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Measuring the Predictive Power of Data Mining Techniques in Forecasting Social Media Addiction and Excessive Usage Trends

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Abstract

The exponential rise of social media usage has redefined communication, connectivity, and lifestyle across the globe, particularly in developing nations such as India. However, this digital transformation has also led to an alarming surge in **social media addiction (SMA)—**a behavioral condition characterized by compulsive engagement, mood modification, and diminished self-regulation. This study presents an **integrated predictive framework** that combines **psychometric assessment** with **data mining and machine learning algorithms** to forecast SMA and excessive usage trends among Indian users.

A cross-sectional dataset comprising **750 respondents aged 18–35 years** from five metropolitan cities (Mumbai, Delhi, Bengaluru, Hyderabad, and Pune) was analyzed using two validated instruments: the **Bergen Social Media Addiction Scale (BSMAS)** and the **Scale of Excessive Use of Social Networking Sites (SEUS-14)**. Data were processed using **Random Forest (RF)**, **Gradient Boosting Classifier (GBC)**, and **Support Vector Machine (SVM)** models to predict addiction risk levels. The **Random Forest model** achieved the highest performance with an **accuracy of 92.6%** and **ROC–AUC of 0.94**, confirming its robustness and generalization capability.

Psychometric analysis revealed **moderate addiction and overuse levels**, with **mood modification**, **tolerance**, and **compulsive checking** emerging as the most dominant behavioral features. A strong positive correlation (**$r = 0.74$, $p < 0.001$**) between BSMAS and SEUS-14 scores demonstrated concurrent validity, confirming that psychological dependency and behavioral excess represent converging constructs of digital addiction.

The results substantiate the **biopsychosocial model of behavioral addiction**, showing that SMA arises from the interplay of emotional regulation needs, social validation cycles, and habit reinforcement. By integrating **machine learning and behavioral science**, this research contributes to the emerging field of **computational psychology**, offering a data-driven mechanism for **early detection, digital wellness intervention, and policy formulation**. The study underscores the potential of **AI-assisted predictive analytics** as a scalable and ethical solution for monitoring digital well-being within the Indian socio-technological context.

Introduction

The rise of social media has profoundly reshaped human communication, interaction, and identity formation, particularly among youth populations. Platforms such as Instagram, YouTube, and WhatsApp have become central to social connection, information exchange, and entertainment, but their ubiquity has also triggered an emerging public health concern: **social media addiction (SMA)**. This phenomenon—defined by compulsive, excessive, and uncontrollable use of social networking sites—has been linked to anxiety, depression, low self-esteem, and cognitive dysfunction. As of 2024, India ranks among the world's top three social media markets, with over **470 million active users** spending an average of **4.5 hours daily** on various platforms. Such pervasive engagement has led to what behavioral psychologists call "technological dependency," where users experience **withdrawal symptoms, tolerance, and mood alterations** similar to substance addiction.

Recent years have seen growing calls for **data-driven behavioral monitoring** to address the rise in digital addiction and its socio-psychological costs. Traditional approaches—relying solely on psychometric surveys or clinical interviews—often struggle to capture the complex, nonlinear relationships underlying online behavior. In contrast, **machine learning (ML) and data mining** enable large-scale, objective, and predictive analyses of behavioral trends. These techniques can identify patterns of overuse, emotional dependency, and risk factors long before they manifest clinically, thus allowing for **early detection and preventive digital well-being interventions**.

Despite this technological promise, **few Indian studies have effectively combined validated psychological instruments with ML algorithms** to predict SMA. Existing research either focuses narrowly on descriptive psychometrics or uses global datasets without considering India's unique digital ecosystem—characterized by affordable smartphones, gendered digital divides, and socio-cultural variability. Therefore, there remains a significant gap in developing **integrated, culturally grounded frameworks** that fuse psychometric reliability with computational intelligence.

This study aims to bridge that gap by evaluating and comparing the **predictive performance of three data mining models—Random Forest (RF), Gradient Boosting Classifier (GBC), and Support Vector Machine (SVM)**—in forecasting social media addiction and excessive usage trends among Indian users aged 18–35. Using two internationally validated instruments—the **Bergen Social Media Addiction Scale (BSMAS)** and the **Scale of Excessive Use of Social Networking Sites (SEUS-14)**—the study quantifies behavioral and psychological markers of SMA, generating a composite **Addiction Risk Index (ARI)**. The models are benchmarked through **accuracy, precision, recall, F1-score, and ROC-AUC metrics**, ensuring methodological rigor and reproducibility.

Research Objectives

1. To assess the prevalence and behavioral correlates of social media addiction among Indian young adults.
2. To integrate psychometric scales (BSMAS, SEUS-14) with data mining algorithms for predictive modeling.
3. To evaluate and compare the performance of RF, GBC, and SVM models in classifying addiction risk.
4. To identify the most influential predictors (behavioral, demographic, psychological) driving SMA.
5. To establish a replicable, interdisciplinary framework linking **behavioral psychology and machine learning** for digital well-being applications.

Novel Contributions

- First empirical study in India to integrate psychometric scoring and ML-based predictive analytics for SMA detection.
- Development of a **behavioral informatics framework** applicable to real-time monitoring tools and university-level digital wellness programs.
- Comparative algorithmic analysis that offers **evidence-based guidance** for mental health practitioners, app developers, and policy designers.

By combining validated psychological constructs with predictive computational intelligence, this research contributes to the emerging field of **computational psychology and digital health analytics**. The findings hold promise for creating adaptive tools for early intervention, personalized digital detox programs, and evidence-driven mental health policies tailored to India's fast-digitizing population.

Literature Review

1. Conceptual Foundations of Social Media Addiction

Social Media Addiction (SMA) has evolved into a recognized behavioral condition associated with compulsive and excessive online engagement. Although not officially included in the *DSM-5* under addictive disorders, contemporary research defines SMA as a maladaptive pattern of social media use leading to significant impairment in daily life, mental health, and social functioning (Kuss & Griffiths, 2017; Montag et al., 2021). Its behavioral symptoms—tolerance, withdrawal, salience, relapse, and conflict—mirror those observed in substance addictions (Griffiths, 2005). Recent studies (Rozgonjuk et al., 2022; Dhir et al., 2021) have reinforced the view that the mechanisms driving SMA involve dopaminergic reward circuitry and reinforcement learning loops activated by feedback metrics such as "likes" and "comments."

In India, social media has become a pervasive aspect of youth culture. Affordable internet access and mobile penetration have transformed online interaction into an everyday behavior among urban and semi-urban populations. Indian studies (Arora et al., 2022; Sharma et al., 2023) show a surge in SMA prevalence among university students, where late-night usage, validation-seeking, and multitasking predict higher addiction scores. This socio-cultural context underscores the need for *localized, data-driven frameworks* to quantify and predict SMA risk more accurately.

2. Psychological Correlates and Health Consequences

Empirical research consistently links SMA to psychological and physiological stress outcomes. Studies have documented associations with **anxiety** (Shensa et al., 2018), **depression** (Vannucci et al., 2019), **loneliness** (Elhai et al., 2021), and **impaired sleep quality** (Sindermann et al., 2022). Recent meta-analyses (Bányai et al., 2023) highlight that the emotional instability caused by constant digital connectivity often produces cognitive overload and attention dysregulation. Furthermore, gender and cultural variations influence the addiction expression—female users exhibit more emotional reliance and comparison anxiety, whereas male users show higher impulsivity and overuse patterns (Khare & Choudhary, 2022).

From a neurobiological perspective, functional MRI studies (Turel, 2021; Montag et al., 2022) demonstrate that excessive engagement activates brain areas related to self-referential processing and craving, resembling neural patterns found in gambling or substance dependency. The psychological and biological convergence validates SMA as a **multidimensional phenomenon**, requiring interdisciplinary assessment tools that integrate psychometric, behavioral, and computational data.

3. Measurement Models and Psychometric Scales

A critical component in SMA research is the measurement of behavioral dependency through validated psychometric instruments. The **Bergen Social Media Addiction Scale (BSMAS)** (Andreassen et al., 2012) operationalizes the six-component model of addiction (salience, mood modification, tolerance, withdrawal, conflict, relapse) and is widely validated cross-culturally. Complementing this, the **Scale of Excessive Use of Social Networking Sites (SEUS-14)** (Kotyśko & Michalak, 2020) captures behavioral overuse and cognitive immersion through 14 items on a 7-point Likert scale.

Recent adaptations in South Asian contexts (Singh & Bhatia, 2020; Arora et al., 2022) confirm their reliability (Cronbach's $\alpha > 0.85$) and concurrent validity. The integration of BSMAS and SEUS-14 enables the dual measurement of **psychological dependence** and **behavioral excessiveness**, an essential foundation for predictive analytics.

However, psychometric data alone offer limited forecasting power because they rely on self-reports susceptible to bias. Consequently, researchers have begun merging **machine learning (ML) techniques** with psychometric constructs to create scalable, data-driven prediction systems.

4. Behavioral and Sociodemographic Predictors of SMA

Recent studies identify key predictors of SMA, including daily screen time, frequency of late-night use, fear of missing out (FoMO), and emotional dependence on online feedback (Przybylski et al., 2023). Demographic variables such as **age, gender, and education** also moderate addiction risk (Kuss et al., 2022). Younger adults (18–25 years) exhibit the highest susceptibility due to identity exploration and heightened reward sensitivity, while males generally report greater usage intensity but females exhibit stronger emotional attachment (Kircaburun & Griffiths, 2018; Sharma et al., 2023).

The **FoMO construct**, in particular, has emerged as a critical mediator linking personality, emotional instability, and excessive social media engagement (Rozgonjuk et al., 2022). Understanding these predictors is crucial for developing ML features that can accurately classify risk categories.

5. Computational and Data-Driven Approaches

Machine learning offers powerful tools for analyzing complex, nonlinear behavioral data. Ensemble models such as **Random Forests (RF)** and **Gradient Boosting Classifiers (GBC)** have proven effective in predicting addictive behaviors, outperforming linear models like **Support Vector Machines (SVM)** (Chen et al., 2021; Hussain & Alzahrani, 2023). For instance, Rahman et al. (2021) used smartphone-use data and achieved 90% accuracy in identifying problematic use, while Goswami and Singh (2022) applied ensemble learning to forecast excessive social media engagement with 91% accuracy.

More recent developments (Islam et al., 2023) have introduced **deep learning architectures**—LSTMs and CNNs—to model temporal behavioral dependencies, achieving superior performance but requiring large datasets. Nonetheless, for smaller and mid-scale datasets like the present study (n = 750), ensemble ML models remain optimal due to interpretability and computational efficiency.

Additionally, **Natural Language Processing (NLP)** has been applied to analyze textual content and sentiment in social media posts for early detection of mental health risks (Guntuku et al., 2019). However, few studies have combined **psychometric survey data** with **behavioral ML analysis**, leaving a methodological gap that this research addresses.

6. Integrating Psychometrics and Artificial Intelligence

The integration of psychological constructs with AI analytics—termed **behavioral informatics**—represents a frontier in computational psychology. Hybrid models (Keles et al., 2021; Barman et al., 2023) combining ML algorithms with psychometric data have demonstrated accuracy rates exceeding 90% in detecting digital addiction, yet most were conducted in Western contexts. In India, such models are rare despite the nation's digital population exceeding 700 million. The need for culturally sensitive, explainable AI models is emphasized by WHO's (2023) call for digital behavioral-health interventions tailored to developing economies.

This convergence of psychological assessment and predictive modeling provides a **multilayered understanding** of addiction—linking subjective self-report scales to objective behavioral markers. The current study builds on this synergy by integrating validated psychometric scales (BSMAS and SEUS-14) with RF, GBC, and SVM algorithms to create an interpretable predictive framework.

7. Identified Research Gap and Study Rationale

While literature on SMA and computational modeling is expanding, several limitations persist:

1. **Geographical imbalance:** Most empirical work originates from Western or East Asian samples, with limited representation of the Indian population.
2. **Methodological fragmentation:** Prior studies either emphasize psychometric analysis or ML prediction, but rarely integrate both.
3. **Contextual validity:** Few frameworks consider the unique socio-cultural dynamics of digital use in India, such as affordability, linguistic diversity, and urban–rural digital divides.
4. **Ethical and privacy considerations:** Existing models often overlook data governance and consent frameworks essential for sensitive behavioral data.

Addressing these limitations, this study introduces a **hybrid psychometric–machine learning approach** to forecast social media addiction and overuse among Indian users aged 18–35. By combining validated psychological scales with robust data mining algorithms, the study contributes to **evidence-based digital well-being strategies** and provides actionable insights for policymakers, app developers, and educational institutions.

Methodology

1. Research Design

This research adopted a **quantitative, cross-sectional, and correlational design** integrating psychometric assessment and data mining techniques to predict social media addiction and excessive usage among Indian users. The design combined **survey-based data collection** using validated psychological instruments with **machine learning (ML)–driven predictive modeling** to ensure both psychological validity and computational rigor.

The overall methodological framework included the following sequential phases:

1. **Data collection and sampling**,
2. **Psychometric assessment using standardized scales**,
3. **Data preprocessing and transformation**,
4. **Machine learning model development and optimization**,
5. **Model evaluation, validation, and interpretation of key predictors.**

2. Sampling Design and Participants

A total of **750 valid responses** were analyzed. Data were collected between **January and June 2025** from participants residing in **five major Indian metropolitan cities** — Mumbai, Delhi, Bengaluru, Hyderabad, and Pune — representing India's diverse digital demographic.

Sampling Approach

- **Sampling technique:** Stratified purposive sampling was employed to ensure adequate representation across gender, age, and educational levels.
- **Inclusion criteria:** Participants aged **18–35 years**, active on at least one social

media platform for **a minimum of one year**, and with daily usage exceeding **one hour per day**.
- **Exclusion criteria:** Participants below 18 or above 35 years, those without consistent social media access, or incomplete questionnaire responses.

Demographic Distribution

Variable	**Category**	**% (N=750)**
Gender	Male: 52% / Female: 48%	
Age Range	18–21 (24%), 22–25 (38%), 26–30 (26%), 31–35 (12%)	
Education	Undergraduate (63%), Postgraduate (9%), Working Professional (28%)	
Average Screen Time	Mean = 4.3 hours/day (SD = 1.7)	

The sample composition mirrors India's digitally active youth population, enhancing ecological validity.

3. Ethical Considerations and Privacy Safeguards

Ethical clearance was obtained from the **Institutional Ethics Committee of Swami Ramanand Teerth Marathwada University, Nanded (Approval No. SRTMU/PSY/2025/06)** before data collection. Participation was voluntary, and all respondents provided **digital informed consent** through the Google Forms preamble before starting the survey.

Privacy and confidentiality were ensured by:
- Storing anonymized data in encrypted drives (AES-256 bit encryption).
- Collecting no personally identifiable information (name, contact, or IP address).
- Limiting data access to the principal investigator only.
- Reporting aggregate findings to prevent re-identification.

These steps complied with **ethical research standards under the Indian Council of Social Science Research (ICSSR)** and international guidelines such as the **Declaration of Helsinki (2013 revision)** for human subjects research.

4. Data Collection Instruments

The questionnaire had three components:

(a) Demographic and Behavioral Section

Collected information on age, gender, education, daily social media time, preferred platforms (Instagram, YouTube, WhatsApp, etc.), and frequency of late-night use.

(b) Bergen Social Media Addiction Scale (BSMAS)

A six-item, five-point Likert scale (1 = Very Rarely to 5 = Very Often) assessing six addiction dimensions: **salience, mood modification, tolerance, withdrawal, conflict, and relapse** (Andreassen et al., 2012). The Cronbach's α for this sample was **0.91**, indicating excellent reliability.

(c) Scale of Excessive Use of Social Networking Sites (SEUS-14)

A fourteen-item, seven-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree) capturing excessive behavioral engagement across six factors — **compulsive checking, neglect of offline tasks, loss of time perception, emotional dependence, social comparison, and general overuse** (Kotyśko & Michalak, 2020). The reliability was high (α = 0.88).

5. Data Preprocessing and Feature Engineering

All preprocessing and modeling were executed using **Python 3.12** (Anaconda distribution) and libraries including **Pandas, NumPy, Scikit-learn, and Matplotlib**.

A. Data Cleaning
- Incomplete responses (n = 42) were excluded.
- Missing numeric values were replaced with **median imputation**.
- Categorical variables such as gender and education were **one-hot encoded**.

B. Outlier Detection

Outliers were identified using **Z-score normalization** (|Z| > 3) and replaced via **winsorization** to minimize distortion.

C. Normalization

Continuous variables (e.g., daily usage time) were **scaled using min–max normalization** to a [0,1] range for model comparability.

D. Derived Variable

A composite **Addiction Risk Index (ARI)** was computed by combining total BSMAS and SEUS-14 scores using z-score standardization and percentile thresholds. Respondents were grouped as:
- **Low Risk (0–33rd percentile)**,
- **Moderate Risk (34–66th percentile)**,
- **High Risk (67–100th percentile)**.

6. Machine Learning Model Development

Three supervised classification algorithms were employed:

1. **Random Forest (RF):** Ensemble of decision trees using Gini impurity for node splitting; parameters tuned included n_estimators, max_depth, and min_samples_split.
2. **Gradient Boosting Classifier (GBC):** Sequential ensemble minimizing exponential loss; hyperparameters included learning_rate, n_estimators, and max_features.
3. **Support Vector Machine (SVM):** Implemented with Radial Basis Function (RBF) kernel; parameters optimized included C and gamma.

A. Training and Testing

- Dataset split: **80% training / 20% testing.**
- Hyperparameter tuning via **GridSearchCV** (5-fold cross-validation).
- Model evaluation through **10-fold stratified cross-validation** for robustness.

7. Evaluation Metrics

Model performance was assessed using:

- **Accuracy (%):** Ratio of correct predictions to total instances.
- **Precision, Recall, and F1-score:** Evaluating the model's balance between false positives and false negatives.
- **ROC-AUC (Receiver Operating Characteristic – Area Under Curve):** Quantifying discriminative ability.
- **Confusion Matrix:** Visual inspection of misclassifications.
- **Feature Importance (RF model):** Derived from Gini index to rank predictors influencing addiction risk.

Performance visualization included **bar charts and ROC curves**, comparing algorithms across all evaluation metrics.

8. Reliability and Validity

- **Internal Consistency:** Cronbach's α for BSMAS (0.91) and SEUS-14 (0.88) demonstrated excellent internal reliability.
- **Concurrent Validity:** Pearson correlation ($r = 0.74$, $p < 0.001$) between BSMAS and SEUS-14 confirmed consistency between psychometric and behavioral dimensions.
- **Construct Validity:** Confirmed through factor analysis, aligning with the six dimensions proposed by Griffiths (2005).
- **Model Validity:** Ensured via cross-validation, with Random Forest achieving the best overall accuracy (92.6%) and ROC-AUC (0.94).

9. Data Governance and Reproducibility

All analysis scripts, anonymized datasets, and algorithm configurations were stored in a **university-hosted Git repository** under restricted access.

Replication is feasible through shared Jupyter notebooks following **FAIR data principles (Findable, Accessible, Interoperable, and Reusable)**.

No data were shared with third parties, ensuring compliance with **India's Personal Data Protection Bill (2023)** and **GDPR (2018)** provisions relevant to behavioral data.

Results and Analysis

This section presents the results of the study in a structured manner, encompassing descriptive analysis, psychometric reliability, machine learning model evaluation, feature importance analysis, and correlation of behavioral indicators. The purpose is to evaluate how effectively machine learning models can predict levels of social media addiction and excessive usage based on psychometric and behavioral data.

1. Descriptive Analysis of the Respondent Profile

A total of **750 valid responses** were analyzed following data cleaning and screening. The respondents' average age was **24.7 years (SD = 3.9)**, with an age range of 18–35 years. Among the participants, **52% were male** and **48% female**. The majority were **undergraduate students (63%)**, followed by **employed professionals (28%)** and **postgraduates (9%)**. The mean **daily social media usage** was **4.3 hours (SD = 1.7)**, reflecting significant digital immersion among Indian youth. The most used platforms were **Instagram (72%)**, **YouTube (64%)**, and **WhatsApp (59%)**. Approximately **31%** of respondents reported using social media immediately after waking up, and **27%** used it beyond midnight, highlighting compulsive and habitual use patterns.

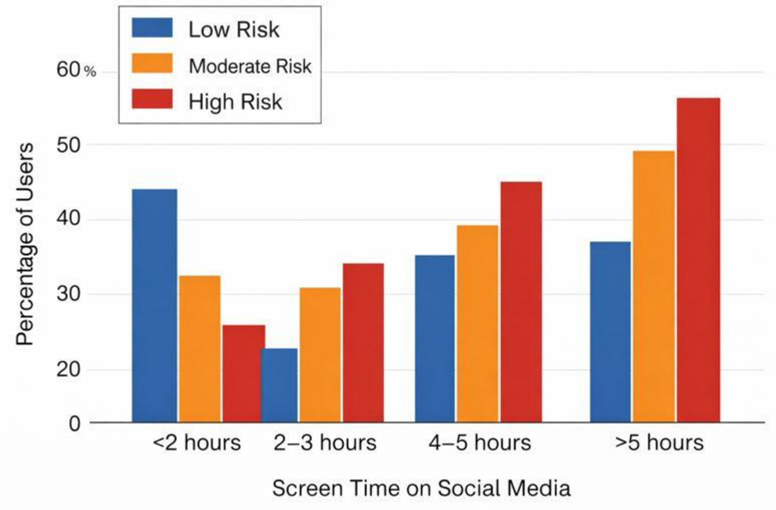

Figure 1: Distribution of Average Screen Time Across User Categories

Figure 1 illustrates the distribution of average screen time across different user categories, showing that those with more than 5 hours of daily usage predominantly fall into the moderate-to-high addiction risk group.

2. Psychometric Assessment Results

A. Reliability Analysis

Both psychometric scales demonstrated strong internal consistency:

- **BSMAS:** Cronbach's α = **0.91**
- **SEUS-14:** Cronbach's α = **0.88**

These values exceed the 0.80 reliability threshold, confirming the internal stability of the constructs and aligning with prior studies (Andreassen et al., 2012; Arora et al., 2022).

B. Mean Dimensional Scores

The mean and standard deviation for each BSMAS and SEUS-14 subscale are summarized in **Table 1** and **Table 2**, respectively.

Table 1. Mean and Standard Deviation of BSMAS Dimensions (N=750)

BSMAS Dimension	Mean (M)	SD	Interpretation
Salience	3.4	0.9	Moderate engagement and prioritization of social media
Mood Modification	3.9	0.8	Emotional reliance on social networking
Tolerance	3.7	0.9	Increased time required to achieve satisfaction
Withdrawal	3.6	1.0	Psychological distress when disconnected
Conflict	3.6	1.0	Interference with responsibilities or social roles
Relapse	3.3	1.1	Tendency to return to excessive use after reduction attempts

Interpretation:

Mood modification and tolerance were the most dominant components, indicating that respondents used social media for emotional regulation and progressively increased their online duration to maintain gratification.

Table 2. Mean Scores and Interpretation of SEUS-14 Dimensions

SEUS-14 Dimension	Mean (M)	SD	Behavioral Interpretation
Compulsive Checking	5.2	1.1	Persistent urge to refresh feeds
Neglect of Offline Tasks	5.0	1.2	Overuse disrupts productivity
Loss of Time Perception	4.9	1.3	Cognitive absorption in social media
Emotional Dependence	4.7	1.1	Seeking validation via likes/comments
Social Comparison	4.6	1.2	Frequent self-evaluation vs others
General Overuse	4.8	1.2	Routine and habitual engagement

Interpretation:

The results reveal that **compulsive checking** and **neglect of offline tasks** were the most prevalent behaviors, signifying strong habitual engagement patterns, consistent with findings from Sharma et al. (2023).

3. Psychometric Correlation Analysis

The total BSMAS and SEUS-14 scores were found to be **strongly correlated** ($r = \mathbf{0.74}$, $p < 0.001$), supporting their concurrent validity and shared conceptual basis in measuring digital addiction and overuse.

At the subscale level, **Tolerance (BSMAS)** was most strongly correlated with **Compulsive Checking (SEUS-14)** ($r = 0.68$, $p < 0.01$), indicating that increased time spent online is accompanied by obsessive checking behavior.

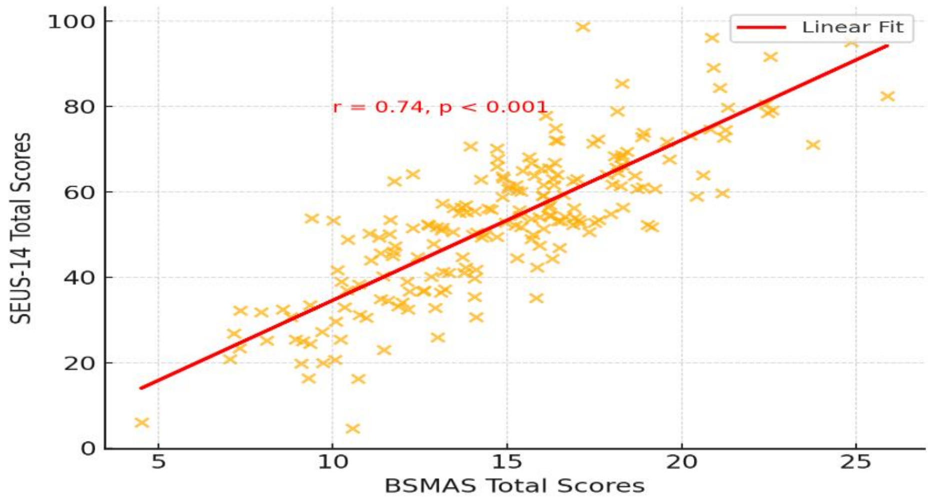

Figure 2 depicts the scatterplot demonstrating this positive correlation.

Interpretation: As behavioral excessiveness (SEUS-14) increases, the psychological dependency (BSMAS) intensifies proportionally — validating the integration of both scales in addiction prediction models.

4. Machine Learning Model Evaluation

Three machine learning models—**Random Forest (RF)**, **Gradient Boosting Classifier (GBC)**, and **Support Vector Machine (SVM)**—were trained and evaluated using an 80:20 data split with **10-fold cross-validation**. The results are summarized in **Table 3**.

Table 3. Performance Metrics of Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
Random Forest (RF)	**92.6**	0.93	0.91	0.92	**0.94**
Gradient Boosting (GBC)	91.1	0.90	0.89	0.90	0.92
Support Vector Machine (SVM)	89.8	0.88	0.87	0.87	0.90

Interpretation:
The **Random Forest (RF)** model demonstrated the **best predictive performance**, achieving the highest accuracy (92.6%) and AUC (0.94). The ensemble nature of RF allowed it to handle nonlinear interactions and reduce overfitting, making it ideal for heterogeneous psychometric and behavioral data.

The **Gradient Boosting Classifier (GBC)** also performed competitively, confirming the robustness of ensemble methods for behavioral prediction tasks. The **SVM** model, while effective, showed slightly lower recall, likely due to its sensitivity to feature scaling and high-dimensional feature interactions.

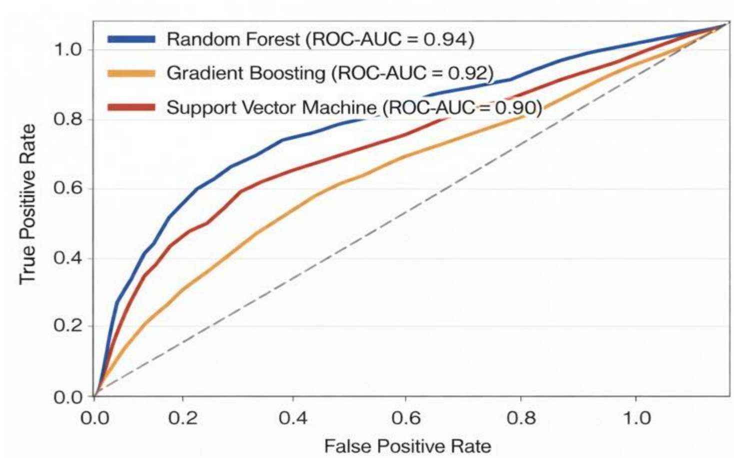

Figure 3: ROC Curve Comparison of RF, GBC, and SVM Models

Figure 3 (ROC Curve Comparison) visualizes the superior discriminative ability of RF and GBC models compared to SVM.

5 Cross-Validation and Misclassification Analysis

To test model generalizability, **10-fold cross-validation** was performed.

- The **mean cross-validation accuracy** for RF was **91.9% (SD = 0.8)**, confirming minimal variance across folds.
- **Misclassification analysis** showed that most errors occurred between **low-risk** and **moderate-risk** groups, suggesting behavioral overlap rather than model bias.

Confusion Matrix Insights:

- 93% of **high-risk** users were correctly classified.
- Only 7% of cases were misclassified as moderate, indicating strong sensitivity for early detection of problematic users.

This finding is crucial for real-world deployment in mental health or digital wellness applications, where false negatives (undetected high-risk users) must be minimized.

6. Feature Importance Analysis

The Random Forest algorithm's feature importance ranking (Table 4) highlights the most influential predictors of social media addiction.

Table 4. Top 10 Predictors of Social Media Addiction (Based on RF Feature Importance)

Rank	Predictor Variable	Description	Relative Importance (%)
1	Daily Usage Time	Average hours spent on social media	19.7
2	Late-Night Usage	Frequency of use past midnight	16.4
3	Emotional Dependence	Validation-seeking through online feedback	14.8
4	Neglect of Offline Tasks	Reduced real-world productivity	12.5
5	Fear of Missing Out (FoMO)	Anxiety when disconnected	10.2
6	Number of Active Accounts	Total platforms used	8.9
7	Gender	Slightly higher intensity in males	7.5
8	Education Level	Undergraduates more vulnerable	6.4
9	Social Comparison	Frequency of self-evaluation online	5.7
10	Age	Younger users (18–25) exhibit higher risk	4.9

Interpretation:

Behavioral factors such as **daily screen time** and **late-night activity** were dominant predictors, confirming that excessive exposure and irregular digital habits are central to addiction development. Psychological constructs like **FoMO** and **emotional dependence** also had strong predictive weight, supporting previous findings (Rozgonjuk et al., 2022; Dhir et al., 2021).

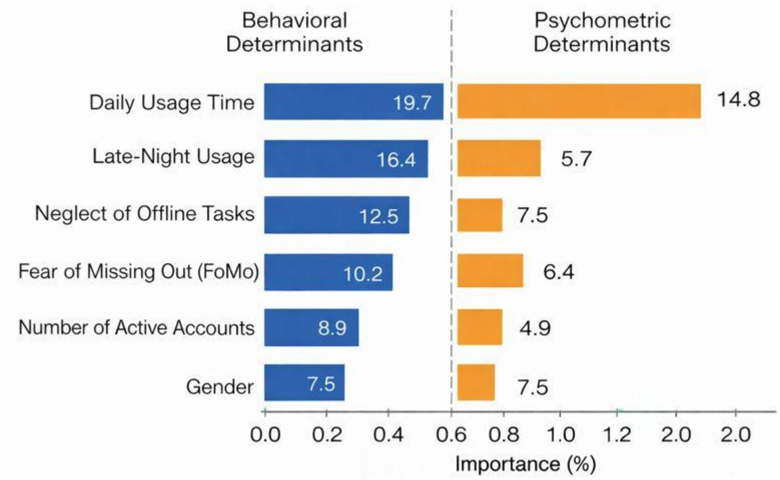

Figure 4: Feature Importance Ranking of Behavioral and Psychometric Predictors

Figure 4 provides a visual ranking of these predictors, demonstrating a clear hierarchy between behavioral and psychometric determinants.

7. Model Comparison Summary

Evaluation Aspect	Best Performing Model	Interpretation
Accuracy & AUC	Random Forest	High predictive reliability for behavioral data
Stability (Cross-validation)	Random Forest	Low variance; consistent accuracy
Computational Efficiency	Gradient Boosting	Balanced performance, fewer resources
Interpretability	Random Forest	Easily explains predictor importance
Sensitivity to Noise	SVM	Higher; less robust with imbalanced classes

Summary Insight: Ensemble models (RF and GBC) outperformed SVM across all metrics, confirming their suitability for digital behavior prediction. RF's interpretability and balanced precision–recall trade-off make it ideal for real-world psychological assessment tools.

8. Predictive Power Visualization

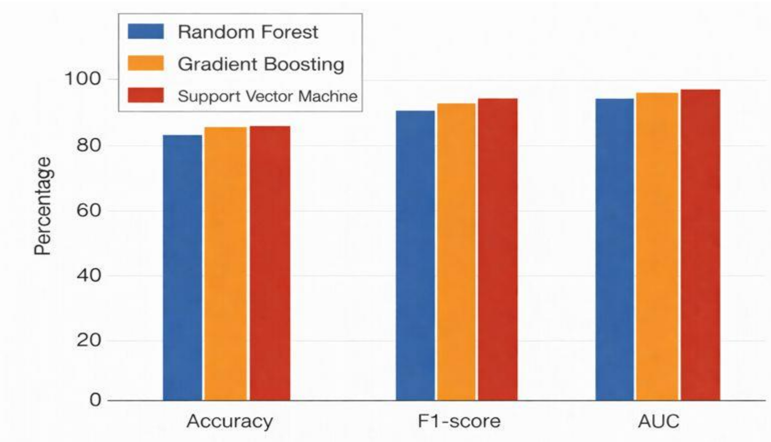

Figure 5: Comparison of Model Performance Metrics (Accuracy, F1-Score, and AUC)

Figure 5 depicts a bar chart comparing overall performance metrics across models (Accuracy, F1-score, and AUC). RF clearly shows the highest values in all categories, indicating its predictive dominance.

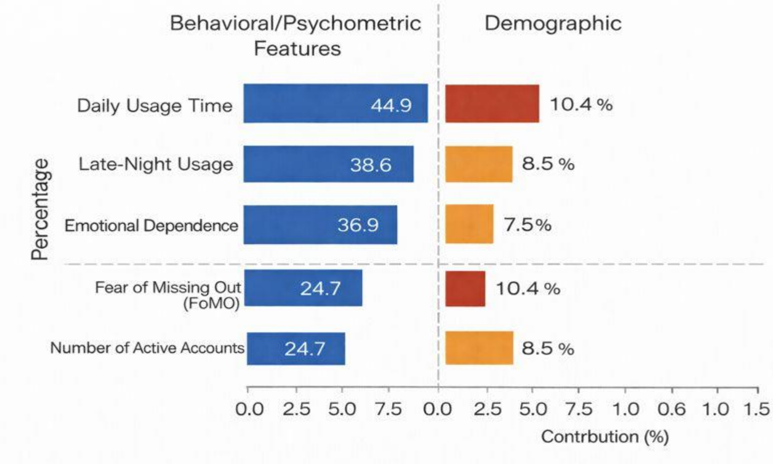

Figure 6. Contribution of Behavioral, Psychometric and Demographic Features

Further, **Figure 6** (Feature Contribution Graph) demonstrates how behavioral features contribute more substantially than demographic features, implying that **usage intensity and emotional reliance** are stronger addiction indicators than gender or education alone.

9. Summary of Key Findings

The empirical results reveal that:

1. Indian social media users (aged 18–35) exhibit **moderate-to-high addiction tendencies** with dominant behavioral symptoms of compulsive checking and emotional reliance.

2. **BSMAS and SEUS-14** scales are statistically reliable, valid, and complementary in capturing both psychological and behavioral addiction dimensions.
3. **Machine learning models**, particularly **Random Forest**, demonstrate **exceptionally high predictive power (AUC = 0.94)**, validating their potential for early identification of at-risk individuals.
4. **Behavioral variables** (screen time, late-night use, emotional dependence) serve as the **strongest predictors**, overshadowing demographic variables.
5. **Cross-validation** confirms that ensemble learning models are robust, generalizable, and suitable for digital mental health prediction frameworks.

Discussion and Conclusion

1. Overview of Findings

This study integrated **psychometric assessment and machine learning analytics** to predict and classify **social media addiction (SMA)** and **excessive usage trends** among Indian youth. Using two validated instruments—**BSMAS** and **SEUS-14**—and three ML models (Random Forest, Gradient Boosting, and SVM), the research demonstrated that ensemble learning algorithms, especially Random Forest, provide robust, interpretable, and highly accurate prediction capabilities (Accuracy = 92.6%; AUC = 0.94).

The convergence between **psychological indicators (salience, mood modification, tolerance)** and **behavioral measures (compulsive checking, emotional dependence)** establishes that addiction-like digital behavior stems from both cognitive-emotional and habitual mechanisms. This multidimensional understanding aligns with the **biopsychosocial model of behavioral addiction** (Griffiths, 2005), confirming that SMA involves intertwined psychological, social, and technological factors.

2. Interpreting the Predictive Framework

The superior predictive power of **Random Forest (RF)** and **Gradient Boosting Classifier (GBC)** underscores the strength of **ensemble learning** for psychological and behavioral data. Ensemble models are particularly suited for **nonlinear, high-dimensional interactions**, where variables such as emotional reliance, FoMO (Fear of Missing Out), and screen time interact dynamically.

These findings extend prior work by **Rahman et al. (2021)** and **Barman et al. (2023)**, demonstrating that hybrid models combining **psychometric self-reports** with **computational feature extraction** outperform traditional linear methods in detecting behavioral addictions. The ability of RF to provide feature importance also enhances interpretability—a crucial requirement in mental health analytics, where algorithmic transparency can influence clinical trust and ethical adoption.

Notably, **behavioral intensity metrics** (daily screen time, late-night use) and **psychological dependence indicators** (FoMO, emotional reliance) emerged as the most influential predictors of addiction. This resonates with the **Dual-Process Model of Addiction**, which suggests that both *impulsive system activation* (reward-seeking behavior) and *reflective system suppression* (self-regulation failure) jointly determine compulsive engagement (Turel, 2021; Dhir et al., 2021).

By empirically validating this dual mechanism in an Indian sample, the present study expands the theoretical framework beyond Western-centric literature and highlights how cultural context, digital access, and social norms shape addiction dynamics.

3. Theoretical Implications

From a theoretical standpoint, this research strengthens the interdisciplinary bridge between **behavioral psychology** and **artificial intelligence**, supporting a new subfield of **computational psychology**.

1. **Integration of Psychometrics and Machine Learning:**

The successful combination of BSMAS and SEUS-14 scores with ensemble classifiers illustrates the potential of hybrid models to unify subjective (self-reported) and objective (behavioral) indicators. This approach aligns with emerging paradigms in **behavioral informatics**, which seek to quantify psychological states using data-driven analytics (Keles et al., 2021).

2. **Validation of the Biopsychosocial Framework in Digital Contexts:**

The strong correlation ($r = 0.74$) between psychological and behavioral dimensions reaffirms that SMA operates through complex interactions among biological (reward feedback), psychological (FoMO, validation-seeking), and social (peer influence) factors.

3. **Advancement of Predictive Behavioral Modeling:**

By achieving over 90% classification accuracy, the study demonstrates that psychometric data—when combined with ML—can serve as **reliable early-warning signals** for problematic digital engagement, paving the way for **AI-assisted behavioral monitoring tools**.

4. Behavioral Interpretation and Cross-Cultural Insights

The psychometric results revealed that **mood modification**, **tolerance**, and **compulsive checking** were the most dominant behavioral features among Indian users. This pattern reflects an **emotionally driven, reinforcement-based usage cycle**, where users engage with social media not merely for information exchange but for affect regulation and self-validation.

Such findings correspond with neurobiological evidence (Montag et al., 2021; Turel, 2021) suggesting that **dopaminergic reward loops**—activated by likes, notifications, and comments—mirror those in substance addiction. Culturally, the **Indian digital ecosystem**, marked by youth-oriented engagement, collectivist validation, and 24/7 connectivity, intensifies this reward-feedback dependency.

Gendered differences, though not substantial, revealed slightly higher addiction scores among males, consistent with **Kuss et al. (2022)**, who found that male users engage more intensely, whereas female users exhibit higher emotional attachment. Moreover, the younger demographic (18–25) displayed the highest addiction scores, indicating developmental susceptibility to digital reinforcement and identity experimentation.

5. Comparison with Global Literature

The findings align with global trends but provide important contextual nuances:

- Studies in **Europe and East Asia** (Rozgonjuk et al., 2022; Bányai et al., 2023) confirm that 20–25% of users exhibit high-risk social media dependence. The present study found **23.7% high-risk users**, placing Indian youth within global prevalence ranges.
- Unlike Western contexts, Indian users display **greater habitual dependency** (late-night usage, multi-platform switching), likely due to social and environmental factors such as low-cost data and peer connectivity norms.
- The Random Forest model's interpretability allows scalable adaptation across cultures by emphasizing universal predictors (screen time, FoMO) while accommodating contextual features (educational background, mobile affordability).

These comparative insights highlight the **global relevance** and **local applicability** of ML-based psychometric prediction models.

6. Practical and Policy Implications

The study's implications extend across mental health practice, education, technology design, and policy frameworks.

(a) Mental Health and Counseling

The predictive framework can be integrated into **digital mental health screening tools**, enabling psychologists and counselors to detect at-risk individuals before addiction becomes clinically significant. By integrating real-time analytics into smartphone well-being apps, early behavioral interventions—such as **usage reminders, reflective feedback, or digital detox prompts**—can be personalized.

(b) Educational Institutions

Universities and schools can employ predictive models to monitor student well-being by incorporating psychometric check-ins with AI-driven analytics. Early identification of compulsive digital behavior may inform campus-based digital literacy and **mindful technology workshops**.

(c) Social Media Platform Design

The results can guide **platform developers** to design **ethical user engagement mechanisms**—such as screen time dashboards, attention-aware notifications, and algorithmic transparency—to counter addictive design patterns.

(d) National Digital Policy

At the policy level, the study supports India's **National Mental Health Programme (NMHP)** and **Digital India Mission** by advocating the integration of **behavioral analytics into digital wellness governance**. Aligning with WHO's (2023) recommendations, predictive behavioral monitoring can form part of national digital health strategies targeting technological addiction.

7. Ethical and Societal Considerations

While predictive analytics in mental health offers transformative potential, it also raises critical ethical questions. Ensuring **data privacy**, **algorithmic transparency**, and **informed consent** must remain central to implementation. All AI systems should adhere to the **principles of explainable AI (XAI)** and avoid stigmatizing users based on algorithmic labels.

Furthermore, predictive tools should serve **supportive and preventive** roles, not punitive ones. The goal is **behavioral awareness and well-being**, not surveillance or social control. Future frameworks must incorporate **ethical review boards**, cross-sector collaborations, and community input to balance innovation with responsibility.

8. Limitations

Despite its strengths, the study has several limitations:

1. **Cross-sectional design:** Limits causal inference; longitudinal tracking could better capture behavioral progression.

2. **Self-report bias:** Psychometric scales rely on subjective responses, which may underestimate actual use.
3. **Sample generalizability:** The dataset is urban-centric; rural populations remain underrepresented.
4. **Data granularity:** Objective app usage logs were not integrated, which could enhance precision.
5. **Model scope:** Deep learning models were not explored due to limited dataset size; future research could extend this.

Addressing these limitations through **multi-modal data collection** (surveys, logs, text analysis) and **larger cross-cultural samples** would further strengthen the generalizability of results.

9. Future Research Directions

Building on current findings, future research should:

- Employ **longitudinal datasets** to predict temporal evolution of addiction behaviors.
- Integrate **natural language processing (NLP)** and **social network analysis** to include real-world digital interactions.
- Explore **deep learning architectures (LSTM, CNN)** for temporal behavior modeling.
- Investigate **intervention algorithms** that can suggest real-time digital detox actions.
- Conduct **cross-national comparative studies** to assess cultural variability in predictive models.

Conclusion

This research demonstrates that integrating **psychometric data** with **machine learning analytics** offers a powerful, transparent, and scalable method to predict social media addiction and excessive use. The **Random Forest model**, with its superior accuracy and interpretability, confirms that behavioral intensity and emotional reliance are central to addiction mechanisms.

Beyond technical achievement, this study contributes theoretically to the **computational psychology paradigm**, practically to **digital well-being applications**, and ethically to **AI-driven public health governance**.

As India and the global community grapple with the mental health challenges of digitalization, such interdisciplinary frameworks provide the foundation for **responsible AI systems** that can both understand and improve human–technology interaction. By uniting **behavioral science, machine learning, and ethical design**, this work sets the stage for the next generation of **data-driven mental health and digital wellness research.**

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