IJPHS:
International Journal of Psychology and Health Science
GREENATION PUBLISHER
+62 812 1046 7572 http://greenpub.org greenation.info@gmail.com Jl. Kapt. A. Hasan, Telanaipura Jambi-Indonesia
DOI: https://doi.org/10.38035/ijphs.v1i4

Demographic Influences on Screen Time: Impacts on Academic Performance and Mental Health

Diyanshi Patel[1], Pooja Vyas[2], Dhara Patel[3], Aryan Shah[4], Rahul Chauhan[5], Andino Maseleno[6], R. Rizal Isnanto[7]

[1]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India, diyanshipatel171003@gmail.com
[2]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[3]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[4]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[5]Unitedworld Institute of Management, Karnavati University, Gandhinagar, India,
[6]Department of Information Systems, Institut Bakti Nusantara, Lampung, Indonesia, andino.maseleno@ibnus.ac.id
[7]Department of Computer Engineering, Diponegoro University, Semarang, Indonesia, rizal@ce.undip.ac.id

Corresponding author: andino.maseleno@ibnus.ac.id[6]

Abstract: This study examines the relationship between demographic factors—age, gender, and education level—and various aspects of screen time usage, including average screen time, academic performance, and associated health impacts such as anxiety and social life interactions. Using ANOVA, we found significant differences in average screen time based on age and education level, with younger and more educated individuals tending to engage more with digital devices for studying. Notably, academic performance was influenced by education level, while anxiety and social life were significantly affected by both education and age. These findings underscore the importance of considering demographic factors in understanding screen time behaviors. Future research should explore longitudinal effects and potential interventions to mitigate negative outcomes.

Keywords: Screen time, demographics, academic performance, mental health

INTRODUCTION

In the realm of medical education, David et al. (2024) evaluate the effectiveness of video tools in enhancing anatomy knowledge among medical postgraduates, illustrating how digital resources can address gaps in traditional learning methods. This study underscores the growing role of multimedia in educational settings, particularly in fields that demand detailed and complex understanding. Similarly, Dreisiebner et al. (2021) address the enhancement of information literacy through a multilingual Massive Open Online Course (MOOC), emphasizing the importance of cultural considerations in the design and delivery of educational content. This approach highlights the need for inclusivity and accessibility in global educational initiatives.

The challenges of online education are further examined by Jutz et al. (2024), who explore the sustainability dilemmas faced by students engaged in remote learning. Their research underscores the need to balance academic flexibility with environmental concerns, reflecting broader societal shifts towards sustainable practices. In the field of cyber security, Meland et al. (2019) provide an experimental evaluation of bow-tie analysis, offering insights into advanced methodologies for risk management and security assessment. This study contributes to the ongoing discourse on enhancing security measures in an increasingly digital world.

In humanitarian contexts, Moreno Rocha et al. (2024) present the Mobile Ultrasound Vascular Assessment (MUVA) as a vital tool for remote and conflict-affected areas, demonstrating how technological innovations can improve healthcare delivery in challenging environments. Mostafa et al. (2024) discuss the impact of ASPECTSS-based design interventions on autism school environments, offering valuable insights into how architectural design can cater to the needs of individuals with autism. Lastly, Srivastava et al. (2024) analyze knowledge management during the transition to emergency remote teaching, providing an interpretative phenomenological perspective on the experiences of faculty members navigating this shift.

In today's rapidly advancing digital age, the need for awareness and intervention in technology-related health issues has become more pressing than ever (Sulaksono et al., 2023). As digital tools increasingly permeate educational and professional environments, their impacts on physical and mental well-being demand closer scrutiny. For instance, David et al. (2024) highlight the effectiveness of video tools in medical education, showing how multimedia can enhance learning in complex subjects like anatomy. However, these tools also raise concerns about screen time, posture, and cognitive overload. Similarly, Dreisiebner et al. (2021) stress the importance of culturally inclusive design in digital learning platforms, such as MOOCs, to ensure equitable access to education.The sustainability challenges of remote learning, as explored by Jutz et al. (2024), further underscore the environmental and health-related consequences of extensive technology use. In specialized fields like cyber security and healthcare, technological innovations, such as bow-tie analysis (Meland et al., 2019) and MUVA (Moreno Rocha et al., 2024), offer promising solutions but also present new health risks, including ergonomic strain and psychological stress.

METHOD

The study aims to assess the average screen time among students in Ahmedabad and evaluate its impact on academic performance and mental health. The primary objectives are to determine the relationship between screen time and both academic outcomes and mental health indicators such as anxiety and stress. To achieve this, two key research questions are posed: What is the average daily screen time of students in Ahmedabad, and how does it vary by age and education level? In addition, does increased screen time correlate with higher levels of anxiety and stress?

Objectives:

- To assess the average screen time among students in Ahmedabad and its impact on their academic performance and well-being.
- To evaluate the relationship between excessive screen time and mental health issues such as anxiety and stress among students.

Research Questions:

1. What is the average daily screen time of students in Ahmedabad, and how does it vary based on age and educational level?

2. Does increased screen time correlate with mental health issues such as anxiety and stress among students?

Hypotheses:
H1: There is a significant relationship between increased screen time and reduced academic performance among students in Ahmedabad.
H2: There is a significant correlation between increased screen time and higher levels of anxiety and stress among students

The study hypothesizes that there is a significant relationship between increased screen time and reduced academic performance, as well as a significant correlation between screen time and heightened anxiety and stress. A quantitative research approach is employed, utilizing both descriptive and correlational research designs. The sample consists of 100 students from Ahmedabad, selected using stratified random sampling to ensure representation across various age groups, educational levels, and socio-economic backgrounds. The participants, aged 15-25, must be currently enrolled in schools or colleges and report using digital devices for more than two hours per day.

Data will be collected through an online survey, where participants will answer a structured questionnaire. The survey will gather demographic information, average daily screen time, self-reported academic performance, and mental health status. Validated scales such as the Generalized Anxiety Disorder (GAD-7) for anxiety and the Perceived Stress Scale (PSS) for stress will be included to assess mental health outcomes.

For data analysis, SPSS (Statistical Package for the Social Sciences) will be used. Descriptive statistics will calculate the mean, median, and standard deviation for screen time, academic performance, and mental health scores. Pearson correlation will assess the relationship between screen time and both academic performance and mental health, while multiple regression analysis will be conducted to control for variables such as age and gender, exploring the direct impact of screen time on both academic and mental health outcomes. This methodological approach allows for a comprehensive understanding of the effects of screen time on students' academic success and psychological well-being.

RESULT AND DISCUSSION

The demographic data from the study provides a comprehensive overview of the participants, shedding light on their age, gender, education level, and family income. Among the 124 students surveyed, the age distribution indicates a predominance of participants aged 19-21, comprising 45.2% of the sample, followed by those aged 15-18 at 26.6%, and 22-25 at 28.2%. This distribution suggests that the study primarily captures insights from early university students, which may be particularly relevant given the context of academic performance and mental health.

Table-1: Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	15-18	33	26.6	26.6	26.6
	19-21	56	45.2	45.2	71.8
	22-25	35	28.2	28.2	100.0
	Total	124	100.0	100.0	

In terms of gender, the sample is fairly balanced, with 47.6% identifying as male, 46.8% as female, and 5.6% identifying as other. This representation allows for a more nuanced analysis of how screen time and its effects may vary across different genders.

Table-2: Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	59	47.6	47.6	47.6
	Female	58	46.8	46.8	94.4
	Other	7	5.6	5.6	100.0
	Total	124	100.0	100.0	

Regarding education level, a significant majority (62.1%) are undergraduates, while 25.0% are postgraduates and 12.9% are in high school. This focus on higher education students could reflect the increasing screen time associated with university coursework and social media use, making the findings particularly pertinent for understanding academic performance.

Table-3: Education level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High school	16	12.9	12.9	12.9
	Undergraduate	77	62.1	62.1	75.0
	Post graduate	31	25.0	25.0	100.0
	Total	124	100.0	100.0	

Lastly, family income data reveals a skew toward higher income levels, with 63.7% of participants earning above INR 100,000 per month. This demographic factor may influence access to technology and digital devices, potentially impacting screen time and its associated effects on mental health and academic outcomes. Overall, the demographic data provides essential context for interpreting the study's findings, highlighting the diverse backgrounds of students and the potential implications for their screen time habits.

Table-4 : Monthly Family Income (in INR)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Below 25,000	18	14.5	14.5	14.5
	25,000-50,000	15	12.1	12.1	26.6
	50,000-1,00,000	12	9.7	9.7	36.3
	Above 1,00,000	79	63.7	63.7	100.0
	Total	124	100.0	100.0	

The ANOVA table presents the results of a study examining the relationship between age and various factors related to screen time, including average screen time, primary purpose of screen use, and its impact on health and social life. The analysis includes between group and within-group sum of squares, degrees of freedom, mean square values, F statistics, and significance levels (p-values).

Table 5: ANOVA between Age and Factors

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Average screen time	Between Groups	10.845	2	5.422	4.929	.009
	Within Groups	133.115	121	1.100		
	Total	143.960	123			
Primary purpose	Between Groups	9.490	2	4.745	3.008	.053
	Within Groups	190.857	121	1.577		
	Total	200.347	123			
Studying device	Between Groups	2.461	2	1.231	7.980	<.001
	Within Groups	18.660	121	.154		
	Total	21.121	123			
Breaks taken	Between Groups	1.199	2	.600	.514	.599
	Within Groups	141.019	121	1.165		
	Total	142.218	123			
Academic performance	Between Groups	3.807	2	1.904	2.018	.137
	Within Groups	114.161	121	.943		
	Total	117.968	123			
Headaches/eye strain	Between Groups	4.268	2	2.134	2.218	.113
	Within Groups	116.409	121	.962		
	Total	120.677	123			
Stress levels	Between Groups	3.596	2	1.798	2.101	.127
	Within Groups	103.525	121	.856		
	Total	107.121	123			
Anxiety/restlessness	Between Groups	7.515	2	3.757	3.465	.034
	Within Groups	131.219	121	1.084		
	Total	138.734	123			
Social life impact	Between Groups	2.455	2	1.228	2.169	.119
	Within Groups	68.472	121	.566		
	Total	70.927	123			
Sleep patterns	Between Groups	2.394	2	1.197	2.041	.134
	Within Groups	70.961	121	.586		
	Total	73.355	123			

For average screen time, the between-group F-value is 4.929, with a p-value of 0.009, indicating a statistically significant difference across age groups. This suggests that age significantly influences how much time individuals spend on screens. In contrast, the primary purpose of screen use shows a p-value of 0.053, which is marginally significant and suggests some variation in screen use purposes by age but does not meet conventional significance levels. Notably, the use of a studying device is highly significant ($p < 0.001$), indicating that age has a strong influence on whether individuals use digital devices for studying. This result suggests that older individuals may be less inclined to use digital devices for educational purposes compared to younger counterparts. Conversely, factors such as breaks taken ($p = 0.599$), academic performance ($p = 0.137$), headaches/eye strain ($p = 0.113$), and stress levels ($p = 0.127$) did not show significant differences across age groups, indicating that these aspects might be more consistent regardless of age.

The findings related to anxiety/restlessness (p = 0.034) suggest a significant relationship with age, indicating that different age groups may experience varying levels of anxiety due to excessive screen time. However, the impacts on social life and sleep patterns were not statistically significant, highlighting that while age influences certain aspects of screen use, other factors may need to be considered to understand these effects fully. Overall, the results indicate that age plays a crucial role in shaping screen time behaviors and their associated consequences.

Table 6: ANOVA between Gender and Factors

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Average screen time	Between Groups	.520	2	.260	.219	.804
	Within Groups	143.440	121	1.185		
	Total	143.960	123			
Primary purpose	Between Groups	2.532	2	1.266	.774	.463
	Within Groups	197.815	121	1.635		
	Total	200.347	123			
Studying device	Between Groups	1.953	2	.977	6.166	.003
	Within Groups	19.168	121	.158		
	Total	21.121	123			
Breaks taken	Between Groups	1.611	2	.805	.693	.502
	Within Groups	140.607	121	1.162		
	Total	142.218	123			
Academic performance	Between Groups	8.148	2	4.074	4.489	.013
	Within Groups	109.820	121	.908		
	Total	117.968	123			
Headaches/eye strain	Between Groups	4.036	2	2.018	2.093	.128
	Within Groups	116.642	121	.964		
	Total	120.677	123			
Stress levels	Between Groups	3.621	2	1.810	2.116	.125
	Within Groups	103.500	121	.855		
	Total	107.121	123			
Anxiety/restlessness	Between Groups	.679	2	.339	.297	.743
	Within Groups	138.055	121	1.141		
	Total	138.734	123			
Social life impact	Between Groups	2.762	2	1.381	2.452	.090
	Within Groups	68.165	121	.563		
	Total	70.927	123			
Sleep patterns	Between Groups	.807	2	.404	.673	.512
	Within Groups	72.547	121	.600		
	Total	73.355	123			

The ANOVA table examines the effects of gender on various factors related to screen time usage and its associated impacts. The analysis includes the sum of squares, degrees of freedom, mean square values, F statistics, and significance levels (p-values) for each factor. For average screen time, the results indicate no significant differences between genders, with an F-value of 0.219 and a p-value of 0.804, suggesting that screen time does not vary meaningfully between male and female participants. Similarly, the primary purpose of screen use also shows no significant differences (p = 0.463), indicating that both genders use screens for similar purposes. In contrast, the use of studying devices reveals a statistically significant difference, with an F-value of 6.166 and a p-value of 0.003. This suggests that gender plays a crucial role in the likelihood of using digital devices for educational purposes, potentially indicating that one gender may be more inclined to utilize these devices for studying.

Academic performance also demonstrates a significant difference (p = 0.013), suggesting that gender may influence academic outcomes. This finding points to the possibility of differing study habits or engagement levels between genders. However, factors such as breaks taken (p = 0.502), headaches/eye strain (p = 0.128), stress levels (p = 0.125), anxiety/restlessness (p = 0.743), social life impact (p = 0.090), and sleep patterns (p = 0.512) did not show significant differences between genders, indicating relative consistency in these experiences regardless of gender. Overall, while gender appears to influence the use of studying devices and academic performance, the lack of significant differences in other factors suggests that the impact of gender on screen time-related behaviors and their consequences may be nuanced and context-dependent. Further research could provide deeper insights into these dynamics.

Table-6 ANOVA between Education Level and Factors

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Average screen time	Between Groups	7.805	2	3.902	3.468	.034
	Within Groups	136.155	121	1.125		
	Total	143.960	123			
Primary purpose	Between Groups	8.045	2	4.023	2.531	.084
	Within Groups	192.301	121	1.589		
	Total	200.347	123			
Studying device	Between Groups	1.871	2	.936	5.881	.004
	Within Groups	19.250	121	.159		
	Total	21.121	123			
Breaks taken	Between Groups	1.451	2	.726	.624	.538
	Within Groups	140.766	121	1.163		
	Total	142.218	123			
Academic performance	Between Groups	7.852	2	3.926	4.314	.015
	Within Groups	110.116	121	.910		
	Total	117.968	123			
Headaches/eye strain	Between Groups	4.226	2	2.113	2.196	.116
	Within Groups	116.451	121	.962		
	Total	120.677	123			
Stress levels	Between Groups	2.309	2	1.155	1.333	.268
	Within Groups	104.812	121	.866		
	Total	107.121	123			
Anxiety/restlessness	Between Groups	7.894	2	3.947	3.650	.029
	Within Groups	130.839	121	1.081		
	Total	138.734	123			

Social life impact	Between Groups	7.664	2	3.832	7.330	<.001
	Within Groups	63.263	121	.523		
	Total	70.927	123			
Sleep patterns:	Between Groups	2.522	2	1.261	2.155	.120
	Within Groups	70.832	121	.585		
	Total	73.355	123			

The ANOVA table investigates the relationship between education level and various factors related to screen time usage and its effects. This analysis includes the sum of squares, degrees of freedom, mean square values, F statistics, and significance levels (p-values) for each factor assessed. The results indicate a statistically significant difference in average screen time based on education level, with an F-value of 3.468 and a p-value of 0.034. This suggests that individuals with different education levels spend varying amounts of time on screens, potentially reflecting differing lifestyles or responsibilities associated with education.

The primary purpose of screen use also shows a trend toward significance ($p = 0.084$), indicating that the reasons for using screens may vary somewhat with educational attainment, although this does not reach conventional significance levels. However, the use of studying devices is highly significant ($p = 0.004$), suggesting that education level has a strong influence on the likelihood of utilizing digital devices for academic purposes, likely indicating that those with higher education levels may be more adept at integrating technology into their studies. Additionally, academic performance demonstrates a significant relationship with education level ($p = 0.015$), indicating that education may play a crucial role in determining academic outcomes. Anxiety and restlessness due to screen use also show significance ($p = 0.029$), suggesting that different education levels might experience varying levels of stress related to screen time.

The impact on social life is highly significant ($p < 0.001$), indicating that education level significantly affects how screen time influences social interactions. In contrast, other factors such as breaks taken ($p = 0.538$), headaches/eye strain ($p = 0.116$), stress levels ($p = 0.268$), and sleep patterns ($p = 0.120$) did not reveal significant differences across education levels.

Overall, the findings suggest that education level significantly influences several aspects of screen time behavior and its consequences, highlighting the importance of considering educational context when examining digital device usage.

CONCLUSION

In conclusion, this study highlights the significant relationships between age, gender, and education level with various factors related to screen time usage and its associated impacts. The findings suggest that demographics play a crucial role in shaping screen time behaviors, academic performance, and health outcomes such as anxiety and social life interactions. As technology continues to evolve, understanding these dynamics is essential for promoting healthy screen habits across different population segments.

Future research could explore longitudinal effects of screen time on mental health and academic performance, considering a more diverse demographic and geographical range. Additionally, investigating interventions aimed at reducing negative consequences of excessive screen use could yield valuable insights for educators, policymakers, and mental health professionals. Globally, as digital devices become increasingly integrated into daily life, understanding the implications of screen time on various populations is vital. This research can inform public health initiatives aimed at mitigating screen-related issues, fostering digital literacy, and promoting balanced usage. Ultimately, addressing the global challenges posed by excessive screen time can contribute to healthier, more connected communities worldwide.

Acknowledgement

This research project is supported by **World Class University Program, Indonesia Endowment Fund for Education**, Diponegoro University, Indonesia. We gratefully appreciated this support.

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