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A Survey Analysis of Social Media Addiction and Its Impact on Students Academic Performance in District Peshawar

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***Abstract*:** Social media addiction, a form of internet addiction, refers to excessive and maladaptive engagement with social media platforms, resulting in significant impairment in various aspects of an individual's life. This study aims to examine the impact of social media addiction among students in different universities of Peshawar. Data were collected from 400 university students in Peshawar using a simple random sampling method. SPSS version 27 was employed for data analysis. Various statistical techniques, including Correlation, Regression, One-way ANOVA, One-sample T-test, and Bayesian Estimator, as well as visual tools descriptive Statistics such as pie charts, bar charts, and histograms, were applied. The results indicate that university students in Peshawar exhibit high levels of social media addiction, with hostel students showing significantly higher addiction levels compared to non-hostel students.

Keyword: social media addiction, university students, academic performance, statistical analysis.

1. Introduction

Social media addiction is a modern phenomenon increasingly seen as a specific type of internet addiction. It is characterized by compulsive, excessive engagement with platforms like Facebook, Instagram, Twitter, and others, which leads to negative effects on multiple facets of life. As Griffiths (2013) suggests, social media addiction can cause severe disruptions in an individual's daily routines and responsibilities. This type of behavioral addiction, as Andersen & Burson (2017) argue, can lead to mental, emotional, and social problems, reducing overall well-being. Over the past decade, social media has revolutionized global communication, transforming how people interact and share information. This transformation, while enabling unprecedented connectivity, also comes with drawbacks. Particularly for university students, social media can serve as both a useful academic tool and a source of continuous distraction. On one hand, students benefit from access to vast online resources, forums, and educational communities, which can enhance their learning experience. Platforms like LinkedIn or academic groups on Facebook allow students to network, gain career insights, and collaborate on projects. Social media also provides entertainment and a sense of belonging through online communities, which can reduce stress and foster social connections, especially for students living away from home. However, these advantages often come with considerable disadvantages. The compulsive nature of social media can lead to procrastination, distract students from their studies, and disrupt their focus on important academic tasks. The constant notifications, updates, and addictive features designed to keep users engaged can significantly reduce productivity. Excessive use can also lead to sleep disturbances and decreased cognitive engagement, which directly impacts academic performance. Students may find it harder to concentrate on assignments, participate fully in learning, or manage their time effectively. Furthermore, the emotional toll of comparing oneself to others on social media platforms can contribute to anxiety and depression, further exacerbating academic struggles. The growing concern among educators and policymakers is that social media addiction is not just about lost study time, but also about the broader consequences it has on students' mental health and overall well-being. This research aims to provide a deeper understanding of how social media addiction impacts academic performance, focusing on university students in Peshawar. By analyzing the patterns and effects of this addiction, the study offers crucial insights for universities and policymakers to mitigate the risks while promoting healthier, more productive use of social media**.**

1.1 Objectives of the Study

a) To determine the impact of social media addiction on student academic performance.
b) To determine those students whose CGPA is low due to social media addiction.
c) To determine those students who are highly Addicted to social media.

2. Literature Review

Social media addiction, defined as excessive engagement with platforms like Facebook, Instagram, and Twitter, significantly impacts university students' academic performance and mental health (Griffiths, 2013; Andreassen et al., 2017). Research indicates that high levels of social media use correlate with lower GPAs. For example, Kirschner and Karpinski (2010) found that frequent Facebook users had diminished academic outcomes. Kuss and Griffiths (2011) further noted that such engagement leads to procrastination and reduced study time.

The compulsive nature of social media, driven by constant notifications, distracts students from their studies (Turel & Qahri-Saremi, 2016). Additionally, social media use is linked to increased anxiety and depression, exacerbated by social comparison, where students feel inadequate compared to idealized online representations (Lin et al., 2016; Vogel et al., 2014). Chen and Lee (2013) found that social media addiction can lead to social withdrawal and lower academic motivation. Similarly, Lepp et al. (2014) reported that increased social media usage negatively affected students' time management skills and academic performance.

Alhassan et al. (2018) highlighted that students who engage excessively with social media tend to have poorer study habits, resulting in lower academic achievements. Awan et al. (2020) indicated that social media addiction is particularly pronounced among students living in hostel accommodations, who often use social media to combat loneliness, further impacting their academic focus. Keles et al. (2020) emphasized that the detrimental effects of social media addiction are compounded by sleep disturbances, with excessive use disrupting sleep patterns and impairing cognitive functioning (Hale & Guan, 2015; Becker et al., 2016).

Recent studies further confirm these trends. For instance, a meta-analysis by Smahel et al. (2021) reported that social media addiction correlates with increased academic procrastination and decreased motivation across various educational contexts. Moreover, Alqahtani et al. (2022) found that high levels of social media use among students led to a significant decline in academic performance and an increase in psychological distress, reinforcing the notion that addiction to social media can detract from academic responsibilities.

A study by Elhussein et al. (2023) explored the impact of social media addiction on students' overall well-being, highlighting that students exhibiting high addiction levels not only struggled academically but also experienced heightened stress and anxiety levels, negatively influencing their educational outcomes. Furthermore, research by Yadav et al. (2023) demonstrated that students' emotional regulation abilities are adversely affected by excessive social media engagement, leading to challenges in managing academic pressures.

In contrast, a study by Sinha et al. (2024) suggested that moderate use of social media can facilitate academic collaboration and enhance learning experiences. However, they warned that excessive use still leads to adverse outcomes, emphasizing the need for balance.

Adding to this discourse, a study by Błachnio et al. (2022) indicated that students who exhibit social media addiction show significant declines in their academic engagement, suggesting that the compulsive nature of social media use leads to diminished participation in academic activities. Similarly, research by O'Keeffe and Clarke-Pearson (2023) found that social media addiction negatively influences time management skills, with students reporting higher instances of procrastination on academic tasks due to distractions from social media platforms. Furthermore, a longitudinal study by Liu et al. (2023) highlighted that social media addiction can exacerbate academic burnout, affecting students' motivation and overall academic performance over time.

Additionally, a study by Zhan et al. (2024) revealed that social media addiction is linked to reduced attention spans among university students, which further contributes to academic difficulties. This decline in attention was associated with diminished retention of academic material, indicating a direct impact on learning outcomes. Another research by Nazari et al. (2024) found that social media addiction negatively affected students' ability to focus on lectures, leading to lower engagement during class and poor academic performance.

To address these issues, educational institutions should implement programs promoting digital literacy and healthy social media habits. Workshops focusing on time management and reducing distractions can support students in balancing their academic responsibilities (Turel & Qahri-Saremi, 2016). Overall, understanding the interplay between social media use and academic performance is essential for educators to mitigate risks and enhance students' educational experiences.

3. Research Methodology

The study utilized primary data collected through a questionnaire-based approach. A specific Social Media Addiction Scale was developed for data collection, with each questionnaire consisting of twenty-eight questions featuring five response options.

3.1 Population of Study

The target population for this research was the university campus, with various departments selected as the sample population.

3.2 Sample Size

The sample size for this research study comprised 400 respondents. Information was gathered from these respondents using the questionnaires.

3.3 Sampling Method

This research employed a simple random sampling technique to select both hostelized and non-hostelized respondents. A total of 400 individuals were randomly chosen from the University of Peshawar Main Campus.

3.4 Data Analysis Method

The responses from the questionnaires were coded, tabulated, and analyzed using the Statistical Package for the Social Sciences (SPSS) version 27. For statistical analysis, multiple linear regression and chi-square tests of association were applied. Furthermore, descriptive statistics, including simple and multiple bar charts, histograms, frequency distributions, percentages, means, and variances, were utilized.

3.5 Limitations of the Study

The study encountered several limitations, including time restrictions. Due to the limited timeframe, the researcher reduced the sample size and narrowed the scope of the research area. However, collecting data from students was manageable since they were largely accessible during the research period.

4. Data Analysis

4.1 Descriptive Statistics

Descriptive statistics consist of techniques used to summarize and highlight the key characteristics of a dataset. These methods include data condensation, visual representations, and the calculation of numerical values that provide insights into the central point and distribution spread. Measures of central tendency, such as the mean, median, and mode, indicate the typical or average values in the dataset. Conversely, measures of variability, including standard deviation, variance, mean deviation, kurtosis, and skewness, capture the extent of dispersion and the shape of the data's distribution. Statistical Analysis and Results

This chapter includes descriptive as well as inferential statistical analysis of our research project.

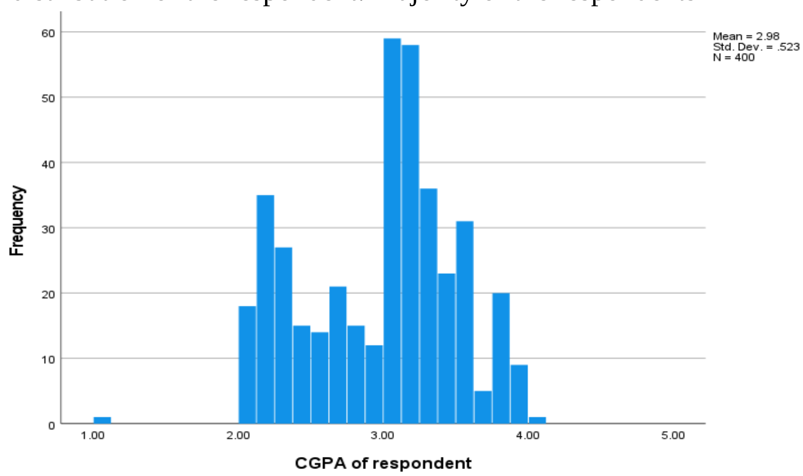
4.2 Mean and Variance

Table 1: provides summary statistics for two variables: Age of respondent and CGPA of respondent.

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*	*Variance*
Age of respondent	400	19	35	22.45	2.316	5.365
CGPA of respondent	400	1.00	4.00	2.9783	.52332	.274
Valid N (listwise)	400					

Key Points:
Sample Size (N): Both variables have a sample size of 400.
Minimum and Maximum:
Age: The youngest respondent is 19 years old, and the oldest is 35.
CGPA: The lowest CGPA is 1.00, and the highest is 4.00.
Mean:
Age: The mean age of the respondents is 22.45 years.
CGPA: The average CGPA is 2.9783.
Standard Deviation:
Age: The standard deviation for age is 2.316, indicating that ages are relatively spread out around the mean.
CGPA: The standard deviation for CGPA is 0.52332, suggesting a moderate spread in CGPA scores
Variance:
Age: The variance for age is 5.365, which is the square of the standard deviation.
CGPA: The variance for CGPA is 0.274.

Figure 1: shows CGPA distribution of the respondent. Majority of the respondents



lies in 3.10 CGPA the minimum CGPA is 2.00 and the maximum is 4.00.

4.3 Age of respondent

		Frequency	Percent	Valid Percent	Cumulative percent
Valid	19	42	10.5	10.5	10.5
	20	52	13.0	13.0	23.5
	21	40	10.0	10.0	33.5
	22	72	18.0	18.0	51.5
	23	83	20.8	20.8	72.3
	24	44	11.0	11.0	83.3
	25	28	7.0	7.0	90.3
	26	21	5.3	5.3	95.5

27	12	3.0	3.0	98.5
28	3	.8	.8	99.3
29	1	.3	.3	99.5
33	1	.3	.3	99.8
35	1	.3	.3	100.0
Total	400	100.0	100.0	

Table 1.2 shows the age of the respondent. Majority of the respondents age are 23 minimum is 19 and maximum is 35.

4.4 Bar Chart

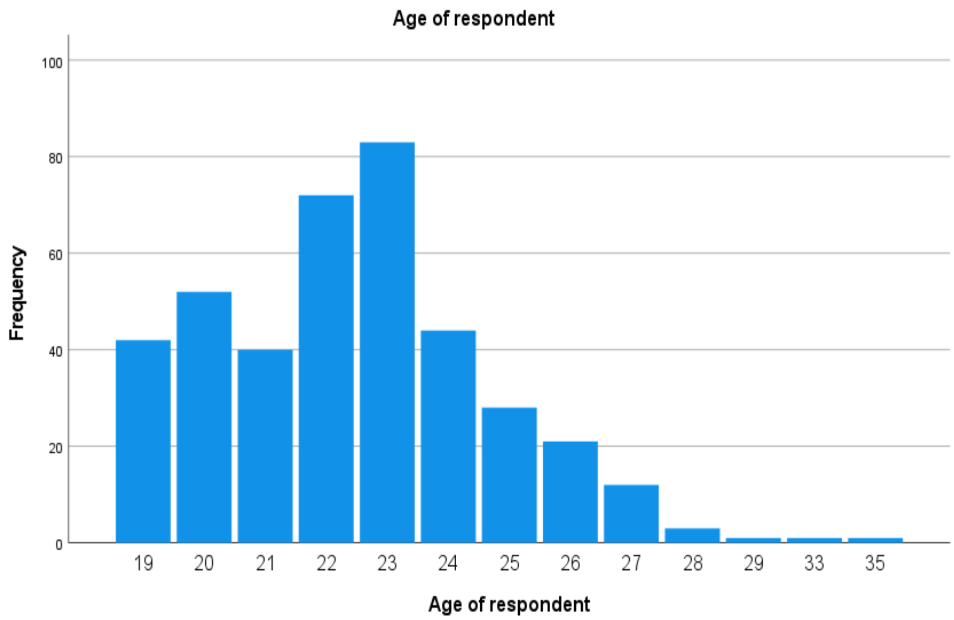
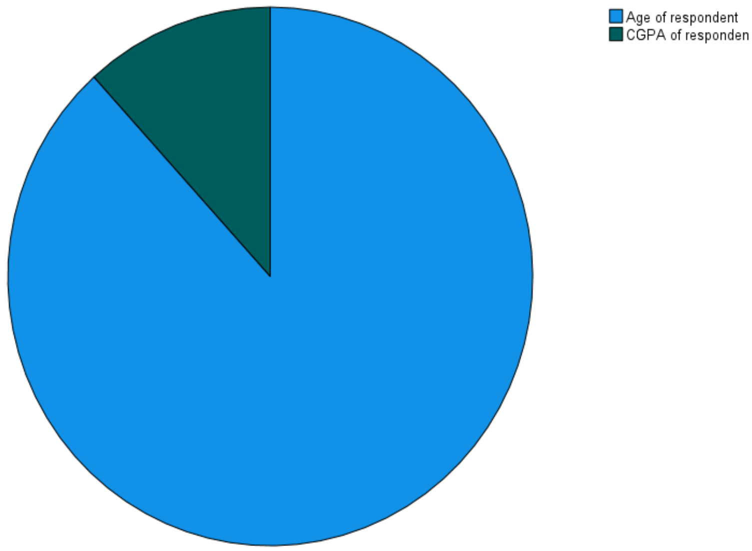
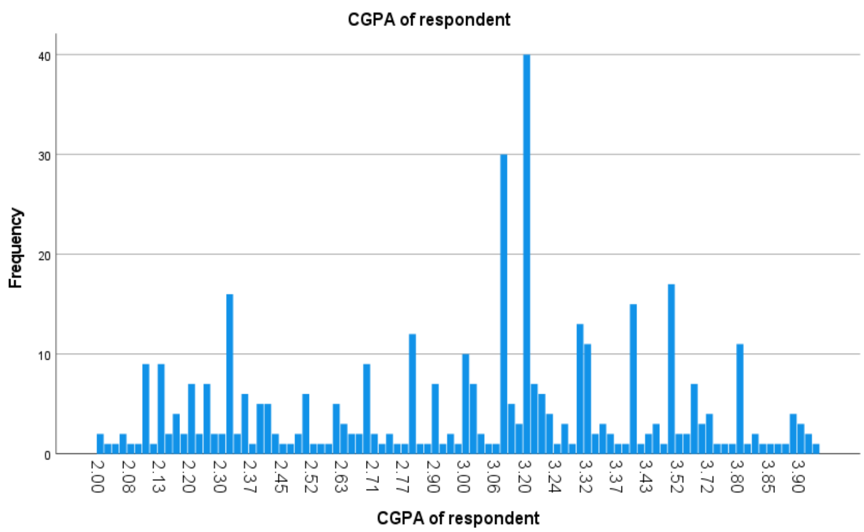


Figure 1.2 shows the age of the respondent. Majority of the respondents age are 23 minimum is 19 and maximum is 35.

Pie Chart 1.3



Simple bar chart 1.4



		Age of respondent	SMA_Mean
Age of respondent	Pearson Correlation	1	-.156**
	Sig. (2-tailed)		.002
	N	400	395
	Pearson Correlation	-.156**	1

	Sig. (2-tailed)	.002	
	N	395	395

4.5 Correlations
Weak negative correlation (Pearson's $r = -0.156$, $p < 0.01$) between the "Age of respondent" and "SMA Mean." As age increases, the SMA Mean slightly decreases, but the relationship is weak. The analysis includes 400 respondents for age and 395 for SMA Mean. Overall, older respondents tend to have lower SMA Means, though the effect is minimal.

4.6 Bayesian Estimates of Coefficients[a,b,c]

	Posterior			95% Credible Interval	
Parameter	Mode	Mean	Variance	Lower Bound	Upper Bound
HOSTEL = YES	2.974	2.974	.001	.008	.001
HOSTEL = NO	2.991	2.991	.002	2.912	3.069
HOSTEL = 11.00	3.200	3.200	.267	2.186	4.214

a. Dependent Variable: CGPA of respondent

b. Model: HOSTEL

c. Assume standard reference priors.

The model predicts "CGPA of respondent" based on the "HOSTEL" variable, which includes three categories: "YES," "NO," and "11.00." Posterior estimates for each coefficient show slight differences, with "HOSTEL = YES" having a marginally lower CGPA compared to the other categories. However, these differences are small, and the 95% credible intervals overlap, indicating weak evidence for any significant impact. Further research with larger samples is needed for stronger conclusions.

4.7 Bayesian Estimates of Error Variance[a]

	Posterior			95% Credible Interval	
Parameter	Mode	Mean	Variance	Lower Bound	Upper Bound
Error variance	.265	.267	.000	.003	.007

a. Assume standard reference priors.

The Bayesian estimates for the error variance show a posterior mode of 0.265, mean of 0.267, and a 95% credible interval between 0.003 and 0.007, indicating low error variance. This suggests the model's predictions are likely accurate, though other factors like model fit should be considered.

4.8 One-Sample Statistics
The table shows descriptive statistics for "HOSTEL" and "CGPA of respondent" based on a sample of 400 respondents. The average hostel stay is about 1.45 years (SD = 0.68786), and the mean CGPA is 2.98 (SD = 0.51467), indicating moderate variability. The small standard errors (0.00439 for hostel stay and 0.00573 for CGPA) suggest accurate estimates of the population means.

	N	Mean	Std. Deviation	Std. Error Mean
HOSTEL	400	1.4450	.68786	.00439

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
HOSTEL	42.014	399	.000	1.44500	1.3774	1.5126
CGPA of respondent	115.871	399	.000	2.98176	2.9312	3.0323

CGPA of respondent	400	2.9818	.51467	.00573

1.6:The table summarizes one-sample t-test results for "HOSTEL" and "CGPA of respondent." Key findings include:
Test value: 0, representing the null hypothesis that the population mean equals 0.
t-statistic: 42.014 for "HOSTEL" and 115.871 for "CGPA," showing strong evidence against the null hypothesis.
Degrees of freedom (df): Both tests have 399 df.
Sig. (2-tailed): Both p-values are 0.000, indicating strong significance.
Mean difference: 1.4450 for "HOSTEL" and 2.9818 for "CGPA."
95% confidence intervals: (1.3774, 1.5126) for "HOSTEL" and (2.9312, 3.0323) for "CGPA."
In conclusion, the t-tests suggest that the population means for both variables differ significantly from 0.

4.9 One-Sample effect sizes

		standardizer[a]	point Estimate	95% (c I) lower	upper
HOSTEL	cohen's d	.68786	2.101	1.925	2.276
	hedges' correction	.68916	2.097	1.921	2.272
CGPA of respondent	Cohen's d	.51467	5.794	5.380	6.207
	Hedges' correction	.51564	5.783	5.369	6.195

Table 1.7
a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation.
Hedges' correction uses the sample standard deviation, plus a correction factor.

The table shows effect sizes for "HOSTEL" and "CGPA of respondent," calculated using Cohen's d and Hedges' correction.
Effect size: Both methods assess the difference between the sample mean and the hypothesized population mean.
Point estimate: Cohen's d estimates are 2.101 for "HOSTEL" and 5.794 for "CGPA," while Hedges' correction gives 2.097 and 5.783, respectively, indicating large effects.
95% confidence intervals: These indicate where the true effect size likely falls.
Interpretation: Both variables show large effect sizes, significantly above 0.80.
In summary, the results suggest substantial differences between the sample and hypothesized means.

4.10 Regression

Table 1.8: Variables entered/Remove

model	**variables entered**	**Variables remove**	**method**

1	**age of respondent[b]**		**enter**

a. Dependent variable: CGPA of respondent
b. All requested variables entered

Model Summary[b]

model	R	R-square	Adjusted R square	Std. Error of the estimate	Durbin Watson
1	.75[a]	.031	.028	.50738	1.499

a. Predictors: (constant), age of the respondent
b. Dependent variable: CGPA of the respondent

Table (1.9)
The regression analysis reveals that the model, which includes a constant and the respondent's age, accounts for 3.1% of the variation in CGPA ($R^2 = 0.031$). The adjusted R^2 is 0.028, and the standard error of 0.50738 suggests moderate predictive accuracy. With a Durbin-Watson value of 1.499, there is no evidence of significant autocorrelation in the residuals. Overall, the model explains only a small fraction of the variance in CGPA.

ANOVA[a]

model	Sum of squares	df	mean square	F	Sig.
Regression	3.229	1	3.229	12.541	.000b
Residual	102.459	398	.257		
Total	105.688	399			

a. Predictors: (constant), age of the respondent
b. Dependent variable: CGPA of the respondent

Table 2.1
The ANOVA analysis shows that the regression model, which incorporates a constant and the respondent's age, is statistically significant. The regression sum of squares is 3.229, and the residual sum of squares is 102.459. The F statistic is 12.541, with a significance level of 0.000, indicating strong evidence that the predictors account for a significant portion of the variance in CGPA.

Coefficients[a]

model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% (C.I) for B	
	B	Std. Error	Beta			lower bound	upper bound
(Constant)	2.110	.247	.175	8.528	.ooo	1.624	2.597
age of respondent	.039	.011		3.541	.000	.017	.060

Table 2.2 The regression analysis shows that both the constant and "age of the respondent" are significant predictors of CGPA. The unstandardized coefficient for age is 0.039, indicating a slight increase in CGPA with age. The standardized coefficient (Beta) for age is 0.017, suggesting a weak effect. Both predictors have significance levels of 0.000, and their confidence intervals do not include 0, supporting their significance.

4.11 Correlation Coefficients[a]

Model	age of respondent
Correlation age of respondent	1.000
Covariances age of respondent	.000

a. dependent variable CGPA of respondent

Table 2.3 The correlation coefficient for the "age of respondent" with itself is 1.000, indicating a perfect positive correlation. The covariance is 0.000, reflecting that a variable is perfectly correlated with itself.

4.12 Residual Statistics

	minimum	maximum	mean	Std. Deviation	N
Predicted values	2.8480	3.4693	2.9818	.08995	400
Residual	-1.04632	1.07203	.00000	.50674	400
Std. predicted value	-1.487	5.420	.000	1.000	400
Std. Residual	-2.062	2.113	.009	.999	400

The residual statistics for the regression model show the following key findings:
Minimum and maximum predicted values: 2.8480 and 3.4693.
Mean of residuals: 0.000, indicating an unbiased model.
Standard deviation of residuals: 0.50674, reflecting variability.
Minimum and maximum residuals: -1.487 and 5.420, indicating the range of model errors.
Standard predicted value: 0.009, representing the standard deviation of predicted values.
Standard residual: 1.000, the standardized residuals.
Overall, the statistics provide insights into the model's accuracy and performance.

5. Discussion and Conclusion

This research focused on examining the impact of social media addiction on the academic performance of university students in Peshawar. The main objective was to identify students who show signs of addiction to social media. Furthermore, the study aimed to determine whether there is a correlation between excessive social media use and lower CGPAs, as well as to assess the broader implications of social media addiction on academic success. A questionnaire was developed, and a sample of 400 students from various departments at the University of Peshawar was selected through simple random sampling. This sample included both students living in hostels and those who did not.

To analyze the data, several statistical techniques were employed, including correlation analysis, one-sample T-tests, one-way ANOVA, along with visual aids such as bar charts, pie charts, and histograms for effective result comparison.

The findings revealed that a significant number of students are impacted by social media addiction. The outcomes of the correlation analysis, ANOVA, and T-tests confirmed the widespread nature of social media addiction among the student body, producing statistically significant results. The study concluded that a considerable proportion of the University of Peshawar's students struggle with social media addiction, which leads to inefficient time management and ultimately results in lower CGPAs.

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