

Student Sleep & Social Media Behavior

STAT 311 Regression Analysis, Fall 2025

Professor Premarathna

Alyson Her

Owen Larson

12/02/2025

Introduction

Since the 1990s social media has become an integral part of the modern world. It has reshaped how people communicate, learn, and build relationships. However its influence extends across education, health, and personal well-being in complex ways.

The *Students' Social Media Addiction* dataset, available on Kaggle, is a multi-country survey that recruited students ages 16-25 enrolled in high school, undergraduate, or graduate programs in 2025. 705 students completed the one-time online survey, collecting the students' demographic information, measures of social media use, and its impact on academic performance, mental health, sleep, and relationships.

The purpose of this paper is to investigate the multifaceted relationship between sleep and social media behavior. We not only to predict sleep patterns but also to interpret the data accurately, ensuring that the findings are both meaningful and reliable for understanding how social media and additional underlying factors affects student well-being

Data

Study Design and Data Description

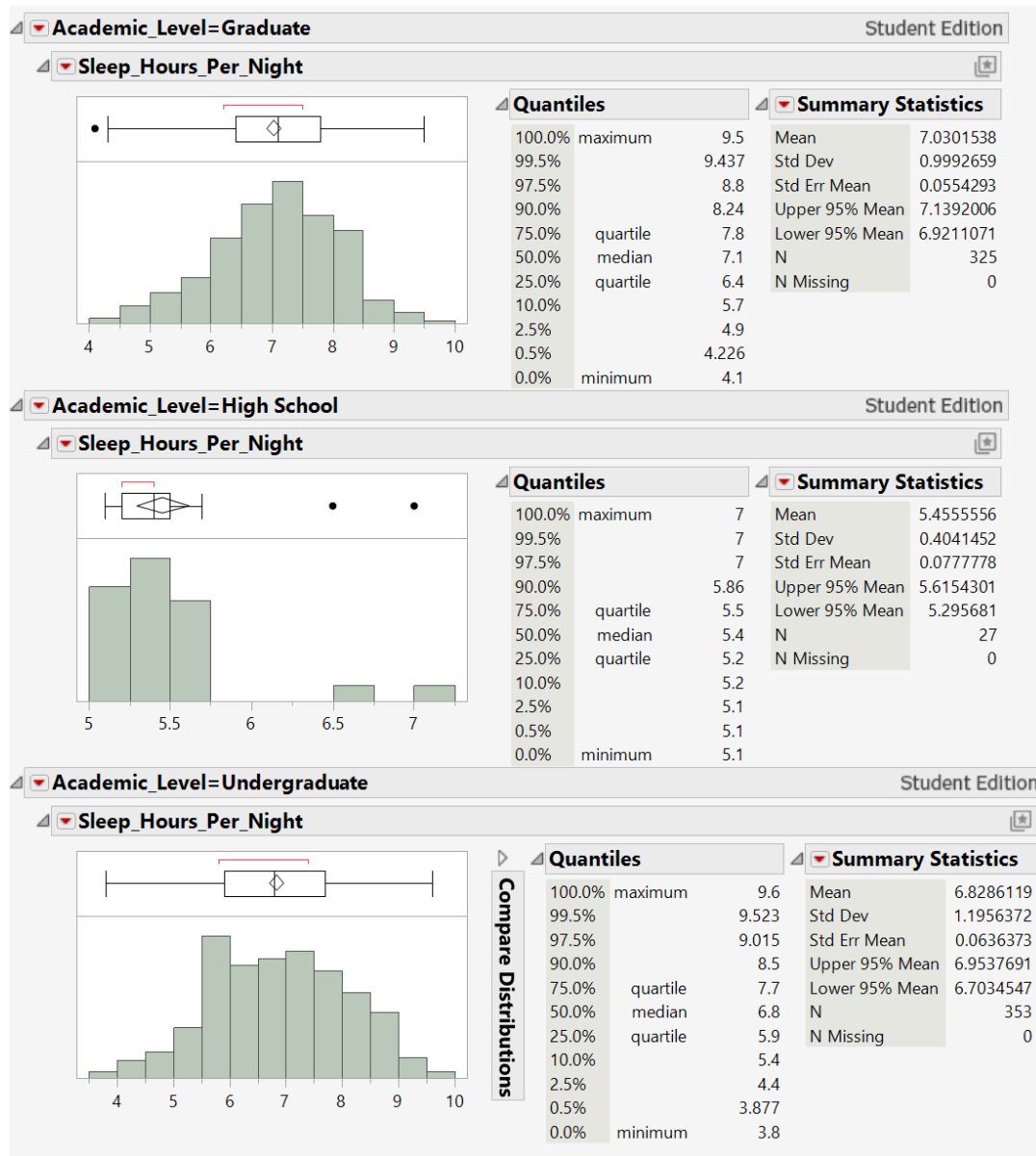
The *Students' Social Media Addiction* dataset includes:

Variable	Description	Type
Sleep_Hours_Per_Night (Y)	Average nightly sleep hours	Continuous

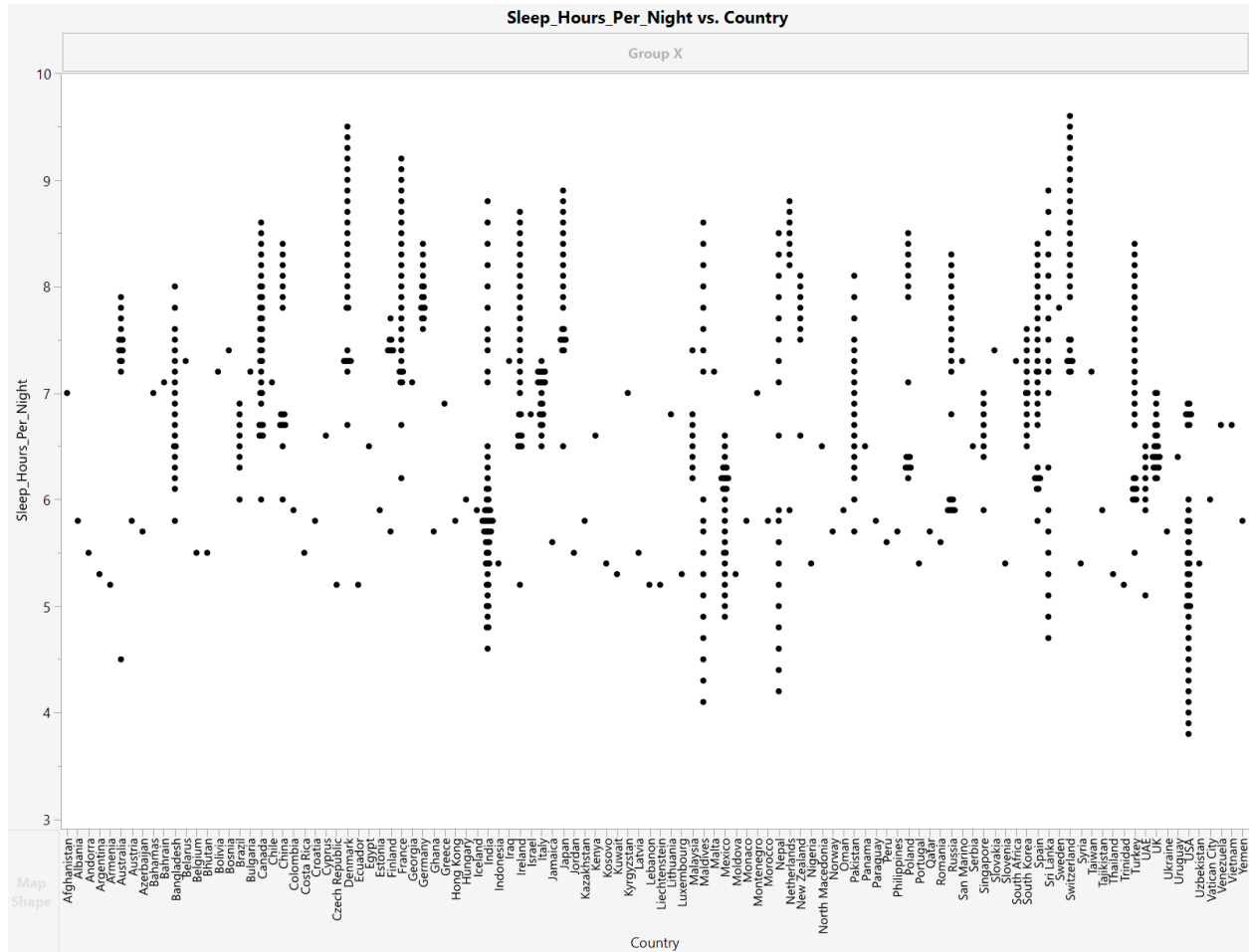
Avg_Daily_Usage_Hours (x_1)	Average hours per day on social media	Continuous
Addicted_Score(x_4)	Social Media Addiction Score (1 = low to 10 = high)	Continuous
Conflicts_Over_Social_Media(x_3)	Number of relationship conflicts due to social media	Continuous
Mental_Health_Score (x_2)	Self-rated mental health (1 = poor to 10 = excellent)	Continuous
Academic_Level	High School / Undergraduate / Graduate	Nominal
Country	Country of residence	Nominal

Descriptive Statistics and Exploratory Visuals

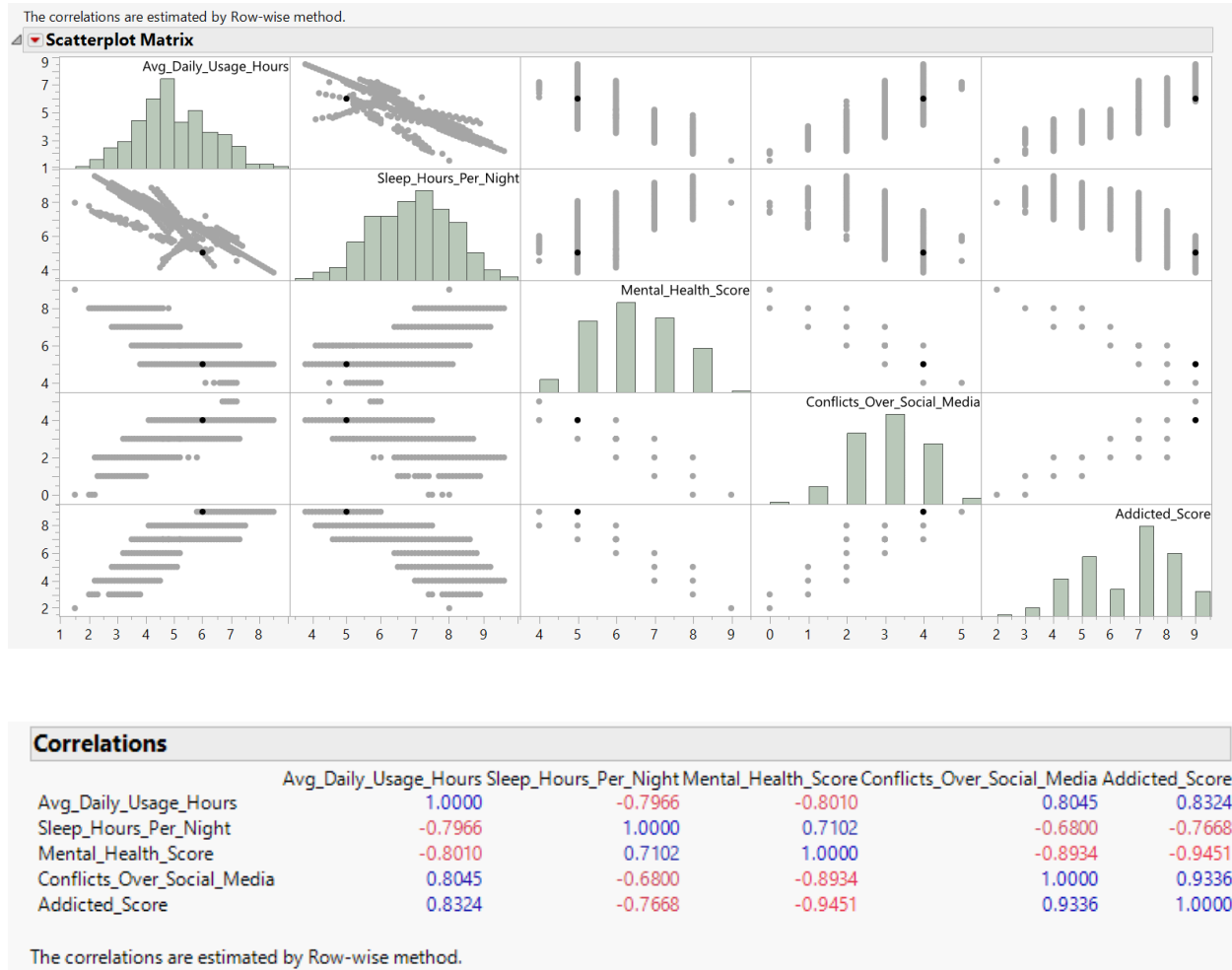
- Sleep: mean= 6.9 hours, max= 9.6 hours, min= 3.8 hours
- Avg Daily Usage Hours: mean= 4.9, max= 8.5 hours, min 1.5, slightly right skewed indicating lower usage hours were more common
- Addicted score: mean= 6.4, max= 9, min=2, left-skewed, occasional high scores
- # of conflicts: mean= 2.8, max= 5, min=0, slightly left-skewed, some high numbers of conflicts
- Mental Health: mean = 6.2, max=9, min=4, slightly right skewed, most neither



When comparing sleep hours to academic level we see that undergraduates and graduates sleep relatively the same hours. Graduates tend to get more sleep while undergraduates sleep a little less. However, high schoolers were extremely right skewed due to the smaller sample size. On average, high schoolers slept 2 hours less than the other groups. We do want to mention that the range of sleep is capped at 10 hours, which may limit our ability to fully capture the upper range of the sample's sleep behavior.



The survey was conducted across 110 countries, but sample sizes were not evenly distributed. Smaller countries, particularly African and Caribbean countries, had less student participants. Despite these differences, the overall pattern is similar to what we observed with academic level: sleep varies from country to country, but most students report between 6 and 8 hours per night. This lines up with the overall median of 6.9 hours, showing a consistent trend across the dataset despite uneven representation.



The scatter matrix overall shows very strong linear correlation between sleep hours, social media addiction score, daily usage hours, mental health score, and number of relationship conflicts. This means the data has multicollinearity, making it hard to understand how these predictors actually influence sleep. This is further proven by the very high correlations, all greater than ± 0.60 .

Overall, there were no missing data. There do seem to be outliers within the groups but these may be removed later if proven to be significantly influential. Our main problem is deciding how to approach building our models with extreme multicollinearity.

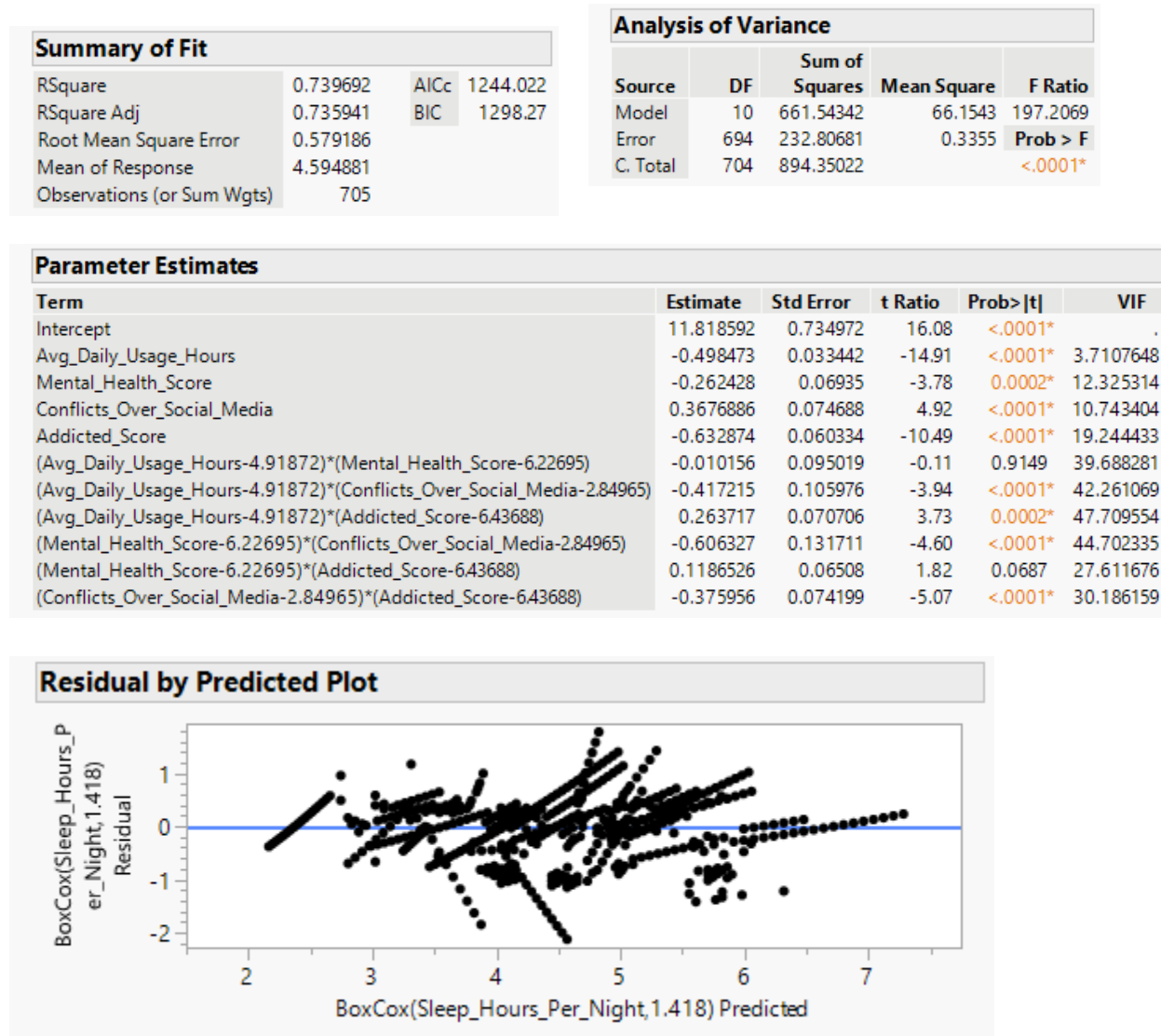
Statistical Methods

We want to understand:

- Is less sleep associated with low mental health, high hours on social media, and addiction score?
- What predictors can best predict hours of sleep?
- What underlying factors contribute to sleep?

Before starting model building we assessed the normality using the Shapiro-Walker test. All regular and transformed model residuals rejected the null, meaning it did not pass the normality test. We ultimately decided to do a mix of methods, mainly a Box-Cox transformation or Weighted Least Squares (WLS).

Model 1: Box-cox of Numerical predictors and two-way interactions



For model 1, average usage hour, mental health, number of conflicts, addition score, and their interactions were centered and transformed using box-cox after removing outliers with large residuals. We can see that this model p-value < 0.05, rejects the null. Although the model explains 74% of the variance in sleep hours, the remaining unexplained variance and diagnostic issues limit its practical predictive accuracy. High variance inflation (VIF) values indicate

multicollinearity, which inflates standard errors and makes it difficult to interpret individual coefficients even after controlling for other predictors.

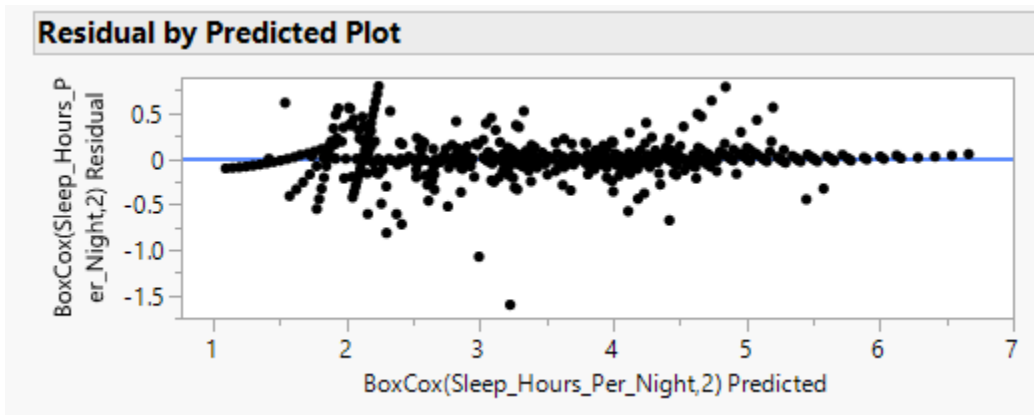
The residual plot shows no obvious curvature, but the fanning pattern suggests heteroscedasticity, consistent with earlier tests indicating non-constant variance and normality issues. Together, these issues undermine both predictive reliability and coefficient interpretability, suggesting this model is not an appropriate fit for the data and improvements could be made.

Model 2: Box-cox of Numerical, Categorical predictors, and two-way interactions

Summary of Fit			
RSquare	0.974421	AICc	279.4114
RSquare Adj	0.962169	BIC	1103.62
Root Mean Square Error	0.220995		
Mean of Response	3.496526		
Observations (or Sum Wgts)	705		

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	228	885.58371	3.88414	79.5300
Error	476	23.24720	0.04884	Prob > F
C. Total	704	908.83092		<.0001*

Parameter Estimates						
Term		Estimate	Std Error	t Ratio	Prob> t	VIF
Academic_Level[High School]*Country[Turkey]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[UAE]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[UK]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[Ukraine]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[Uruguay]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[USA]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[Uzbekistan]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[Vatican City]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[Venezuela]	Zeroed	0	0	.	.	0
Academic_Level[High School]*Country[Vietnam]	Zeroed	0	0	.	.	0
Academic_Level[Graduate]*(Avg_Daily_Usage_Hours-4.91872)	Biased	-0.243685	0.041588	-5.86	<.0001*	38.319678
Academic_Level[High School]*(Avg_Daily_Usage_Hours-4.91872)	Zeroed	0	0	.	.	0
Academic_Level[Graduate]*(Mental_Health_Score-6.22695)	Biased	-5.796796	1.170212	-4.95	<.0001*	22754.603
Academic_Level[High School]*(Mental_Health_Score-6.22695)	Zeroed	0	0	.	.	0
Academic_Level[Graduate]*(Conflicts_Over_Social_Media-2.84965)	Biased	-5.416897	1.051843	-5.15	<.0001*	13593.131
Academic_Level[High School]*(Conflicts_Over_Social_Media-2.84965)	Zeroed	0	0	.	.	0
Academic_Level[Graduate]*(Addicted_Score-6.43688)	Biased	-0.31082	0.219888	-1.41	0.1582	1645.0325
Academic_Level[High School]*(Addicted_Score-6.43688)	Zeroed	0	0	.	.	0
Country[Afghanistan]*(Avg_Daily_Usage_Hours-4.91872)	Zeroed	0	0	.	.	0
Country[Albania]*(Avg_Daily_Usage_Hours-4.91872)	Zeroed	0	0	.	.	0
Country[Andorra]*(Avg_Daily_Usage_Hours-4.91872)	Zeroed	0	0	.	.	0
Country[Argentina]*(Avg_Daily_Usage_Hours-4.91872)	Zeroed	0	0	.	.	0



Model 2 follows the same procedure as model 1, centering and box-cox transformation, but expands the predictors to include academic level and 110 countries along with their interactions.

This dramatically increases the model complexity. We observed significant increase in $\text{adj } R^2$ and a decrease in both ACC and BC metrics, suggesting improved fit. The model is significant at the 0.05 level which initially appears good. However, closer examination of the parameter estimates reveals severe multicollinearity. VIF values are even more extreme than in Model 1, with many

being 0, meaning there are structural issues in the data or model. Ideally, VIF should be between 1 and 5, anything outside of this range indicates instability in coefficient estimation and inflated standard errors.

These drastic changes are likely from overfitting due to the model's complexity and high dimensionality. While Model 2 outperforms Model 1 in predictive accuracy, residuals still show heteroscedasticity. Although we cannot make meaningful interpretations, country and academic level have proven to be significant predictors of sleep. Our next approach is to further refine the model to improve predictive ability and interpretability by reducing the dimensionality and accounting for unequal variance.

Model 3: Weighted final model with key interaction effects

Model 2 incorporated Academic Level and several behavioral interaction terms, improving interpretability but revealing persistent heteroscedasticity and some unnecessary complexity. Before finalizing the specification, additional demographic and categorical variables including: Age, Academic Level, and Relationship Status, were re-evaluated using a stepwise selection procedure. The stepwise process showed that while Academic Level and Relationship Status produced only small explanatory gains, their inclusion slightly reduced AIC and BIC when treated as control variables with interactions and combining relationship status of single and in relationship.

Further inspection indicated that Age interacts meaningfully with average daily social-media use, moderating its negative effect on sleep. Relationship Status also exhibited a statistically significant contrast: participants reporting "Complicated" relationships slept differently

(typically less) than those who were single or in a relationship, even after accounting for other predictors.

Attempts to include multiple categorical factors simultaneously (e.g., Country, Academic Level, and Relationship Status) increased complexity and information criteria, so only the most informative categories were retained. The Country variable was kept using stepwise-defined regional groupings to capture cultural differences without overparameterization.

Finally, to correct some of the residual fanning observed in Model 2, the model was refitted using WLS with weights of $1 / \hat{y}$, this helped stabilize variance and make predictions more viable across the full range of sleep hours (unweighted AICc and BIC included). We also removed five statistical oddities wherein our data could not explain the lack of sleep, their studentized residuals were over 5. The resulting Model 3 balances interpretability, expected behavior regarding our variables, and explanatory power; Capturing key behavioral and demographic influences while maintaining excellent model efficiency.

Results

Effect test: Here are the top 20 effects, although there are 56 effects total, the effect tests revealed that all key behavioral predictors: average daily usage, addiction score, mental health score, and conflicts over social media were highly significant ($p < 0.001$), along with several critical interactions. Age showed both a direct effect and an interaction with social media use, suggesting usage impacts sleep differently across age groups. Academic Level and mainly its interactions were also significant, indicating that the influence of social media habits on sleep varies across education levels (graduate vs undergrad). Additionally, most regional groupings were statistically

significant, reflecting meaningful cross cultural differences in sleep behavior after accounting for our individual and psychological factors.

Interpretation of Region combinations and high P values

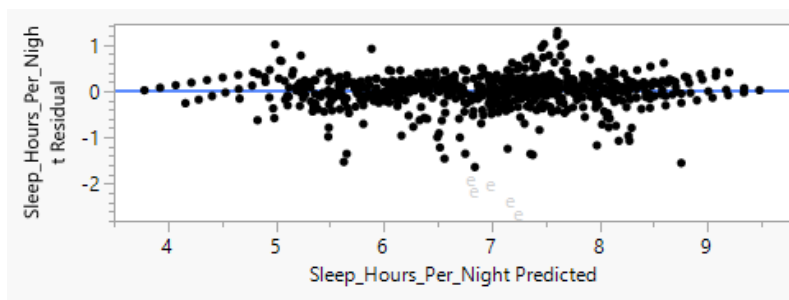
The dataset originally included a large number of individual countries, so we applied JMP's

Analysis of Variance					Summary of Fit			
Source	DF	Sum of Squares	Mean Square	F Ratio	RSquare	0.906018	AICc	-697.088
Model	57	121.38290	2.12952	108.5812	RSquare Adj	0.897674	BIC	-439.636
Error	642	12.59108	0.01961	Prob > F	Root Mean Square Error	0.140044		
C. Total	699	133.97398		<.0001*	Mean of Response	6.709425	AICc	663.9864
					Observations (or Sum Wgts)	104.3459	BIC	913.0989

stepwise regression to merge those with statistically similar effects on sleep hours into broader regional clusters. These clusters represent similar behavioral patterns across variables and interactions rather than strict geographic proximity, which explains why some combinations appear unconventional (for example, the United States grouped with Indonesia or Slovenia). This data driven grouping captures cross cultural similarities in social media and sleep behaviors while maintaining model simplicity. A subset of regional clusters, approximately 80 percent of those showing statistical significance, was retained to achieve a balance between explanatory power and practical interpretability.

Source	1	1	0.9115822	46.4802	<.0001
Age	1	1	1.2681454	64.6608	<.0001
Avg_Daily_Usage_Hours	1	1	1.0899585	55.5753	<.0001
Mental_Health_Score	1	1	2.7598949	140.7228	<.0001
Conflicts_Over_Social_Media	1	1	0.1081133	5.5125	0.0192
Addicted_Score	1	1	0.8588897	43.7935	<.0001

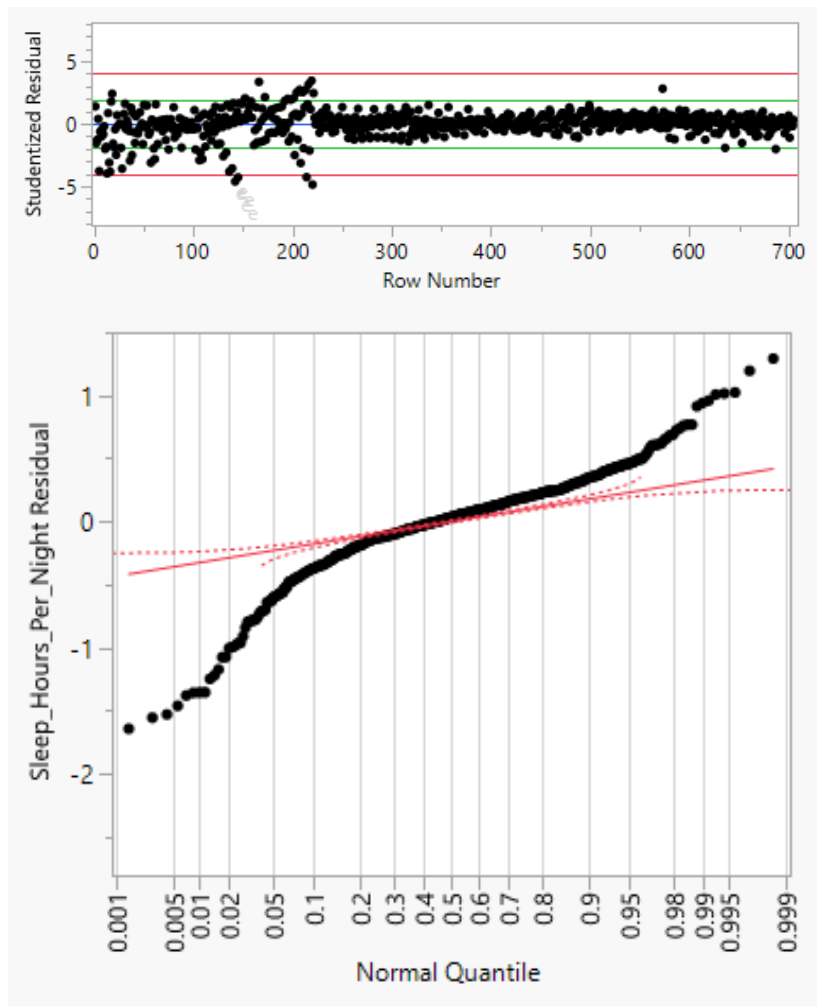
Age*Avg_Daily_Usage_Hours	1	1	1.58564	80.8493	<.0001
Mental_Health_Score*Conflicts_Over_Social_Media	1	1	0.0234687	1.1966	0.2744
Conflicts_Over_Social_Media*Addicted_Score	1	1	3.5848677	182.7869	<.0001
Global Mixed Region (Baseline)	1	1	0.9950239	50.7347	<.0001
Global Cluster vs. Southern–Asian Group	1	1	0.0620918	3.166	0.0757
Western Global vs. Eastern Eurasian Cluster	1	1	0.0546657	2.7873	0.0955
Globalized vs. Mixed Developing Regions	1	1	0.2514178	12.8194	0.0004
Low-Engagement vs. High-Engagement Regions	1	1	0.211685	10.7935	0.0011
Low-Connectivity vs. High-Connectivity Regions	1	1	0.2737015	13.9556	0.0002
U.S. vs. Developing & Transitional Regions	1	1	1.1001039	56.0926	<.0001
Transitional Eurasia vs. Developed Global Regions	1	1	0.5503956	28.0638	<.0001
Mexico vs. Smaller Global Regions	1	1	0.9540086	48.6434	<.0001
South Asia & Central Europe vs. Urbanized Global Regions	1	1	0.2886889	14.7198	0.0001
Central Europe vs. South Asia	1	1	0.4767032	24.3064	<.0001



Residual Diagnostics

Residual analyses confirm that the final weighted model meets some key assumptions from the predicted plot; we see no clear pattern or curvature aside from the tails, indicating reduced heteroscedasticity. Studentized residual plot reveals several outside of the ideal range, suggesting heavier tails and some influential observations. After excluding statistical oddities no evidence of structural bias or model misspecification. The normal QQ plot similarly shows mild tail

deviations, consistent with the slightly tailed residual distribution noted earlier. Overall, while a few outliers persist, the residuals behave predictably, supporting the model's validity and interpretive reliability. Taken together, these diagnostics tell us that model 3 provides a well balanced and statistically sound representation of the relationship between social media use and sleep duration.



Model Validation

To evaluate the generalizability and ensure we weren't overfitting, a random 70/30 data split was

Summary of Fit				Summary of Fit			
RSquare	0.919574	AICc	-510.461	RSquare	0.90726	AICc	-134.171
RSquare Adj	0.908851	BIC	-294.954	RSquare Adj	0.883343	BIC	15.12856
Root Mean Square Error	0.128854			Root Mean Square Error	0.156777		
Mean of Response	6.70295			Mean of Response	6.721965		
Observations (or Sum Wgts)	68.81338			Observations (or Sum Wgts)	35.53248		

performed (weighted with the same weights), creating independent training and validation subsets. Here we have the training summary of fit on the left and validation summary on the right, the model achieved an R^2 of 0.92 on the training data and 0.91 on the validation data, with corresponding RMSE values of 0.1289 and 0.1568, respectively. The small difference between these metrics indicates that Model 3 maintains strong predictive accuracy when applied to

Lack Of Fit					Lack Of Fit				
Source	DF	Sum of Squares	Mean Square	F Ratio	Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	393	6.6860391	0.017013	5.3287	Lack Of Fit	185	4.6593556	0.025186	11.8166
Pure Error	12	0.0383124	0.003193	Prob > F	Pure Error	5	0.0106569	0.002131	Prob > F
Total Error	405	6.7243516		0.0011*	Total Error	190	4.6700125		0.0054*
			Max RSq	0.9995				Max RSq	0.9998

unseen observations. Although the lack-of-fit tests were statistically significant ($p < 0.01$), this outcome is common in large, complex models and does not suggest major specification issues, as the residual diagnostics showed no visible bias or structural trend. Overall, validation results confirm that the final weighted model is both stable and reliable in explaining variation in sleep duration across different demographic and behavioral contexts.

Conclusion

Through a stepwise data driven modeling approach, this project explored how behavioral and demographic factors influence sleep duration in the context of social media use. Average daily usage, social media conflict, and addiction scores emerged as the strongest and most consistent predictors of reduced sleep, while mental health scores interacted with these variables to amplify the effects. Including age revealed a moderating role, older participants showed a weaker negative relationship between social media use and sleep, and the addition of regional clusters captured more broad cultural similarities in online behavior and sleep habits.

The final weighted least squares model achieved an R^2 of 0.90 and demonstrated strong goodness of fit, effectively correcting the heteroscedasticity observed in earlier models. Residual diagnostics confirmed balanced variance and minimal bias after removing statistical oddities. Although a few regional contrasts and higher order interactions had weaker statistical support, their inclusion enhanced the models explanatory power without compromising efficiency.

Limitations of this analysis include reliance on self reported data, uneven sampling across regions, and the cross sectional nature of the dataset itself, which restricts cause and effect explanatory power. Nonetheless, the findings consistently show social and emotional factors surrounding media use, especially conflict, addiction, and mental health, were far more influential on sleep duration than usage time alone. Age also moderated the relationship between screen time and sleep, with younger participants being more negatively affected by heavy usage. Relationship stress and cultural context further shaped sleep outcomes, as participants in “complicated” relationships and those from certain regional clusters reported systematically lower sleep despite similar behavioral patterns. Our results demonstrate that social media usage is associated with sleep and mental health status of students worldwide.

Appendix

