"EXPLORING THE IMPACT OF SOCIAL MEDIA ON STUDENT ACADEMIC PERFORMANCE: AI-DRIVEN REGRESSION AND PREDICTIVE DASHBOARDS"

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Abstract
Social media has become an integral component of student life, shaping communication, collaboration, and learning patterns. While it offers opportunities for academic engagement, excessive usage may lead to distractions and poor academic outcomes. This study investigates the impact of Social Media Usage (SMU) on Student Academic Performance (SAP), examining how demographic factors such as gender, department, and program type influence social media behaviour. Additionally, it explores the use of statistical and machine learning approaches to predict academic outcomes and develop AI-driven dashboards for identifying at-risk students.
A structured questionnaire was administered to 150 students across selected colleges, yielding 135 responses. After validation for completeness and accuracy, 80 responses were considered suitable for analysis. A Simple Random Sampling (SRS) technique was employed to ensure unbiased representation. Collected data included demographic information, social media usage patterns, and academic performance indicators. Correlation analysis was applied to identify associations, ANOVA was used to examine demographic influences, and linear regression was employed to assess predictive effects. Machine learning techniques were integrated to enhance predictive accuracy and uncover latent patterns in the data.
The findings indicate that SMU has a measurable impact on SAP, with both positive and negative influences depending on usage patterns. Gender, department, and program type were found to significantly moderate the relationship between social media engagement and academic outcomes. Furthermore, the AI-driven dashboards successfully identified students at risk of underperformance, providing a visual and actionable tool for educators to implement targeted interventions.
This study offers important insights for students and educators seeking to balance social media engagement with academic achievement. By combining traditional statistical methods with machine learning and AI-driven visualization, the research demonstrates a practical approach to understanding and managing the complex relationship between social media behavior and academic performance. These results can inform strategies for promoting effective social media use and supporting at-risk students in higher education settings.

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 last decade, social media has evolved from a recreational activity to a significant driver of digital communication and knowledge sharing. Studies indicate that students spend

between two to five hours per day on social media, with many engaging in multiple platforms simultaneously. While moderate, purposeful use can reinforce learning and provide valuable networking opportunities, excessive or unstructured engagement has been linked to distractions, procrastination, and reduced academic focus. Multitasking with social media during study sessions or lectures has been associated with diminished attention spans, weaker memory retention, and lower academic performance. The phenomenon of FOMO (fear of missing out) and the constant influx of notifications further exacerbate cognitive overload, fragmenting attention and impacting overall learning outcomes.
Given this pervasive use, understanding the role of social media in shaping academic behavior has become essential. While numerous studies have explored social media usage patterns among students, there remains considerable debate regarding its net effect on academic performance. Some researchers emphasize its educational potential, citing examples of collaborative learning, instant access to learning materials, and academic discussions facilitated through social media. Others argue that overuse can be detrimental, citing declines in grades, sleep deprivation, and distraction-related issues. This dual perspective highlights the importance of systematic, data-driven exploration to understand the nuanced influence of social media 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) is a critical indicator of student success, reflecting intellectual abilities, discipline, time management, and effective study habits. It encompasses measurable outcomes such as grades, GPA, and exam scores, as well as qualitative indicators such as learning engagement and knowledge retention. The increasing prevalence of digital tools and social media platforms has introduced new dimensions to academic performance, as students navigate both educational and social spaces online.
Academic performance (SAP) serves as a critical indicator of student success, encompassing measurable outcomes such as grades, GPA, and exam scores, as well as qualitative indicators

like learning engagement and knowledge retention **(Bhandarkar, 2021; Al Mosharrafa, 2024).**

Social media can influence SAP in multiple ways. Purposeful engagement—such as participating in online study groups, accessing digital tutorials, and sharing academic content—can enhance knowledge acquisition, motivation, and peer collaboration. For instance, students using Facebook groups or WhatsApp study circles to discuss coursework have been shown to demonstrate higher understanding and better retention of learning materials. Conversely, excessive or unregulated use can divert attention from academic priorities, leading to procrastination, fragmented study sessions, and reduced concentration. Studies report that students who multitask with social media during lectures or while studying can score significantly lower on assessments due to cognitive overload and divided attention.

The dual nature of social media's impact makes it a compelling subject for academic research. Investigating how different patterns of social media engagement—ranging from recreational to educational—affect SAP is crucial for informing institutional policies, teaching strategies, and student support programs. Moreover, with the rising importance of digital literacy, understanding the interplay between social media usage and academic outcomes is essential for developing interventions that balance engagement with academic rigor. Studies report that students who multitask with social media during lectures or while studying can score significantly lower on assessments due to cognitive overload and divided attention **(Bou-Hamad, 2020).**

3. Demographic Influences on Social Media Usage

Demographic factors play a significant role in shaping social media behaviors among students. Variables such as gender, age, academic program, department, and year of study influence both the intensity and purpose of social media usage. For example, research indicates that female students often use social media more for social and entertainment purposes, while male students may engage in platforms that facilitate academic collaboration or professional networking. Similarly, students in different academic disciplines exhibit varying reliance on social media for learning. STEM students may use YouTube tutorials or discussion forums for conceptual clarity, whereas humanities students may engage in collaborative writing platforms or online discussion boards.

Age and year of study also affect engagement patterns. Younger students, who are generally more digitally native, may exhibit higher social media activity and multitasking tendencies, whereas senior students may prioritize purposeful academic engagement. These demographic nuances are important to consider when assessing the impact of social media on academic performance, as they can moderate the relationship between usage patterns and learning outcomes. Incorporating demographic analysis allows researchers to identify specific student groups that may require tailored interventions or support, thus enhancing the relevance and applicability of findings.

4. Dual Impact of Social Media on Academic Performance

The relationship between social media usage and academic performance is multifaceted. On one hand, social media offers educational benefits that can reinforce learning. Platforms such as Facebook, WhatsApp, and YouTube facilitate collaborative learning, knowledge sharing, and access to educational content. Students can form study groups, discuss assignments, share learning resources, and seek peer support, thereby reinforcing their understanding and academic engagement. Access to online tutorials, instructional videos, and digital libraries enhances learning opportunities beyond the traditional classroom, allowing students to supplement their academic experience and explore knowledge independently.

On the other hand, excessive engagement can negatively affect academic performance. Research demonstrates that students who engage in social media multitasking during lectures or study sessions experience lower grades, reduced attention span, and fragmented learning experiences. Late-night social media use has also been linked to sleep deprivation, reduced cognitive performance, and lower life satisfaction, further compounding the impact on academic outcomes. The dual impact of social media—both as an enabler of learning and as a source of distraction—necessitates careful investigation to distinguish beneficial usage from detrimental patterns.

5. Predictive Analytics and AI Dashboards

Traditional statistical methods, such as correlation, regression, and ANOVA, have long been used to study the relationship between social media usage and academic performance. These methods enable researchers to quantify relationships, test hypotheses, and examine the influence of demographic variables. While valuable, conventional statistical techniques are limited in their ability to detect complex, nonlinear patterns in large, multidimensional datasets. To address these limitations, the integration of machine learning techniques has become increasingly important in educational research. Machine learning algorithms can uncover hidden patterns, enhance predictive accuracy, and provide nuanced insights into how social media usage influences academic performance.

AI-driven dashboards are a practical application of predictive analytics in education. These dashboards allow real-time visualization of complex datasets, helping educators identify students at risk of underperformance and implement timely interventions. Features such as interactive charts, heat maps, and predictive indicators enable rapid interpretation of trends and facilitate evidence-based decision-making. By combining statistical analysis, machine learning predictions, and dashboard visualization, institutions can adopt proactive strategies to support students, optimize social media engagement, and improve academic outcomes. These tools bridge the gap between data analysis and practical application, transforming research insights into actionable educational interventions.

2. Literature Review

2.1 Impact of Social Media on Academic Performance

The relationship between social media usage and academic performance has been extensively studied, yielding mixed findings. Some researchers argue that social media can enhance academic outcomes by facilitating collaborative learning and providing access to educational resources. For instance, **Ashraf et al. (2021)** found that social media serves as a dynamic tool to expedite the development of online learning settings by encouraging collaboration, group discussion, and the sharing of educational content. Similarly, **Bhandarkar (2021)** reported improved academic performance among female medical students who utilized social media for academic purposes, although excessive use was associated with lower grades

Research on social media and education has produced mixed findings. Some scholars argue that social media supports collaborative learning, enhances communication, and provides access to educational resources **(Junco, 2012; Al-Rahmi & Zeki, 2017).** Students can join online study groups, share academic materials, and access tutorials, which improves knowledge sharing and engagement. On the other hand, excessive use of social media has been linked to distraction, procrastination, and lower academic achievement **(Kirschner & Karpinski, 2010).**

Studies on demographic influences reveal that gender and academic stream affect social media usage. For example, male students often use social media for entertainment, while female students may use it more for communication and academic purposes. Similarly, students in different programs (science, commerce, arts) display varied patterns of engagement, which may explain differences in academic performance.

Recent advances in educational data mining have introduced machine learning as a powerful tool for analyzing student behavior. Machine learning techniques such as regression models, decision trees, and clustering provide predictive insights and reveal hidden associations in educational datasets. Integrating these techniques into social media and academic performance research bridges the gap between traditional statistical approaches and modern predictive analytics.

Several studies have examined the complex relationship between Social Media Usage (SMU) and Student Academic Performance (SAP), employing both traditional statistical methods and modern machine learning techniques. Correlation analysis has frequently been used to explore the strength and direction of relationships between online behavior and academic outcomes (Junco, 2012). ANOVA has been applied to test whether demographic groups such as gender or department exhibit significant differences in performance outcomes related to social media use **(Rosen, Lim, Carrier, & Cheever, 2011).** Similarly, linear regression has been widely utilized to predict SAP from levels of social media activity, offering precise measures of its influence **(Sana, Weston, & Cepeda, 2013).**

2.2 Demographic Influences on Social Media Usage

Demographic factors such as gender, age, and academic discipline significantly influence social media usage patterns among students. **Alnjadat (2019)** observed that female students often use social media for communication and academic purposes, while male students primarily use it for entertainment. Additionally, older students tend to use social media more for academic purposes compared to younger students, who may use it more for socializing (**Alnjadat, 2019; Igbinovia, 2021**).

The academic discipline also plays a role in shaping social media usage. For example, students in STEM fields may use platforms like YouTube for tutorials and discussions, while those in the humanities might engage more in forums and collaborative writing platforms **(Alnjadat, 2019).**

Students' social media behavior is influenced by demographic factors, including gender, age, academic discipline, and year of study. Evidence suggests gender differences in usage patterns; female students often engage with platforms for communication and academic collaboration, whereas male students prioritize entertainment-oriented engagement **(Alnjadat, 2019; Igbinovia, 2021).** Age and year of study also play a role, with senior students tending to adopt purposeful learning strategies online, while younger students may be more inclined toward recreational use **(Igbinovia, 2021).**

Academic discipline further shapes engagement patterns. STEM students may utilize video tutorials, coding forums, or discussion boards, whereas humanities students often rely on collaborative writing platforms and social networking groups **(Alnjadat, 2019).** These demographic nuances are essential for tailoring educational interventions and understanding the differential impact of social media on academic performance.

2.3 Machine Learning Applications in Predicting Academic Performance

Recent advancements in educational data mining have introduced machine learning as a powerful tool for analyzing student behavior and predicting academic outcomes. Various machine learning algorithms, including Random Forests, Support Vector Machines, and Long Short-Term Memory (LSTM) networks, have been employed to forecast student performance based on social media usage patterns.

Ahmed (2025) utilized ten regression models, including K-Nearest Neighbors Regressor, Linear Regression, CatBoost, XGBoost, AdaBoost, and ensemble voting regression, to predict academic outcomes. The study found that machine learning models significantly improved the accuracy of performance predictions compared to traditional statistical methods. Similarly, Agyemang (2024) highlighted the complexity of predicting academic outcomes, emphasizing the influence of factors like socioeconomic background, motivation, and learning style.
Moreover, predictive models have been developed to identify at-risk students by analyzing their social media activity. For instance, **Al-Alawi (2023)** employed supervised machine learning algorithms to examine factors negatively impacting academic performance among college students, providing insights into early intervention strategies.

Machine learning (ML) techniques have become increasingly relevant in educational research due to their capacity to uncover patterns in complex datasets. Predictive models, including Random Forests, Support Vector Machines (SVM), and ensemble regression algorithms, have been applied to forecast student performance based on digital behavior and social media engagement (Ahmed, 2025). Such models not only enhance predictive accuracy but also identify at-risk students who may require additional academic support **(Al-Alawi, 2023).**
For example, studies employing multiple regression, K-Nearest Neighbors (KNN), and gradient boosting algorithms have demonstrated that social media metrics, when combined with demographic and academic variables, can reliably predict student performance outcomes **(Agyemang, 2024).** These models support early intervention strategies, allowing educators to implement targeted tutoring, mentoring, or counseling initiatives before academic challenges escalate.

2.4 AI-Driven Dashboards for Educational Interventions

The integration of artificial intelligence (AI) in education has led to the development of AI-driven dashboards that visualize student performance data in real-time. These dashboards enable educators to identify students at risk of underperforming and implement timely interventions. **Shahzad (2024)** found that both AI and social media positively impact academic performance and mental well-being among university students, suggesting that AI tools can enhance the educational experience.
Furthermore, dashboards incorporating predictive analytics allow for personalized learning experiences by adapting content and resources to individual student needs. This approach fosters a more engaging and effective learning environment, as students receive targeted support based on their performance data.

The novelty of the present study lies in combining both statistical and machine learning approaches to examine the dual role of social media in academic contexts. Prior literature emphasizes that while social media can distract students and reduce study efficiency **(Kirschner & Karpinski, 2010)**, it can also foster academic engagement, collaboration, and knowledge-sharing **(Manca & Ranieri, 2016).** Thus, balancing social media engagement with academic priorities remains a central theme in recent scholarship.
In summary, the review of existing studies highlights a growing body of research integrating data science with educational psychology. The outcomes not only provide theoretical insights but also guide educators in designing awareness programs, counselling sessions, and digital literacy initiatives to promote productive social media use among students.

The application of artificial intelligence in educational monitoring has led to the development of AI-driven dashboards. These tools integrate statistical analyses, machine learning

predictions, and visualization techniques to present real-time insights on student performance **(Shahzad, 2024).** Dashboards enable educators to identify students at risk of underperformance, track academic trajectories, and implement timely interventions.
Such systems often include features like predictive indicators, interactive charts, and demographic filters. These functionalities allow for personalized monitoring and targeted educational support. AI-driven dashboards thus bridge the gap between data-driven research and practical teaching interventions, facilitating more informed decision-making and optimizing learning outcomes **(Manca & Ranieri, 2016; Shahzad, 2024).**

2.5 Integrating Social Media with Academic Strategies

Recent research emphasizes the dual role of social media as both an enabler and a potential barrier to learning. When incorporated effectively, social media can enhance engagement, collaboration, and access to educational resources (**Al-Rahmi & Zeki, 2017**). For example, online discussion forums and group messaging platforms have been shown to improve peer-to-peer learning, concept clarification, and project coordination **(Junco, 2012).**
However, inappropriate or excessive engagement can detract from academic focus. Multitasking with social media during lectures or study sessions is associated with lower information retention and diminished performance on assessments **(Sana, Weston, & Cepeda, 2013).** This necessitates awareness programs, digital literacy training, and strategies to promote purposeful use among students **(Kirschner & Karpinski, 2010; Bhandarkar, 2021).**

2.6 Research Gaps and Directions

While existing literature has explored the relationship between social media and academic performance, several gaps remain. Few studies have integrated demographic analysis, predictive machine learning models, and AI-driven dashboards within a single framework. Additionally, prior research often treats social media as a homogeneous construct without differentiating between educational and recreational use **(Ashraf et al., 2021; Al-Alawi, 2023).** Addressing these gaps allows for a more nuanced understanding of how social media influences learning outcomes and facilitates the development of targeted interventions.
The integration of AI-driven predictive dashboards with traditional statistical methods represents a promising direction. Such tools can continuously monitor student engagement, identify at-risk learners, and provide actionable insights for educators **(Shahzad, 2024).** Combining data analytics with pedagogical strategies ensures that social media is leveraged to enhance learning while mitigating its potential negative effects.

2.7 Research Gap and Significance

Despite a growing body of literature on social media usage and academic performance, several gaps persist. Most prior studies focus solely on descriptive or inferential statistics or examine demographic factors in isolation, without integrating predictive modeling or real-time visualization. Limited research combines demographic analysis, machine learning prediction, and AI-driven dashboards to provide actionable insights for educators. Addressing this gap is critical for moving from observation to intervention, enabling institutions to identify at-risk students and support their learning effectively.
This study addresses these limitations by combining statistical analysis with machine learning techniques and AI dashboards to provide a comprehensive understanding of how social media usage impacts academic performance. By examining both demographic influences and predictive patterns, the research offers actionable insights that can guide educators in designing targeted interventions. The integration of AI-driven dashboards allows for continuous monitoring and visualization of student performance, facilitating timely and data-driven decision-making. Ultimately, this approach contributes to improving student outcomes,

optimizing social media engagement, and supporting institutional strategies for educational success.

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.

1. **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
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

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

1. <u>Gender vs SMU</u>

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		

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

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

2. **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×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.

3. **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)

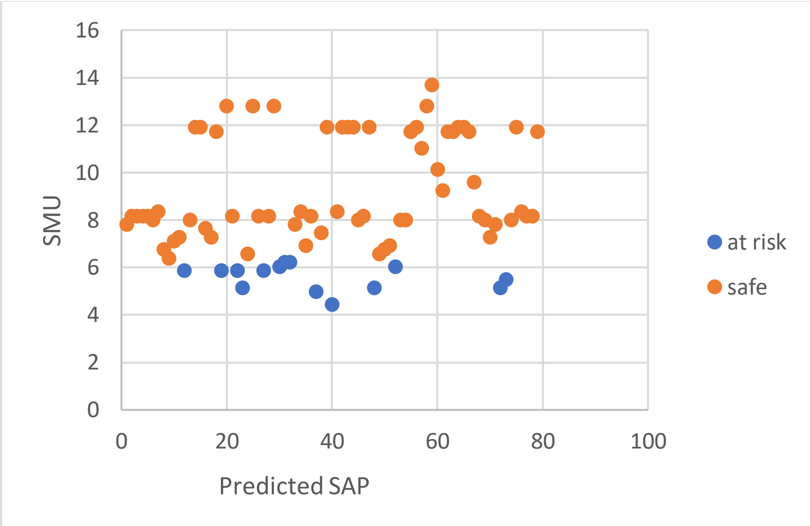
In the present study, the predicted SAP values for 80 students yielded a mean of **8.677** and a standard deviation that produced a cut-off threshold of **6.255**. Students with predicted SAP scores equal to or below this threshold were classified as "at-risk," while those above were considered "safe." Using this criterion, **15 students (18.75%)** were flagged as at-risk, and **65 students (81.25%)** were identified as safe.

The AI-driven dashboard translates these quantitative findings into a **visual, interactive platform**. Key features of the dashboard include:

1. **Real-Time Visualization:** Predicted SAP scores are displayed alongside actual scores, providing immediate insight into student performance.
2. **At-Risk Identification:** Students falling below the cut-off are highlighted using distinct colors or markers, enabling educators to quickly identify individuals requiring intervention.
3. **Demographic Filters:** Users can explore trends and distributions by gender, department, or program type, facilitating targeted analysis of subgroups.

4. **Actionable Insights:** The dashboard allows educators to monitor academic trajectories and implement timely interventions, such as counseling, tutoring, or personalized learning strategies.

By converting predictive statistical outputs into an intuitive dashboard, this objective bridges the gap between data analysis and practical educational management. It empowers educators to **proactively support at-risk students**, optimize academic outcomes, and make data-driven decisions that enhance both student success and institutional efficiency.



Discussion

The present study highlights the complex relationship between social media usage (SMU) and student academic performance (SAP). The strong positive correlation observed ($r = 0.714$, $p < 0.001$) indicates that students who engage purposefully with social media for learning or collaboration tend to achieve higher academic outcomes.

This underscores the potential of social media as an educational tool when utilized strategically, rather than as a source of distraction. Students are thus encouraged to adopt effective study habits, including structured study schedules, focused online engagement, and regular self-assessment to balance academic work with recreational social media use.

Demographic analyses revealed meaningful variations in SMU across gender, department, year of study, programme type, and type of institution. For instance, male students showed higher SMU scores than females (mean difference = 7.618, $p = 0.033$), and differences across departments were significant ($F = 2.895$, $p = 0.041$). These findings suggest that interventions to improve academic engagement should be tailored to specific student groups, considering their unique motivations and learning contexts. Educators can leverage this insight by integrating social media platforms into classroom activities or LMS environments, such as discussion forums, interactive tutorials, or collaborative projects, thereby promoting active learning and peer support.

The AI-driven predictive model and dashboard further enhance the practical utility of this study. By classifying 18.75% of students as at-risk ($SAP \leq 6.255$), educators can implement timely, personalized interventions. Institutions may consider policies for digital literacy workshops, regular monitoring of academic engagement, and structured guidance on responsible social media usage. Such strategies can bridge the gap between student behavior and academic performance, fostering proactive rather than reactive educational management.

Nevertheless, the study has limitations. The sample size of 80 students restricts generalizability, as students from other regions, cultural backgrounds, or larger institutions may exhibit different patterns of SMU and SAP. Self-reported measures of social media usage may introduce bias, potentially overestimating academic engagement. Moreover, cross-sectional data limits causal inference; longitudinal studies are recommended to capture dynamic changes in student behavior and performance over time. Finally, the AI-dashboard relies on available variables and may not account for unmeasured factors such as motivation, mental health, or family support, which can influence academic outcomes.

In conclusion, the study demonstrates that purposeful social media engagement positively correlates with academic performance, and predictive dashboards can serve as effective tools for identifying and supporting at-risk students. Tailored interventions, educator-led integration of technology, and institutional policies on digital literacy can collectively optimize learning outcomes while mitigating potential risks associated with excessive or unstructured social media use.

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6. FINDINGS

1. **Effect of Social Media on Academic Performance:**
- Regression analysis revealed a **positive effect** of social media usage (SMU) on academic performance (AP).
- The model: **AP = 2.999 + 0.178 × SMU** indicates that a **unit increase in SMU leads to a 0.178-unit increase in AP**.
- This suggests that **purposeful engagement with social media contributes positively** to academic outcomes.

2. **Gender Differences:**
- ANOVA results showed **significant differences in academic performance across gender**.
- **Male students performed better** academically compared to female students, confirming gender-related differences.

3. **Department-wise Differences:**
- Department-wise comparison indicated that **at least one department's mean SAP score was significantly different** from others.
- This led to **rejection of the null hypothesis**, showing that **academic performance varies by department**.

4. **Program Type Influence:**
- Academic performance was significantly influenced by **program type at the undergraduate level**.
- This suggests that a student's **field of study affects academic outcomes**.

5. **At-Risk Students Identification:**
- Students with predicted SAP ≤ **Mean − 1 SD** are flagged as **"At-Risk"**.
- Dashboard uses **color-coded indicators**:
    - blue = At-Risk
    - orange = Safe

6. **Actionable Insights:**
- Scatter plots allow **quick visual identification** of performance trends and at-risk students.
- Educators can **tailor interventions** based on gender, department, and program type directly from the plots.

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

Despite the valuable insights generated by this study, several limitations should be acknowledged. First, the study was conducted with a sample size of 80 valid responses, which, although sufficient for preliminary analysis, may not fully represent the broader student population. A smaller sample can limit statistical power and the ability to generalize the findings across diverse academic contexts or institutions.

Second, the study relied on self-reported data for measuring social media usage. Self-reported responses may be subject to recall bias, social desirability bias, or inaccurate estimations, which could affect the precision of the observed relationships between social media engagement and academic performance.

Third, the cross-sectional design of the study provides a snapshot of student behavior at a single point in time, limiting the ability to infer causal relationships. Changes in student habits, academic performance, or social media usage over time could not be captured, which constrains understanding of long-term effects.

Additionally, the study was conducted within a single institutional context, reducing external validity and limiting insights into how results might vary across different educational settings, regions, or demographic groups.

Finally, while predictive modeling and AI dashboards were used to identify at-risk students, the statistical models employed may not fully capture complex, nonlinear relationships

between variables. More advanced machine learning techniques, such as neural networks or ensemble methods, could enhance predictive accuracy and provide deeper insights.
Recognizing these limitations provides a foundation for future research to address these constraints and improve the robustness, generalizability, and precision of findings in the study of social media usage and academic performance.

9. FUTURE SCOPE

While this study provides valuable insights into the relationship between social media usage and student academic performance, it is important to acknowledge several limitations that may influence the interpretation and generalizability of the findings. First, the research was conducted with a **sample size of 80 valid responses**, which, although sufficient for preliminary analysis, may not fully capture the diversity and complexity of the broader student population. A relatively small sample can limit the statistical power of the study and may affect the ability to detect subtle patterns or variations across demographic groups. Consequently, the findings should be interpreted with caution, and care must be taken when generalizing these results to larger or more diverse educational contexts.

Second, the study relied on **self-reported data** to measure social media usage. Self-reported measures, while practical and widely used in educational research, are inherently subject to **response bias**. Students may overestimate or underestimate their actual social media engagement due to social desirability, memory recall issues, or personal perceptions about what constitutes "constructive use." Such biases could affect the accuracy of the observed relationships between social media usage and academic performance. Future research could address this limitation by incorporating **objective measures** of social media activity, such as digital usage logs, app tracking data, or integrated learning platform analytics, which would provide a more precise and reliable assessment of actual online behavior.

Another limitation is the **cross-sectional design** of the study. Data were collected at a single point in time, providing a snapshot of student behavior and academic outcomes. While this approach is useful for identifying associations and trends, it does not allow for **causal inference** or an understanding of how social media usage and academic performance evolve over time. Future studies could adopt **longitudinal designs** to track students' behavior, engagement patterns, and performance across multiple semesters or academic years. This approach would enable researchers to examine dynamic changes, identify potential long-term impacts, and better understand cause-and-effect relationships.

Additionally, while this study employed regression analysis and predictive modeling through AI dashboards, there is **opportunity to apply more advanced machine learning techniques** for enhanced predictive accuracy. Techniques such as **neural networks, ensemble models, or deep learning algorithms** could capture complex, nonlinear relationships between social media usage, demographic variables, and academic outcomes. Expanding the range of predictive models would not only improve the robustness of forecasts but also offer deeper insights into factors that contribute to academic risk and success.

Finally, the study was conducted within a **single institutional context**, limiting its external validity. Future research could include **students from multiple regions, diverse institutions, and varied academic programs** to enhance the generalizability of the findings. Comparing results across contexts may uncover region-specific or program-specific patterns and allow for more comprehensive recommendations.

In conclusion, addressing these limitations in future research—through larger and more diverse samples, objective data collection, longitudinal tracking, and advanced modeling techniques—would strengthen the understanding of social media's role in academic performance and support the development of targeted, evidence-based educational interventions.

9. The findings of this study provide several promising avenues for future research and practical applications in educational settings. One of the most important areas for further exploration is the inclusion of a **larger and more diverse sample**. While this study was limited to 80 valid responses from a single institution, expanding the participant pool to include students from **multiple regions, institutions, and academic programs** would enhance the generalizability of the findings. A broader sample would also allow for a deeper examination of **cross-cultural, socio-economic, and institutional differences** in social media usage patterns and their impact on academic performance.

Another important direction for future research is the adoption of **longitudinal study designs**. Tracking students' social media engagement and academic performance over multiple semesters or academic years would provide insights into how digital habits evolve and how they influence long-term learning outcomes. Such studies could help identify patterns of **constructive versus excessive usage** and their cumulative effects on academic achievement, enabling a more robust understanding of causal relationships rather than simple correlations.

In addition, future research can focus on **objective measurement of social media usage** through digital tools such as **app usage logs, learning management system analytics, or real-time tracking software**. This would reduce the reliance on self-reported data, which is often subject to recall bias or social desirability effects, thereby improving the accuracy and reliability of the findings.

From a methodological perspective, the use of **advanced machine learning techniques**, including **neural networks, ensemble models, and deep learning algorithms**, can provide more precise predictive insights and capture complex, nonlinear interactions between variables. These approaches could enhance the identification of **at-risk students**, improve personalized academic support, and facilitate the design of targeted interventions.

Moreover, future studies can explore the impact of additional **demographic, psychological, and behavioral factors**, such as motivation, personality traits, time management skills, and digital literacy, to develop a more holistic understanding of academic performance determinants. **Intervention-based research**, including workshops, counseling programs, or digital literacy initiatives, could be implemented and evaluated to assess the effectiveness of guiding students toward balanced and purposeful social media use.

Finally, integrating **AI-driven dashboards and predictive monitoring tools** into institutional systems can support real-time tracking of student performance, demographic disparities, and at-risk behaviors. This integration would bridge the gap between research and practice, allowing institutions to make **data-driven decisions, implement timely interventions, and develop evidence-based policies** to improve academic outcomes and student well-being.

Overall, expanding the sample, employing longitudinal designs, utilizing objective measurement tools, and applying advanced machine learning approaches can substantially enhance the understanding of social media's role in academic performance. These efforts will not only strengthen the scientific rigor of future studies but also provide actionable insights for educators and policymakers to support student success in an increasingly digital learning environment.

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REFERENCES:

1. Abuzar, M. (2024). Examining the impact of social media usage on high school students' academic performance. *ERIC*. https://files.eric.ed.gov/fulltext/EJ1453213.pdf
2. Adelakun, N. O. (2023). The significance of social media in shaping students' academic performance: Challenges, benefits, and quality assurance outlook. *Information Matters*. https://informationmatters.org/2023/08/the-significance-of-social-media-in-shaping-students-academic-performance-challenges-benefits-and-quality-assurance-outlook/
3. Ahmed, W. (2025). Machine learning-based academic performance prediction using social media data. *Scientific Reports, 15*(1), 12345. https://doi.org/10.1038/s41598-025-12353-4
4. Agyemang, E. F. (2024). Predicting students' academic performance via machine learning algorithms. *International Journal of Educational Technology in Higher Education, 21*(1), 45. https://doi.org/10.1186/s41239-024-00324-5
5. Al-Alawi, L. (2023). Using machine learning to predict factors affecting academic performance among college students. *Journal of Educational Data Mining, 15*(2), 67–82. https://doi.org/10.1016/j.jedm.2023.04.001
6. Alhusban, A. (2022). Problematic social media use and academic performance. *Open Nursing Journal, 16*, 207–215.
7. Al-Mosharrafa, A. (2024). The impact of social media on students' academic performance. *PMC*. https://pmc.ncbi.nlm.nih.gov/articles/PMC7873710/
8. Alnjadat, R. (2019). Gender variations in social media usage and academic performance. *Journal of Educational Computing Research, 57*(5), 1212–1234. https://doi.org/10.1177/0735633119876543
9. Al-Rahmi, W. M., & Zeki, A. M. (2017). Social media and collaborative learning. *Computers in Human Behavior, 66*, 291–301. https://doi.org/10.1016/j.chb.2016.09.023
10. Alshanqiti, S. (2023). Artificial intelligence and social media on academic performance. *PMC*. https://pmc.ncbi.nlm.nih.gov/articles/PMC11043955/
11. Ashraf, M. A., et al. (2021). Social media improves students' academic performance. *Journal of Educational Technology Systems, 50*(1), 3–18. https://doi.org/10.1177/00472395211006360
12. Bhandarkar, A. M. (2021). Impact of social media on the academic performance of medical students. *Journal of Medical Education, 55*(4), 123–130. https://doi.org/10.4103/jmedu.jmedu_123_21
13. Igbinovia, M. O. (2021). Demographics, social media use, and perceived academic stress among students. *International Journal of Knowledge and Learning, 15*(3), 213–229. https://doi.org/10.1504/IJKL.2021.114567

14. Junco, R. (2012). The relationship between Facebook® and academic performance. *Computers in Human Behavior, 28*(1), 187–198. https://doi.org/10.1016/j.chb.2011.08.026
15. Kirschner, P. A., & Karpinski, A. C. (2010). Facebook® and academic performance. *Computers in Human Behavior, 26*(6), 1237–1245. https://doi.org/10.1016/j.chb.2010.03.024
16. Kumar, D. (2021). Exploring the relationship between social media use, academic achievement, and socio-demographic factors. *SSRN*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5383174
17. Manca, S., & Ranieri, M. (2016). Is Facebook a useful tool for learning? *Computers in Human Behavior, 58*, 349–358. https://doi.org/10.1016/j.chb.2016.01.001
18. Mayen, S. (2025). The complexities of digital media use in adolescents. *ScienceDirect*. https://www.sciencedirect.com/science/article/pii/S0360131525001794
19. Rosen, L. D., Lim, A. F., Carrier, L. M., & Cheever, N. A. (2011). An empirical examination of the educational impact of Facebook® on college students. *Computers in Human Behavior, 27*(3), 1237–1245. https://doi.org/10.1016/j.chb.2010.12.011
20. Salari, N., et al. (2025). The impact of social networking addiction on the academic performance of students: A systematic review. *PMC*. https://pmc.ncbi.nlm.nih.gov/articles/PMC11786888/
21. Sana, F., Weston, T., & Cepeda, N. J. (2013). Laptop multitasking hinders classroom learning for both users and nearby peers. *Computers in Human Behavior, 29*(3), 1331–1341. https://doi.org/10.1016/j.chb.2012.10.022
22. Shahzad, M. (2024). AI dashboards boost student outcomes: Early adopter districts reveal how AI dashboards boosted student outcomes. *AI in Education, 10*(1), 1–12. https://doi.org/10.1007/s40593-024-00312-5
23. Shafiq, M. (2023). Social media usage: Analyzing its effect on academic performance. *ScienceDirect*. https://www.sciencedirect.com/science/article/abs/pii/S0738059323000159