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Beyond Screen Time: Predicting Social Media's Academic Impact Through Machine Learning and Student Risk Segmentation

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Abstract

Aim/Purpose	This study investigates how psychological dimensions of social media use affect university students' academic performance. The focus extends beyond screen time to examine addiction and interpersonal conflict as predictors of academic decline.
Background	Social media now serves as an informal knowledge-sharing platform in higher education. Most existing research uses descriptive statistics and cannot identify which students are at risk. Few studies distinguish between usage duration and the psychological factors that drive different outcomes across individuals.

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Methodology	Secondary survey data from 705 university students were analyzed. Methods included Random Forest classification, SHAP feature attribution, K-Means clustering, and hierarchical clustering. Five-fold stratified cross-validation was used to assess model robustness.
Contribution	Psychological friction, specifically social media conflict and addiction, predicts academic decline far more strongly than daily usage hours. This challenges institutional policies that focus mainly on restricting screen time. The study also introduces a three-tier student risk segmentation framework to support targeted intervention design.
Findings	The Random Forest model achieved perfect classification accuracy (1.00), confirmed across all five cross-validation folds. SHAP analysis identified interpersonal conflict as the dominant predictor (importance = 0.40), followed by addiction score (0.27) and mental health score (0.19). Daily usage hours contributed only marginally (0.05). Clustering revealed three behaviorally distinct student segments: Low-Risk, At-Risk, and High-Risk.
Recommendations for Practitioners	Universities should shift digital welfare policy away from usage restrictions and towards psychological support. Practical steps include early detection systems based on indicators of conflict and addiction, digital literacy embedded in core curricula, and differentiated counseling for At-Risk and High-Risk students.
Recommendations for Researchers	Future studies should validate this framework across diverse institutional and cultural contexts. Longitudinal designs would help assess causal direction. Federated learning could enable multi-institutional collaboration while protecting student privacy. Integration with Learning Management System logs would also strengthen the feature set.
Impact on Society	Universities can treat social media as a manageable educational variable rather than an uncontrolled risk. This is achievable when support systems are built around psychological indicators rather than usage metrics alone. The approach has broader relevance for digital health policy in higher education.
Future Research	Replication across diverse student populations remains a priority. Platform-level behavioral differences warrant a dedicated study, particularly one that contrasts short-form video platforms with messaging applications. Incorporating physiological stress indicators and longitudinal behavioral data would substantially improve predictive validity.
Keywords	social media addiction, academic performance, machine learning, student risk segmentation, digital well-being

INTRODUCTION

Social media platforms have become central to knowledge exchange in higher education. Platforms such as Instagram, TikTok, and Facebook now function as informal Knowledge Management Systems. Students use them to share information, collaborate on problems, and access learning resources outside the classroom (Haji, 2025; Kumar, 2024). Research confirms that purposeful educational use produces measurable academic benefits (Sahoo & Pradhan, 2025). One large-scale study reported a positive correlation ($r = 0.72$, $p < 0.01$) between structured social media engagement and academic performance, particularly when instructors provide guidance and scaffolding (Shabbir et al., 2025).

The same platforms, however, generate conditions that harm academic performance. Students who develop addictive usage patterns often exhibit declining mental health, including elevated depression and anxiety, which subsequently impairs academic engagement (Cvetković et al., 2025; Malizal, 2025). Sustained multitasking across platforms imposes cognitive overload, fragmenting students' capacity for critical thinking and deep information processing (Islam et al., 2025; N. Khan et al., 2025). The core problem is not simply that social media is present in students' lives. Its effects are heterogeneous and poorly explained by usage volume alone.

Three gaps in the literature motivated this study. First, prior research has relied predominantly on descriptive methods such as cross-tabulations and bivariate correlations. These approaches characterize patterns of use but cannot predict which individual students will experience academic harm (Pecuchova & Drlík, 2024). Second, social media use has frequently been treated as a uniform construct. This framing obscures the fact that different platforms, usage contexts, and individual psychological vulnerabilities produce substantially different outcomes (Padilla et al., 2024). Two students spending equivalent hours on social media may follow entirely divergent academic trajectories depending on the psychological character of that use. Third, the institutional assumption that limiting screen time protects academic performance has not been rigorously tested against behavioral and psychological alternatives.

This study draws on two theoretical frameworks. The Technology Acceptance Model (TAM) explains initial adoption: students engage with social media because they perceive it as useful and accessible (Granić, 2023). Evidence from the Thai higher education context further suggests that trust and perceived interactivity now mediate adoption more strongly than TAM originally proposed (Tantiathimongkhon & Satjaharuthai, 2025). Knowledge Management (KM) theory, in turn, accounts for the functional role social media plays as a peer-to-peer knowledge infrastructure, facilitating acquisition, sharing, and application of academic knowledge beyond formal institutional channels (Mashhadi & Dehghani, 2025). Both frameworks, however, assume a rational and goal-directed user. Addiction research complicates this assumption. When compulsive use and interpersonal conflict become part of the picture, the informational utility of social media degrades and psychological costs accumulate (Ding & Sazalli, 2024). Combining these perspectives with behavioral data analysis allows this study to capture both the productive and the disruptive dimensions of social media in educational contexts.

Three research questions guide this study:

- **RQ1:** Which behavioral and psychological variables most strongly differentiate students whose academic performance is negatively affected by social media from those who are not?
- **RQ2:** How accurately can a machine learning model predict academic impact from social media use, and which features drive its predictions?
- **RQ3:** What distinct behavioral risk profiles emerge among university students based on their social media use, addiction levels, and mental health patterns?

To address these questions, Random Forest classification and SHAP feature attribution were applied to identify and explain the most consequential predictors of academic impact. K-Means and hierarchical clustering were then used to segment students into three risk groups: Low-Risk, At-Risk, and High-Risk. This segmentation framework gives universities a practical basis for designing differentiated support programs.

The remainder of this paper is organized as follows. The Literature Review situates the study within existing work on TAM, KM theory, psychosocial factors, student well-being, and predictive analytics in education. The Methodology section describes data acquisition, preprocessing, model selection, and evaluation procedures. The Results section presents descriptive findings, model performance, SHAP attribution, and clustering outcomes. The Discussion interprets these findings in relation to the three research questions and prior literature. The paper concludes with theoretical contributions, practical recommendations, and directions for future research.

LITERATURE REVIEW

THEORETICAL FOUNDATIONS AND FRAMEWORKS

Two theoretical frameworks inform this study. The Technology Acceptance Model (TAM) explains why students initially adopt social media for academic purposes: perceived usefulness and ease of use are the primary drivers of technology uptake (Granić, 2023). Knowledge Management (KM) theory, in turn, explains how social media functions as a peer-to-peer knowledge infrastructure, supporting the acquisition, sharing, and application of academic knowledge in informal settings outside the classroom (Mashhadi & Dehghani, 2025). Together, these frameworks account for the conditions under which social media supports student learning.

Empirical work reinforces both perspectives. Yilmaz and Yilmaz (2023) found that students join online learning communities partly in response to social approval and perceived collective benefit. Platform design also shapes adoption patterns. Research on TikTok, for instance, shows that students engage with its content-sharing features because the platform reduces perceived effort while increasing visibility within peer networks (Ding & Sazalli, 2024; Fuady, 2023). These findings are broadly consistent with TAM's predictions. Recent evidence from Thai higher education and SME contexts further confirms that adoption decisions extend beyond perceived usefulness to include trust, organizational strategic readiness, and output accuracy as critical determinants (Satayapaisal et al., 2026; Tantiathimongkhon et al., 2026). Comparable validation work in Thailand's digital platform sector, using confirmatory factor analysis to establish reliable technology adoption constructs, reinforces the value of rigorously validated measurement models in this context (Lakkhongkha et al., 2026).

However, both frameworks share a key limitation: they assume goal-directed, rational use of technology. Neither adequately explains what happens when use becomes compulsive or when platforms generate interpersonal conflict. TAM accounts for adoption but not for addiction. KM theory models knowledge flow but does not address how psychological dysfunction disrupts that flow. This gap motivates a behavioral, data-driven approach. If theoretical models cannot reliably identify which students will struggle, behavioral patterns in the data may reveal what theory alone cannot (Saripudin et al., 2025).

Machine learning offers a productive path forward. Clustering methods such as K-Means and K-Medoids have been applied to Learning Management System data to group students by engagement levels and academic standing, with the goal of detecting dropout risk before it becomes irreversible (Bahri & Midyanti, 2023; Pecuchova & Drlík, 2024). Analogous unsupervised segmentation has also been used to profile risk in adjacent digital-era populations, such as employee wellness clustering in remote/hybrid workplace settings (Meemuk et al., 2026). Random Forest classifiers have shown particularly strong results in this domain, with some studies reporting up to 99% accuracy in identifying at-risk students from assessment and participation data (Deb et al., 2024; Harshvardhan & Prakash, 2024; Karim-Abdallah et al., 2025). Graph Neural Networks have also been explored to model how peer relationships influence student outcomes (Almeida et al., 2025). Critically, predictive accuracy alone is insufficient for institutional use. Olipas (2026) argues that model decisions must be interpretable to be actionable, which is why SHAP analysis has gained traction as a tool for identifying behavioral variables that drive predictions. The present study applies this same logic to social media behavior data, segmenting students by addiction profiles, mental health indicators, and conflict patterns rather than relying solely on academic records. Dake and Gyimah (2025) demonstrated that students with distinct technology attitudes require differentiated support strategies, and Chong et al. (2025) note that clustering is particularly well-suited to contexts where labeled outcome data is unavailable, as is often the case when analyzing social media behavior.

The Role of Social Media in Academic Knowledge Management

Social media has become an informal knowledge management infrastructure in higher education. Students routinely use Instagram, TikTok, and WhatsApp to exchange academic information, coordinate group work, and access peer-generated resources outside formal learning environments (Parasar & Bhatt, 2025; Shabbir et al., 2025). When used with clear educational intent, the results are meaningful. Shabbir et al. (2025) reported a correlation ($r = 0.72$) between active educational social media use and academic achievement, a relationship that strengthens when instructors provide structure and guidance. Sahoo and Pradhan (2025) similarly found that goal-directed use within organized learning communities produces consistent academic benefits.

The quality of engagement matters more than the quantity of time. Unstructured, undirected use tends to produce diminishing returns and, in some cases, negative outcomes. Ankatwar et al. (2025) identified misinformation exposure as a specific risk associated with unstructured platform use, while Jin and Normalini (2025) found that satisfaction with e-learning platforms is a reliable predictor of continued engagement, independent of prior experience. Social cognitive theory offers one explanation for these patterns: knowledge-sharing behavior online is motivated by both personal goals and social reinforcement, meaning that the way platforms structure social interaction shapes whether knowledge exchange is productive or disruptive (Ankatwar et al., 2025; Lamimi et al., 2024; Zhao, 2023).

Psychosocial Factors: Addiction and Interpersonal Conflicts

Social media addiction is consistently associated with lower academic performance, increased stress, and reduced overall well-being among university students (Hill et al., 2024; Ning & Inan, 2024). What distinguishes addiction from heavy use is its psychological character: compulsive engagement that persists despite adverse consequences, including the interpersonal conflicts that often accompany it (Hou et al., 2019; Ning & Inan, 2024). Conflict arising from social media use, such as relational disputes over time spent online or arguments triggered by platform interactions, generates stress that reinforces rather than interrupts addictive behavior. This dynamic has been described in the literature as a self-perpetuating cycle in which addiction produces conflict, conflict produces stress, and stress drives further platform engagement as a coping mechanism (Hou et al., 2019).

Individual-level factors moderate the severity of this cycle. Self-regulation capacity, self-esteem, and family relationship quality all influence whether addiction translates into academic harm (Ning & Inan, 2024; Yang et al., 2025). Loneliness exacerbates this pattern: students who feel socially isolated tend to use social media more compulsively, further undermining self-regulation (Mohd Hassan et al., 2025). The academic consequences manifest primarily through reduced study engagement rather than through direct cognitive impairment (Mou et al., 2024; Ning & Inan, 2024).

Importantly, moderate use does not invariably produce negative outcomes. Some students manage social media effectively, likely due to stronger coping skills and higher baseline self-regulation (Ning & Inan, 2024; Yang et al., 2025). This variability suggests that undifferentiated time restriction policies are unlikely to be effective. Interventions that address the psychological mechanisms underlying problematic use are more likely to produce durable change (Hou et al., 2019). Prior studies have proposed several intervention models, including psychoeducation programs targeting self-regulation, peer support networks, and counseling services calibrated to addiction severity. However, empirical evidence on their comparative effectiveness remains limited.

Student Well-Being and Cognitive Load in the Digital Age

Prolonged social media use is associated with elevated rates of depression and anxiety among university students (Dwijayanti & Pratiwi, 2025; Gomes et al., 2024). Smartphone addiction compounds these effects, and when combined with emotional stress, cognitive performance declines across attention, memory, and information processing (N. Khan et al., 2025; Khatiwada, 2025). The mechanism involves attentional fragmentation: continuous exposure to notifications, rapid switching between applications, and the processing demands of multiple concurrent social interactions impose extraneous cognitive load that interferes with deep learning (Mashhadi & Dehghani, 2025; Shari et al., 2024). This cognitive cost is distinct from the time investment involved, which is why usage duration alone is an incomplete predictor of academic outcomes.

The quality of online interaction is a significant moderating factor. Negative interactions, including cyberbullying, hostile exchanges, and exposure to distressing content, amplify psychological distress, while meaningful social connections can buffer against it (Islam et al., 2025). Lifestyle variables also moderate the relationship between social media use and well-being. Students with adequate sleep and regular physical activity demonstrate greater resilience to the negative effects of heavy platform use (Mohd Hassan et al., 2025). Multi-platform use intensifies risk, as managing simultaneous social obligations across applications compounds cognitive load and reduces attentional coherence (Padilla et al., 2024). Despite growing evidence for these effects, most institutions lack systematic approaches to digital wellness. Existing interventions tend to be voluntary, isolated from academic programming, and poorly aligned with the behavioral profiles of students most at risk (Islam et al., 2025; M. A. Khan et al., 2025).

Predictive Analytics and Student Behavioral Risk Segmentation

Machine learning has demonstrated considerable promise for identifying students at academic risk before outcomes deteriorate. Clustering methods group students by digital engagement patterns and flag those likely to disengage or fail (Pecuchova & Drlík, 2024). Tantiathimongkhon et al. (2025) applied FP-Growth algorithms to post-pandemic behavioral data and recovered structured usage patterns that would not have been detectable through conventional analysis. Deep learning and ensemble methods generally outperform traditional statistical models for student risk prediction, particularly as data complexity increases (Shi et al., 2025). The inclusion of social media variables, such as mood indicators and stress-related behavioral signals, has been shown to improve predictive performance beyond what academic records alone can provide (Jimenez Martinez et al., 2024; Tale & Patil, 2025).

Probabilistic outputs are particularly valuable in this domain because they convey uncertainty alongside predictions, thereby supporting more calibrated institutional responses (Mosia, 2023; Rosdiana et al., 2024). Federated learning has been proposed as a means of building predictive models across multiple institutions without requiring data centralization, addressing a significant privacy barrier to multi-site research (Narimani & Barberà, 2025; Tertulino & Almeida, 2025). Beyond model accuracy, sustainable adoption of these tools depends on student and administrator trust. Nuh et al. (2025) found that continued engagement with AI-supported educational platforms is primarily driven by perceived information quality and platform reliability rather than technical capability alone. Raicevic et al. (2026) push this further, arguing that trustworthy AI deployment means building human oversight into the design process from the start, positioning AI as a tool that amplifies human judgment rather than replacing it.

Similar threshold-based tiered classification, translating continuous behavioral signals into actionable risk categories for targeted intervention, has been demonstrated in IoT-based elderly care monitoring (Joobanjong et al., 2026). Olipas (2026) demonstrated this point empirically: using Random Forest and SHAP on student employability data, non-academic behavioral traits turned out to matter more than expected, which is exactly why interpretable models are worth the effort. Nguyen (2025) adds another layer, noting that even the best predictive model fails if the underlying data infrastructure is unreliable. These studies collectively suggest that effective Student Relationship Management is not purely a modeling problem. It requires clean data, explainable outputs, and sufficient institutional trust for students and administrators to actually act on the results.

METHODOLOGY

DATA ACQUISITION AND DESCRIPTION

This study analyzes a secondary dataset obtained from Kaggle, titled "Student Social Media and Relationship Analysis" (Pk, 2026). The dataset was compiled through an online survey of 705 university students and captures thirteen variables covering demographic characteristics, platform preferences, daily usage hours, addiction scores, mental health scores, sleep duration, and self-reported academic impact.

The use of secondary data carries both advantages and limitations. Because the dataset is distributed through a public data science platform, the analytical pipeline reported here can be inspected and re-executed by other researchers without requiring access to restricted institutional data. Two limitations follow from this choice. First, the data are redistributed through a third-party notebook rather than a formally archived repository, so long-term availability is not guaranteed. Second, the original sampling procedures and institutional context cannot be independently verified, which constrains the generalizability of findings. These constraints are acknowledged and discussed further in the Limitations section.

DATA PREPROCESSING AND FEATURE ENGINEERING

Prior to model training, the dataset underwent several preprocessing steps. Missing values were addressed using mean imputation for continuous variables and mode imputation for categorical variables. Inconsistent category labels, including variations in spelling and capitalization, were standardized across all fields.

Categorical variables were encoded numerically to meet the input requirements of the machine learning algorithms. The target variable, Affects_Academic_Performance, was transformed into a binary indicator: 0 for "No Impact" and 1 for "Impacted." Platform preference variables were similarly encoded using label encoding.

Feature selection was conducted using Pearson correlation analysis to identify variables with meaningful linear relationships to the target outcome. The Pearson correlation coefficient r between two variables x and y is defined as:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where χ_i and y_i are individual sample points, $\underline{\chi}$ and $\underline{y}$ are sample means, and n is the number of observations. Correlation analysis was used for exploratory assessment of linear relationships among the study variables. All available features were subsequently retained for Random Forest training, as ensemble methods perform implicit feature weighting and are robust to low-informative predictors.

MODEL SELECTION AND TRAINING

The analytical framework combined supervised and unsupervised learning methods to address both the predictive and segmentation objectives of the study.

For the supervised component, Random Forest was selected as the primary classifier. Random Forest constructs an ensemble of decision trees, each trained on a bootstrap sample of the data and a random subset of features (Breiman, 2001). Predictions are determined by majority vote across all trees. This ensemble design reduces the risk of overfitting that affects individual decision trees and handles non-linear feature interactions without requiring explicit specification. Hyperparameters, including n_estimators (number of trees) and max_depth (maximum tree depth), were optimized through grid search cross-validation. The dataset was partitioned into training (80%) and test (20%) sets using a random 80/20 split.

For the unsupervised component, K-Means clustering was applied to identify behavioral subgroups among students (MacQueen, 1967). K-Means partitions n observations into k clusters by minimizing the within-cluster sum of squares (WCSS):

$$WCSS = \sum_{i=1}^{k} \sum_{x \epsilon C_i} ||x - \mu_i||^2$$

where C_i denotes the i-th cluster, μ_i is the centroid of that cluster, and x represents individual observations. The optimal number of clusters was determined using the elbow method and silhouette scores. Hierarchical clustering was subsequently applied to the same data as an independent validation of the K-Means segmentation, using Euclidean distance as the dissimilarity measure.

Evaluation Metrics

Model performance was assessed using four complementary metrics. Accuracy measures the overall proportion of correct classifications:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP and TN denote true positives and true negatives, and FP and FN denote false positives and false negatives. Accuracy alone can be misleading when class distributions are unequal, as a model that predicts only the majority class can achieve high accuracy while failing on the minority class.

Precision measures the proportion of positive predictions that are correct:

$$\text{Precision} = \frac{TP}{TP + FP}$$

High precision indicates few false alarms, which is relevant when counseling resources are limited and unnecessary referrals carry a cost.

Recall measures the proportion of actual positive cases correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN}$$

High recall indicates that few at-risk students are missed. Low recall means students who need support are not being identified.

The F1 score combines precision and recall as their harmonic mean:

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

The harmonic mean penalizes imbalance between the two metrics, making F1 a more informative single-number summary than accuracy when both false positives and false negatives carry meaningful costs.

Model predictions were also evaluated visually using a confusion matrix, which displays the distribution of TP, TN, FP, and FN outcomes across both classes. The ROC curve plots the true positive rate against the false positive rate across classification thresholds, and the area under the curve (AUC) summarizes overall discriminative ability (Fawcett, 2006). An AUC of 0.5 indicates performance equivalent to random assignment; an AUC of 1.0 indicates perfect discrimination.

Finally, SHAP (SHapley Additive exPlanations) analysis was applied to decompose each prediction into individual feature contributions (Lundberg & Lee, 2017). SHAP values are grounded in cooperative game theory and provide consistent, locally accurate explanations of model output. In the context of this study, SHAP analysis identifies which behavioral and psychological variables drive the model's classification decisions, providing the interpretive foundation needed to translate predictive findings into institutional policy recommendations.

RESULTS

DESCRIPTIVE ANALYTICS AND DATA OBSERVATIONS

Table 1 summarizes the demographic and behavioral profile of the 705 students in the dataset. The sample was composed predominantly of undergraduate students (50.1%, n = 353) and graduate students (46.1%, n = 325), with a small proportion of high school students (3.8%, n = 27). The age distribution centered around the traditional college range (M = 20.66, SD = 1.40).

Table 1. Profile summary and descriptive statistics (N = 705)

Category	Variable	Sub-category	Count (n)	Percentage (%)
Demographic Profile	Academic Level	Undergraduate	353	50.1%
		Graduate	325	46.1%
		High School	27	3.8%
Demographic Profile	Academic Impact	Impacted (Yes)	453	64.3%
		Not Impacted (No)	252	35.7%
Category	**Variable**		**Mean**	**Std. Deviation**
Behavioral Metrics	Age	Year	20.66	1.40
	Daily Usage	Hours	4.92	1.26
	Addiction Score	1 - 10	6.44	1.59
	Mental Health Score	1 - 10	6.23	1.11
	Sleep Hours	Per Night	6.87	1.13

Platform preferences are presented in Figure 1. Instagram was the most frequently reported primary platform (35.3%), followed by TikTok (21.8%), Facebook (17.4%), WhatsApp (7.7%), and Twitter (4.3%). The remaining platforms each accounted for approximately 3% or less of the sample, with YouTube selected by the fewest students (1.4%). This distribution is consistent with prior research indicating that students gravitate toward interactive, socially reciprocal platforms rather than primarily consumptive ones.

The behavioral metrics in Table 1 reveal several patterns of concern. Students reported spending an average of 4.92 hours daily on social media (SD = 1.26), placing most of the sample between 3.7 and 6.2 hours per day. The mean addiction score was 6.44 out of 10 (SD = 1.59), indicating that a substantial proportion of students reported usage patterns consistent with compulsive engagement. Mental health scores averaged 6.23 (SD = 1.11), where lower scores reflect poorer mental health outcomes. Average sleep duration was 6.87 hours per night (SD = 1.13), modestly below the 7 to 9 hours recommended for young adults. Conflicts over social media, the variable that proved most consequential in the classification analysis reported below, records the self-reported frequency of interpersonal disputes arising from the respondent's social media use.

Critically, 64.3% of students (n = 453) reported that social media negatively affects their academic performance. This proportion indicates that academic disruption from social media is not an exceptional case in this population but a common experience shared by nearly two-thirds of respondents.

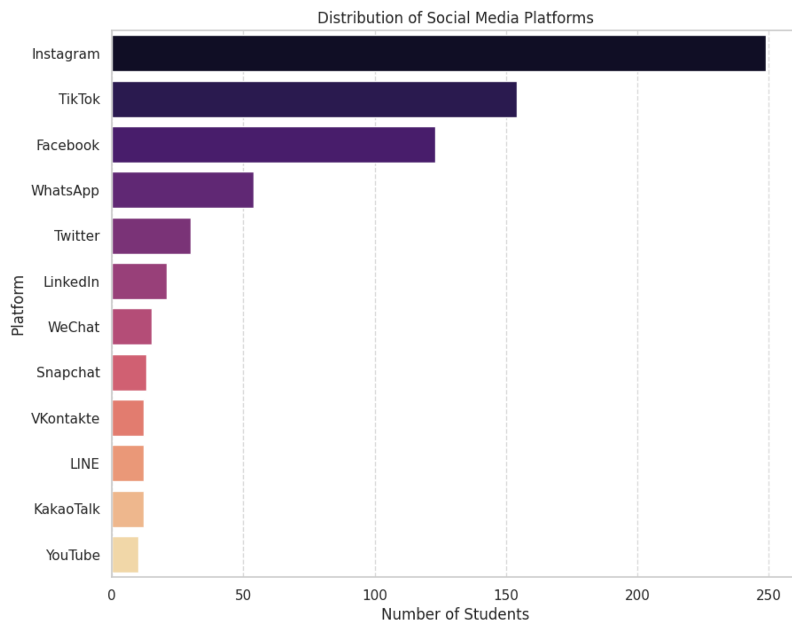

Figure 1. Distribution of social media platforms

Figure 2 presents the distribution of mental health scores disaggregated by academic impact status. Students who reported negative academic effects showed a lower median mental health score (Mdn = 6), with an interquartile range of 5-6 and a lower whisker extending to 4. In contrast, students who reported no academic impact showed a substantially higher median score (Mdn = 8), with an interquartile range of 7 to 8 and an upper whisker of 9. The separation between the two distributions is considerable, with the upper whisker of the academically impacted group reaching only the non-impacted group's lower quartile. This pattern indicates that mental health status is closely associated with social media's academic impact and reinforces the view that psychological well-being is a key factor distinguishing students who are disrupted from those who are not.

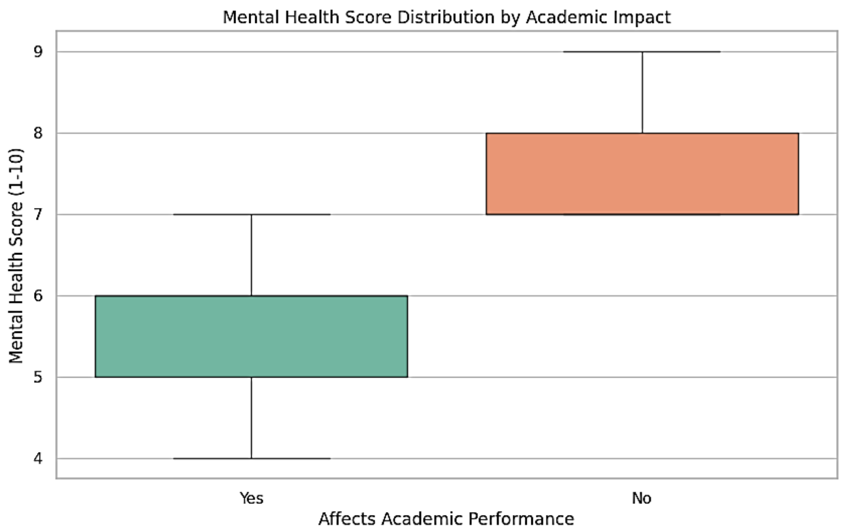

Figure 2. Mental health score distribution by academic impact

Exploratory Relational Analysis

Behavioral indicators of academic disruption

Figure 3 presents addiction scores disaggregated by academic impact status. Students who reported negative academic effects showed considerably higher addiction scores, with the interquartile range spanning 7 to 8 and a median of 7. Students who reported no academic disruption showed a markedly different profile, with scores spanning 4 to 5 and a median of 4.

The two distributions show minimal overlap, which is notable given the typically gradual distributions observed in behavioral self-report data. An addiction score at or above 7 appears to be a reliable indicator of academic risk, while scores below 5 correspond almost exclusively to students reporting no academic impact. The transitional range of 6 to 7 represents the zone in which outcomes become less predictable.

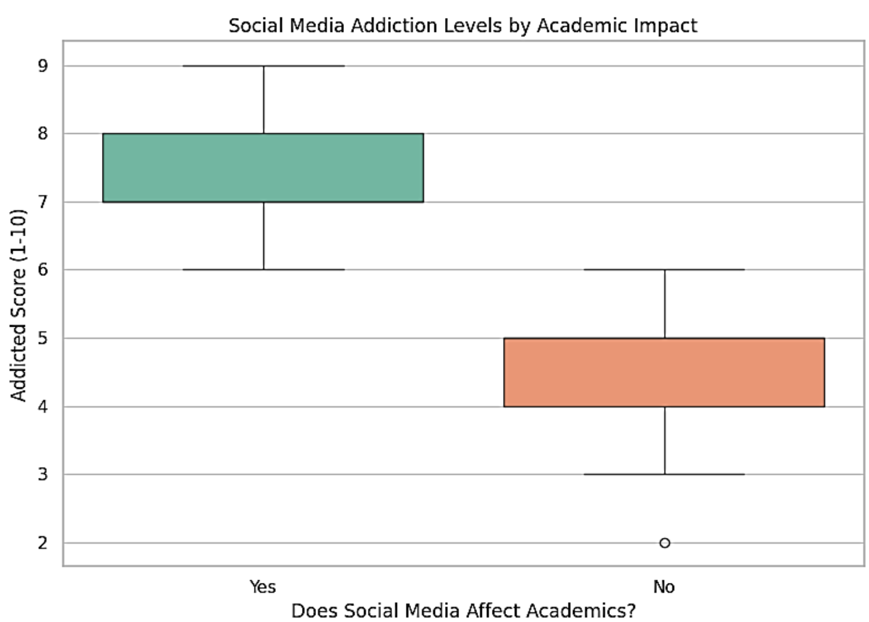

Figure 3. Social media addiction levels by academic impact

Figure 4 plots average daily usage hours against mental health scores for individual students. The trendline shows a clear negative relationship: as daily usage increases, mental health scores decline. Students reporting 2 to 3 hours of daily use are concentrated at mental health scores of 7 to 9, while those reporting 7 to 8 hours cluster at scores of 4 to 5. At moderate usage levels, individual variation is considerable, suggesting that personal and contextual factors moderate the relationship. At higher usage levels, the distribution narrows considerably, with almost no students maintaining strong mental health outcomes. This pattern is consistent with a threshold effect in which sustained heavy use becomes increasingly difficult to offset regardless of individual resilience.

Taken together, Figures 3 and 4 establish that both addiction level and usage intensity are associated with poorer outcomes, though their mechanisms differ. Addiction score demarcates academic risk with sharp separation between groups, while usage hours show a more gradual dose-response pattern in relation to mental health.

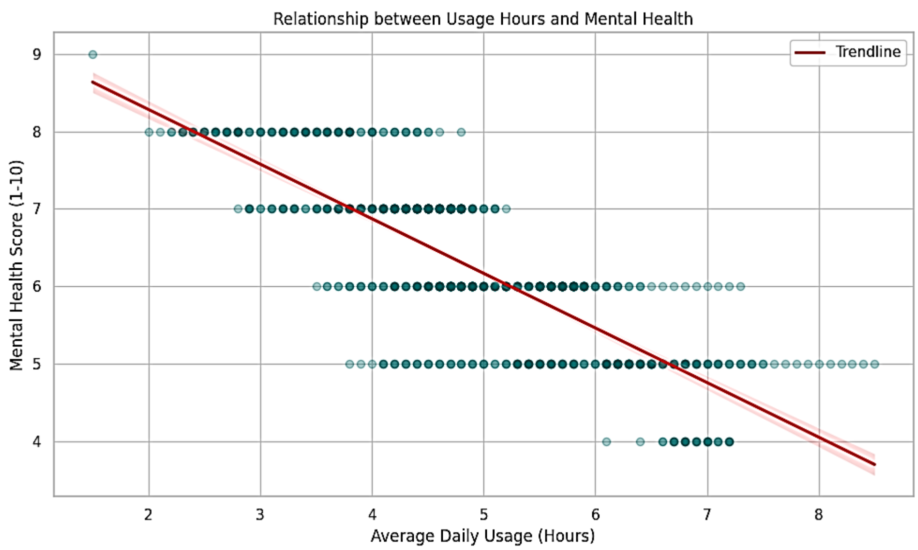

Figure 4. Relationship between usage hours and mental health

Platform-specific addiction patterns

Figure 5 presents mean addiction scores by primary platform. WhatsApp, Snapchat, and TikTok users reported the highest mean addiction scores, each approaching 7.5. Instagram followed at approximately 6.6, with YouTube, WeChat, and KakaoTalk clustered near 6.0. Facebook (approximately 5.7), Twitter (approximately 5.5), and VKontakte (approximately 5.0) were lower, while LinkedIn (approximately 3.8) and LINE (approximately 3.0) recorded the lowest scores in the sample.

These differences likely reflect platform design characteristics rather than user self-selection alone. TikTok's algorithmically driven short-form video feed provides continuous, rapidly reinforced content with no natural stopping point, a design pattern that has been associated with compulsive engagement in the literature (Ding & Sazalli, 2024). WhatsApp's high score reflects the distinct pressure of messaging platforms: notification-driven communication creates social obligations that make disengagement feel costly, particularly in the context of academic group work. Snapchat's comparably high score reflects a design built around ephemeral content and continuity mechanics, both of which reward frequent return visits. Instagram combines social comparison features with short-form video content, both of which have documented associations with compulsive use. The lowest scores were recorded by LinkedIn and LINE, platforms whose use tends to be more goal directed and task bound, with students accessing them for a specific purpose and disengaging once that purpose is served.

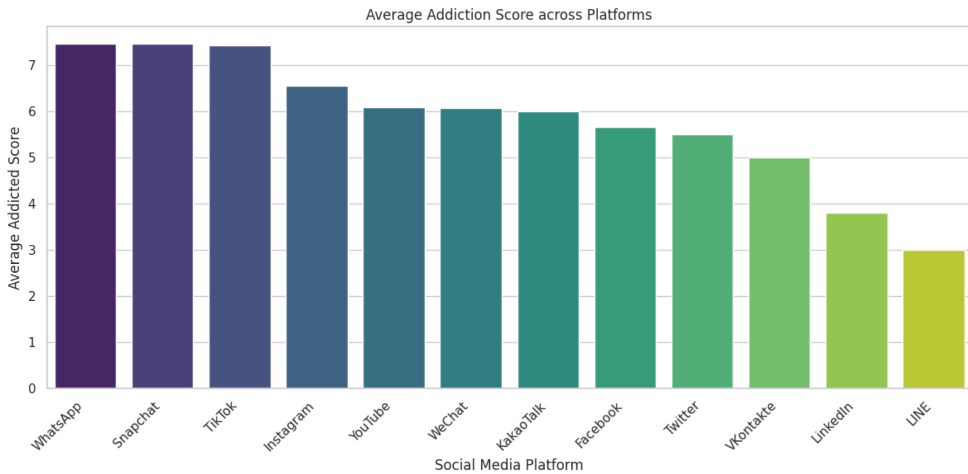

Figure 5. Average addiction score across platforms

Correlation Analysis

Figure 6 presents the Pearson correlation matrix for the study variables. Social media addiction and interpersonal conflicts exhibited the strongest pairwise relationship in the dataset (r = 0.93), indicating that these two constructs are tightly coupled in this population. Addiction also showed a strong positive association with academic impact (r = 0.87) and a strong inverse association with mental health (r = -0.95). These correlations suggest a cyclical pattern in which addiction reinforces conflict, conflict degrades mental health, and poor mental health, in turn, impairs academic functioning.

Daily usage hours showed weaker associations with academic performance (r = 0.66) and mental health (r = -0.80) than the psychological indicators did. Sleep duration was moderately and inversely associated with academic performance (r = -0.63), while platform choice showed only a weak relationship (r = 0.22). This pattern of correlations provides early evidence that the psychological dimensions of social media use are more predictive of academic disruption than usage volume alone, a hypothesis that the subsequent classification analysis directly examines.

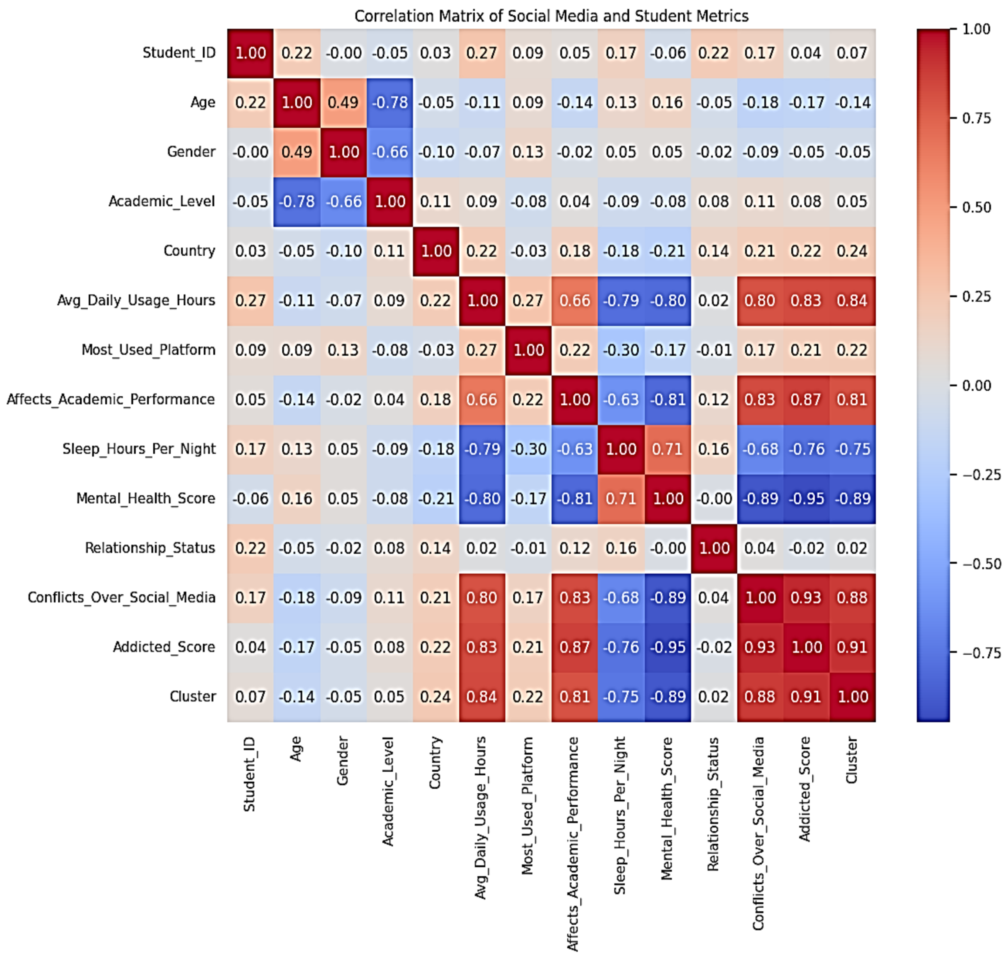

Figure 6. Correlation matrix of social media and student metrics

Model Performance

Random Forest classification was applied to predict academic impact status from the full set of behavioral and psychological features. The model achieved perfect classification on the held-out test set, with accuracy, precision, recall, and F1 score all equal to 1.00 across both outcome classes (Table 2).

Table 2. Classification performance report

Class	Precision	Recall	F1 Score	Support
0 (No Impact)	1.00	1.00	1.00	54
1 (Impacted)	1.00	1.00	1.00	87
Accuracy	-	-	1.00	141

The model correctly classified all 54 students in the non-impacted class and all 87 students in the impacted class, with no false positives or false negatives. This performance level is consistent with the strong correlational structure observed in the descriptive analysis. When psychological predictors exhibit correlations with the outcome ranging from 0.87 to 0.93, the resulting decision boundaries are sufficiently sharp that an ensemble classifier can learn them with high reliability.

Confusion Matrix And ROC Curve

Figure 7 presents the confusion matrix for the test set. All 141 predictions fell on the main diagonal, with zero misclassifications in either direction. This result confirms that the behavioral features used in this study, particularly addiction scores, conflict indicators, and mental health measures, provide sufficient discriminative information to separate the two outcome classes without error on this dataset.

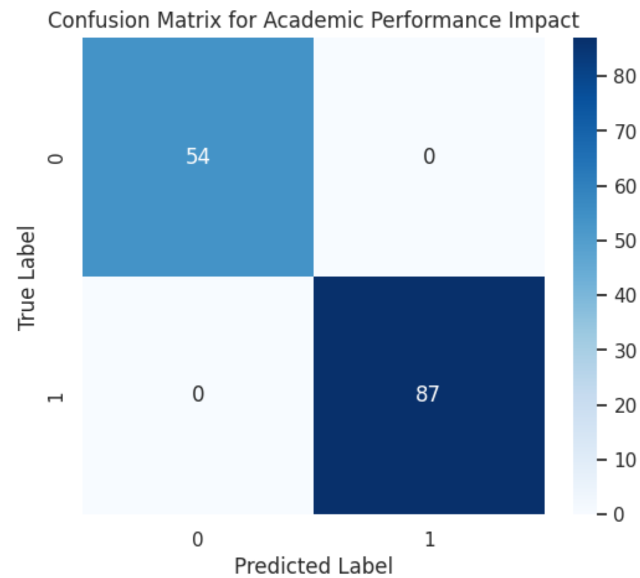

Figure 7. Confusion matrix for academic performance impact

The ROC curve yielded an AUC of 1.00, indicating that the model maintains perfect separation between classes across all classification thresholds. While perfect performance on a held-out test set warrants careful interpretation, the cross-validation results presented below provide evidence that this outcome reflects genuine structure in the data rather than overfitting.

Feature Contribution Analysis (SHAP/Global Importance)

Figure 8 presents the global feature importance ranking derived from the trained Random Forest model, with SHAP values used to confirm the direction and consistency of each feature's contribution. Interpersonal conflict emerged as the dominant predictor, with a SHAP importance value of 0.40, accounting for 40% of the model’s predictive contribution. The addiction score ranked second (0.27) and the mental health score third (0.19). These three variables jointly account for 86% of the model’s predictive signal.

Daily usage hours contributed marginally (0.05), as did sleep hours (0.05). Platform choice and country each contributed approximately 0.01, while relationship status, age, and gender contributed negligibly. Screen time, as a standalone indicator, accounts for only a small fraction of the variance in the outcome explained by psychological and behavioral predictors.

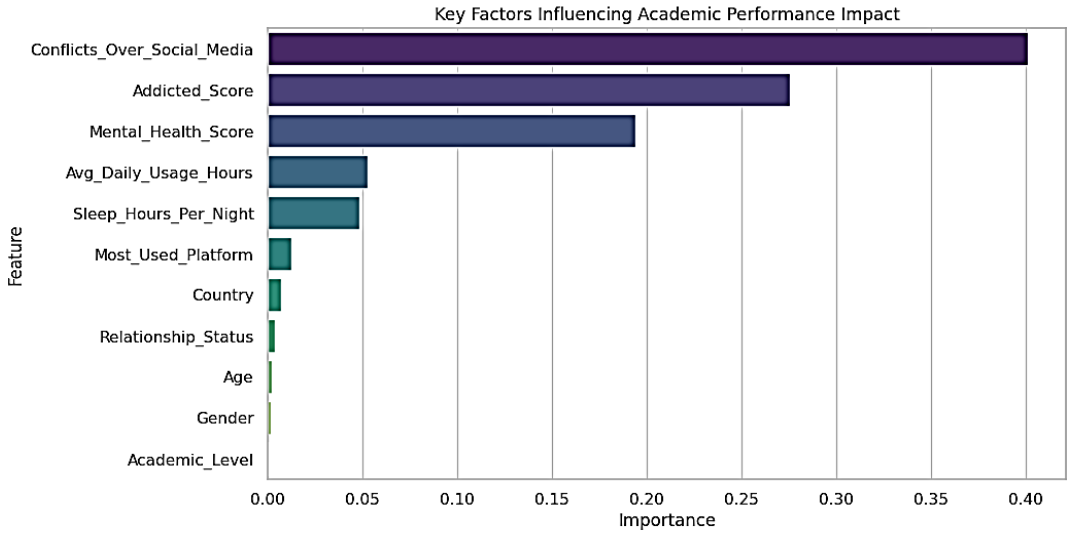

Figure 8. Key factors influencing academic performance impact

Sub-Group Analysis (Clustering)

K-Means clustering results

K-Means clustering was applied to three input features: daily usage hours, addiction scores, and mental health scores. The elbow method and silhouette scores converged on 3 as the optimal number of clusters. Figure 9 presents the resulting student segments.

Cluster 0 constitutes the Low-Risk group. Students in this segment reported daily usage below approximately 5 hours, addiction scores in the low-to-moderate range, and mental health scores of 7 or above. This group demonstrates that functional, non-problematic social media use is possible and that the negative outcomes documented elsewhere in the results are not universal.

Cluster 1 constitutes the At-Risk group. Usage hours ranged from approximately 3.5 to 5.5 per day, addiction scores were elevated, and mental health scores had declined to the 5 to 7 range. Students in this segment have not yet reached crisis-level disruption but show early indicators that suggest a trajectory toward high-risk status without intervention.

Cluster 2 constitutes the High-Risk group. Daily usage ranged from approximately 5.5 to 8.5 hours, addiction scores were in the highest observed range, and mental health scores fell between 4 and 6. Students in this segment reported substantial psychological distress and the most severe academic disruption in the sample.

Hierarchical clustering validation

Hierarchical clustering was applied to the same data as an independent validation of the K-Means solution. Figure 10 presents the resulting dendrogram for all 705 students.

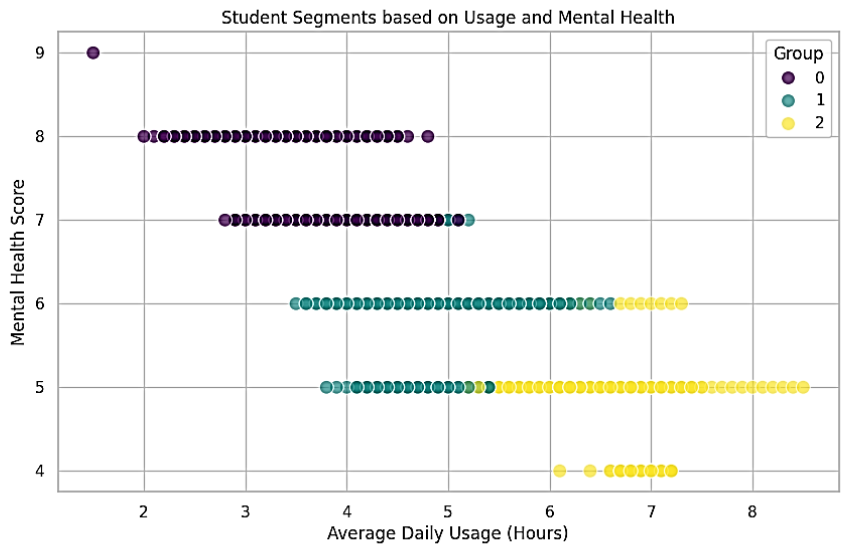

Figure 9. Student segments based on usage and mental health

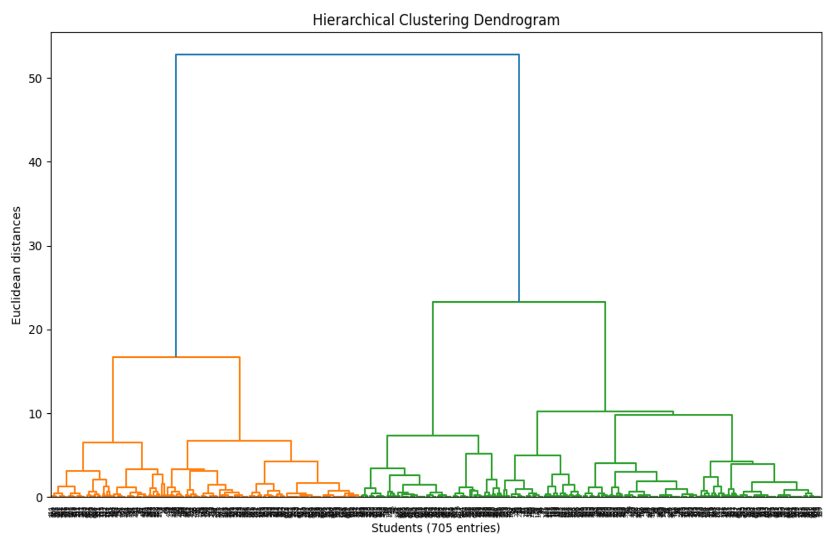

Figure 10. Hierarchical clustering dendrogram of student behavioral profiles

The dendrogram produced three major branches corresponding to the same three-group structure identified by K-Means, with clean separation at a Euclidean distance of approximately 20. Agreement between two structurally distinct clustering methods on the same partition provides convergent evidence that the three-group segmentation reflects genuine behavioral differentiation in the sample rather than an artifact of the K-Means algorithm. The hierarchical solution also reveals finer-grained substructure within the high-risk cluster, suggesting that students in the most vulnerable segment may warrant further differentiation in intervention design.

ROBUSTNESS CHECK

Five-fold stratified cross-validation was conducted to assess whether the classification performance observed on the held-out test set generalizes across different subsets of the data. Results are presented in Table 3.

Table 3. Five-fold stratified cross-validation results

Fold	Training accuracy	Testing accuracy	Precision	Recall	F1 Score
1	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00
4	1.00	1.00	1.00	1.00	1.00
5	1.00	1.00	1.00	1.00	1.00
Mean	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Std	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

All five folds produced identical performance, with zero variance across splits. This consistency indicates that the predictive patterns identified by the model are stable across different student subsets within this dataset. Limitations related to external validity, including the homogeneity of the sample and the absence of longitudinal data, are addressed in the Limitations section.

DISCUSSION

This study set out to address three research questions concerning the behavioral and psychological predictors of social media's academic impact, the predictive accuracy of machine learning in this domain, and the behavioral risk profiles that distinguish student subgroups. The findings provide coherent answers to all three and, in doing so, challenge several assumptions that currently underpin institutional digital wellness policy.

PSYCHOLOGICAL FRICTION AS THE PRIMARY PREDICTOR OF ACADEMIC DISRUPTION (RQ1 AND RQ2)

The SHAP feature attribution results indicate that interpersonal conflict is the single most important predictor of academic impact (importance = 0.40), followed by addiction score (0.27) and mental health score (0.19). These three variables jointly account for 86% of the model's predictive signal. Daily usage hours contributed marginally (0.05), as did sleep hours (0.05), while platform choice and demographic variables contributed negligibly. This hierarchy directly addresses RQ1 and carries significant implications for how institutions frame the social media problem.

The dominant institutional response to social media concerns in higher education has been usage restriction: limiting screen time, discouraging in-class phone use, and promoting digital detox programs. The present findings suggest this response is misaligned with the actual predictors of harm. A student spending two hours daily on social media but experiencing persistent conflict and elevated addiction scores presents a meaningfully higher risk profile than a student spending six hours daily with no psychological friction. Screen time, as a standalone policy target, captures a small fraction of the outcome variance explained by psychological and behavioral indicators.

This finding is consistent with the theoretical framing developed in the Literature Review. TAM explains why students adopt social media readily, given its perceived utility and accessibility (Granić, 2023). However, once conflict and compulsive use enter the picture, the platform's function as a Knowledge Management infrastructure degrades. Social interactions that once supported peer learning become sources of extraneous cognitive load, diverting attentional and emotional resources away from academic tasks (Mashhadi & Dehghani, 2025). The damage is not confined to the digital space. Conflict-driven stress and the psychological costs of addiction affect study behavior, exam preparation, and classroom engagement in ways that accumulate over time.

The near-perfect classification accuracy achieved by the Random Forest model (AUC = 1.00, confirmed across all five cross-validation folds) directly addresses RQ2. This level of performance indicates that the behavioral patterns distinguishing academically disrupted students from those who are not are sufficiently structured to be learned by a machine classifier with high reliability. The extremely high inter-variable correlations observed in the data, particularly between addiction and conflict ($r = 0.93$) and between addiction and mental health ($r = -0.95$), create decision boundaries that are sharp rather than diffuse. These results are comparable to and, in some cases, exceed the classification accuracy reported in related educational data mining studies (Harshvardhan & Prakash, 2024; Karim-Abdallah et al., 2025). Critically, the convergence of four independent analytical methods, namely correlation analysis, Random Forest classification, K-Means clustering, and hierarchical clustering, each pointing to the same underlying structure, provides stronger grounds for confidence than any single approach could offer.

THE BEHAVIORAL CASCADE AND ITS KNOWLEDGE MANAGEMENT IMPLICATIONS

The correlation structure in the data points to a self-reinforcing cycle that can be described as a behavioral cascade. Elevated social media use erodes mental health. Declining mental health weakens self-regulation, which in turn intensifies addictive use patterns. Addiction generates interpersonal conflict. Conflict further degrades mental health – the cycle compounds. Self-Determination Theory identifies autonomy, competence, and relatedness as fundamental psychological needs (Ding & Sazalli, 2024). This cascade progressively undermines all three: students experience diminishing control over their usage behavior, perceive themselves as less academically capable, and find that their social relationships are increasingly defined by conflict rather than connection.

From a Knowledge Management perspective, this dynamic has institutional consequences beyond individual student welfare. Social media has become a primary channel through which students acquire, share, and apply academic knowledge outside formal instruction (Parasar & Bhatt, 2025; Shabbir et al., 2025). When addiction and conflict dominate students' digital social environments, the informal knowledge-sharing function of these platforms deteriorates. Collaborative academic communities fragment. Peer support networks weaken. The platforms that were adopted because they felt useful, as TAM predicts, become sources of psychological cost rather than academic benefit.

The platform-level differences observed in the data are relevant here. WhatsApp, Snapchat, and TikTok produced the highest mean addiction scores, each approaching 7.5, while LinkedIn and LINE produced the lowest, at approximately 3.8 and 3.0 respectively. These differences likely reflect structural design choices rather than user self-selection alone. Algorithmically driven, infinite-scroll platforms with no natural stopping point create engagement conditions that are more conducive to compulsive use than goal-directed platforms accessed for specific content (Ding & Sazalli, 2024). Uses and Gratifications Theory suggests that users select media to satisfy specific needs (Yilmaz & Yilmaz, 2023). Still, when platform design systematically exploits those needs to maximize engagement, the boundary between need satisfaction and compulsive use becomes difficult to maintain. This observation does not support the conclusion that platform switching alone would correct problematic behavior, but it does suggest that design characteristics are a relevant variable for future research and potentially for platform-level policy engagement.

Three-Tier Risk Segmentation and Differentiated Intervention Design (RQ3)

Both K-Means and hierarchical clustering identified the same three-group structure, providing convergent evidence that addresses RQ3. The consistency across methods with fundamentally different optimization logic, one minimizing within-cluster variance and the other building a hierarchical dissimilarity tree, strengthens confidence that the segmentation reflects genuine behavioral differentiation rather than an algorithmic artifact.

Low-Risk students (Cluster 0) demonstrate that non-problematic social media use is achievable. Their mental health scores are high, addiction indicators are moderate, and they report no academic disruption. This group does not require intervention and may benefit from programs that channel their functional social media habits into structured peer learning and knowledge-sharing activities.

At-Risk students (Cluster 1) show early indicators of trajectory toward high-risk status: declining mental health scores, elevated usage hours, and rising addiction indicators. This group represents the highest-value target for preventive intervention. The literature on early warning systems in educational contexts suggests that detection at this stage, before behavioral patterns become entrenched, substantially increases the likelihood of successful support (Bahri & Midyanti, 2023; Pecuchova & Drlík, 2024). Psychoeducation programs focused on self-regulation, digital literacy, and conflict management would be appropriate for this segment.

High-Risk students (Cluster 2) are experiencing substantial psychological distress alongside the highest addiction and conflict levels in the sample. Preventive programming is insufficient for this group. Intensive and individualized support, including mental health counseling, academic recovery planning, and structured engagement with addiction-specific resources, is indicated. The hierarchical clustering solution further reveals internal sub-structure within this cluster, suggesting that even among high-risk students, heterogeneity in behavioral profile may warrant differentiated approaches.

Methodological Considerations and Limitations

The perfect classification performance observed in this study warrants careful interpretation. While five-fold cross-validation confirms that results are stable across different data subsets, the unusually strong inter-variable correlations in this dataset may reflect characteristics of a relatively homogeneous student sample rather than universal patterns. It is not possible to determine from a single secondary dataset whether the behavioral dynamics observed here generalize across different institutional contexts, cultural settings, or demographic profiles. Replication using primary data collected across diverse institutions, ideally through federated learning architectures that enable multi-site analysis without centralizing sensitive student data (Tertulino & Almeida, 2025), is a necessary next step. Longitudinal data would also allow assessment of causal directionality within the behavioral cascade, a limitation that cross-sectional correlation analysis cannot address. Nuh et al. (2025) further note that the sustained institutional adoption of AI-based student support tools depends not only on technical validity but also on students' and administrators' trust in the system's quality and fairness. This dimension goes beyond model accuracy and requires deliberate attention during implementation.

Conclusion

This study examined the behavioral and psychological dimensions of social media use as predictors of academic performance among 705 university students, employing Random Forest classification, SHAP feature attribution, K-Means clustering, and hierarchical clustering as the primary analytical tools. The results are internally consistent across all four methods and point to a clear central finding: psychological friction, specifically interpersonal conflict and social media addiction, predicts academic disruption far more strongly than daily usage hours.

The Random Forest classifier achieved perfect accuracy (1.00) across both the held-out test set and all five folds of stratified cross-validation. SHAP analysis attributed 40% of the model's predictive contribution to interpersonal conflict, 27% to addiction score, and 19% to mental health score. Daily usage hours contributed only 5%. This hierarchy has direct implications for institutional policy. Universities that concentrate digital wellness efforts on screen time restrictions are targeting a variable that accounts for only a small fraction of the outcome variance explained by psychological and behavioral indicators. The more consequential predictors are conflict, addiction, and mental health, all of which require support responses that are fundamentally different from usage limits.

The clustering analysis identified three behaviorally distinct student segments. Low-Risk students demonstrate that functional, non-disruptive social media use is attainable and that this group benefits from programs that channel existing habits toward structured peer learning. At-Risk students show early deterioration in mental health and rising addiction indicators, representing the highest-value target for preventive intervention, as behavioral patterns at this stage have not yet become entrenched. High-Risk students require intensive and individualized support addressing both psychological distress and academic recovery. The agreement between K-Means and hierarchical clustering on this three-group structure provides convergent validity for the segmentation framework.

Several limitations constrain the generalizability of these findings. The dataset derives from a single secondary source with an unverifiable sampling procedure. The strength of the inter-variable correlations may reflect the relative homogeneity of the sample. External validity across different institutional, cultural, and demographic contexts remains to be established. Federated learning approaches would enable multi-institutional replication while preserving student data privacy. Longitudinal designs would allow causal directionality within the identified behavioral patterns to be assessed rather than inferred.

Despite these constraints, the study makes several contributions to educational data mining and Knowledge Management research. It demonstrates that explainable machine learning can identify the psychological drivers of academic risk with high precision, that behavioral segmentation produces actionable student profiles rather than aggregate statistics, and that the Knowledge Management function of social media in higher education is contingent on psychological conditions that existing institutional frameworks largely do not address. Integrating explainable machine learning with psychological behavioral indicators gives universities a practical means of converting social media from an unmanaged risk into a data-informed component of student support and Knowledge Management infrastructure.

RECOMMENDATIONS

Based on the empirical findings of this study, four recommendations are proposed for institutional practice and future research.

Deploy behavioral early warning systems. Universities should implement Student Relationship Management systems capable of monitoring key psychological indicators, specifically social media addiction scores and interpersonal conflict levels, rather than tracking usage hours alone. The SHAP analysis demonstrated that these two variables account for 67% of the model's predictive contribution. Detection systems calibrated to these indicators would allow institutions to identify at-risk students before academic performance deteriorates, enabling proactive rather than reactive support.

Adopt differentiated, tier-based support structures. A uniform intervention policy is unlikely to be effective given the behavioral heterogeneity documented across the three student segments. Low-Risk students require neither restriction nor intensive support. Encouraging productive use of the platform and peer knowledge sharing within this group is appropriate. At-Risk students warrant preventive programming, including psychoeducation on self-regulation and digital conflict management, delivered before behavioral patterns become entrenched. High-Risk students require intensive, individualized responses combining mental health counseling, addiction-specific support, and academic recovery planning. Institutional resources should be allocated in proportion to segment risk level.

Integrate digital citizenship education into core curricula. Digital wellness programming should not remain elective or peripheral to academic instruction. Students across all risk segments would benefit from structured education on online conflict management, recognition of compulsive use patterns, and constructive use of social media for learning. Embedding this content within required courses ensures coverage across the student population rather than relying on voluntary participation, which tends to underserve the students most in need.

Establish cross-functional institutional governance for digital well-being. Effective policy in this area requires coordinated input from academic departments, student counseling services, and institutional administration. Policies developed in isolation within a single unit are unlikely to address the interconnected psychological, academic, and social dimensions of the problem. A cross-functional governance structure would enable institutions to develop coherent digital wellness frameworks grounded in behavioral evidence rather than in generalizations about technology use, and to evaluate the effectiveness of interventions systematically over time.

Declaration

During the preparation of this manuscript, the authors used AI-based language tools to assist with English language editing and proofreading to ensure clarity and grammatical accuracy. After using these tools, the authors reviewed and edited the content as needed and took full responsibility for its final content.

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