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An AI-Driven Predictive Regression Approach to Examine Social Media's Effect on Student Academic Performance

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Abstract

Social media has become an integral part of student life, influencing communication, collaboration, and learning behaviors. While it provides valuable opportunities for academic engagement, excessive use can lead to distractions and diminished academic outcomes. This study examines the impact of Social Media Usage (SMU) on Student Academic Performance (SAP), with a focus on how demographic factors such as gender, department, and program type shape social media behaviors. It also investigates the application of statistical and machine learning techniques to predict academic outcomes and develop AI-driven dashboards for identifying at-risk students.

A structured questionnaire was distributed to 150 students from selected colleges, resulting in 135 responses. After validating the data for completeness and accuracy, 80 responses were retained for analysis. Using a Simple Random Sampling (SRS) method ensured unbiased representation of participants. The collected data comprised demographic variables, social media usage patterns, and academic performance indicators. Correlation analysis was used to identify relationships between variables, ANOVA examined demographic influences, and linear regression assessed predictive effects. Additionally, machine learning methods were integrated to improve predictive accuracy and reveal hidden patterns in the data.

The findings reveal that SMU has a significant and measurable impact on SAP, with both positive and negative effects depending on usage patterns. Demographic factors such as gender, department, and program type significantly moderated the relationship between social media engagement and academic performance. Moreover, the AI-driven dashboards effectively identified students at risk of underperformance, offering educators a visual and actionable tool to design targeted interventions.

This study provides valuable insights for students and educators seeking to strike a balance between social media engagement and academic success. By combining traditional statistical methods with machine learning and AI-based visualization, the research demonstrates a comprehensive and practical framework for understanding and managing the complex interplay between social media behavior and academic performance. These insights can inform institutional strategies aimed at promoting responsible social media use and supporting at-risk students in higher education.

Keywords: Social Media Usage, Academic Performance, Machine Learning, Regression Analysis, AI Dashboards, At-Risk Students

I. Introduction

1. Background and Context

The widespread adoption of social media has fundamentally transformed the way students communicate, interact, and access information. Platforms such as Facebook, Instagram, WhatsApp, YouTube, and Twitter/X have become deeply integrated into students' daily routines, influencing not only personal interactions but also academic behaviors. Social media provides a virtual environment where students can exchange ideas, collaborate on assignments, access academic resources, and participate in discussion forums. (Al Mosharrafa, 2024; Bhandarkar, 2021)

These platforms are not merely tools for socializing; they have emerged as potential facilitators of collaborative learning, peer engagement, and lifelong learning opportunities. (Ashraf, 2021; Sharma, 2022).

Over the past decade, social media has shifted from a leisure activity to a key tool for communication and knowledge sharing. Students now spend 2–5 hours daily on various platforms, often multitasking. While purposeful use can enhance learning and networking, excessive or unstructured use is linked to distractions, procrastination, and reduced academic performance. Issues like FOMO and constant notifications contribute to cognitive overload and fragmented attention.

Given its widespread use, understanding social media's impact on academic behavior is crucial. While some studies highlight its educational benefits—such as collaborative learning and easy access to resources—others point to negative effects like lower grades and sleep disruption. This mixed evidence underscores the need for systematic, data-driven research to clarify social media's true influence on student outcomes.

Social Media

Social media refers to digital platforms that allow users to create, share, and interact with content. Its key features include interactivity, real-time communication, user-generated content, and community building. These platforms are used for communication, education, marketing, entertainment, and networking.

Types of Social Media:

- Social Networking (Facebook, LinkedIn)
- Media Sharing (Instagram, YouTube)
- Microblogging (X/Twitter, Tumblr)
- Discussion Forums (Reddit, Quora)
- Messaging Apps (WhatsApp, Telegram)

- Professional Sites (LinkedIn, AngelList)

Usage Among Adolescents:

Students typically spend 2–5 hours daily on social media. While such use can lead to distractions, poor sleep, and reduced focus, it also supports collaborative learning, peer engagement, and access to educational content.

Social Media Multitasking:

Over 90% of students multitask with social media while studying. Research shows this behavior reduces cognitive performance, weakens memory retention, and lowers academic scores. For example, students multitasking during lectures scored 11% lower on post-tests.

2. Academic Performance and Digital Behavior

Academic performance (SAP) reflects both quantitative outcomes (GPA, grades) and qualitative indicators (engagement, retention). The rise of digital tools and social media has reshaped how students learn and interact. Purposeful social media use—like joining study groups or accessing tutorials—can enhance learning, motivation, and collaboration. However, excessive or distracted usage often leads to procrastination, reduced concentration, and lower academic performance due to cognitive overload (Bou-Hamad, 2020).

3. Demographic Influences on Social Media Usage

Demographic factors—such as gender, age, academic discipline, and year of study—significantly influence how students use social media. Female students often use it for social and academic communication, while males may lean toward entertainment or professional networking. STEM students typically engage with technical platforms like YouTube, whereas humanities students prefer collaborative tools. Younger students tend to multitask and show higher activity levels, while older students use social media more strategically. Understanding these patterns helps tailor interventions to specific student groups.

4. Dual Impact of Social Media on Academic Performance

Social media presents both opportunities and risks in academic contexts. It supports collaborative learning, peer interaction, and access to educational resources, enhancing academic engagement. However, excessive or unregulated use—especially during lectures or late at night—can harm focus, sleep, and overall academic outcomes. This dual impact highlights the importance of promoting purposeful usage while addressing potential distractions.

5. Predictive Analytics and AI Dashboards

While traditional statistical methods (e.g., correlation, regression) help quantify social media's impact on performance, they struggle with complex data patterns. Machine learning (ML) overcomes these limits by identifying nuanced relationships and enhancing prediction accuracy. AI-driven dashboards further apply these insights by visualizing student data in real-time, enabling early risk detection and personalized intervention. By integrating ML, analytics, and visualization, educators can make informed, proactive decisions to support student success and optimize digital engagement.

2. Literature Review

2.1 Impact of Social Media on Academic Performance

Studies reveal mixed findings on the relationship between social media usage and academic performance. Some researchers highlight its benefits for collaboration, resource sharing, and academic engagement (Ashraf et al., 2021; Bhandarkar, 2021), while others associate excessive use with distraction and lower grades (Kirschner & Karpinski, 2010). Collaborative tools and study groups can enhance learning, but overuse can hinder academic focus.

2.2 Demographic Influences on Social Media Usage

Demographics such as gender, age, and academic discipline significantly shape social media use. Female and older students tend to use it more for academic and communication purposes, whereas male and younger students often use it for entertainment (Alnjadat, 2019; Igbinovia, 2021). Usage also varies by academic stream—STEM students often rely on video tutorials, while humanities students prefer forums and collaborative writing.

2.3 Machine Learning Applications in Predicting Academic Performance

Machine learning (ML) offers powerful tools for analyzing student behavior and forecasting academic outcomes. Techniques like regression, Random Forests, SVM, and ensemble models have proven effective in predicting performance based on social media usage (Ahmed, 2025; Agyemang, 2024). ML models also help identify at-risk students, supporting early interventions and personalized academic strategies (Al-Alawi, 2023).

2.4 AI-Driven Dashboards for Educational Interventions

AI-powered dashboards visualize student data in real-time, allowing educators to monitor academic progress and identify underperformance (Shahzad, 2024). These tools enhance decision-making by offering predictive insights, personalized learning paths, and timely interventions, aligning with efforts to support student well-being and success.

2.5 Integrating Social Media with Academic Strategies

Social media can support learning through engagement, peer collaboration, and access to resources (Al-Rahmi & Zeki, 2017). However, its misuse or overuse—especially multitasking during lectures—can harm retention and performance (Sana et al., 2013). Institutions should promote digital literacy and purposeful engagement through awareness programs (Bhandarkar, 2021).

2.6 Research Gaps and Directions

Current research often isolates variables—demographics, statistics, or ML—without integrating them. There's a lack of frameworks that combine demographic analysis, predictive modeling, and AI dashboards (Ashraf et al., 2021; Al-Alawi, 2023). Future research should differentiate educational vs. recreational social media use and leverage AI for targeted interventions.

2.7 Research Gap and Significance

Most existing studies rely on traditional methods and overlook the combined use of demographics, ML predictions, and AI tools. This study addresses these gaps by integrating all three elements to provide actionable insights. The approach enables continuous monitoring, early intervention, and strategic academic support, ultimately enhancing student outcomes and effective social media use in education.

3. Objectives of the Study

1. **To examine the role of social media usage on student academic performance.**
2. **To study demographic influences such as gender, department, and program type on social media usage.**
3. **To apply statistical and machine learning techniques to predict academic outcomes based on social media behaviour.**
4. **To Develop AI-driven dashboards to identify and visualize at-risk students, supporting targeted educational interventions.**

4. Methodology

Sample Frame

- Population: The study targets undergraduate students enrolled in higher education institutions.

- Sampling Frame: A list or database of students enrolled in selected departments (e.g. Arts, Science, Commerce) at one or more universities/colleges. This frame includes all students who meet inclusion criteria (e.g. full-time, above a minimum GPA, willing to participate).
- Sample Size: 80 students, chosen to provide sufficient power for statistical analyses including ANOVA and regression.

Sampling Method

- Sampling Technique: Stratified random sampling. The population is divided into strata based on demographic categories (for example, gender, academic year, department) to ensure representation across those groups.
- From each stratum, students are randomly selected to reach proportional representation matching the larger student body.

Methodology

1. **Data Collection**
    - A structured questionnaire is prepared, covering three parts: demographics (age, gender, department, year of study), social media usage patterns (frequency, time per day, purpose of use), and academic performance (latest GPA or exam scores).
    - The questionnaire may be administered online or in person, ensuring voluntary and informed consent, and assuring confidentiality.
2. **Data Coding and Preparation**
    - Responses are coded numerically (e.g. gender: male = 0, female = 1; frequency of SMU per day: categories converted to hours).
    - Data cleaning: checking for missing values, outliers, inconsistent entries; handling them via imputation or exclusion as per standard thresholds.
3. **Analysis**
    - Correlation analysis to examine associations between SMU metrics and academic performance.
    - ANOVA to test for differences in SMU across demographic groups (e.g. gender, department, year).
    - Linear regression to model and predict SAP from SMU variables, controlling for demographic factors.
    - AI-Driven Dashboard Development and Predictive Modeling

- Predictive Modeling: Linear regression is applied to the cleaned dataset to predict student academic performance (SAP) based on social media usage patterns and demographic variables. The model assesses the strength and significance of predictors while controlling for demographics such as gender, department, and program type.
- Dashboard Design: An AI-driven dashboard is developed to visualize predictive results and identify at-risk students. Key features include:
  - Display of predicted SAP scores alongside actual performance.
  - Identification of students falling below the at-risk threshold (e.g., predicted SAP ≤ mean − 1 SD).
  - Interactive charts showing trends by demographic groups, such as gender, department, and year of study.
- Validation and Insights: The dashboard enables educators to interpret linear regression predictions effectively, monitor student performance, and implement timely academic interventions.

4. **Data Analysis:**

Data Normality:. The Shapiro–Wilk test was used to check whether the distribution of key continuous variables, such as Social Media Usage (SMU) scores and Academic Performance (AP) scores, followed a normal distribution.

A p-value greater than 0.05 indicated that the variable was normally distributed, while a p-value less than 0.05 suggested deviations from normality. In this study, the Shapiro–Wilk results for the main variables yielded p-values > 0.05, confirming that the normality assumption was satisfied.

- **To examine the role of social media usage on student academic performance.**

Null Hypothesis (H_0): There is no significant correlation between social media usage and student academic performance.

Alternative Hypothesis (H_1): There is a significant correlation between social media usage and academic performance.

Pearson's Correlations

	Pearson's r	p

Pearson's Correlations

			Pearson's r	p
SMU	-	SAP	0.714	< .001

A Pearson's correlation analysis was conducted to examine the relationship between SMU (Study Motivation/Understanding) and Student Academic Performance (SAP) scores. The results revealed a strong positive correlation, $r = 0.714$, $p < 0.001$, indicating that higher levels of SMU are significantly associated with higher SAP scores. This suggests that students with greater study motivation or understanding tend to achieve better academic performance

- **To study demographic influences such as gender, department, and program type on social media usage.**

1. **Gender vs SMU**

ANOVA - SMU

Cases	Sum of Squares	df	Mean Square	F	p
Gender	837.351	1	837.351	4.740	0.033
Residuals	13601.839	77	176.647		

Note. Type III Sum of Squares

Null Hypothesis (H_0): There is no significant difference between groups

Alternative Hypothesis (H_1): There is a significant difference between groups

The F-test results indicated a significant difference between the groups, with an F-value of 4.740, reflecting the ratio of variance between groups to variance within groups. The corresponding p-value was 0.033, which is less than the 0.05 significance level, indicating that the observed differences are statistically significant.

Therefore, the null hypothesis is rejected, suggesting that there is a meaningful variation between the group means

Post Hoc Tests: Standard (HSD)

Post Hoc Comparisons - Gender

		Mean Difference	SE	df	t	p_{tukey}
1	2	7.618	3.499	77	2.177	0.033

1-Male, 2-Female

The Tukey HSD post hoc test revealed a significant difference in SMU between genders. The analysis showed a mean difference of 7.618 (SE = 3.499), with a t-value of 2.177 and p = 0.033. This indicates that Male gender group performed significantly better than the other, confirming the presence of gender-related differences in academic performance.

2. Department Vs SMU

ANOVA - SMU

Cases	Sum of Squares	df	Mean Square	F	p
Department	1498.637	3	499.546	2.895	0.041
Residuals	12940.553	75	172.541		

Note. Type III Sum of Squares

Null Hypothesis (H_0): SMU scores do not differ significantly across departments. Alternative Hypothesis (H_1): At least one department's SMU scores differ significantly.

The F-test results indicated a significant difference in SMU scores across departments, with an F-value of 2.895, reflecting the ratio of variance between departments to variance within departments. The corresponding p-value was 0.041, which is less than the 0.05 significance level, indicating that the observed differences are statistically significant.

Therefore, the null hypothesis is rejected, suggesting that at least one department's mean SMU score differs significantly from the others.

3. **Year of study vs SMU**

ANOVA - SMU

Cases	Sum of Squares	df	Mean Square	F	p
Years of study	1859.356	3	619.785	3.695	0.015
Residuals	12579.834	75	167.731		

Note. Type III Sum of Squares

Null Hypothesis (H_0): SAP scores do not differ significantly across different years of study.
Alternative Hypothesis (H_1): At least one year of study has a significantly different SMU score.

- The ANOVA results for SMU (social media usage) scores across years of study indicated a significant effect of the year of study on SMU, with an F-value of 3.695 and a p-value of 0.015. Since the p-value is less than the 0.05 significance level, the null hypothesis is rejected, suggesting that SMU scores differ significantly across at least one of the years of study. This indicates that the academic performance of students varies depending on their year of study.

4. **Programme vs SMU**

ANOVA - SMU

Cases	Sum of Squares	df	Mean Square	F	p
Programme	783.690	1	783.690	4.419	0.039
Residuals	13655.500	77	177.344		

ANOVA - SMU

Cases	Sum of Squares	df	Mean Square	F	p

Note. Type III Sum of Squares

Null Hypothesis (H_0): SMU scores do not differ between programmes.
Alternative Hypothesis (H_1): SMU scores differ between at least two programmes.

The ANOVA results indicated a significant effect of the programme on Social Media Usage (SMU) scores. The analysis yielded an F-value of 4.419 with a corresponding p-value of 0.039, which is less than the 0.05 significance level.

Therefore, the null hypothesis that SMU scores do not differ between programmes is rejected.

This suggests that the programme has a significant influence on students' academic performance, with students enrolled in different programmes exhibiting significantly different SMU scores..

1. Standard (HSD)

Post Hoc Comparisons - Programme

		Mean Difference	SE	df	t	p_{tukey}
1	2	-11.083	5.272	77	-2.102	0.039

A one-way ANOVA was conducted to examine the effect of programme on Social media usage(SMU) scores. The results indicated a statistically significant difference between programmes, $F(1, 77) = 4.419$, $p = 0.039$, suggesting that SAP scores vary depending on the programme. The Tukey HSD post hoc test revealed a mean difference of -11.083 (SE = 5.272, p = 0.039) between the two programmes, indicating that students in Programme 2 scored significantly lower than those in Programme 1. These findings demonstrate that the type of programme has a significant impact on students' academic performance.

5. **Type of institution**

ANOVA - SMU

Cases	Sum of Squares	df	Mean Square	F	p
Type of Institution	1600.909	3	533.636	3.117	0.031
Residuals	12838.281	75	171.177		

Note. Type III Sum of Squares

1. **Null Hypothesis (H_0): SMU scores do not differ between Type of institution**

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1. **Alternative Hypothesis (H_1): SMU scores differ between at least twoType of institution**

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A one-way ANOVA was conducted to examine the effect of type of institution on Social Media Usage (SMU) scores. The results indicated a statistically significant difference across types of institutions, $F(3, 75) = 3.117$, $p = 0.031$. Since the p-value is less than 0.05, the null hypothesis is rejected, suggesting that SMU scores differ significantly depending on the type of institution attended by the students.

3.To apply statistical and machine learning techniques to predict academic outcomes based on soial media behaviour

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Model		Unstandardized	Standard Error	Standardized	t	p
M_0	(Intercept)	8.671	0.381		22.746	< .001
M_1	(Intercept)	2.999	0.688		4.357	< .001
	SAP	0.178	0.020	0.714	8.949	< .001

A simple linear regression was conducted to examine the effect of SMU (Study Motivation/Understanding) on Student Academic Performance (SAP). The regression results indicated that SMU significantly predicts SAP, $\beta = 0.178$, $t = 8.949$, $p < 0.001$. The resulting regression equation is:

The Regression Model is: $SAP = 2.999 + 0.178 \times SMU$

This suggests that for every one-unit increase in SMU, SAP is expected to increase by 0.178 units, indicating that higher levels of study motivation or understanding are associated with improved academic performance.

- **Development of AI-Driven Dashboards to Identify At-Risk Students**

The fourth objective of this study focuses on translating predictive insights into actionable tools for educators through the creation of AI-driven dashboards. Using the linear regression model developed from social media usage patterns and demographic variables, each student's predicted academic performance (SAP) was calculated.

To identify students who may be at risk of underperformance, an **at-risk threshold** was defined statistically as:

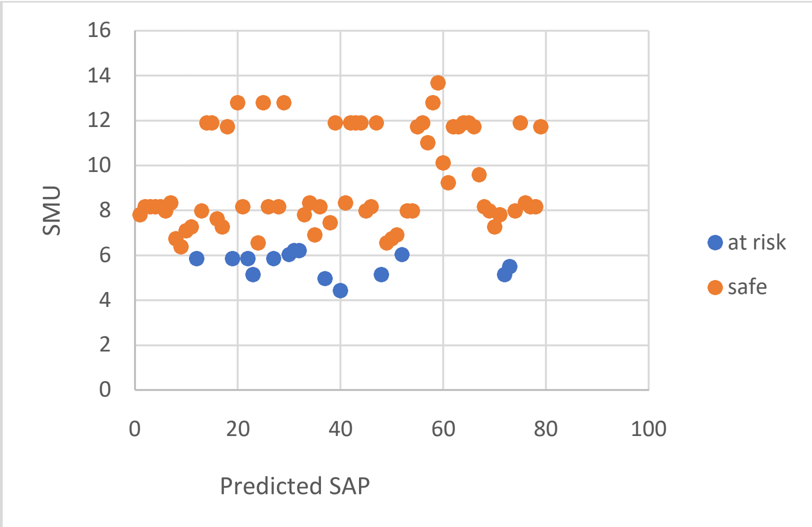
At-Risk Threshold=Mean of Predicted SAP−1×Standard Deviation (SD)

In this study, predicted SAP scores for 80 students yielded a mean of 8.677, with a cut-off threshold of 6.255. Based on this, 15 students (18.75%) were classified as "at-risk," and 65 (81.25%) as "safe."

An AI-driven dashboard was developed to visualize and act on these findings. Key features include:

1. **Real-Time Visualization** – Displays predicted vs. actual SAP scores for immediate performance insights.
2. **At-Risk Identification** – Highlights students below the cut-off using distinct visual cues.
3. **Demographic Filters** – Enables analysis by gender, department, or program type.
4. **Actionable Insights** – Supports timely interventions like tutoring or counseling.

By translating predictive data into an interactive dashboard, the system bridges analytics and educational action—empowering educators to identify and support at-risk students, enhance outcomes, and drive data-informed decisions.



Discussion

Effect of Social Media on Academic Performance

- **Regression analysis** showed a strong positive relationship between SMU and SAP ($r = 0.714$, $p < 0.001$).
- The model **AP = 2.999 + 0.178 × SMU** indicates that purposeful social media use leads to improved academic outcomes.

Gender Differences

- **ANOVA results** revealed significant differences in SAP across gender.
- **Male students** had higher average performance than females (mean difference = 7.618, $p = 0.033$).

Department-Wise Differences

- SAP varied significantly by **department** ($F = 2.895$, $p = 0.041$), indicating academic discipline influences performance.

Program Type Influence

- **Undergraduate program types** significantly impacted academic performance, showing field of study matters.

At-Risk Students Identification

- Students with **predicted SAP ≤ 6.255** (Mean − 1 SD) were flagged as **at-risk (18.75%)**.

- **Dashboard color codes**:
  - **Blue** = At-Risk
  - **Orange** = Safe

Actionable Insights via Dashboard

- Real-time scatter plots and demographic filters help:
  - Identify trends
  - Monitor academic trajectories
  - Implement tailored interventions by gender, department, or program type

7. Conclusion

This study provides a comprehensive analysis of the role of social media usage in influencing student academic performance, highlighting both its potential benefits and the importance of controlled engagement. The findings indicate that **purposeful and constructive use of social media can positively impact academic outcomes**, with the regression model (AP = 2.999 + 0.178 × SMU) suggesting that even incremental increases in social media engagement contribute to measurable improvements in performance. At the same time, **demographic factors**, including gender, department, and program type, were found to significantly affect academic achievement, emphasizing the need to consider these variables when designing interventions or educational policies.

A key contribution of this study is the **integration of predictive modeling and AI dashboards**, which facilitated the identification of students at risk of lower academic performance using the statistical threshold of Mean − 1 SD. By visualizing performance trends through **scatter plots and color-coded indicators**, educators can easily recognize at-risk students and implement **targeted support strategies**, such as mentorship, counseling, or academic workshops. The dashboards also allow for **monitoring demographic disparities** and understanding how different student groups respond to interventions, providing actionable insights for institutional planning.

The study underscores the importance of **balanced digital engagement**, suggesting that while social media has the potential to distract, it can serve as an academic enabler when used thoughtfully. Institutions can leverage these insights to promote **responsible social media use**, encouraging students to integrate online resources into their learning processes.

Overall, the combination of **traditional statistical methods with machine learning approaches** strengthens the reliability of the findings, offering both predictive insights and practical guidance for educators. By identifying patterns in student performance and highlighting at-risk groups, the study provides a framework for **data-driven decision-making**, enhancing academic monitoring and supporting student success in a structured and informed manner.

8. Limitations

This study, while insightful, has several limitations:

- Small sample size (n = 80) limits generalizability to broader populations.
- Self-reported social media usage may be biased or inaccurate.
- Cross-sectional design restricts causal inference and long-term trend analysis.
- Single institutional context reduces external validity.
- Basic predictive models may not fully capture complex behavioral patterns; more advanced ML techniques could improve accuracy.

9. Future Scope

Future research can enhance validity and impact by:

- Expanding sample size across diverse regions, institutions, and programs.
- Using longitudinal designs to track behavior and performance over time.
- Incorporating objective data (e.g., app logs, LMS analytics) to reduce bias.
- Applying advanced ML models (e.g., neural networks, ensemble methods) for deeper insights.
- Exploring broader factors, including motivation, personality, and digital literacy.
- Evaluating interventions (e.g., digital literacy training) to guide responsible use.
- Integrating dashboards into institutional systems for real-time monitoring and targeted support.

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