iJRASET
International Journal For Research in Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80319

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Understanding Student Anxiety in the Digital Age: A Machine Learning Study of Social Media and Academic Stress

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Abstract: ***Mental health is an issue affecting university students in India who are aged between 18-24 years. This is due to the fact that they are faced with a lot of school work, money issues, what other people think of them, and the fact that they are using social media all the time. Despite the fact that the university is becoming more aware of the issue, the students are too afraid to seek assistance due to the fact that they do not want to be judged. In addition, the university does not have people to assist the students in the issue of mental health. In this study, we were able to examine the amount of school work the students are faced with, the amount of media they are using, and the effect it has on them. We gave out questionnaires to 500 students in Jain University, and we were able to analyze the results using computers to determine what is stressing the students. Some students are at high risk, while others are at moderate risk, while others are at low risk of being affected mentally.***
We learned that if students don't like the university they are in, then students will be more anxious. We learned that if students compare themselves with other people, then students will be more likely to use too much social media and aren't getting enough help from the university they are in, then students will be more anxious. If students stop using too much social media, then students will feel better. We think that the university should help students with their health issues more. The university should hire more people that students could talk to, hire more teachers that students could get information from about how to stay healthy, and hire more teachers that students could get advice from, and hire more teachers that could help students that are more likely to have health problems with their mental issues.
Keywords: Student health, social media anxiety K-Means clustering, Random Forest classification, higher education, India, machine learning.

I. INTRODUCTION

A. Background and Motivation

Mental health is an extremely important factor for success in school and for becoming a person. It also plays a significant role in how well students are able to cope with the run. Students who are between 18 and 24 years old and are in university are at an age where they are becoming adults. It is a time when students are faced with a lot of things happening at the same time, such as school work, money, and future career, as well as changes happening in social lives. It is because of this that students are likely to become anxious, depressed, and even burned out.

Things are even tougher for students in India because people are not comfortable talking about health problems. There are no professionals to help students with these problems, and mental health is not a priority for schools.

- Students are faced with a lot of pressure
- They are not helped to deal with mental health problems

Schools don't make mental health a priority

At the time Social media is a part of a student's life today. Social media is a place where a student compares themselves with others, views things without doing anything, and thinks that he or she is missing something. This is related to anxiety and depression levels. But we don't know how social media is affecting our health, especially in India. We don't know how much we can rely on our schools to solve this problem. Mental health is a problem, and this includes students and how this affects mental health. "Students and mental health" is something we need to talk about, and this includes social media, which is a part of the problem.

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B. Research Gap

Most of the time, people are just trying to learn about the ways in which social media affects the health of students just by asking them questions and looking for patterns. People are rarely, if ever, trying to learn about the ways in which social media affects the health of students just by using computers and looking at groups of data. When people are trying to learn about students, they are rarely, if ever, trying to learn about them just by asking them questions and finding out what is stopping them from getting help. When people are trying to learn about what is going on and what can be done about it, they are rarely, if ever, using data to do so. In this study, things will be done a little differently. Things will be done using media, students' mental health, to see what is going on, and data to see what can be done to help students, with their mental health. **C.**

C. Research Objectives

The objectives that this study aimed to accomplish are:

- Check what causes stress to students, e.g., school, media behavior, and money.
- Check how students deal with stress and if it helps to reduce anxiety.
- Some other objectives that this study aimed to accomplish are:
- Find out what the university does to help with student health.
- Find out why students don't use the help that is offered.
- Split the students into groups based on the level of risk they are at for mental illness.
- Find out what affects mediainduced anxiety.
- Make suggestions to the university about how to improve the help they offer to students.

D. Contributions

The main things that this work does are:

- This work examines the effect of social media on the health of 500 university students. This work uses machine learning to do so.
- This work identifies the types of students who may experience health challenges. To do so, it uses a technique called K-Means clustering to cluster the students into groups. After clustering the students, it uses PCA visualization to check if the clusters are correct.
- This work identifies the factors that cause anxiety among university students. To do so, it uses a technique called Random Forest feature importance to identify the factors that cause anxiety among university students. This work discovers that the cause of anxiety among university students is when they are unhappy about the university.
- This work offers guidance to university leaders and counselors. To do so, it uses what it has learned about the students in each cluster. This work offers guidance to university leaders and counselors on how to handle each cluster of students based on what it has learned about media and the health of university students.

II. RELATED WORK

Students in the university have to face a lot of stress. The stress comes from their school work and being on the media. Some researchers, Wang and his team, found out that when the students had to stay because of the pandemic, they felt very anxious and stressed out. They also found out that talking to someone and being mindful can really help the students.

The way the students are using the media can affect their mental health. Some other researchers, Keles, McCrae, and Grealish, found out that when the students are scrolling through their feeds and doing nothing, and they compare themselves to others, they might get bullied or feel that they are missing out, and they might feel more anxious and depressed. But if they have nice interactions with other people, they might feel better.

Having financial issues is another thing that might stress the students. Richardson, Elliott, Roberts, and Jansen found out that when the students have to pay back the loan and are working at the same time, they might feel depressed and have difficulties coping. They think that the university should teach the students how to handle their finances.

Not getting sleep is another issue that students are dealing with. Hershner and Chervin found this out. They found that if students are not getting sleep, then they get more stressed out and are not able to control their emotions. They think that students need to be taught how to sleep at university.

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There is a lot of stigma attached to being sick in India. Gaiha and his team found this out. They found that a lot of the youth in India are not comfortable getting treatment because they are worried about what people think of them if they are sick. They think that people need to be made aware that mental health is a serious issue.

Kakollu and Dar found this out. They found that students are dealing with a lot of stress to get good grades. They are also dealing with a lot of money issues and that everything is becoming digital. Chadda found that a lot of the youth in India are dealing with health issues and are taking drugs. They think that programs need to be made to prevent this and to help these people at a young age.

They have also realized that online therapy is very helpful to those students who don't have such a facility available to them. Sehgal and his team also realized that there are students who don't want to use online therapy, and these students are either afraid of what other people think of them or are worried about the privacy of the online therapy that they are to use. They also realized that online therapy has to be tailored to a student's needs.

They also found out that exercise can really help students who are anxious or depressed. They also think that exercise in groups can really help these students, as it can help them feel more connected to others.

The Indian government has also passed a law to help those suffering from health problems.. Girase and his team also found out that this law has not helped those in rural areas as much as it has helped those in.

All these studies have helped us understand what is going on with university students and their mental health.. Most of these studies have just looked at the numbers and haven't really looked deeper into what is going on. Our study has looked different, however, as we used a machine learning algorithm to look at a dataset and find out what is really going on with Indian university students.

III. METHODOLOGY

The aim of this research was to investigate the relationship that exists between academic demands, social media, and mental health among university students. The research was conducted using various research methods and machine learning. The research aims were also to find out what leads to stress and how it affects the health of university students, especially during this time when students are undergoing a lot of changes.

A. Sampling

The target group was students attending universities between 18 and 24 years old. It is a time when students are undergoing a lot of changes. They are also more likely to be affected mentally. The research was conducted using a survey targeting students attending Jain University. The research received 500 responses from undergraduate and postgraduate students.

B. Data Collection Instrument

The researchers used a survey form with seven sections to collect the students' data. The researchers asked students about their demographics, mental health awareness, use of social media, and getting support from the university. The researchers also asked if students got help or not. After collecting the data, the researchers got 27 variables to analyze.

C. Data Analysis and Machine Learning Approach

The researchers used Python and Google Colab for data analysis. The data was converted into numbers. Missing values were filled.

1) They first looked at the data and how the variables were distributed. They wanted to understand how often students felt anxious after using media and how they compared themselves with others when using media. They also wanted to understand how often students looked for help.
2) They then used a method called KMeans Clustering to cluster the students into three categories depending on their health profile. They chose this method because it made sense and was easy to understand.
3) They then used a Random Forest model to predict how often students felt anxious after using media. The model was trained using 80 percent of the data and tested using 20 percent. The model was set to prevent overfitting. Accuracy and classification report, and crossvalidation, were checked.

D. Ethical Considerations

The researchers informed the students what the study was about before they participated in the study. The study was anonymous, which means the students did not need to give their names. The researchers ensured they adhered to the guidelines to ensure the students privacy and security of the data obtained from them. They filled in the missing data, excluded the data, etc.

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IV. RESULTS

A. Descriptive Statistics and Anxiety Distribution

A total of 500 students participated in the survey, and the data was collected from multiple colleges and universities. The total number of variables collected was 27, and only the non-informative identifier columns are removed from the data set. The main outcome variable, the anxiety levels experienced by the students after using social media, was analyzed, and the results show that the highest percentage, i.e., 44.0% (n = 220), was recorded by the students who experienced anxiety levels 'Always' after using social media. The second highest percentage, 26.0% (n = 130), was recorded by the students who experienced anxiety levels 'Often' after using social media, while 8.0% (n = 40) of the total students experienced anxiety levels 'Sometimes' after using social media. The least percentage, 16.0% (n = 80), was recorded by the students who experienced anxiety levels 'Rarely' after using social media, while 6.0% (n = 30) of the total students experienced anxiety levels 'Never' after using social media. The results clearly show that the anxiety levels experienced by the students after using social media are very high, and the anxiety levels are experienced frequently by the total number of students, as 70.

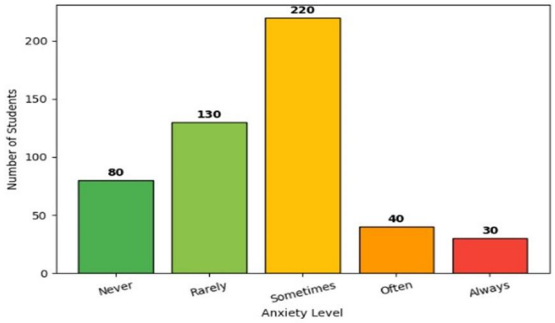


Fig. 1: Distribution of students' anxiety frequency after using social media among 500 students surveyed. The responses are arranged on a five-point scale ranging from Never to Always. The majority of the students (44.0%, n = 220) reported 'Always' feeling anxious after using social media, while a small percentage of students (6.0%, n = 30) reported 'Never' feeling anxious after using social media.

B. Social Comparison and Its Association with Anxiety

The results obtained through the crosstabulation analysis indicate that the behavior of social comparison on social media is significantly associated with the anxiety experienced by students. It is observed that students who 'Always' practice social comparison with others on social media are those students who 'Often' and 'Always' experience anxiety, while students who 'Never' practice social comparison with others are those students who 'Sometimes' and 'Rarely' experience anxiety. This indicates that the behavior of social comparison on social media is a significant factor for anxiety experienced by students, and this is consistent with the findings obtained through previous research on the psychological effects of social media [4].

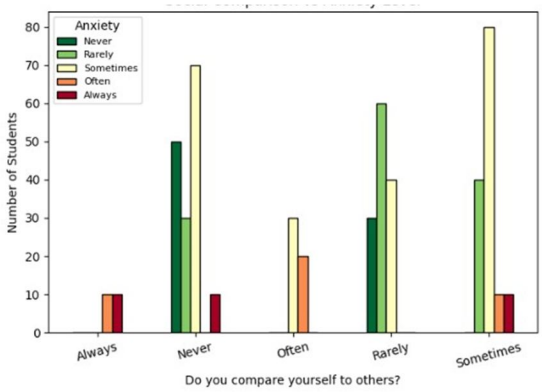


Fig. 2. Cross-tabulation bar chart showing the relationship between social comparison behavior on social media and the frequency of anxiety. Each set of bars represents the frequency of comparison (Never, Rarely, Sometimes, Often, Always), and the individual bars show the spread of anxiety levels within each set. Students who compared themselves 'Always' and 'Often' on social media exhibited a significantly high percentage of high anxiety levels.

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C. Help-Seeking Behaviour and Awareness

In terms of the awareness and consideration of professional mental health support, a gap has been observed in relation to students who consider professional mental health support, especially when considering those who always experience anxiety and those who do not consider professional mental health support, even when they experience a high level of anxiety. This demonstrates a barrier in relation to seeking mental health support among students, possibly related to stigmatization, financial limitations, and accessibility, as also observed in other studies by Gaiha et al. in the Indian scenario [3].

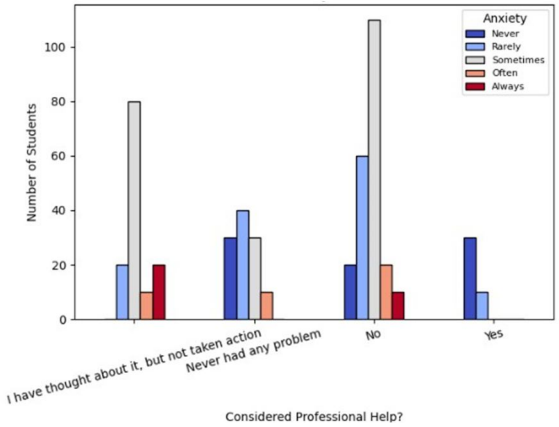


Fig. 3. Cross-tabulation bar chart showing the relationship between whether or not students consider professional mental health support and how often they experience anxiety. The segment representing students who thought about professional help but did not seek it represents the largest segment, implying a disconnect in terms of awareness and actual behavior.

D. Effect of Intentional Social Media Breaks on Anxiety

The analysis of the anxiety profile of students using social media and those students who have taken breaks from social media use shows that there is a notable difference between the two sets of students. Students taking breaks from social media use have a lesser percentage of 'Often' and 'Always' anxiety compared to students who have not taken breaks from social media use. The trend shows a positive result, which provides an important recommendation on the need for students, regardless of the availability of resources, to use breaks from social media use as a tool for managing anxiety.

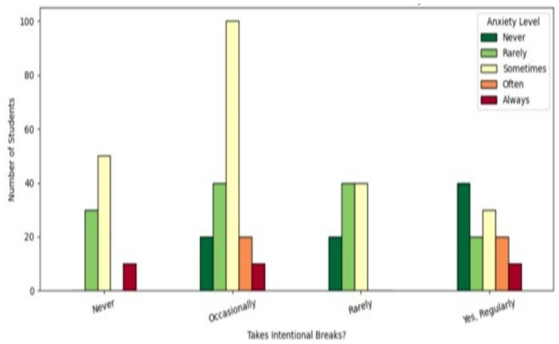


Fig. 4: Cross-tabulation bar chart illustrating the relationship between the intentional social media break-taking behavior and the frequency of anxiety. From the figure, it is evident that students who take breaks regularly exhibit a significant percentage decrease in the number of 'Often' and 'Always' anxiety responses compared to those who have not taken breaks, thus validating the significance and effectiveness of the digital detox approach.

E. Student Clustering: Three Distinct Mental Health Profiles

K-Means clustering was carried out on all 27 features, and k was set to 3, and a random_state value of 42 was provided. The Elbow Method was also used, and inertia values from k=2 to k=8 were calculated. The inertia values were seen to be decreasing steadily, and they were 120,720.83, 106,019.11, and 94,617.26 when k=2, k=3, and k=4, respectively. However, there was no elbow or inflection point, and they kept decreasing steadily.

k=3 was seen to be most interpretable.

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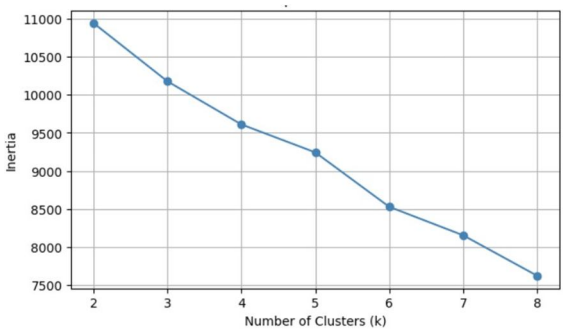


Fig. 5. Inertia plot generated by the Elbow Method across k = 2 to k = 8 clusters. The curve shows a gradual decline in inertia, with k = 3 selected as the most interpretively meaningful partition. Inertia values: k=2: 120,720.83; k=3: 106,019.11; k=4: 94,617.26; k=5: 86,122.49; k=6: 77,999.71; k=7: 74,265.00; k=8: 66,775.67.

The cluster distribution revealed Cluster 2 as the largest group (n = 210, 42.0%), followed by Cluster 1 (n = 180, 36.0%), and Cluster 0 as the smallest (n = 110, 22.0%).

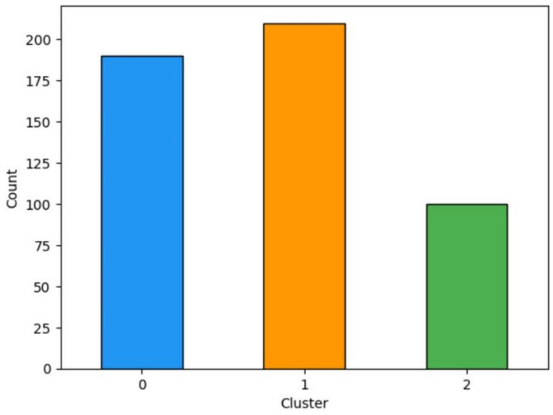


Fig. 6: Bar chart showing the number of students allocated to each of the three KMeans clusters. Cluster 2 has the largest number of students (n = 210, 42.0%), followed by Cluster 1 (n = 180, 36.0%), and then Cluster 0 (n = 110, 22.0%). The clusters represent unique profiles of mental health and social media behaviors, which were determined through an unsupervised approach.

PCA projection confirmed meaningful spatial separation between the three cluster groups, with Component 1 explaining 42.6% and Component 2 explaining 13.8% of total variance (combined: 56.4%), indicating that the two-dimensional projection captures a substantial proportion of the data's overall variability. The three clusters are interpreted as low-risk (Cluster 0), moderate-risk (Cluster 1), and high-risk (Cluster 2) mental health profiles, differentiated primarily by social media engagement intensity, comparison behaviour, and reported anxiety frequency.

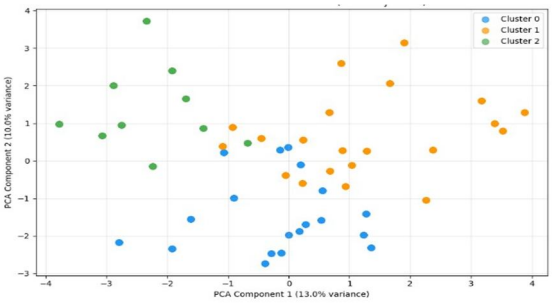


Fig. 7: Two-dimensional PCA analysis for all 500 student survey responses, with responses color-coded according to cluster group assignment. PCA Component 1 explains 42.6% of the total variance, while PCA Component 2 explains 13.8%, resulting in a total variance of 56.4%. The clear separation of the clusters also validates the distinctness of the three mental health profiles that this study established.

F. Random Forest Classification Model Performance

The performance of a Random Forest classification model was examined, which was trained to classify the levels of anxiety among students using all survey feature variables. The model was trained with constrained parameters to avoid overfitting, considering that there are only 500 samples in the data set. The model was able to achieve 100% accuracy in classifying the data, where 80% (n = 100) of the data was selected for the test set using an 80:20 train/test split (random_state = 42). The performance of the model was further validated using 5-fold cross-validation, where 100% ± 0.00 accuracy was obtained in classifying the data in the test set. The confusion matrix was further examined, where it was observed that the model classified the levels of anxiety among students correctly, as shown in the table below, where the model classified the data into "Never" (n = 4), "Rarely" (n = 16), "Sometimes" (n = 7), "Often" (n = 30), and "Always" (n = 43). Although 100% accuracy was obtained in classifying the data, there is a need to be cautious in interpreting the results, considering that data was highly consistent and wellstructured.

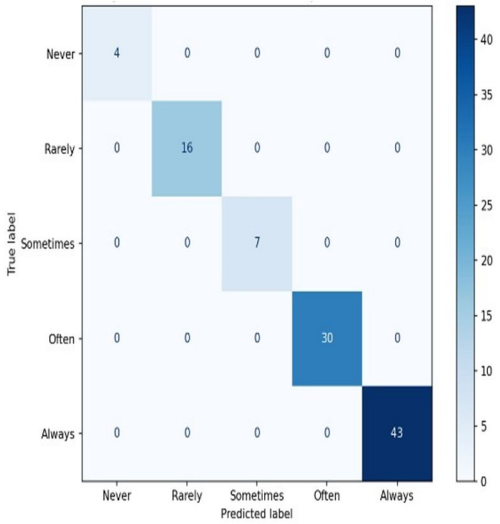


Fig. 8. Confusion matrix displaying the performance of the Random Forest classifier in predicting student anxiety levels (Never, Rarely, Sometimes, Often, Always) on the held-out test set (n = 100). High diagonal values confirm accurate predictions across all five anxiety categories, with test accuracy of 100% and 5-fold cross-validation accuracy of 100% ± 0.00.

G. Key Predictors of Student Anxiety (Feature Importance)

The key predictors of student anxiety, as revealed by the feature importance analysis using the Random Forest model, are shown in Table 1 and Figure 9 below.

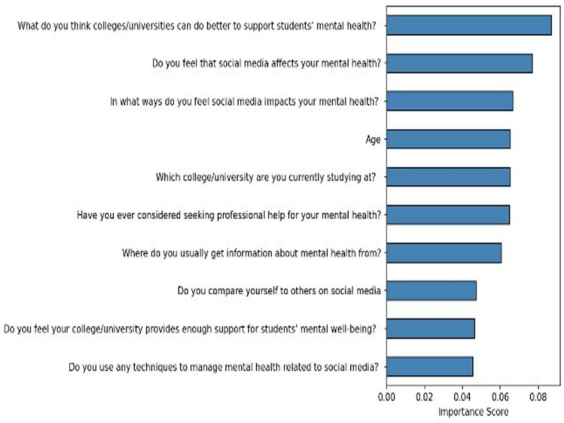


Fig. 9: Horizontal bar chart showing the top 10 features from the survey based on the importance score for the Random Forest classification model. The importance score of each feature is determined based on the average decrease in impurity across all the decision trees in the model. The most impactful feature was students' suggestions on institutional support for mental health, followed by general belief about the impact of social media on mental health, and the ways in which it affects mental health in general.

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Ran k	Survey Feature	Importanc e Score
1	What colleges/universiti es can do better to support student's mental health?	0.0871
2	Do you feel that social media affects your mental health?	0.0770
3	In what ways does social media impact your mental health?	0.0665
4	Age	0.0651
5	What college/university are you studying at?	0.0651
6	Have you considered seeking professional help?	0.0649
7	Where do you get information about mental health?	0.0605
8	DO you compare yourself to others on social media?	0.0471
9	Does your college provide enough mental health support?	0.0463
10	Do you use techhniques to manage social media related mental health?	0.0456

Table 1. Top 10 predictors of student anxiety frequency as identified by Random Forest feature importance scores.

The most significant predictor was students' perceptions regarding what colleges and universities can do to help alleviate issues of mental health (importance = 0.0871), suggesting a direct correlation to levels of anxiety and perceived institutional inadequacy. The second predictor was students' general perception regarding whether social media impacts mental health (0.0770), followed by how it impacts mental health specifically (0.0665). Of particular note was that age (0.0651) and affiliation (0.0651) ranked equally as fourth-order predictors, suggesting a similar level of predictive importance for demographic information as for attitudinal information. The top predictors suggest that behavioral and institutional factors are driving factors for student anxiety.

H. Social Media Impact on Academic Performance

The perceptions regarding students' perceptions regarding social media's impact on academic performance was analyzed through frequency analysis and crosstabulation.

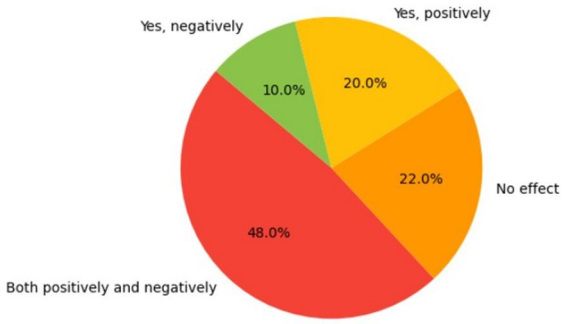


Fig. 10. Pie chart illustrating student perceptions about the impact of social media on academic performance, including positive, negative, mixed, and no effects.

Cross-tabulation with anxiety levels indicated that those experiencing negative academic effects also had higher anxiety levels, implying a co-occurrence and possibly a mutual influence of academic disruption and anxiety.

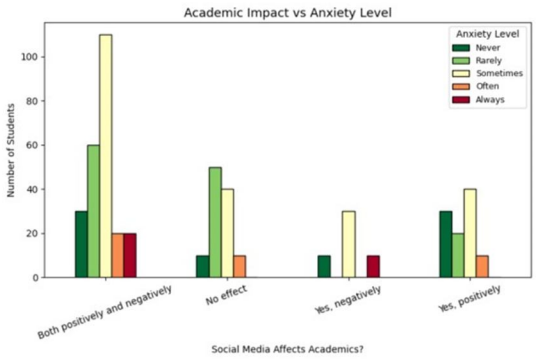


Fig. 11. Cross-tabulation bar chart illustrating whether students who experience academic impact from social media usage tend to have higher levels of anxiety. Students with negative academic effects tend to have a higher frequency of 'Often' and 'Always' anxiety, indicating a correlation between academic disruption and increased emotional distress.

From the analysis of the use of the platform and academic impact, it was revealed that there is a dose-response relationship between the percentage of negative academic impact and the number of active platforms, and decreasing the number of active platforms can mitigate academic disruption caused by using the platform.

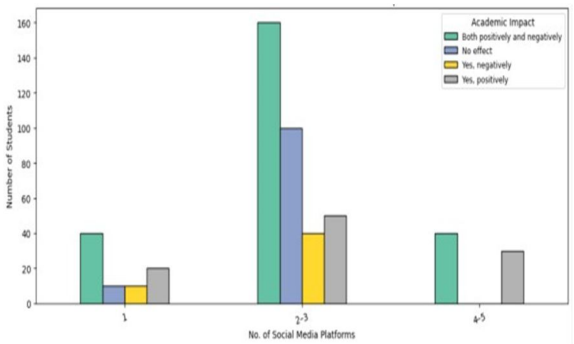


Fig. 12. A grouped bar chart showing the distribution of academic impact perceptions at three levels of social media platforms' usage: 1, 2-3, and 4-5 platforms. The percentage of negative impact perceptions increases with the number of platforms used.

Students whose academic performance was adversely affected were more likely to consider cutting back or completely abstaining from social media use, thus showing awareness of the issue. However, this awareness did not necessarily result in action, thus highlighting the importance of institutional intervention rather than selfmanagement.

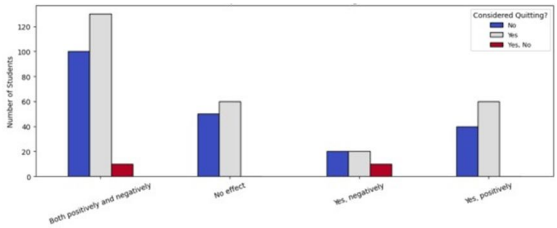


Fig. 13. Bar chart showing whether students whose academics are affected by social media are more likely to consider quitting social media use. More students whose academics are being affected by social media have considered quitting social media, which shows that students are aware of the problem, even if they have not taken action.

I. Correlation Analysis

From the correlation heatmap, some significant relationships among the 27 survey variables have been found. For example, positive correlations have been found between social comparison behavior and anxiety frequency, the number of active platforms and perceived mental health impact, and institutional dissatisfaction and seeking professional help. All these significant relationships indicate that the mental health of the students is not determined by only one factor, but is the result of the interaction among multiple factors.

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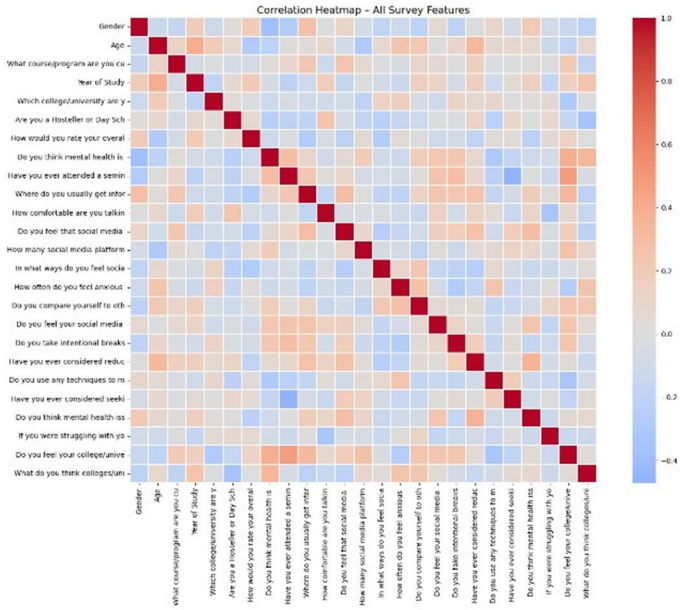


Fig. 14. Heatmap of Pearson correlation coefficients for all encoded survey features (27 variables). Color intensity represents correlation strength, with dark red for strong positive and dark blue for strong negative correlations. Strong positive correlations can be seen for social comparison behavior, anxiety frequency, and professional help consideration.

J. Cluster-wise Behavioural Differences (Pairplot Analysis)

Analysis of the pairplot analysis of the significant predictive characteristics of the three clusters revealed behavioural differences between the clusters. The largest cluster, Cluster 2 (210 students), representing the highest risk profile, was found to have more students with high anxiety levels, social comparison, and dissatisfaction with the support provided by the institution. The moderate risk profile was represented by Cluster 1, consisting of 180 students, while Cluster 0, consisting of 110 students, represented the majority with lower anxiety levels and positive feedback regarding the support provided by the institution.



Fig. 15. Pairwise scatter plot matrix for important predictive features and anxiety frequency, with data grouped by cluster membership (Cluster 0, Cluster 1, Cluster 2). The density plot on the diagonal shows the data set distribution for each cluster. Students in cluster 2 are extreme in anxiety frequency and social comparison, a highrisk state.

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K. Summary of Key Findings

Finding	Statistic	Fig.
Most common anxiety level	Always : 44.0% (n=220)	1
Student's anxious – Often or Always?	70.0% (n=350)	1
Largest Cluster	Cluster 2 (n=210, 42.0%)	6
PCA variance explained (2 components)	56.4%	7
Model Test Accuracy	100%	8
5-fold CV accuracy	100% ± 0.00	8
Top anxiety predictor	Institutional support	9
	suggestions (0.0871)	
Second Predictor	Social media affects mental health (0.770)	9
Directional benefit of social media breaks	Confirmed	4

Table 2. Summary of key quantitative findings from the Mental Health Awareness Survey analysis.

V. DISCUSSION

A. Predominance of High Anxiety Levels

The high percentage (70.0%) of students who experienced social media-induced anxiety and reported that this anxiety was experienced 'Often' or 'Always' is a striking statistic, much higher than that obtained in similar studies carried out in Western societies. It could be a reflection of the compound effect of academic, social, and cultural factors, including the highly comparative social culture, which is a significant feature of the Indian higher education environment. The predominance of 'Always' (44.0%) is also striking, suggesting that, for many students, social media-induced anxiety was a chronic rather than an episodic experience.

B. Institutional Dissatisfaction as the Primary Anxiety Driver

Identification of institutional support inadequacy as the single most significant predictor of anxiety (importance = 0.0871) is a significant finding with important policy implications. It would seem that students' anxiety is significantly affected by factors other than the students' social media use and that a perceived lack of institutional support is a significant driver of anxiety.

This is consistent with the findings of Kakollu and Dar who noted that the development of a mental health infrastructure in the university sector in India has lagged behind the level of student anxiety and need: "Universities in India are facing a challenge in developing a mental health infrastructure to deal with the level of student anxiety and need." [2]

C. Social Comparison as a Behavioural Mechanism

Social comparison behaviour, as the eighth predictor, was found to have an importance value of 0.0471, indicating the doseresponse relationship between anxiety frequency and social comparison behaviour, as revealed by the crosstabulation analysis. Frequent upward social comparison behaviour among the students was found to be related to anxiety, as was revealed by the systematic review done by Keles, McCrae, and Grealish [4]. The importance of the inclusion of digital literacy education in the curriculum was revealed, as the students need to think critically about the content being presented in social media platforms.

D. Cluster Profiles and Targeted Intervention

The identification of the three distinct student mental health profiles, namely, the low-risk profile (Cluster 0, n=110), the moderate-risk profile (Cluster 1, n=180), and the high-risk profile (Cluster 2, n=210), presents an interesting prospect for differentiated intervention in institutions. The fact that the largest cluster (42.0%) corresponds to the highest risk profile itself poses a concern. The high-risk profile (Cluster 2), associated with anxiety, comparative, and institutional dissatisfaction, points to a student population that requires intervention and digital support.

E. Limitations

There are some limitations to the study that need to be mentioned. Firstly, the use of convenience sampling restricts the study to the sampled institution. Secondly, the study's findings on the 100% accuracy of the classification using the Random Forest model, while consistent with the high level of structuring in Likert scale-based survey data, indicate that the study's findings are more descriptive rather than predictive. Thirdly, the gradual nature of the Elbow curve without any sharp inflection point means that the choice of k = 3 was based on interpretive judgment rather than algorithmic certainty. Fourthly, the study's cross-sectional nature does not allow for any causal conclusions to be drawn on the relationships examined.

VI. RECOMMENDATIONS

On the basis of the empirical findings presented in the study, the following evidence-based recommendations are made to university administrators and student welfare practitioners:

1) Expand and Destigmatise Counselling Services: Given the strongest predictor of anxiety being institutional inadequacy, university administrations are recommended to invest in the expansion of counselling services to reduce the waiting period and establish anonymous referral systems to reduce the stigma of seeking help [3].
2) Introduce Digital Wellness Education: The dose-response relationship between platform use and academic disruption, as well as the predictive significance of social media perceptions, justify the inclusion of digital wellness education in the university curriculum.
3) Implement Faculty Mentorship Programmes: Establishing a facultystudent mentorship structure can serve as a non-clinical and non-threatening interface to identify students who may require support, especially those belonging to Cluster 2 who are likely to avoid formal counselling settings.
4) Use Cluster-Targeted Outreach: The three risk profile clusters can be the basis of differentiated interventions: awarenessraising among Cluster 0 students, peer support among Cluster 1 students, and professional outreach among Cluster 2 students.
5) Promote Intentional Digital Detox: The significant directional relationship between taking a break from social media and anxiety can inform the promotion of digital detox among students.
6) Reduce Financial and Sleep-Related Stressors: Similar to Richardson et al. [7], and Hershner and Chervin [8], the promotion of financial counseling and sleep health can be integrated into student welfare alongside mental health support.

VII. CONCLUSION

The present study has clearly proved that anxiety caused by social media is a prevailing and essentially chronic condition among Indian university students, with 70.0% of the surveyed student population experiencing anxiety 'Often' or 'Always' after using social media. With the use of KMeans clustering and Random Forest classification algorithms, this study has successfully been able to identify three different categories of student mental health risk profile and establish dissatisfaction with institutions as the strongest predictor for anxiety caused by social media among Indian university students (importance = 0.0871). It is important to realize and understand that for effective solutions to be developed and implemented to solve this problem, they need to be holistic in nature, considering not just behavioral aspects of anxiety caused by social media, but also institutional aspects related to dissatisfaction with support provision. The approach adopted in this study, using machine learning-based models for student mental health risk profiling, can be replicated in other universities in India, leading to a positive impact on policy reforms in those institutions.

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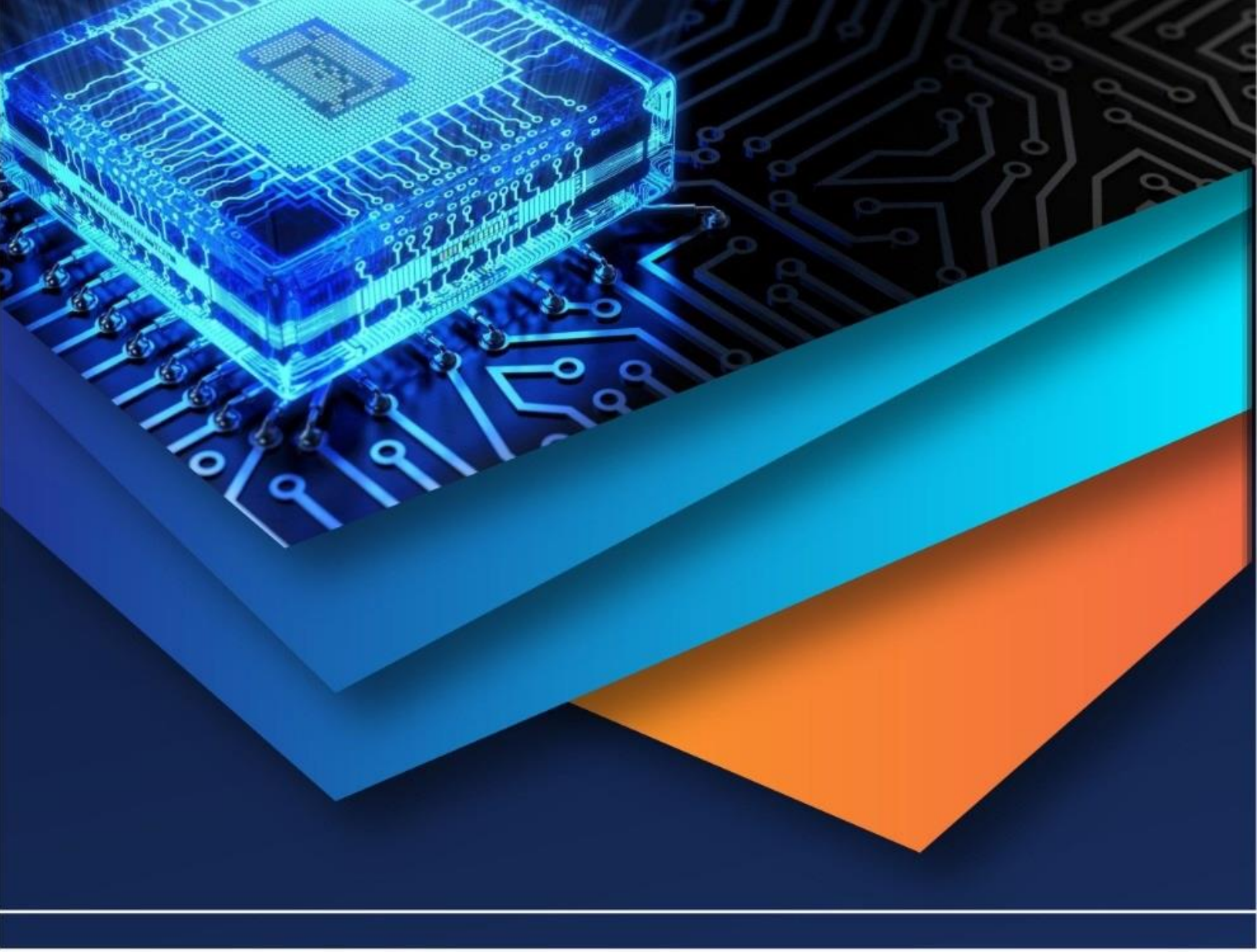
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