digital context, where the survey was distributed online through WhatsApp groups and academic platforms, making it easy to reach students randomly without physical constraints. This approach ensured fairness and accessibility for both Computer Science and Data Science students.

2.2 Sample Calculation

The sample size calculation utilized the finite population formula with a total population of 785 B27 students from Computer Science and Data Science programs at BINUS University Kemanggisan campus. Using a 95% confidence level (Z-score = 1.96), estimated proportion of 0.5 (most conservative estimate), and margin of error of 10%, the calculation yielded a required sample size of approximately 86 respondents. This sample size was justified as providing adequate statistical power while maintaining practical feasibility for data collection within the given timeframe and resources.

2.3 Sample Selection from Sampling Frame

The random sample selection process involved accessing official student groups for Computer Science (classes LA01-LI01) and Data Science (classes LA09-LC09) through WhatsApp groups. Students were individually approached via personal messages after random selection, ensuring equal probability of participation. The sampling frame consisted of 785 students total, with 600 from Computer Science and 185 from Data Science programs.

2.4 Life Cycle Design and Quality

2.4.1 Measurement Process

Construct (μi)

The construct is the core concept or information the researcher wants to study. In this project, the construct is to explore the relationship between students' phone screen time and their academic performance (measured by Grade Point Semester) during the odd semester of 2024/2025. The study focuses on students from the Computer Science and Data Science majors at BINUS University.

Validity

The survey demonstrates strong construct and content validity, refined through pre-testing, using screen time and GPS. Face validity is decent due to clear questions. External validity is moderate due to sampling frame and potential non-response error, limiting generalizability. Internal validity is low as it identifies relationships but not causation. Despite limitations, statistical conclusion validity is strong through appropriate data analysis.

Measurement (Y_i)

An online questionnaire collected quantitative and qualitative data including average daily phone screen time, last semester GPS, top 3 smartphone app categories, frequency of non-academic phone distraction during study, and personal opinion on screen time's effect on academic performance. Screen time and GPS were recorded in categorical ranges, and other items were categorical or ordinal (e.g., Likert scale).

Measurement Error

Measurement error may occur due to inaccurate self-reporting by respondents. Since screen time and academic performance are self-reported, students might underreport or overreport based on memory or social desirability bias. For example, a student may report 5 hours of screen time but actually uses their phone for 7 hours daily. Similarly, some might misreport their GPS range to appear more academically successful.

Response (y_i)

The responses refer to the raw answers submitted by students through the questionnaire. These include the reported screen time per day, selected app categories (e.g., social media, games), self-reported academic distractions, behavior regarding screen time reduction, reasons behind that behavior, GPS range, and personal reflection on how screen time affected academic performance.

Processing Error

Although the data was cleaned, preprocessing errors may still exist. Manual corrections to open-ended responses could introduce interpretation bias, and using categorical ranges for key variables may reduce precision and limit deeper analysis.

Edited Response (y_i□)
In the data cleaning process, null values were found only in the open-ended question about reasons for reducing screen time. These nulls were treated as “no reason” since only respondents who previously answered "yes" were shown this question. Additionally, typos and inconsistent spelling in open-text responses were manually corrected to ensure data consistency.

2.4.2 Representation Process

Target Population ($\bar{Y}$)
The target population of this study is B27 students majoring in Computer Science and Data Science at BINUS University, Kemanggisan campus, with an estimated total of 785 students. These students are assumed to have a similar academic environment, making the analysis more consistent.

Coverage Error
Coverage error stems from the mismatch between the target population (all active B27 Computer Science and Data Science students) and the sampling frame (official student WhatsApp groups). This leads to undercoverage, as active B27 students not in these groups had no chance of selection. If these excluded students possess different characteristics, their omission introduces bias, limiting the study's generalizability.

Sampling Frame ($\bar{Y}c$)
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 Error
Sampling error is the inherent deviation between a sample (86 students) and the population (785 students). Even with perfect random sampling, the sample won't perfectly reflect the population's average GPA and screen time. Therefore, the correlation from the sample is an estimate of the true correlation, and the 10% margin of error acknowledges this sampling error.

Sample ($\bar{y}$□)
The sample is the subset of individuals that we select from the sampling frame to participate in the survey. Using a standard formula with a 95% confidence level and 10% margin of error, the required sample size from a population of 785 was calculated to be 86 respondents.

Non-Response Error
Non-response error arises when survey participants differ systematically from non-participants. Despite random sampling and reminders, some selected students didn't respond, potentially causing bias if non-participation reasons relate to study variables. For example, high screen time students might have been too busy or self-conscious, while those with high GPS and low screen time might deem the survey

a distraction. Underrepresentation of these groups could underestimate actual screen time habits, weakening correlation strength.

Respondents ($\bar{y}_r$)
A total of 86 valid responses were collected, meeting the target sample size, with 44 from Computer Science and 42 from Data Science students.

Adjustment Error
Adjustment error refers to potential inaccuracies introduced during the post-survey processing phase. Although the dataset was complete and no responses were removed, minor manual editing, such as correcting typos in open-ended answers, may introduce subjective interpretation or human error.

Post Survey Adjustment ($\bar{y}_r w$)
After survey completion, the dataset was checked for quality. No outliers or inconsistent answers were found, so no responses were removed. Minor edits were made to correct open-ended text, and all data was confirmed to be complete and ready for analysis.

Survey Statistics ($\bar{y}\square_r w$)
A total of 86 valid responses were collected, successfully meeting the calculated target sample size based on a 95% confidence level and 10% margin of error. The respondents consisted of 44 Computer Science students (51.2%) and 42 Data Science students (48.8%). All responses were complete and usable, as the survey was designed with mandatory questions to reduce missing data. This final dataset became our foundation for the correlation analysis and interpretation later.

CHAPTER III: QUESTIONNAIRE DESIGN

The following questions are measuring variable from the Chapter I such as respondent field of study, average daily phone screen time in hours, Grade Point Semester (GPS) from the previous semester, frequency of phone distraction during study sessions, types of applications most frequently used, and students' perceived impact of screen time on their academic performance. Below is the list of questions with respect to what it measures.

1. Field of study
    - *What is your field of study? (Data Science or Computer Science)*
2. Average daily phone screen time in hours
    - *What is your average daily smartphone screen time (in hours)? (Continuous Answer)*
3. Grade Point Semester (GPS) from the previous semester
    - *What is your Semester Grade Point (GPS) range in the odd semester of 2024/2025? (Strata Range of GPS)*
4. Types of applications most frequently used
    - *Of your total smartphone screen time, what types of apps take up the most of your time? (Multiple Choices)*
5. Frequency of phone distraction during study sessions
    - *How often do you feel distracted by smartphone use for non-academic purposes (e.g. social media, games, video streaming) while studying? (Likert Scale)*

6. Students' perceived impact of screen time on their academic performance
    - *Have you consciously reduced your smartphone usage last semester? (Yes or No)*
    - *What was the main reason you reduced your smartphone usage last semester? (Multiple Choices with Addition of Open-Ended Answer)*
    - *In your opinion, from scale one to five, how did screen time affect academic performance last semester (odd semester 2024/2025)? (Likert Scale)*
    - *How screen time habits affect your performance in studying in the odd semester of 2024/2025? (Open-Ended Answer)*

CHAPTER IV: DATA COLLECTION

4.1. Data Collection Method

The data collection method utilized an entirely online approach through Google Forms, chosen for its accessibility, cost-effectiveness, and ease of distribution among the university student population. This method was justified by the unavailability of an official student database and the need to reach students efficiently across multiple classes. The online format also ensured consistent data capture and reduced transcription errors compared to paper-based methods.

4.2. Performed Data Collection

The data collection process spanned approximately three weeks, from May 21, 2025, to June 10, 2025. Students were systematically approached through individual WhatsApp messages containing research objectives, confidentiality assurances, and questionnaire links. Each selected student received personalized invitation messages to ensure proper understanding of the research purpose and voluntary participation nature.

4.3. Effort to Address Challenge

The primary challenge encountered was participant non-response, with a significant portion of initially selected students not responding to invitation messages. This was addressed through systematic follow-up procedures, including polite reminder messages sent after several days of non-response. When students remained unresponsive after two follow-up attempts, replacement participants were randomly selected from the sampling frame. This approach successfully increased the response rate and maintained sample size integrity, ultimately achieving the target of 86 responses with a 100% response rate from contacted participants.

4.4. Actual Sample Obtained

The actual sample obtained consisted of 86 valid responses, meeting the calculated target sample size exactly. The demographic breakdown included 44 Computer Science students (51.2%) and 42 Data Science students (48.8%), providing representation from both target programs and forming the basis for subsequent data analysis.

CHAPTER V: VALIDITY AND RELIABILITY CHECK

5.1 Validity Check

Validity calculation was performed with python through construct validity assessment using Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity. The KMO score of 0.434 indicated low sampling adequacy, suggesting the dataset may not be ideal for factor analysis. However, Bartlett's Test yielded a p-value of 0.03889, showing sufficient correlation between variables to justify the analysis. Factor analysis extracted two main factors with eigenvalues greater than 1 (Factor 1: 1.25, Factor 2: 1.08), revealing that phone distraction frequency and screen time were associated with one factor representing distraction level, while screen time impact aligned with a second factor representing usage behavior. The validity conclusion indicated weak construct validity, requiring cautious interpretation of factor structure.

5.2 Reliability Check

Cronbach's Alpha calculation was conducted with python focusing on screentime_spend, phone_distraction_freq, and screentime_impact variables, producing a value of 0.238. This result indicates very low internal consistency, suggesting these variables do not correlate strongly with one another and are not measuring a single underlying construct. The conclusion drawn from this result is that the low Cronbach's Alpha is reasonable and expected, as each variable captures distinct aspects of smartphone use: total daily usage, distraction frequency during study, and perceived academic impact. Given these differences in focus, the low internal consistency does not undermine data validity but rather confirms that the variables measure different dimensions of smartphone usage behavior

CHAPTER VI: DATA ANALYSIS

In this chapter, we are using python for descriptive analysis, and preprocessing. The detailed result will be provided below.

6.1. Descriptive Analysis

6.1.1 Missing Value Identification

During the data analysis process, a thorough check was performed for missing values across all variables with python. Since all survey questions were set as mandatory, there were no missing values in the main responses. However, on the reduction_reason (reason for reducing smartphone use) column, there are several missing values because the question is intended only to those who answered “Yes” to reduced_phone_use (who reduced their screen time intentionally). Therefore, missing values in this column were expected.

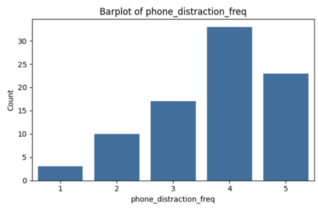
6.1.2 Summary Statistics

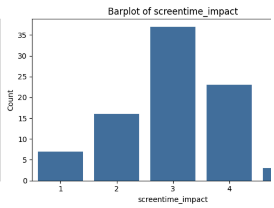
Summary statistics revealed that the majority of respondents (44 Computer Science, 42 Data Science) reported high daily screen time, with most spending more than 8 hours daily on smartphones, followed by 4-6 hours and 6-8 hours. This indicates that high daily screen time is typical among respondents, highlighting a potential concern regarding excessive smartphone usage in the student population. The most common application categories were social media, video, and gaming applications.

Phone distraction frequency showed a mean score of 3.78 (on a 5-point scale), indicating frequent distractions during study sessions. The perceived impact of screen time on academic performance showed a mean score of 2.86, suggesting neutral to slightly negative perceived effects. GPS distribution was relatively balanced across different ranges, with weighted analysis accounting for disproportionate major representation.

Barplot results show that most students feel highly distracted by phone use while studying, but their views on screen time’s impact on academic performance are more

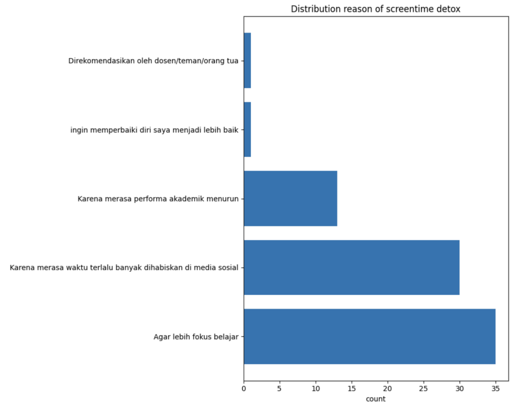
Variation in Screen Time Impact and Distraction Levels balanced, with many selecting a neutral or slightly negative effect. This indicates that while distraction is common, its perceived academic impact varies across individuals.





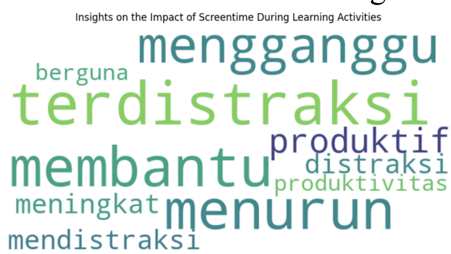
These findings highlight that students are becoming more self-aware of how their smartphone use affects their academic life. The fact that internal academic goals are the main drivers for screen time reduction suggests a proactive attitude toward improving study habits. However, the relatively low influence of external recommendations indicates that students may be more responsive to personal goals than to advice from others.

Screen Time Detox Effect



The most frequent words from open-ended responses reveal both negative and positive views on screen time during learning. While many students feel distracted, others see it as a helpful tool, showing that its impact varies based on individual usage habits

Screen Time in Learning



6.2. Preprocessing

6.2.1 Missing Values Imputation

There were several missing values on the reduction_reason column because the question was only intended for those who reduced their screen time intentionally in the previous semester. These expected missing values are interpreted as "no reason" or "did not reduce phone usage". Additionally, manual correction of typos and spelling errors in the open-ended responses was performed to ensure consistency and facilitate subsequent analysis.

6.2.2 Cross Tabulation

The cross-tabulation analysis reveals that social media and video apps are popular across all GPA levels, particularly among students with mid (3.00-3.49) and high (≥3.5) GPAs, while productivity apps are more frequently used by higher-GPA students, indicating more balanced digital habits. Phone distraction levels (3-5) are commonly reported regardless of GPA, suggesting that frequent distraction does not necessarily correlate with lower academic performance. Additionally, most students perceive a moderate impact (level 3) of screen time on academic performance, with some high-GPA students also reporting noticeable effects. Overall, the findings suggest that while screen time and distraction are prevalent, their relationship with academic success is not strictly negative and varies by individual behavior and app usage.

6.2.3 Correlation Test

The correlation matrix reveals that most variables in the dataset have weak or very weak correlations with each other, indicating no strong monotonic relationships. The only strong correlation appears between reduced_phone_use and reduction_reason ($\rho \approx 0.90$), which is expected due to their conditional dependency. Weak positive correlations were found between screentime_spend and phone_distraction_freq ($\rho \approx 0.26$), and between GPS and screentime_impact ($\rho \approx 0.25$), suggesting slight trends but no major predictive power. Overall, no variable shows a strong influence on academic performance or screen time impact in this dataset.

CHAPTER VII: CONCLUSION

7.1 Conclusion

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.

7.2 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.

7.3 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