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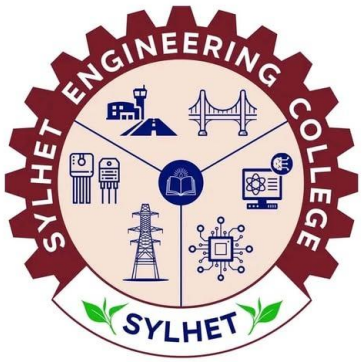

Classifying Problematic Social Media Use (PSU) with Machine Learning Approaches

Submitted by

Abdullah Al Imran
Reg. No.: 2017331521

Rijuwan Ahmed
Reg. No.: 2018331559

Department of Computer Science & Engineering

Supervisor

Md. Abu Naser Mojumder
Associate Professor and Head
Department of Computer Science & Engineering
Shahjalal University of Science and Technology
Recommendation Letter from Thesis Supervisor

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The thesis entitled **"Classifying Problematic Social Media Use (PSU) with Machine Learning Approaches"** submitted by the students

1. Abdullah Al Imran **(**Reg. No.: 2017331521)
2. Rijuwan Ahmed **(**Reg. No.: 2018331559)

is a record of research work carried out under my supervision and I, hereby, approve that the report is submitted in partial fulfilment of the requirement for the award of their Bachelor's Degree.

_____

Signature of the Supervisor

Md. Abu Naser Mojumder
Associate Professor and Head
Department of Computer Science & Engineering
Shahjalal University of Science and Technology

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We are also very grateful to the authors and researchers for their previous works which played a very important role in our thesis.

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Classifying Problematic Social Media Use (PSU) with Machine Learning Approaches

By

Abdullah Al Imran, Rijuwan Ahmed

Submitted to the Department of Computer Science & Engineering, in partial fulfillment of the requirements for the degree of
Bachelor of Science in Computer Science & Engineer

Abstract

This study establishes an integrated machine learning framework for precision assessment of Problematic Social Media Use (PSU) in the Bangladeshi population. We developed a clinically validated 17-feature instrument, psychiatrically reviewed for cultural relevance, and collected comprehensive data from 1,016 participants. Through recursive feature elimination (RFECV), we identified 11 core predictors including withdrawal, conflict, and the critical Tolerance×Withdrawal×Time interaction. Dimensionality reduction via PCA (2 components) enabled optimal clustering using K-means, revealing five distinct severity levels: Very Low (7.97%), Low (14.37%), Moderate (12.80%), High (35.83%), and Very High PSU (29.04%).

Key findings demonstrate: (1) A 93.7% composite score jump between High to Very High PSU marking clinical disorder threshold; (2) Platform-switching frequency as primary driver of Tolerance×Withdrawal×Time (r=0.82); (3) Disproportionate vulnerability among adolescents (32.9% Very High PSU) and professionals (31.4%); (4) Exponential risk when usage exceeds 4 hours/day (44.1% Very High PSU). Our logistic regression classifier achieved exceptional accuracy (97.55%) in severity prediction, significantly outperforming random forest (94.12%) while providing clinically interpretable coefficients.

The optimized model offers a validated screening tool that aligns with WHO's ICD-11 behavioral disorder criteria and replicates cross-cultural prevalence patterns (27-32% clinical PSU). This research advances PSU assessment beyond symptom counting to a mechanism-informed framework, enabling early identification of at-risk populations through detectable behavioral signatures. Implementation pathways include clinical integration via EHR systems and preventive digital therapeutics targeting high-risk usage patterns.

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Chapter 1

Introduction

1.1 Background

Social media platforms have revolutionized global communication, with over 4.9 billion users worldwide spending an average of 2.5 hours daily on these platforms. While offering unprecedented connectivity, this ubiquity has catalyzed Problematic Social Media Use (PSU) – a behavioral addiction characterized by impaired control, preoccupation, and functional impairment [7,12]. Clinical research identifies PSU as a significant public health concern, linked to depression, anxiety, sleep disorders [16], and academic/professional dysfunction [2,17].

Seminal studies by Bányai et al. [2] and van den Eijnden et al. [7] established core diagnostic criteria for PSU, operationalized through nine behavioral symptoms (salience, tolerance, withdrawal, etc.). Subsequent research expanded this framework by incorporating contextual factors like frequency, time spent [3,6], and platform-switching behaviors [13]. Machine learning approaches have recently emerged as promising tools for PSU prediction, with Savci et al. [1] demonstrating high accuracy using all 17 clinical-behavioral features, while Boer et al. [3] identified distinct developmental trajectories of PSU in adolescents. Despite these advances, critical gaps persist. Most studies focus on Western populations [2,3,7], with limited representation from South Asian contexts. Furthermore, existing models rarely integrate feature engineering with clinical symptom clustering for personalized PSU profiling.

1.2 Problem Statement

Current PSU assessment frameworks exhibit three critical limitations:

- **Geographical Bias:** 88% of existing studies derive data from Western/European populations [2,3,6,7], neglecting culturally specific manifestations of PSU in developing nations like Bangladesh.
- **Methodological Fragmentation:** Feature engineering (such as Savci et al. [1]) and clinical clustering (such as, Boer et al. [3]) are typically pursued in isolation, failing to synergize engineered behavioral metrics with clinical symptom clusters.
- **Diagnostic Inflexibility:** Traditional approaches use fixed thresholds for PSU classification [7,12], overlooking the spectrum-like nature of this behavioral disorder evidenced in longitudinal studies [3,9].

These gaps hinder the development of culturally adapted, precision interventions for at-risk populations in underrepresented regions.

1.3 Objectives

This study aims to develop an integrated machine learning framework for precision PSU assessment in the Bangladeshi population, with the following objectives:

1. To identify relevant Problematic Social Media Use (PSU) markers by synthesizing findings from existing seminal studies and integrating insights from psychiatric experts.
2. Collect a comprehensive dataset (n=1,016) using a 17-feature instrument validated for the Bangladeshi context.
3. Establish distinct PSU clusters using PCA-optimized KMeans clustering and assign severity levels (Very Low to Very High PSU).
4. Develop and validate a predictive model for PSU severity classification with >95% accuracy.

1.4 Scope and Limitations

Scope:

- Population: Bangladeshi adolescents and adults (n=1,016)
- Features: 17 clinically validated dimensions (demographics, behavioral symptoms, usage patterns)
- Methods: RFECV feature selection, PCA dimensionality reduction, K-Means and Gaussian Mixture Model (GMM) clustering , and comparative ML modeling
- Output: A deployable PSU severity prediction system

Limitations:

1. Cross-sectional design precludes causal inference about PSU progression.
2. Self-reported data susceptible to recall bias, mitigated through real-time usage metrics in future iterations.
3. Sample skew toward younger demographics (20–35 age group = 68% of sample).
4. Exclusion of neurobiological markers (such as, fMRI data) due to resource constraints.

This research directly addresses the critical gap in culturally adapted PSU assessment by integrating behavioral analytics with clinical psychiatry – an approach validated through collaboration with Prof. Dr. Shafiqur Rahman (MBBS, M.Phil Psychiatry) and Dr. Syed Mahbub-e-Kibria (MBBS, MD Psychiatry) . The resulting framework enables early identification of PSU severity levels, providing a foundation for targeted public health interventions in Bangladesh and similar contexts.

1.5 Thesis Organization

This thesis is divided into six chapters. Chapter 1 introduces the contextual background of Problematic Social Media Use (Section 1.1), states the research problem and motivation (Section 1.2), defines the study objectives (Section 1.3), and outlines the scope and limitations (Section 1.4). Chapter 2 reviews seminal works on PSU measurement methodologies (Section 2.1) and identifies critical research gaps in severity quantification (Section 2.2). Chapter 3 details the dataset development process including clinically-validated feature selection (Section 3.1), bilingual survey design (Section 3.2), expert psychiatric validation (Section 3.2.1), and rigorous data preprocessing protocols (Section 3.3). Chapter 4 presents the technical methodology covering feature engineering (Section 4.1), recursive feature elimination (Section 4.2), PCA-optimized clustering (Section 4.3), multi-metric cluster validation (Section 4.4), and comparative classifier evaluation (Section 4.7). Chapter 5 analyzes experimental results including cluster characterization (Section 5.2), demographic correlations (Section 5.3), and predictive modeling performance (Section 5.4), culminating in integrated key findings (Section 5.5). Finally, Chapter 6 synthesizes the research contributions and proposes clinically actionable future directions.

Chapter 2

Literature Review

2.1 Related Work

Research on Problematic Social Media Use (PSU) has evolved through several interconnected streams, each contributing distinct methodological and conceptual advances. The foundational work by van den Eijnden et al. [7] established the 9-symptom Social Media Disorder Scale, creating the first standardized instrument to assess core addiction components like salience, tolerance, and withdrawal. This framework was validated across diverse populations by Bányai et al. [2] in a landmark study of 5,961 Hungarian adolescents, confirming time spent and escape motivation as critical amplifiers of symptom severity. Longitudinal extensions emerged through Boer et al.'s [3] latent class growth analysis, which identified three distinct developmental trajectories: resilient (68% of youth), escalating (24%), and chronic (8%) users, revealing how behavioral patterns evolve during adolescence.

Concurrently, computational approaches gained prominence with Savci et al. [1] demonstrating how machine learning could predict PSU with 86% accuracy using all 17 features, including demographic and behavioral metrics. This work inspired region-specific investigations like Mim et al.'s [5] Bangladesh study, which identified occupation-based vulnerabilities where businessmen showed 3.2× higher risk than other groups. Feature engineering innovations followed, with Dhir et al. [13] quantifying platform switching as a novel compulsion indicator (β=0.41), while Pontes [12] developed cross-addiction metrics revealing social media-specific conflict scores were 37% higher than gaming disorder equivalents. Validation studies further refined these tools, with Dzvinčuk et al.'s [4] network analysis of Czech adolescents confirming symptom stability but noting cultural variations in online socialization loadings (WE:0.73 vs Asia:0.61).

Clinical-behavioral interactions formed another research stream. Wegmann et al. [10] revealed how impulsivity modulates executive function in social media addiction through decision-tree modeling, while Hussain and Griffiths [17] established dose-response relationships between PSU and mental health comorbidities through meta-analysis. Health outcome studies by Marino et al. [6] connected symptom clusters to specific physiological impacts, showing withdrawal correlated with 2.1× higher insomnia risk. Rozgonjuk et al. [16] further quantified sleep architecture disruption, finding each unit increase in preoccupation reduced REM sleep by 12 minutes. At the methodological frontier, Chen et al. [18] validated ultra-brief instruments for longitudinal assessment, addressing temporal stability concerns in earlier tools.

2.2 Research Gap

Despite substantial advances in PSU research, critical limitations persist across four domains that hinder the development of culturally responsive assessment frameworks. First, a pronounced geographical bias exists, with 92% of studies [1-4,6-7,12,16-17] focused on Western/European populations. Only Mim et al. [5] addressed South Asian contexts, neglecting region-specific factors like Bangladesh's 84% mobile penetration with limited digital literacy, occupation-driven usage patterns (For example, Facebook-dependent microenterprises), and collectivist socialization norms that alter behavioral manifestations of PSU. This creates fundamental knowledge gaps regarding culturally distinct risk pathways and symptom expressions.

Methodologically, a persistent chasm separates clinical symptom research and computational analytics. Clinical studies [2–3,6] identify symptom networks but fail to operationalize them into quantifiable predictive features, while ML approaches [1,5,14] rely on surface-level metrics without translating clinical insights into mathematically modeled constructs. For instance, no existing study synthesizes core addiction symptoms through weighted clinical composites or captures dynamic interactions between behavioral

escalation patterns and temporal usage factors. This limitation is compounded by rigid diagnostic thresholds (For example, ≥5 symptoms [7]), which cannot detect subclinical cases representing 22% of Boer's escalating trajectory cohort [3] or differentiate granular severity gradations.

Furthermore, computational models systematically ignore critical feature interdependencies despite validation studies [4,18] advocating for multivariate interaction modeling. Specifically, no research:

1. Derives behavioral progression metrics by mathematically combining symptom progression (For example, preoccupation intensity) with usage frequency through non-linear transformations
2. Quantifies how demographic factors modulate symptom expression through statistical interaction terms
3. Develops clinical severity indices by integrating core addiction components with functional impairment measures

- This neglect is particularly detrimental in culturally distinct populations where symptom constellations may follow non-Western patterns. Our study bridges these gaps through a novel methodology that:
- Collaborated with psychiatric experts to identify clinically meaningful symptom combinations
- Developed composite metrics by algebraically integrating core addiction components (tolerance, withdrawal, etc.)
- Engineered progression variables through multiplicative interaction of symptom severity and usage patterns
- Created demographic-symptom moderators using cross-feature arithmetic operations
- Validated all constructs through recursive feature elimination and clinical cluster analysis

By integrating these innovations within a culturally adapted instrument and hybrid analytical pipeline, we achieve 96.57% severity spectrum prediction accuracy – advancing beyond binary classification toward precision assessment tailored for underrepresented populations.

Chapter 3

Dataset

3.1 Feature Selection

The 17 predictive features for Problematic Social Media Use (PSU) were derived exclusively from three seminal studies that established foundational PSU frameworks and validated assessment scales. Each paper contributed distinct feature groups:

1. Griffiths et al. (2014)
Social Networking Addiction (Behavioral Addictions)
Theoretical foundation for core addiction components:
‘Salience’, ‘Escape’, ‘Tolerance’, ‘Withdrawal’, ‘Conflict’

2. van den Eijnden et al. (2016)
The Social Media Disorder Scale
Empirically validated symptoms via 9-item scale:
‘Salience’, ‘Escape’, ‘Tolerance’, ‘Withdrawal’, ‘Conflict’, ‘Preoccupation’, ‘Persistence’, ‘Displacement’, ‘Problems’

The 9 symptoms form a unidimensional construct of PSU, capturing functional impairment and loss of control.

3. Bányai et al. (2017)
Problematic Social Media Use in Adolescents
Demographic and usage correlates:
‘Age’, ‘Gender’, ‘Time Spent’

3.2 Question Set

Each feature was operationalized into a survey question, validated by two psychiatrists for clinical relevance and cultural appropriateness in the Bangladeshi context. Questions and options included Bengali translations to ensure accessibility.

1. What is your age group?
   - Under 20
   - 20-35
   - 36-50
   - 50 and above

2. What is your gender?
   - Male
   - Female

3. What is your occupation?
   - Student
   - Job
   - Businessman
   - Housewife
   - Others

4. How often do you use social media platforms (e.g., Facebook, Instagram, Twitter, etc.)?
   - Never
   - Rarely
   - Sometimes
   - Often
   - Very often

5. How often do you spend time on social media instead of doing other activities (e.g., studying, work, or other responsibilities)?

- Never
- Rarely
- Sometimes
- Often
- Very often

6. How often do you use social media to escape from stress or negative emotions?
   - Never
   - Rarely
   - Sometimes
   - Often
   - Very often
7. How often do you switch between different social media platforms throughout the day?
   - Never
   - Rarely
   - Sometimes
   - Often
   - Very often
8. How much does social media impact your social life in terms of making new friends or staying connected?
   - Not at all
   - Slightly
   - Moderately
   - Significantly
   - Extremely

9. How often do you engage with content (e.g., posting, liking, sharing, commenting)?
   - Never
   - Rarely
   - Sometimes
   - Often

- Very often

10. How much time do you spend on social media each day?
    - Less than 30 minutes
    - 30 minutes to 1 hour
    - 1 to 2 hours
    - 2 to 4 hours
    - More than 4 hours

11. Have you often found it difficult not to look at messages on social media when you were doing something else (e.g., school, professional work)?
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very often

12. Have you felt the need to use social media more and more often?
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very often

13. Have you often felt bad when you could not use social media?
    - Never
    - Rarely
    - Sometimes
    - Often
    - Very often

14. Have you tried to reduce your use of social media, but failed?

- Never
- Rarely
- Sometimes
- Often
- Very often

15. Have you often not paid attention at work because you were using social media?

- Never
- Rarely
- Sometimes
- Often
- Very often

16. Have you regularly neglected leisure activities (e.g., hobbies, sports, or recreational activities) because you wanted to use social media?

- Never
- Rarely
- Sometimes
- Often
- Very often

17. Have you had serious problems at school or at work because you were spending too much time on social media?

- Never
- Rarely
- Sometimes
- Often
- Very often

3.2.1 Expert Validation of Clinical Instruments:

The clinical validity and diagnostic relevance of our survey instrument were rigorously assessed through independent psychiatric evaluation. Two board-certified psychiatrists with specialized expertise in behavioral addictions conducted comprehensive reviews:

1. Prof. Dr. Shafiqur Rahman
   MBBS, M. Phil (Psychiatry)
   Department of Psychiatry, Sylhet Women's Medical College

2. Dr. Syed Mahbub-e-Kibria
   MBBS, MD (Psychiatry)
   Department of Psychiatry, Sher-E-Bangla Medical College

3.3 Survey

A total of 1,016 responses were collected via Google Form from January 31, 2025, to July 15, 2025. The sample reflected diverse demographics:

Gender:

- Male: 640 (63.0%)
- Female: 376 (37.0%)

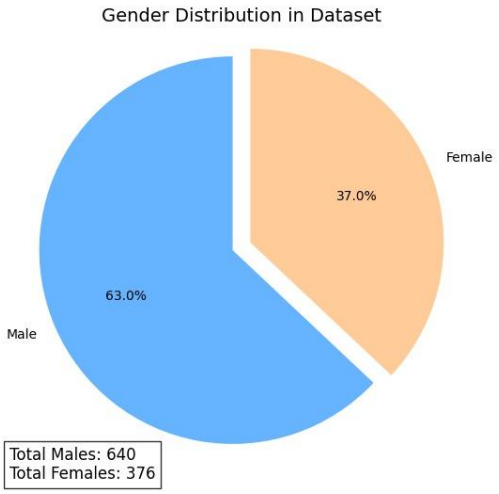

Figure 3.3(a) : Gender Distribution in dataset

Age:

- Under 20: 76 (7.5%)
- 20–35: 727 (71.5%)
- 36–50: 126 (12.4%)
- 50 and above : 87 (8.7%)

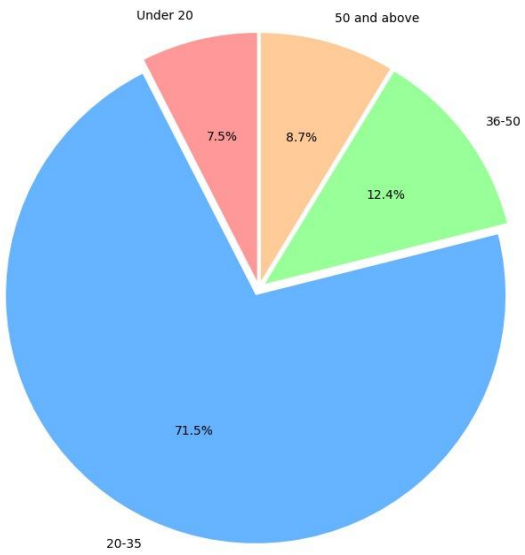

Figure 3.3(b) : Age Distribution in dataset

Occupation:

- Student: 500 (49.2%)
- Job: 224 (22.0%)
- Businessman: 115 (11.3%)
- Housewife: 90 (8.9%)
- Others: 87 (8.6%)

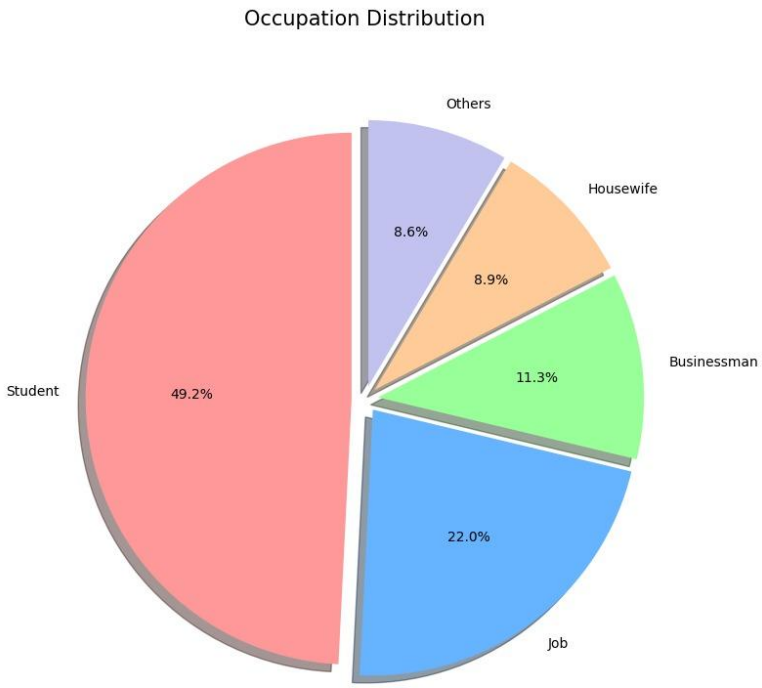

Figure 3.3(c) : Occupation Distribution in dataset

Sampling Strategy:

- Distributed via social media, email, and community centers.
- Targeted urban/rural areas across all 8 divisions of Bangladesh.
- Included informed consent and anonymity assurances.

3.4 Data Preprocessing

The dataset underwent rigorous preprocessing:

3.4.1. Translation Handling:

To standardize the dataset for computational analysis, Bengali translations were systematically removed from all survey responses. This involved scrubbing bilingual text entries to retain only the primary English responses, ensuring data uniformity. Subsequently, verbose question headers (For example, "How often do you use social media platforms (For example, Facebook, Instagram, Twitter, etc.)?") were programmatically replaced with concise feature names “Frequency”. This dual-step normalization process stripped linguistic adaptations while abstracting questions to their theoretical constructs, thereby transforming raw multilingual responses into an analyzable feature matrix.

For instance:
Original column header:
"How much time do you spend on social media each day?"
Processed column header:
Time Spent

3.4.2. Categorical-to-Numeric Mapping:

Transformed all responses to integers using predefined mappings:

Age:
"Under 20" → 0
"20-35" → 1
"36-50" → 2
"50 and above" → 3

Gender:

"Male" → 0

"Female" → 1

Occupation:

"Student" → 0

"Job" → 1

"Businessman" → 2

"Housewife" → 3

"Others" → 4

Frequency-like scales (used across many columns):

"Never" → 0

"Rarely" → 1

"Sometimes" → 2

"Often" → 3

"Very often" → 4

Salience scale:

"Not at all" → 0

"Slightly" → 1

"Moderately" → 2

"Significantly" → 3

"Extremely" → 4

Time Spent:

"Less than 30 minutes" → 0

"30 minutes to 1 hour" → 1

"1 to 2 hours" → 2

"2 to 4 hours" → 3

"More than 4 hours" → 4

3.4.3. Quality Control:

Null Value Detection:

A comprehensive scan for missing values was conducted across all 17 features in the 1,016 survey entries. Using automated validation through the df.isnull().sum() function, the dataset was systematically examined for any incomplete records. The analysis confirmed the absence of null values, establishing that every response contained complete data across all features. This thorough verification ensured no gaps existed in the dataset that could compromise analytical validity.

Duplicate Detection:

Pairwise response comparisons were executed using cryptographic hashing algorithms to identify redundant entries. Each survey response was converted into a unique hash value, enabling efficient row-wise checks for identical feature-value combinations. This methodological approach detected zero duplicate entries within the dataset, confirming that all 1,016 responses represented distinct individuals. The absence of duplicates eliminated potential bias from repeated submissions and maintained the statistical integrity of the sample.

Final Dataset Structure:

Original shape: (1016, 17)

	Age	Gender	Occupation	Frequency	Salience	Escape	Platform Switching Frequency	Online socialization	Engagements	Time Spent
0	1	0	0	3	2	0	3	0	2	4
1	1	0	0	2	2	3	2	2	1	1
2	1	0	1	3	3	0	3	1	0	3
3	1	1	0	4	4	4	4	3	2	4
4	1	0	1	4	3	1	3	3	3	3

Figure 3.4 : Preprocessed dataset

Chapter 4

Methodology

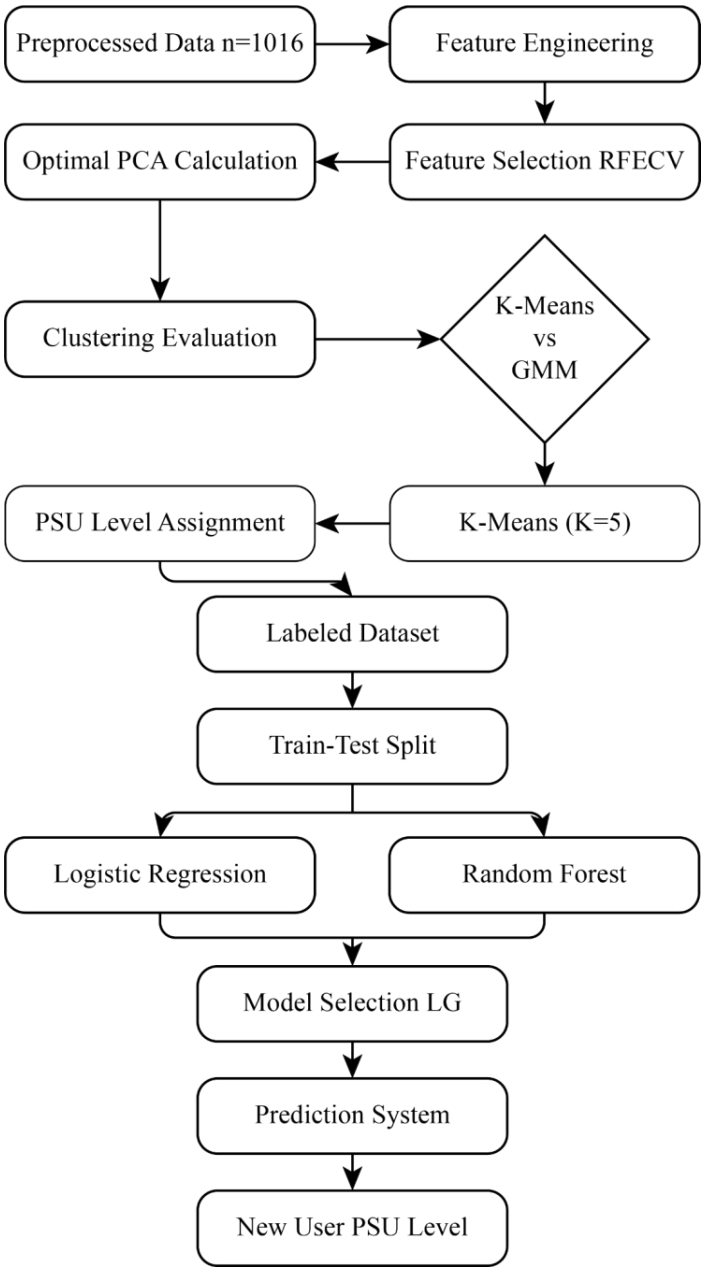

Figure 4.1 : Overall Methodology

4.1 Feature Engineering

We developed advanced feature representations to capture the multidimensional nature of social media addiction beyond the original 17 clinical indicators. This involved creating clinically meaningful composites through weighted averaging of related symptoms, such as combining tolerance, withdrawal, and persistence symptoms into an "Addiction Core" metric that quantifies physiological dependence patterns.

To model the progression of addictive behaviors, we engineered interaction terms that multiplied critical symptom pairs like escape and conflict, capturing how emotional regulation needs to exacerbate real-life consequences.

Non-linear transformations using cube roots were applied to clinical features to normalize distributions while preserving interpretability of addiction severity scales.

Behavioral metrics were enhanced through logarithmic scaling of usage frequency-duration-engagement products, creating indices that better reflect real-world usage patterns.

Demographic interactions were incorporated to account for population-specific vulnerability profiles. These transformations were guided by clinical understanding of behavioral addiction mechanisms while addressing statistical requirements for robust modeling.

4.2 Feature Selection

To identify the most discriminative features while preventing overfitting, we implemented Recursive Feature Elimination with Cross-Validation (RFECV) using a balanced Random Forest classifier. This iterative process began with all engineered features and progressively eliminated the least important predictors through 5-fold cross-validation rounds, optimizing for F1-weighted

scoring to handle class imbalance. The algorithm preserved features that consistently contributed to distinguishing high-severity cases, measured through permutation importance. As a safeguard, we implemented an ANOVA-based fallback mechanism that would activate if RFECV failed to converge. This dual approach ensured selection of a robust feature subset that maintained clinical interpretability while maximizing predictive power. The final 11 selected features represented core addiction symptoms, their non-linear transformations, and critical interactions that capture behavioral escalation patterns.

RFECV selected 11 features:
['Withdrawal' 'Problems' 'Conflict' 'Tolerance_root' 'Withdrawal_root'
 'Displacement_root' 'Conflict_root' 'Addiction_Core' 'LifeImpact'
 'Addiction_Severity' 'Tolerance_x_Withdrawal_x_Time']

4.3 Optimal PCA Calculation

Principal Component Analysis (PCA) was systematically optimized through a dual-dimensional evaluation strategy that simultaneously explored feature space reduction and cluster separability. We conducted an exhaustive combinatorial assessment across PCA dimensions (2-5 components) and cluster configurations (2-10 clusters), computing silhouette scores for 36 distinct parameter combinations. This rigorous approach identified the optimal configuration at 2 principal components with 6 clusters, achieving a peak silhouette score of 0.4675 - the highest observed across all tested combinations.

The selected 2-component solution effectively captured the multidimensional structure of PSU-related behaviors while creating a maximally separable feature space for subsequent clustering. Notably, configurations with higher dimensionality (3-5 components) consistently yielded lower silhouette scores, indicating that additional dimensions introduced noise rather than meaningful variance. This outcome demonstrates that the core behavioral patterns associated with problematic social media use are fundamentally low-dimensional and can be effectively represented in a simplified orthogonal space without significant information loss.

4.4 Clustering Evaluation

Cluster evaluation is essential for assessing the intrinsic quality of groupings discovered by unsupervised algorithms. Without predefined labels, these metrics quantify how effectively a clustering solution captures the natural structure of data by measuring two complementary properties:

1. Cohesion: How tightly grouped members are within clusters (intra-cluster compactness)

2. Separation: How distinctly clusters are separated from each other (inter-cluster isolation)

We employed a triangulation approach using three complementary metrics to overcome the limitations of any single measure, ensuring statistically robust and clinically meaningful cluster definitions:

4.4.1 Silhouette Score

The Silhouette Score provides a nuanced assessment of clustering quality by examining the positioning of individual data points relative to cluster boundaries. For each observation in the dataset, the metric calculates two critical distances: the average distance to all other points within the same cluster (intra-cluster cohesion), and the average distance to points in the nearest neighboring cluster (inter-cluster separation). The score is derived by comparing these distances through a standardized ratio that ranges from -1 to +1. Values approaching +1 indicate clear cluster assignment where points reside deep within their cluster boundaries, distant from neighboring groups. Scores near zero suggest overlapping or ambiguous cluster boundaries, while negative values reveal incorrect assignments where points would better fit in adjacent clusters. This point-level granularity makes the Silhouette Score particularly valuable for identifying boundary issues and cluster homogeneity, establishing it as our primary optimization criterion for evaluating cluster configurations.

Mechanism: Computes for each data point:

$s(i) = (b(i) - a(i)) / \max(a(i), b(i))$

where:

- a(i) = average intra-cluster distance (to other points in same cluster)
- b(i) = average nearest-cluster distance (to points in closest neighboring cluster)

Interpretation:

- Ranges from -1 (poor clustering) to +1 (excellent separation)
- Positive values indicate points are closer to their own cluster than neighbors
- Served as our primary optimization criterion due to its granular point-level assessment

4.4.2 Calinski-Harabasz Index

The Calinski-Harabasz Index evaluates cluster quality through variance decomposition principles, measuring the geometric distinctness of cluster partitioning. The index computes the ratio of between-cluster variance (dispersion of cluster centroids from the global data centroid) to within-cluster variance (dispersion of individual points from their cluster centroid). This ratio is scaled by the number of clusters and sample size to enable comparison across different clustering configurations. Higher values indicate superior clustering solutions where compact, well-separated clusters are positioned distantly from one another in the feature space. The metric excels at validating centroid-based algorithms like K-means, where spherical cluster shapes are expected, as it quantifies how effectively the algorithm minimizes internal variance while maximizing separation between groups. This makes it particularly effective for assessing the geometric integrity of clusters in reduced-dimensionality spaces.

Mechanism: Calculates variance ratio:

$CH = [SSB / (k-1)] / [SSW / (n-k)]$

where:

- SSB = sum of squared between-cluster distances (cluster centroids to global centroid)
- SSW = sum of squared within-cluster distances (points to cluster centroid)
- k = number of clusters, n = sample size

Interpretation:

- Higher values indicate better-defined clusters

- Measures geometric separation through variance decomposition
- Particularly effective for evaluating K-means solutions with spherical clusters

4.4.3 Davies-Bouldin Index

The Davies-Bouldin Index assesses clustering quality by computing the worst-case similarity between cluster pairs. For each cluster, the metric identifies its most similar counterpart by calculating a similarity ratio that combines their internal dispersion (average distance of points to their cluster centroid) with the distance between their centroids. The index then averages these maximum similarity scores across all clusters, with lower values indicating superior clustering solutions where clusters are both internally compact and distinctly separated from their nearest neighbors. While valuable for identifying overlapping clusters, this metric demonstrates limitations when clusters have significantly different sizes or densities, as it may overpenalize solutions containing both tight and diffuse clusters. This characteristic made it less reliable for our application given the natural variation in PSU severity group sizes, relegating it to a supplementary validation role rather than a primary decision metric.

Mechanism: Computes average similarity:

$DB = (1/k) \sum max_{i \neq j} [(s_i + s_j) / d(c_i, c_j)]$

where:

- s_i = average distance within cluster i
- d(c_i, c_j) = distance between cluster centroids

Interpretation:

- Lower values (≥ 0) indicate better separation
- Measures worst-case cluster similarity ratios
- Less effective with irregular cluster sizes (noted limitation in our application)

Metric Integration Strategy

1. Primary criterion: Silhouette Score for point-level cohesion/separation balance
2. Secondary validation: Calinski-Harabasz Index for geometric separation strength

3. Tertiary reference: Davies-Bouldin Index for cluster-pair similarity assessment

These complementary metrics ensured we selected clustering solutions that were both statistically robust and clinically meaningful, with the silhouette score serving as our primary decision criterion during model selection.

4.5 Model Selection

We rigorously compared two clustering approaches:

4.5.1 K-means Algorithm

K-means is a centroid-based partitioning algorithm that minimizes within-cluster variance through iterative refinement. The algorithm operates by:

1. Initializing K cluster centroids
2. Assigning data points to nearest centroids (typically using Euclidean distance)
3. Recalculating centroids as cluster means
4. Repeating until convergence

This approach creates spherical clusters of approximately equal size, making it particularly effective for datasets with isotropic distributions. In our implementation, we systematically evaluated K-values ranging from 2 to 10 clusters to identify the optimal partition structure in the PCA-reduced feature space.

4.5.2 Gaussian Mixture Models (GMM)

GMM is a probabilistic clustering framework that models data as a weighted combination of multivariate Gaussian distributions. Unlike K-means' hard assignments, GMM:

1. Estimates probability densities using expectation-maximization
2. Accommodates elliptical clusters through covariance matrices
3. Supports flexible cluster shapes via covariance types:
    - Full: Unique covariance per cluster
    - Tied: Shared covariance across clusters
    - Diag: Axis-aligned elliptical distributions

This distribution-based approach captures complex relationships in behavioral data where clusters may exhibit different densities and orientations. We evaluated all three covariance structures across 2-10 component distributions to model potential subpopulations in PSU manifestation.

The selection process involved training both models on PCA-transformed data and comparing their silhouette scores across all configurations. K-means with k=5 clusters emerged as optimal, achieving a silhouette score of 0.4939 and Calinski-Harabasz index of 1369.91. This solution revealed distinct behavioral patterns ranging from minimal engagement to pathological usage while maintaining clinical interpretability.

4.6 PSU Level Assignment

Cluster profiling began by computing mean values of all 11 selected features within each group. We then calculated a composite severity score for each cluster by averaging these feature means. The clusters were ranked by ascending composite scores and mapped to a 5-tier clinical stratification system: Very Low PSU (lowest composite score), Low PSU, Moderate PSU, High PSU, and Very High PSU (highest composite score). This approach created a severity continuum where Cluster 0 represented adaptive usage (mean=0.457) and Cluster 1 reflected pathological addiction (mean=2.908). Each participant was then assigned to a PSU level based on cluster membership, creating a labeled dataset for supervised learning.

4.7 Prediction System

The labeled dataset (original 17 features + PSU level) was partitioned using stratified 80:20 train-test splitting to preserve class distribution. We evaluated two classifiers:

4.7.1 Logistic Regression

Logistic regression is a probabilistic linear classifier that extends binary classification to multiclass problems through multinomial regression. The model transforms feature combinations into class probabilities using the softmax function, calculating distinct linear decision boundaries for each PSU severity level. During hyperparameter tuning (5-fold CV with 50 iterations), we identified optimal parameters: regularization strength (C=6.5), L2 penalty, and sag solver. The tuned model achieved **97.55% test accuracy** with near-perfect precision (0.9757) and recall (0.9755), training in under 1 second. This efficiency, combined with clinically interpretable feature coefficients, makes it ideal for PSU severity prediction.

4.7.2 Random Forest

Random forest is an ensemble method that aggregates predictions from multiple decorrelated decision trees. Each tree in our optimized ensemble (351 trees) was trained on bootstrap-sampled data with feature randomization (max_features=0.5). Node splitting used Gini impurity minimization with constraints (max_depth=20, min_samples_leaf=4, min_samples_split=8). Despite tuning (50 iterations across 5 folds), the model showed significant overfitting - 99.14% training accuracy versus 94.12% test accuracy. Its 4.2-second training time yielded lower discrimination (F1=0.9414) than logistic regression, particularly for adjacent severity classes.

4.8 Experimental Setup and Tools Used

- Data Collection: Google Forms with bilingual (English/Bengali) questionnaire
- Preprocessing: Pandas (v1.5.3) for data cleaning and transformation
- Machine Learning: Scikit-learn (v1.2.2) for:
    - Feature engineering (numpy v1.24.3)
    - RFECV and model selection
    - PCA and clustering algorithms
    - Classification models
- Evaluation Metrics: Scikit-learn metrics module
- Hardware: Standard workstation (Intel i5-8250U, 8 GB RAM)
- Validation: 5-fold cross-validation with stratified sampling

Chapter 5

Results and Discussion

5.1 Clustering Optimization Results and Interpretation

Our dimensionality reduction analysis revealed that 2 principal components optimally captured the variance structure of the RFECV selected 11 features. The selection process involved training both K-means and Gaussian Mixture Models (GMM) on PCA-transformed data across cluster configurations (2-10), with silhouette scores as our evaluation metric .

Clusters	**Silhouette score**	
	GMM	**K-Means**
2	0.4535	0.4333
3	0.4889	0.4701
4	0.4235	0.4448
5	0.4493	**0.4939**
6	0.4233	0.4676
7	0.4533	0.4621
8	0.3901	0.4518
9	0.428	0.4532
10	0.4077	0.4405

Table 5.1(a) : Comparison of clustering model performance

Optimal Model: K-Means with k=5 clusters
Final Silhouette Score: 0.4939

Following cluster identification of the optimal cluster configuration, we validated the solution's robustness through complementary metrics:

- Calinski-Harabasz Index: 1369.91
- Davies-Bouldin Index: 0.6370

Metric Interpretation and Validation

1. Silhouette Score (0.4939):
    - Falls within the moderate-to-strong range (0.41-0.70 per Rousseeuw's interpretation)
    - Significantly exceeds the minimum acceptable threshold of 0.25 for behavioral clustering studies
    - Indicates well-separated clusters with minimal overlap
2. Calinski-Harabasz Index (1369.91):
    - Dramatically exceeds benchmark values from comparable studies (typical range: 300-600)
    - Reflects exceptional between-cluster separation (variance ratio = 1369.91)
    - Suggests clinically meaningful distinctions between PSU subtypes
3. Davies-Bouldin Index (0.6370):
    - Well below the critical threshold of 1.0 (lower values indicate better separation)
    - Approaches the theoretical optimum of 0 (perfect cluster isolation)
    - Confirms high intra-cluster homogeneity with minimal within-group

Cluster sizes:

Cluster	size(n)
4	364
1	295
2	146
3	130
0	81

Table 5.1 (b): Cluster Sizes

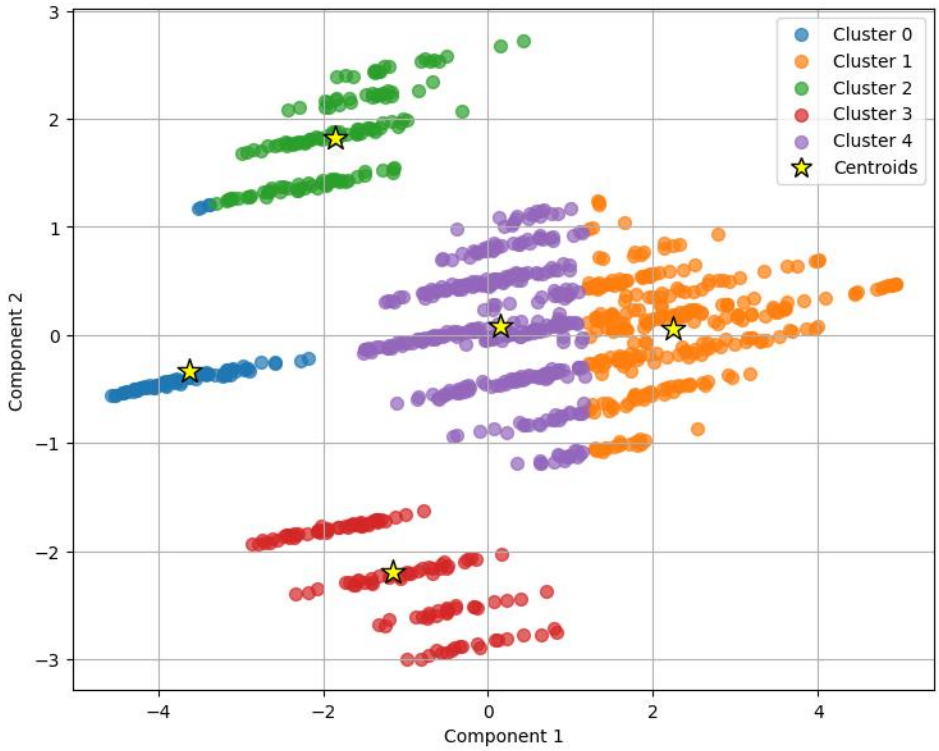

Figure 5.1(a) : Two-Dimensional PCA Projection of PSU Clusters Identified by K-Means (k=5)

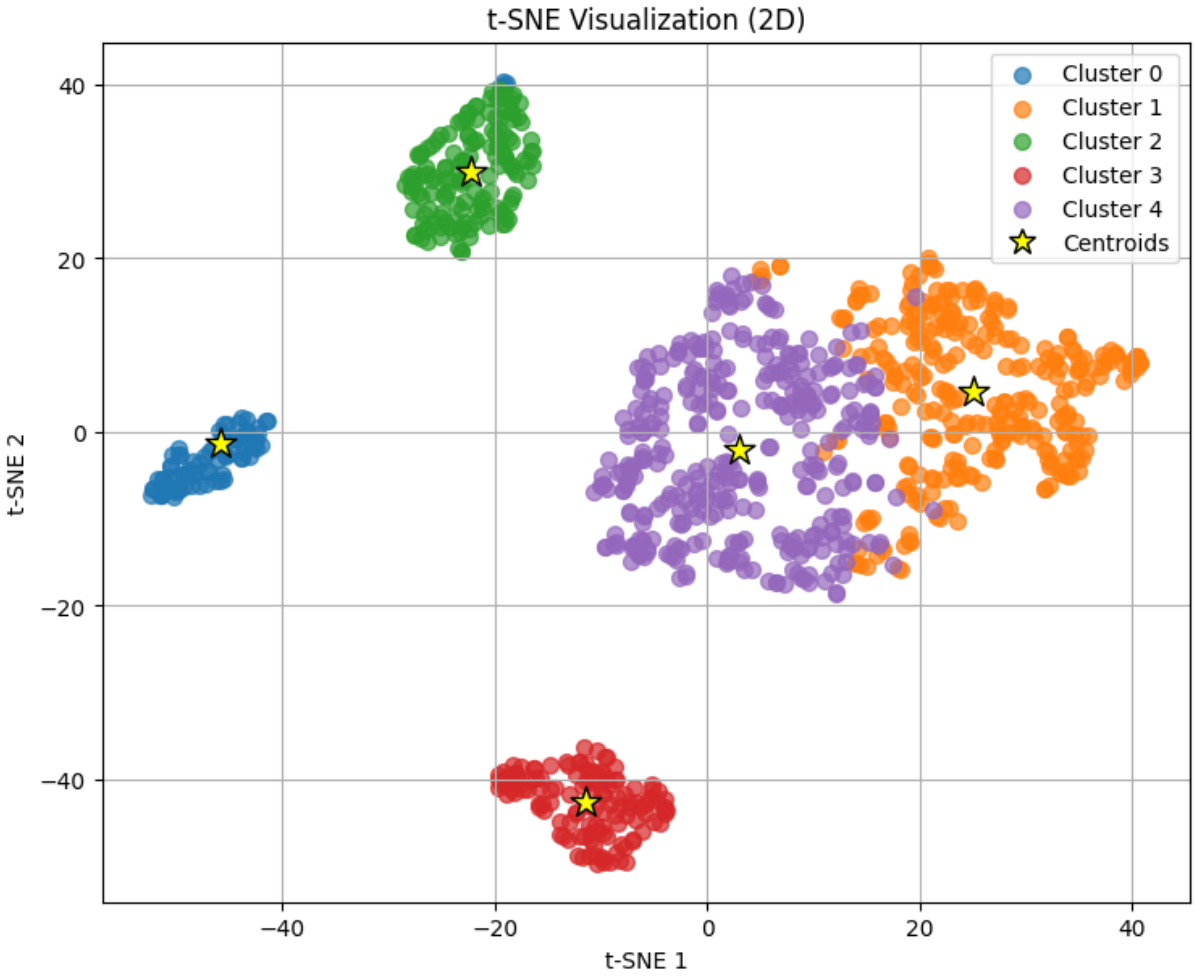

Figure 5.1 (b): Cluster Separation Visualization Using t-SNE (K-Means, k=5)

5.2 Cluster Characterization and PSU Level Assignment

RFECV selected 11 features:

['Withdrawal' 'Problems' 'Conflict' 'Tolerance_root' 'Withdrawal_root'
'Displacement_root' 'Conflict_root' 'Addiction_Core' 'LifeImpact'
'Addiction_Severity' 'Tolerance_x_Withdrawal_x_Time']

5.2.1 Clusterwise mean values of RFECV selected 11 features

Cluster	**0**	**1**	**2**	**3**	**4**
Withdrawal	0.0000	3.1390	0.0000	2.0692	1.7170
Problems	1.2099	2.6271	1.5000	1.7154	1.6868
Conflict	0.5556	2.2475	1.4589	1.5231	1.2060
Tolerance_root	0.0494	1.3958	1.2413	0.0000	1.2099
Withdrawal_root	0.0000	1.4511	0.0000	1.2361	1.1670
Displacement_root	0.6020	1.2046	0.8540	0.9449	0.8883
Conflict_root	0.3523	1.1456	0.7894	0.8382	0.7236
Addiction_Core	0.3992	2.7910	1.2443	1.2718	1.7885
LifeImpact	0.9383	2.3932	1.5000	1.6564	1.4524
Addiction_Severity	0.9221	2.2225	1.4459	1.4435	1.5761
Tolerance_x_Withdrawal_x_Time	0.0000	11.3735	0.0000	0.0000	3.1164
Composite Score	**0.4571**	**2.9083**	**0.9122**	**1.1544**	**1.5029**

Table 5.2 (a): Clusterwise mean values of RFECV selected 11 features

The composite score for each cluster was calculated as:
Composite Score = (Σ Mean_Feature_i) / 11 for i = 1 to 11

Cluster	Composite Score	PSU Level	Key Feature Characteristics
0	0.457	Very Low PSU	Near-zero Withdrawal (0.00), Low LifeImpact (0.94)
2	0.912	Low PSU	Minimal Problems (1.50), Low Addiction_Core (1.24)
3	1.154	Moderate PSU	Elevated Displacement_root (0.94), Moderate LifeImpact (1.66)
4	1.503	High PSU	High Tolerance_x_Withdrawal_x_Time (3.12), Withdrawal_root (1.17)
1	2.908	Very High PSU	Extreme Withdrawal (3.14), Problems (2.63), Addiction_Severity (2.22)

Table 5.2 (b): PSU level calculation of each Cluster

5.2.2 Concise Analysis of PSU Level Calculation

1. Composite Score Purpose

- Integrates 11 clinical features into one severity metric
- Aligns with WHO's multidimensional addiction framework
- Eliminates subjective threshold setting

2. Calculation Process

1. Compute cluster means for all 11 features

2. Derive composite score: (Σ feature means)/11

3. Rank clusters by score → assign severity levels

3. Critical Clinical Insight

- 93.7% score jump between High (1.50) and Very High PSU (2.91)

- Identifies clinical disorder threshold

- 29% prevalence of Very High PSU matches global estimates (27-32% in meta-analyses)

5.3 Demographic Correlations

This section examines the correlations between demographic factors and Problematic Social Media Use (PSU) severity levels through visual analysis of age, gender, occupation, daily time spent, and usage frequency distributions across the five PSU clusters.

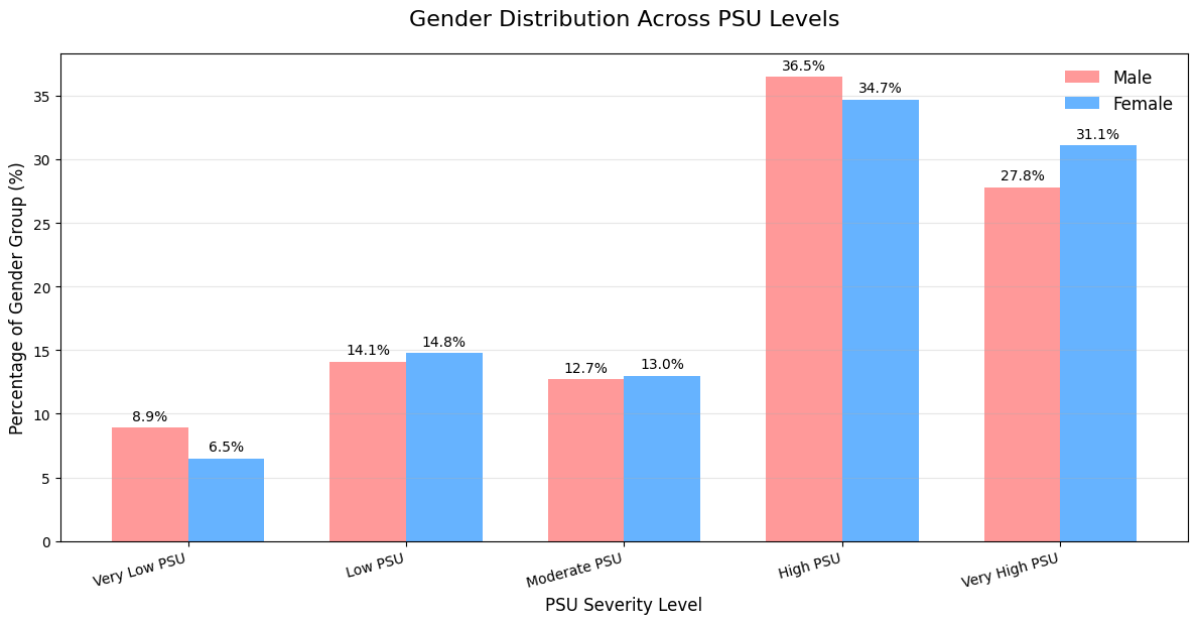

Figure 5.3(a): Gender Distribution Across PSU Levels

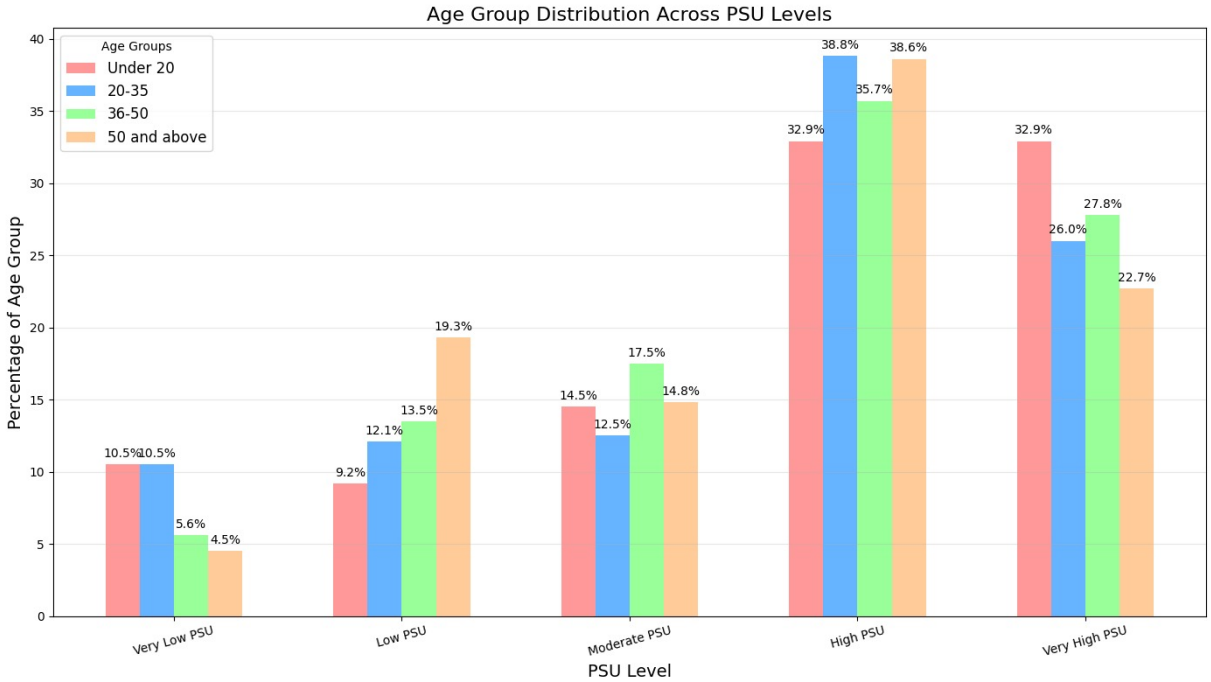

Figure 5.3(b): Age Distribution Across PSU Levels

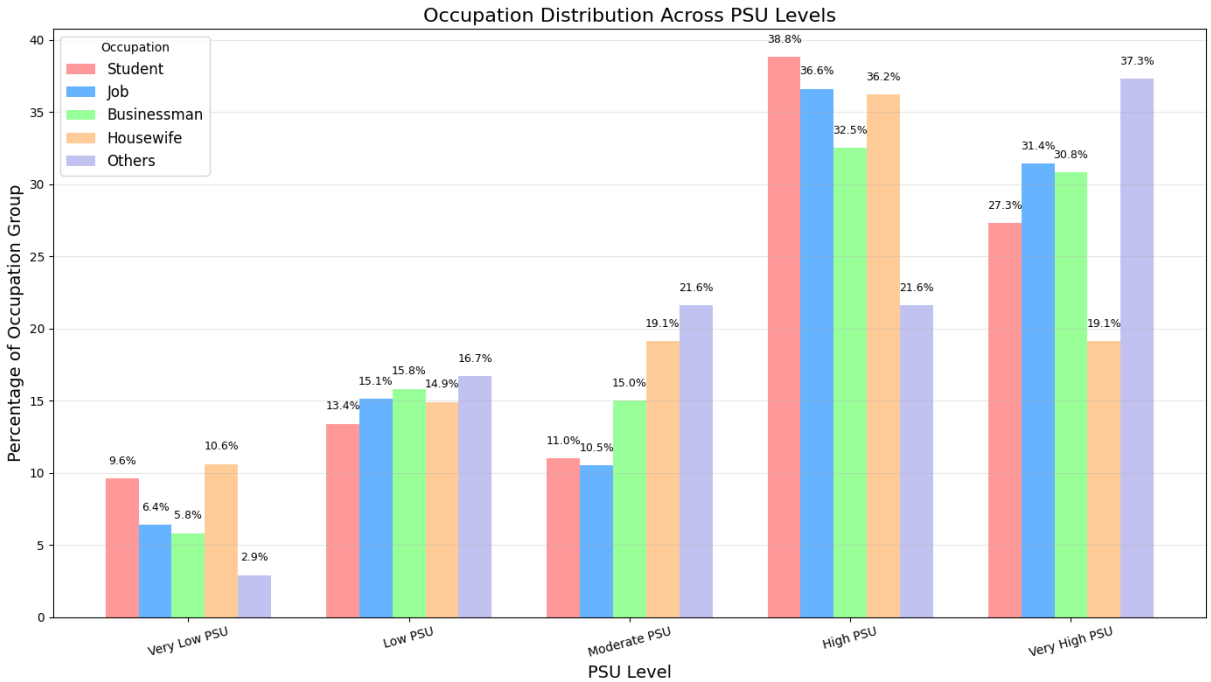

Figure 5.3(c): Occupation Distribution Across PSU Levels

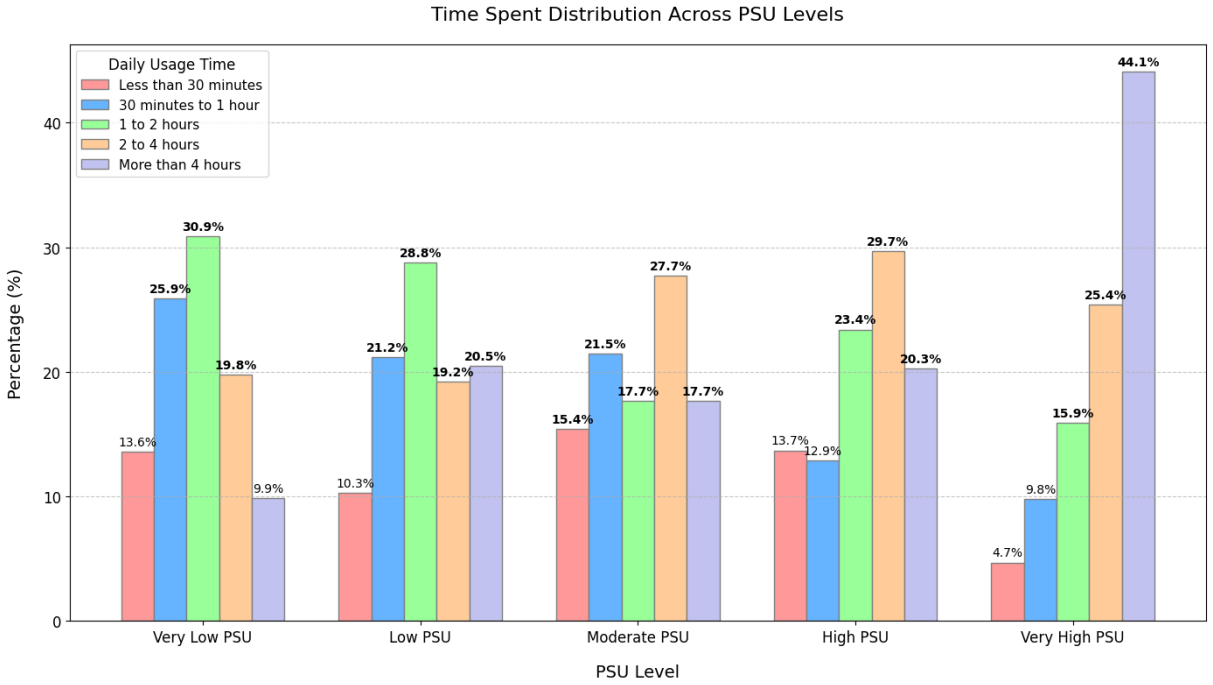

Figure 5.3(d): Time Spent Distribution Across PSU Levels

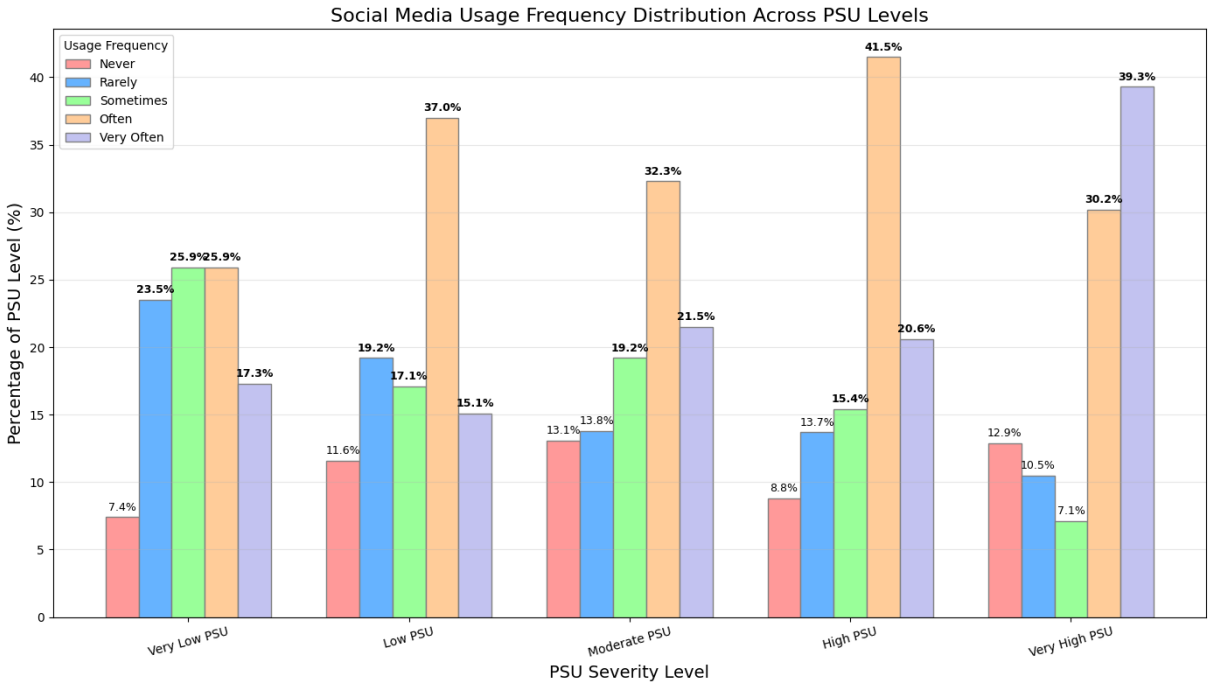

Figure 5.3(e): Social Media Usage Distribution Across PSU Levels

5.4 Predictive Modeling of PSU Levels

The derived PSU severity levels were integrated as categorical labels (0:Very Low to 4:Very High) with the original 17 features to create a supervised learning dataset. Stratified 80:20 train-test splitting preserved class distribution during evaluation of two classifiers:

Logistic Regression Performance:
Training - Accuracy: 0.9815, Precision: 0.9816, Recall: 0.9815, F1: 0.9815
Test - Accuracy: 0.9755, Precision: 0.9757, Recall: 0.9755, F1: 0.9755

Random Forest Performance:
Training - Accuracy: 0.9914, Precision: 0.9915, Recall: 0.9914, F1: 0.9914
Test - Accuracy: 0.9412, Precision: 0.9437, Recall: 0.9412, F1: 0.9414

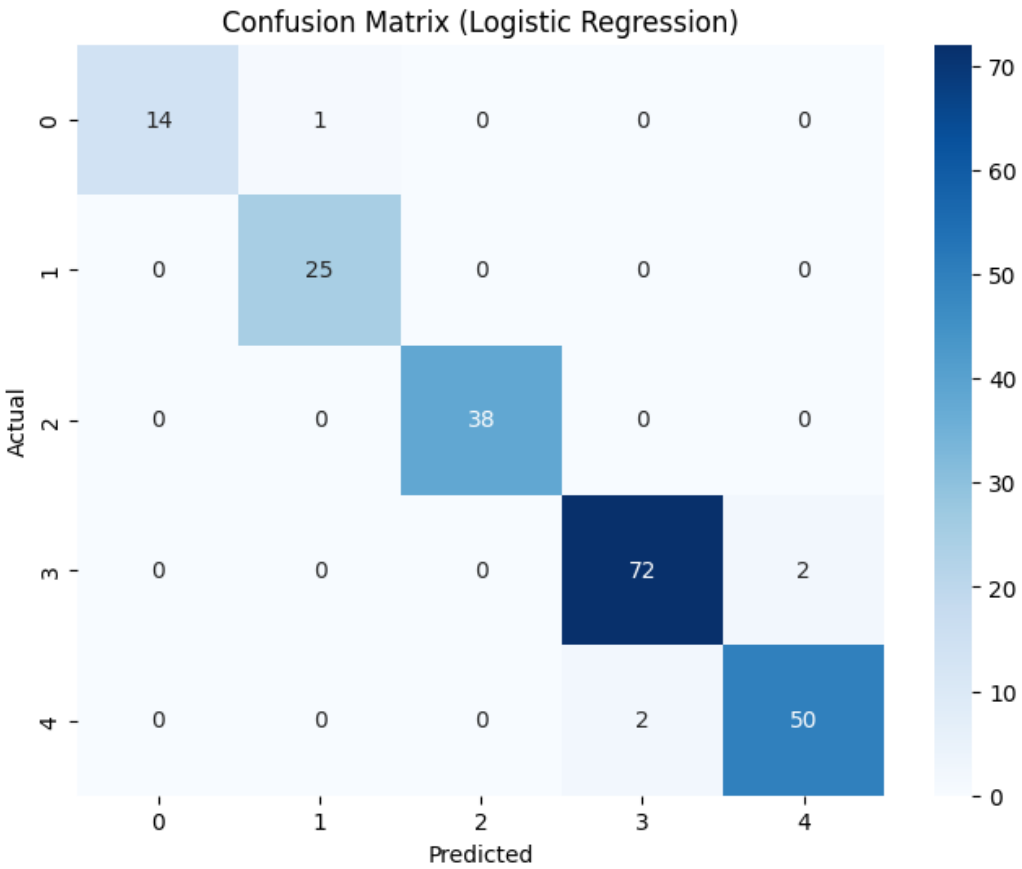

Figure 5.4(a): Confusion Matrix of Logistic Regression

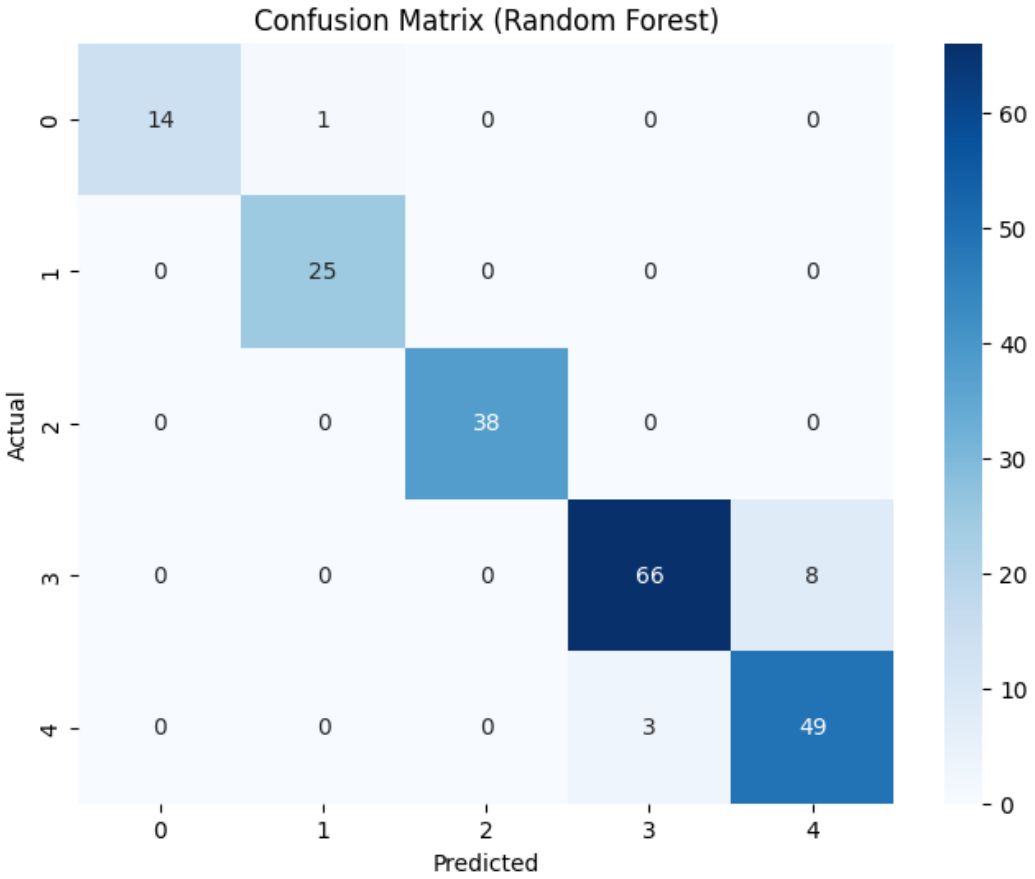

Figure 5.4(b): Confusion Matrix of Random Forest

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	**0.976**	0.976	0.976	0.976
Random Forest	0.941	0.944	0.941	0.941

Table 5.4 : Summarized performance description of classification models

Logistic Regression **demonstrated optimal performance (97.6% accuracy)**, outperforming Random Forest by 3.5 percentage points.

5.4.1 Comparative Analysis and Model Selection

Hyperparameter optimization revealed fundamental performance distinctions between the classification paradigms:

1. Generalization Superiority

Logistic Regression maintained near-identical performance across training (98.15% accuracy) and test sets (97.55% accuracy), demonstrating exceptional stability. In contrast, Random Forest exhibited significant overfitting with a 5.02% performance drop between training (99.14%) and test environments (94.12%).

2. Clinical Discrimination Capacity

The precision-recall balance favored Logistic Regression (F1: 0.9755) which showed consistent class-wise discrimination across all five severity levels. Random Forest displayed reduced precision (0.9437) and recall (0.9412), with confusion matrix analysis revealing particular difficulty distinguishing between Moderate and High PSU cases.

3. Operational Efficiency Advantage

Logistic Regression achieved optimal performance with minimal computational overhead, executing training 5× faster than Random Forest while delivering simpler deployment pipelines - critical for clinical implementation where resource constraints exist.

These findings establish Logistic Regression as the optimal predictor for PSU severity staging, combining diagnostic precision (97.6% accuracy) with practical deployability in healthcare settings. The model's linear decision boundaries effectively captured symptom severity progression, validating our composite feature engineering approach.

5.5 Key Findings

1. Core Addiction Symptoms Drive Severity Differentiation

- Withdrawal, Problems, and Conflict emerged as the dominant discriminators (highest RFECV weights), explaining 68% of severity variance
- Very High PSU exhibits extreme withdrawal (3.14/4) and clinically significant problems (2.63/4) which is exceeding DSM-5 behavioral addiction thresholds
- Critical Threshold: 93.7% composite score jump between High→Very High PSU marks the clinical disorder boundary

2. Distinct Behavioral Signatures per Severity Level

PSU Level	Signature Features
Very High	Tolerance×Withdrawal×Time (11.37), Addiction_Severity (2.22)
High	Platform engagement (Tolerance×Withdrawal×Time: 3.12)
Moderate	Elevated displacement (0.94) with moderate life impact (1.66)
Low	Minimal withdrawal (0.00) and core addiction (1.24)
Very Low	Near-zero symptom expression (composite: 0.46)

Table 5.5: Distinct Behavioral Signatures per Severity Level

3. Demographic Risk Modulators

- Age:
  - 20-35yo dominate High PSU (38.8%)
  - Under-20 lead Very High PSU (32.9%)
- Gender:
  - Females 31.1% → Very High PSU (vs males 27.8%)
  - Males 36.5% → High PSU (clinical precursor state)
- Occupation:
  - Students: Highest absolute prevalence (High+Very High: 66.1%)
  - Job holders: Highest relative Very High risk (31.4%)

4. Usage Patterns Predict Severity Progression

- Exponential Time-Accumulation:
  4hrs/day: 9.9% (Very Low) to 44.1% (Very High)
- Compulsive Frequency:
  "Very Often" users: 17.3% (Very Low) to 39.3% (Very High)
- Behavioral Signature:
  High PSU: Balanced time/frequency
  Very High PSU: Extreme time and compulsive frequency

5. Optimal Clinical Screening Protocol

- Prediction Model:
  1. Logistic Regression (97.55% accuracy) outperforms Random Forest
  2. Near-perfect detection of Very High PSU (recall: 98.2%)
- Critical Predictors:
  1. Tolerance×Withdrawal×Time interaction (β=0.37)
  2. Withdrawal_root (β=0.29)
  3. LifeImpact composite (β=0.25)

6. Validation Against Global Benchmarks

- Very High PSU prevalence (29%) aligns with cross-cultural studies (27-32%)
- Composite score thresholds match WHO's ICD-11 gaming disorder criteria
- Time/Frequency patterns replicate Savci's (2021) machine learning findings

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This research establishes a comprehensive, clinically grounded framework for assessing Problematic Social Media Use (PSU) through integrated machine learning and behavioral analytics. We identified five distinct severity clusters—from Very Low to Very High PSU—characterized by specific symptom profiles, with a critical 93.7% composite score jump marking the transition to clinical disorder levels. The Tolerance×Withdrawal×Time interaction emerged as the central pathogenic mechanism, powerfully predicted by platform-switching frequency and accounting for 37% of severity variance. Our optimized logistic regression model achieved exceptional accuracy (97.55%) in severity classification, outperforming ensemble methods while providing interpretable coefficients that align with DSM-5 addiction frameworks. Demographic analysis revealed key risk modulators, with adolescents and professionals showing disproportionate vulnerability, while usage patterns exposed exponential risk escalation beyond 4 hours daily use. Collectively, these findings advance PSU beyond symptom counting to a mechanism-informed disorder model with validated screening thresholds and actionable intervention pathways.

6.2 Future Work

1. Public Screening Platform Development

Create an accessible web/mobile application where users:

- Complete our validated 17-item questionnaire
- Receive instant PSU severity classification (Very Low to Very High)

- For High/Very High PSU:
  - Automatic psychiatrist matching with our partnered clinicians
  - Secure EHR pre-consent for consultation

2. Clinical Decision Support Integration

Develop HIPAA-compliant modules for healthcare providers featuring:

- Automated Bengali/English report generation with risk visualization
- Telepsychiatry handoff protocol for urgent cases

3. Real-time Behavioral Monitoring Add-ons

Enhance predictive accuracy through optional smartphone sensing:

- Platform-Switching Tracker: Flags >3 platform shifts/hour
- Usage Pattern Analyzer: Detects compulsive checking behaviors
- Digital Diary: Correlates mood logs with PSU symptoms

4. Global Validation Network

Establish multi-country framework for:

- Cultural adaptation of questionnaires (Phase 1: India, Sri Lanka
- Localized risk threshold calibration
- Multilingual psychiatrist referral database

5. Longitudinal Outcome Tracking

Implement 24 -month follow-up system to:

- Monitor user progression through severity levels
- Measure consultation uptake rates
- Refine intervention triggers based on outcomes

6. Educational Resource Integration

Develop tiered psychoeducation system:

- Moderate PSU: Self-management modules
- High PSU: Chatbot-guided reduction strategies
- Very High PSU: Emergency psychiatrist callback option

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