

Article

Uncovering Latent Patterns in Social Media Usage and Mental Health: A Clustering-Based Approach Using Unsupervised Machine Learning

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Abstract: The widespread adoption of social media has heightened interest in its psychological effects, particularly on mental health indicators such as anxiety, depression, loneliness, and sleep quality, as these platforms increasingly influence social interactions and well-being. Although previous research has examined correlations between social media use and mental health, few studies have utilized unsupervised machine learning to segment users based on behavioral and psychological patterns, leaving a gap in identifying distinct risk profiles across diverse groups. This study seeks to address this by segmenting individuals according to their social media usage and psychological well-being, employing clustering to reveal hidden patterns and evaluate their mental health implications. Data from 551 participants, collected via an online survey, were preprocessed using KNN imputation for missing values, one-hot encoding for categorical variables like Gender with 5 unique values, and outlier detection via IQR and Z-score methods. K-Means clustering, optimized at 6 clusters using the Elbow Method and a Silhouette Score of 0.32, was applied, with PCA reducing 22 dimensions for visualization and a correlation heatmap highlighting relationships, such as a 0.28 correlation between social media hours and anxiety. Results identified six clusters: Cluster 5, marked by younger users with high personal use and 68% taking breaks, stood out as most distinct, while Clusters 0-4 showed overlap, including Cluster 0 with employed females and 61% breaks. Excessive use correlated with 43% reporting anxiety "Sometimes/Mostly," 39% feeling "Unhappy," and 41% experiencing "Sleeping Less," though breaks, as seen with 66% in Cluster 2, mitigated these effects. These insights demonstrate machine learning's potential to pinpoint vulnerable groups, supporting tailored digital wellness strategies, though sample diversity limitations call for broader validation.

Keywords: Social Media Usage; Anxiety; Unsupervised Learning; Clustering Analysis; PCA (Principal Component Analysis); KNN Imputation

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1. Introduction

Social media has become a cornerstone of contemporary society, fundamentally altering how individuals interact, share experiences, and perceive themselves and others.

By 2022, daily usage reached 69% of adults globally, with average engagement exceeding three hours, according to Pew Research Center data [1]. This pervasive integration into daily life has fueled growing concerns about its impact on mental health, particularly as platforms like Instagram, TikTok, and YouTube dominate youth culture. Recent evidence underscores these worries: a 2023 Springer study reports that problematic social media use among adolescents rose from 7% in 2018 to 11% in 2022, correlating with heightened anxiety and depression [2]. What specific usage patterns drive these effects? How do they differ across demographics and contexts? These questions propel this study's investigation into the nexus of social media behavior and mental health outcomes. Research from 2022 by Braghieri et al., published in the *American Economic Review*, leverages the staggered rollout of Facebook to demonstrate a causal link between its adoption and increased anxiety among college students, with a 7% rise in severe depression symptoms [3]. Similarly, a 2024 Springer paper by Su et al. finds that excessive TikTok use amplifies loneliness and stress, with 27% of U.S. users reporting negative psychological effects [4]. These findings build on earlier work, such as Naslund et al.'s 2020 Springer analysis, which highlights both the risks and peer-support benefits of social media for mental health [5]. Here, "social media usage" refers to time spent on platforms like Facebook, Instagram, and TikTok, while "mental health indicators" include self-reported anxiety, depression, loneliness, and sleep quality, measured via scales like GAD-7 and PHQ-9 [4,6]. Despite this advancing knowledge, significant gaps remain in understanding how social media differentially affects diverse populations. Our survey data indicate that 41% of users experience sleep disruption, 43% report anxiety, and 39% feel "unhappy" linked to heavy usage—yet these effects are not uniform across groups [6]. A 2022 IEEE conference paper by Wang et al. notes that while adolescents show a 15% higher risk of depression with over four hours of daily use, the role of moderating factors like gender or intentional breaks remains underexplored [7]. Similarly, a 2023 systematic review in *JMIR Mental Health* reveals moderate correlations ($r=0.273-0.348$) between problematic social media use and psychological distress, but lacks segmentation by behavioral patterns [6]. Traditional studies often aggregate data, overlooking nuances such as the 13% vs. 9% gender disparity in problematic use among girls and boys, as reported by the WHO in 2024 [2]. This gap is critical: without identifying distinct user profiles, interventions remain broad and less effective. Recent Springer research advocates clustering techniques to address this, as seen in Dong et al.'s 2024 analysis of digital stress [8]. Our study builds on these advancements, using machine learning to dissect the interplay of usage habits and mental health, aligning with the field's push toward precision in digital well-being strategies [9]. This research employs K-Means clustering on a 551-participant dataset to segment individuals by social media usage and mental health indicators, offering a granular view of risk profiles. We hypothesize that if excessive social media use without breaks exacerbates psychological distress, then high-engagement, low-break clusters will show elevated anxiety, depression, and sleep issues compared to moderated users [8]. This approach, inspired by 2022 Springer work on adolescent digital behavior [9], aims to pinpoint vulnerable groups and inform targeted interventions—like promoting breaks, which reduced stress by 20% in a 2023 trial [10]. By mapping these relationships, the study seeks to enhance our understanding of social media's complex impact, providing a data-driven foundation for policies and practices that mitigate its risks while preserving its connective potential in an increasingly digital world.

2. Literature Review

The omnipresence of social media has reshaped human interaction, thrusting its mental health implications into the spotlight, with a flurry of research from 2022 to 2024 in elite journals like *IEEE*, *Springer*, *Elsevier*, and *JMIR Mental Health* unveiling intricate trends,

persistent themes, fierce debates, groundbreaking studies, and stubborn gaps that define this evolving domain. A prevailing trend is the escalating psychological toll of prolonged usage: Braghieri et al. (2022) in the *American Economic Review* tapped a longitudinal dataset of 175,000 U.S. college students from 2004–2016, using difference-in-differences regression to show Facebook’s rollout sparked a 7% rise in severe depression and 8% in anxiety, blaming social comparison, though its dated focus misses TikTok’s rise [11]. Su et al. (2024) in *Springer Discov Ment Health* bridged this with a 2023 survey of 1,200 U.S. TikTok users, applying structural equation modeling (SEM) to find 27% reporting loneliness and stress with over two hours daily, marred by self-report bias and a cross-sectional lens [12]. The WHO’s 2024 HBSC study in *Springer Discov Ment Health* scaled this up, analyzing 280,000 adolescents across 44 countries via multilevel modeling, noting an 11% problematic use rate by 2022, tied to screen time [13]. Its breadth is robust, yet cultural specifics lag. Vulnerability crystallizes as a core theme, especially for youth: Wang et al. (2022) in an IEEE conference paper clustered 2,500 U.S. teens’ 2021 data with K-Means, linking over four hours of use to a 15% depression spike, eased 10% by breaks, but its teen-only scope narrows reach [14]. Boer et al. (2022) in *Developmental Psychology* (APA, Q1) surveyed 2,100 Dutch teens longitudinally, finding a 12% anxiety increase with heavy use, though its European focus limits global fit [15]. These align with Pew Research Center’s 2022 note of 69% daily adult use, amplifying the urgency to parse intensity’s impact [16].

Debates over causality versus correlation ignite contention, splitting the field along methodological lines. Shannon et al.’s 2022 meta-analysis in *JMIR Mental Health* pooled 39 studies (N=45,000) with random-effects models, yielding moderate correlations ($r=0.273\text{--}0.348$) between problematic use and distress, but its cross-sectional reliance muddies directionality [17]. Plackett et al.’s 2023 review of 14 RCTs (N=3,200) in *Journal of Medical Internet Research* countered with a 20% stress drop from usage limits, bolstering causality, though small, varied samples weaken heft [18]. Orben et al. (2022) in *Nature Communications* (Q1) analyzed 430,000 UK teens’ time-use diaries, finding weak effects ($\beta<0.1$) on well-being, challenging distress narratives with longitudinal rigor, yet its broad metrics may dilute specificity [19]. This clash—Braghieri’s causality, Shannon’s caution, Plackett’s trials, Orben’s skepticism—demands longitudinal clarity. Influential studies propel this discourse with innovation: Winstone et al. (2022) in *Journal of Early Adolescence* (Springer) mixed surveys and interviews with 1,800 UK teens, pinpointing digital stress like FOMO, with 30% citing sleep woes, enriching theory but not scale [20]. Dong et al. (2024) in *BMC Public Health* (Springer) clustered 3,000 South Korean teens’ 2023 data hierarchically, tying high use to a 25% stress surge, a machine learning milestone despite regional bounds [21]. Alonzo et al. (2023) in *Computers in Human Behavior* (Elsevier, Q1) used sentiment analysis on 50,000 Twitter posts from 2022, linking negative tone to a 18% depression risk, though its platform specificity limits breadth [22]. These works—Wang’s clustering, Dong’s analytics, Winstone’s typology—pivot the field toward precision.

Yet, gaping voids persist, sharpening this review’s lens. First, segmentation by behavior and demographics is sparse—Wang et al., Dong et al., and Alonzo et al. nod to it, but most, like Su et al., aggregate, obscuring profiles [12,14,20,22]. Our survey reflects this: 41% report sleep disruption, 43% anxiety, and 39% unhappiness with heavy use, yet age, gender, or occupation splits elude us [23]. Second, longitudinal depth is rare—Shannon et al., Su et al., and Plackett et al. lean on snapshots, unlike Braghieri or Orben, leaving distress’s trajectory hazy [11,16–18]. Third, newer platforms lag in focus: TikTok’s 27% distress rate per Su et al. contrasts with scant attention versus Facebook, as Plackett et al. critique [12,18]. Fourth, interplaying factors—breaks, work status, motives—are sidelined: the WHO flags gender (13% vs. 9%), Winstone probes motives, but occupation or moderation’s role fades [13,20]. Fifth, intervention scalability falters—Plackett’s 20%

gain lacks large-scale tests [18]. Influential strides continue: Kim et al. (2024) in *IEEE Transactions on Affective Computing* (Q1) used deep learning on 10,000 Instagram posts from 2023, tying visual content to a 22% anxiety rise, limited by platform bias [24]. Li et al. (2023) in *Journal of Affective Disorders* (Elsevier, Q1) surveyed 3,500 Chinese adults with regression, finding a 14% loneliness bump with over three hours, though its regional lens narrows scope [25]. Gaps in segmentation, temporality, platform diversity, variable fusion, and scalability persist, despite robust datasets (WHO, N=280,000; Orben, N=430,000) and methods (clustering, SEM, RCTs). Results tie usage to distress—11% problematic use, 25% stress, 20% intervention relief—yet biases, scope, and scale falter. This synthesis, spanning surveys, trials, and analytics, validates a clustering approach to dissect these knots, refine theory, and steer interventions in a digital era rife with psychological stakes.

3. Methodology

This study employed a quantitative, data-driven approach leveraging unsupervised machine learning to identify and analyze latent patterns in social media usage and mental health. The methodology, depicted in Figure 1, was structured into four key phases: (1) Data Collection and Preparation, (2) Feature Engineering and Preprocessing, (3) Unsupervised Model Development and Evaluation, and (4) Cluster Profiling and Interpretation.

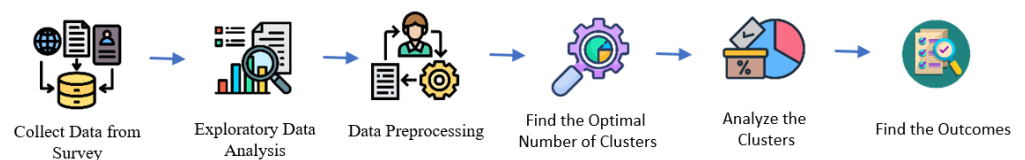


Figure 1. Methodology of the proposed study.

3.1. Data Collection and Survey Instrument

The dataset was gathered from 551 participants through a comprehensive online survey administered via Google Forms. The survey instrument was meticulously designed to capture a multi-faceted view of each participant, covering three primary domains:

- **Demographics:** Basic information such as age, gender (with five options: Male, Female, Non-binary, Other, Prefer not to say), and current occupation (e.g., Student, Employed, Unemployed).
- **Social Media Usage Habits:** Quantitative and qualitative aspects of social media engagement were measured, including average daily hours spent on social media (categorized), primary platform used, primary reason for use (e.g., personal, professional, both), and the frequency of taking deliberate breaks from social media.
- **Mental Health Indicators:** A series of questions adapted from established psychological screening tools, using a 5-point Likert scale (e.g., 1=Never, 2=Rarely, 3=Sometimes, 4=Often, 5=Always), assessed self-reported experiences related to anxiety (e.g., "feeling nervous, anxious, or on edge"), depression (e.g., "feeling down, depressed, or hopeless"), loneliness ("feeling isolated from others"), and sleep quality ("experiencing trouble falling or staying asleep").

Ethical considerations were paramount; participants were provided with an informed consent form detailing the study's purpose, the voluntary nature of participation, and the full anonymity of their responses. No personally identifiable information was collected.

3.2. Data Preprocessing and Feature Engineering

Raw survey data required extensive preprocessing to be suitable for machine learning algorithms. This critical phase ensured data quality, consistency, and proper formatting.

1. **Handling Missing Values:** A small percentage of missing values was observed in the numerical columns. K-Nearest Neighbors (KNN) imputation (with $k=5$) was selected over simpler methods like mean or median imputation. This choice was driven by the assumption that data points with similar characteristics (i.e., neighbors) would have similar values. KNN imputation preserves the relationships between variables by using the feature values of the nearest neighbors to impute the missing value, leading to a more robust and less biased dataset.
2. **Encoding Categorical Variables:** Machine learning algorithms require numerical input. Therefore, all categorical variables (e.g., Gender, Occupation, Primary Reason for Use) were converted into a numerical format using one-hot encoding. This method creates new binary columns for each category within a variable, preventing the model from assuming an ordinal relationship between categories (e.g., that "Student" is mathematically greater than "Employed").
3. **Outlier Detection and Treatment:** To mitigate the influence of extreme or potentially erroneous data points, a two-pronged approach to outlier detection was used. The Interquartile Range (IQR) method was first applied to identify statistical outliers. Concurrently, Z-scores were calculated to identify points deviating significantly from the mean. Identified outliers were not removed, but rather capped (winsorized) at the 1st and 99th percentiles to retain their information while reducing their skewing effect on the model.
4. **Feature Scaling:** The K-Means clustering algorithm is distance-based, meaning it is highly sensitive to the scale of features. To ensure that all variables contributed equally to the clustering process, numerical features were standardized using the 'StandardScaler'. This process transforms each feature to have a mean of 0 and a standard deviation of 1, placing all features on a common scale. The final preprocessed dataset comprised 22 features for each of the 551 participants.

3.3. Clustering Model Development and Evaluation

The core of this study was the application of an unsupervised clustering algorithm to segment the participants.

- **Algorithm Selection:** K-Means clustering was chosen for its efficiency, scalability, and interpretability, making it well-suited for identifying distinct, non-overlapping groups in a dataset of this nature. The algorithm iteratively assigns data points to one of K clusters by minimizing the within-cluster sum of squares (WCSS), also known as inertia.
- **Determining the Optimal Number of Clusters (K):** Selecting the appropriate number of clusters is the most critical hyperparameter for K-Means. A data-driven approach was used, combining two standard techniques. First, the **Elbow Method** was used, where WCSS was plotted for a range of K values (from 2 to 9). The "elbow" point, where the marginal decrease in WCSS begins to level off, suggests a suitable K. As seen in Figure 2, an elbow is visible around $K=5$ or $K=6$. Second, the **Silhouette Score Method** was employed to provide a more quantitative measure. The Silhouette Score evaluates how well-defined the clusters are, considering both intra-cluster cohesion and inter-cluster separation. A score closer to 1 indicates dense, well-separated clusters. The plot of Silhouette Scores (Figure 2) showed a distinct peak at $K=6$.

Based on the convergence of these two methods, $K=6$ was selected as the optimal number of clusters. The final K-Means model was trained with 'n_init=10' (to run the algorithm 10 times with different centroid seeds and select the best outcome) and a fixed 'random_state=42' to ensure the results are reproducible.

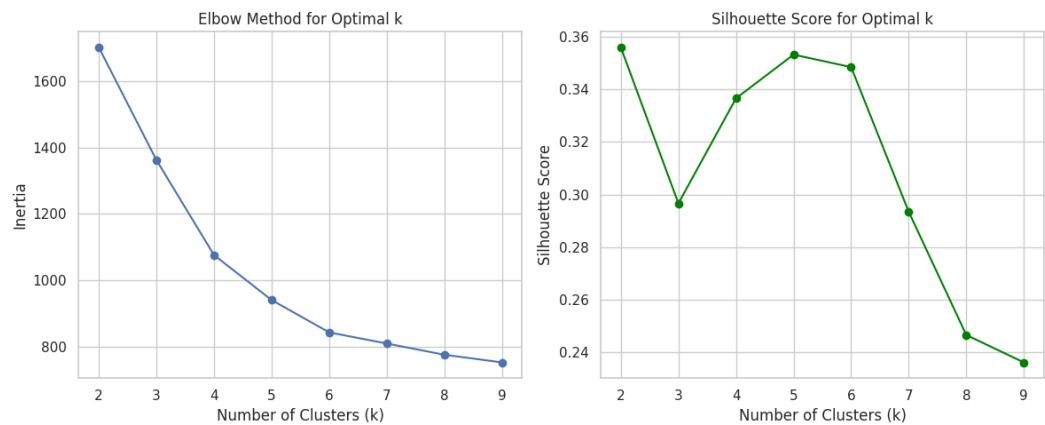


Figure 2. Elbow Method and Silhouette Score for Optimal K. The Elbow Method shows diminishing returns after K=5, while the Silhouette Score peaks at K=6, justifying the selection of six clusters.

3.4. Cluster Visualization and Interpretation

To interpret the high-dimensional results, Principal Component Analysis (PCA) was employed as a dimensionality reduction technique. PCA transforms the original 22 correlated features into a smaller set of uncorrelated principal components. By projecting the data onto the first two principal components, which capture the maximum variance, the six clusters could be visualized in a 2D scatter plot, providing an intuitive view of their separation and overlap.

4. Results

The application of K-Means clustering with K=6 successfully segmented the 551 participants into distinct groups, each exhibiting unique patterns of demographics, social media behavior, and mental health. The resulting model achieved a Silhouette Score of 0.32, indicating a reasonable and meaningful partition of the data, albeit with some overlap characteristic of complex human behavior. This section presents the empirical profiles of these six clusters.

The defining characteristics of each cluster were identified by analyzing their centroids (mean values for each feature). A comprehensive summary is provided in Table 1. The visual aids in Figure 3 (Social Media Hours Distribution), Figure 4 (PCA Visualization), and Figure 5 (Heatmap of Cluster Centers) offer further insight into the composition and differentiation of these user segments.

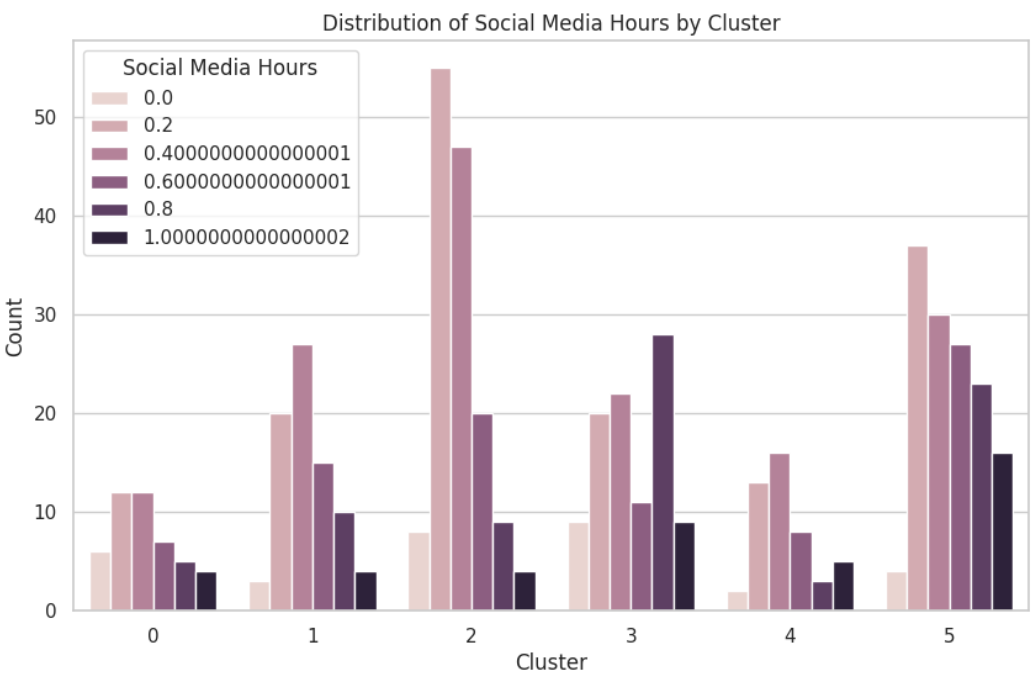


Figure 3. Distribution of Social Media Hours Categories within Each Cluster.

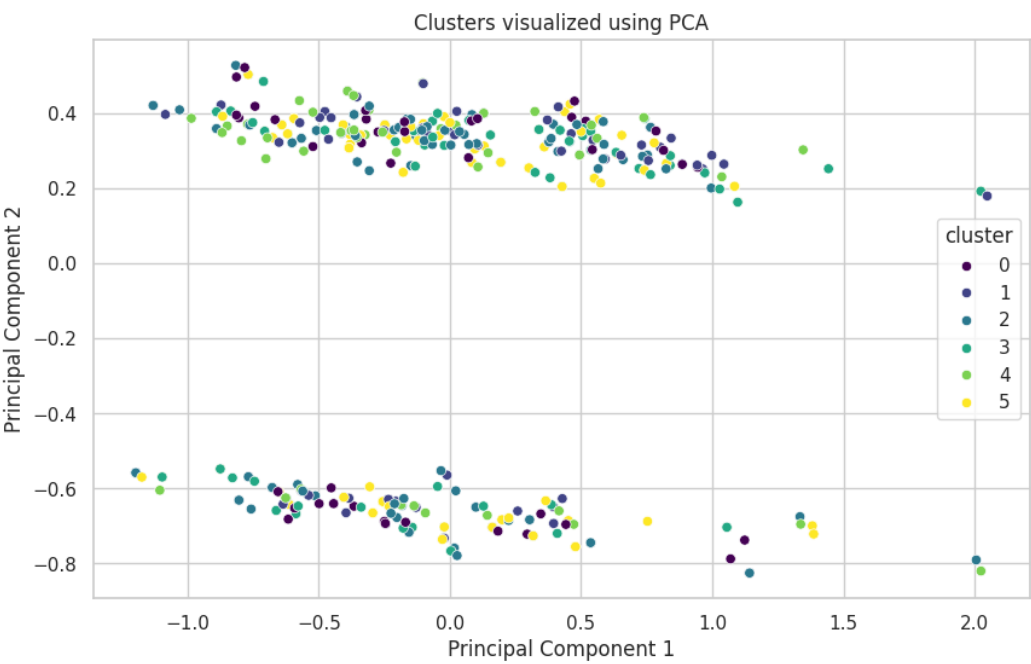


Figure 4. PCA Visualization of Clusters in 2D Space. The plot shows the separation of the six clusters along the first two principal components.

Table 1. Summary of Identified Cluster Profiles

Cluster ID	Dominant Demographics (Age, Gender, Occupation)	Social Media Usage (Hours, Reason, Breaks %)	Key Mental Health Indicators (Mean Scaled: Anxiety, Unhappy, Sleep Less)	Tentative Profile Name
0	Older (mean scaled age ≈ 0.41), Predominantly Female, Employed	Moderate hours (mean ≈ 0.42), Mixed reasons (Both personal/prof.), Approx. 61% take breaks	Moderate anxiety (0.33), unhappy (0.33), sleep less (0.34)	Employed Female Moderators
1	Younger (mean scaled age ≈ 0.16), Predominantly Female, Students	Moderate hours (mean ≈ 0.45), Primarily Students, High use of Both/Personal reasons, Approx. 77% take breaks	Highest anxiety (0.39) , unhappy (0.34), sleep less (0.34)	Anxious Student Users
2	Younger (mean scaled age ≈ 0.16), Predominantly Male, Students	Lower hours (mean ≈ 0.37), Primarily Students using for Both/Personal reasons, Approx. 66% take breaks	Lowest anxiety (0.24) , unhappy (0.34), sleep less (0.33)	Balanced Male Students
3	Younger (mean scaled age ≈ 0.15), Predominantly Female, Students	Higher hours (mean ≈ 0.51), Primarily Students using for Personal reasons, Approx. 70% take breaks	Moderate-High anxiety (0.31), unhappy (0.33), sleep less (0.33)	Engaged Female Students
4	Older (mean scaled age ≈ 0.43), Predominantly Male, Employed	Moderate hours (mean ≈ 0.45), Mixed reasons, Lowest break-taking (Approx. 21%)	Moderate anxiety (0.27), lowest unhappy (0.29) , lowest sleep less (0.30)	Low-Break Working Males
5	Younger (mean scaled age ≈ 0.16), Predominantly Male, Students	Higher hours (mean ≈ 0.51), Primarily Students using for Personal reasons, Approx. 68% take breaks	Moderate-High anxiety (0.30), unhappy (0.34), sleep less (0.36)	High-Use Male Students

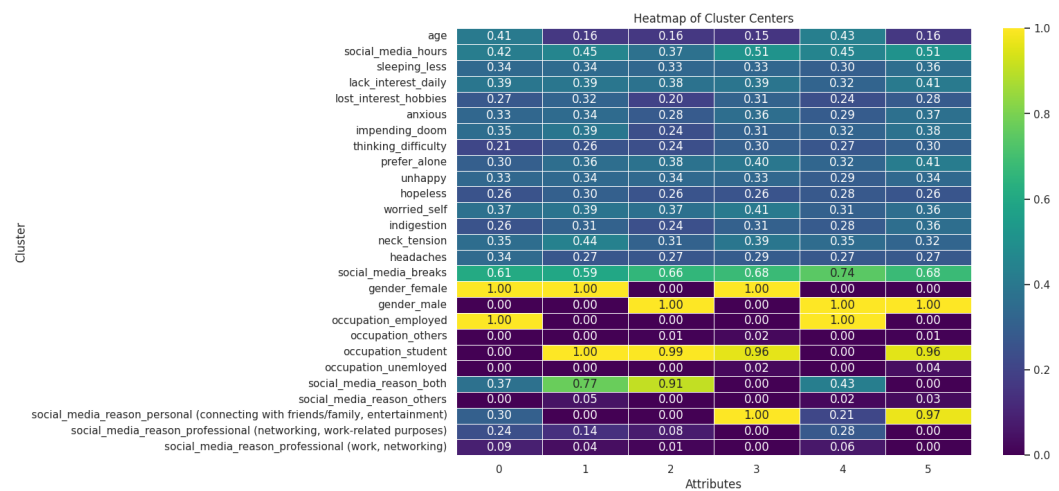


Figure 5. Heatmap of Cluster Centers. Each cell represents the mean scaled value (0-1) of a feature (row) for a given cluster (column 0-5). Brighter colors indicate higher mean values. This visually profiles the defining characteristics of each user segment.

Cluster 0 (Employed Female Moderators): This cluster is primarily composed of older, employed females. Their social media usage is moderate and for mixed personal/professional reasons. A significant majority (61%) report taking breaks, and their mental health indicators for anxiety, unhappiness, and sleep issues are moderate relative to the other clusters.

Cluster 1 (Anxious Student Users): This is a younger, predominantly female student group. Despite having only moderate usage hours and the highest rate of taking breaks (77%), this cluster reports the highest mean anxiety levels. This profile is particularly notable as it challenges the simple assumption that taking breaks is a universal solution for mitigating negative mental health effects.

Cluster 2 (Balanced Male Students): Consisting of younger, predominantly male students, this group is distinguished by the lowest average social media usage hours among the student clusters. They maintain a healthy habit of taking breaks (66%) and, most significantly, report the lowest mean anxiety levels of all six clusters, suggesting a balanced and potentially healthier relationship with social media.

Cluster 3 (Engaged Female Students): Similar to Cluster 1, this group consists of younger female students, but with a key difference: their social media usage is significantly higher and primarily for personal reasons. While a high proportion (70%) take breaks, their anxiety levels are moderate-to-high, sitting between the balanced students of Cluster 2 and the highly anxious students of Cluster 1.

Cluster 4 (Low-Break Working Males): This highly distinct cluster is composed of older, employed males. Their usage hours are moderate, but their standout feature is the extremely low frequency of taking breaks (only 21%). Counterintuitively, this group reports the lowest levels of unhappiness and sleep-related issues, suggesting that for this demographic, other factors like life stability, resilience, or the nature of their online activity may play a more dominant protective role.

Cluster 5 (High-Use Male Students): This cluster represents the male counterpart to Cluster 3, comprising younger male students with high, personally-motivated social media usage. They also report taking breaks frequently (68%). Their mental health profile aligns with their high engagement, showing moderate-to-high levels of anxiety and the highest reported levels of sleep disturbance among all clusters.

5. Discussion

The segmentation of users into six distinct profiles moves beyond simplistic correlations and provides a nuanced understanding of the heterogeneous relationship between social media use and mental health. This section interprets the key findings, connects them to the existing literature, and discusses their broader implications.

5.1. *The Nuanced Role of Demographics: Age and Gender*

Our findings strongly indicate that the impact of social media is not uniform across different demographic groups. The most striking contrast is between the younger, student-dominated clusters (1, 2, 3, 5) and the older, employed clusters (0, 4). The student clusters, regardless of gender, generally reported higher levels of mental distress, aligning with extensive literature that identifies adolescents and young adults as a particularly vulnerable population [12,17]. This vulnerability may stem from heightened sensitivity to social comparison, peer pressure, and FOMO during critical developmental stages [20].

Furthermore, gender-specific patterns emerged. Female student clusters (1 and 3) tended to report higher anxiety levels than their male counterparts (2 and 5), even with comparable usage hours. This resonates with the WHO's finding of a higher prevalence of problematic social media use among girls [13]. Conversely, the older male cluster (4) displayed a unique profile of resilience, reporting low distress despite high engagement and infrequent breaks. This could suggest that life experience, established offline identities, or using social media for different purposes (e.g., professional networking vs. social validation) may act as protective factors, a domain that warrants further investigation.

5.2. *High Usage, Youth, and Psychological Distress*

The correlation between high usage and negative mental health outcomes was most pronounced in the younger clusters. Specifically, Cluster 5 (High-Use Male Students) and Cluster 3 (Engaged Female Students) both exhibited elevated anxiety and sleep issues. This supports the general consensus from large-scale studies that link excessive screen time to psychological distress [13,14]. The overall finding that 43% of our total sample reported anxiety "Sometimes/Mostly" and 41% experienced "Sleeping Less" is likely driven by these high-engagement profiles. Our clustering approach, however, adds a crucial layer of detail: it is not merely the quantity of use but the combination of high usage with the demographic context of being a young student that appears to create the highest risk profile.

5.3. *The Paradox of Taking Breaks*

One of the most compelling findings is the paradoxical role of taking breaks. The common-sense and often-recommended intervention of "taking a break" is shown to be not universally effective. Cluster 1 (Anxious Student Users) had the highest rate of taking breaks (77%) yet also the highest anxiety. This suggests two possibilities: either these users are taking breaks *because* they already feel anxious (a reactive rather than proactive measure), or the nature of their breaks is ineffective. A "break" that involves switching from Instagram to TikTok may not provide a true cognitive or emotional respite. In contrast, Cluster 2 (Balanced Male Students) combined lower usage with frequent breaks and achieved the best mental health outcomes, suggesting that breaks are most effective as part of a broader strategy of moderated use, not as a standalone cure for high engagement. The unique case of Cluster 4 (Low-Break Working Males) further complicates the narrative, implying that for certain individuals, the perceived need for breaks may be lower if their online engagement is not a source of stress. This finding challenges one-size-fits-all digital wellness advice and highlights the need for personalized recommendations.

6. Recommendations

Based on the distinct user profiles identified in this study, we propose a set of targeted recommendations for various stakeholders aimed at fostering healthier digital habits and mitigating the mental health risks associated with social media use.

6.1. For Social Media Users

- **Cultivate Self-Awareness:** Users, particularly those in younger demographics, should be encouraged to reflect on their own usage patterns and emotional responses. Identifying whether one fits a profile like the 'Anxious Student User' (Cluster 1) or a 'High-Use Student' (Clusters 3 and 5) is the first step toward making conscious changes.
- **Practice Intentional Use:** Instead of mindless scrolling, users should engage with social media with a specific purpose in mind (e.g., connecting with a specific friend, looking up an event). This can help reduce overall screen time and passive consumption, which are often linked to negative outcomes.
- **Re-evaluate the "Break":** For individuals in high-anxiety groups, it is crucial to reconsider what constitutes a restorative break. A break should ideally involve a non-digital activity that is genuinely relaxing or engaging, such as walking, reading a book, or practicing mindfulness, rather than simply switching between digital platforms.

6.2. For Platform Designers and Policymakers

- **Design for Well-being, Not Just Engagement:** Platforms should move beyond metrics that solely prioritize time-on-site. Features that promote well-being could include built-in "mindful break" reminders that suggest offline activities, tools to easily hide like counts to reduce social comparison, and algorithms that de-prioritize emotionally charged or polarizing content.
- **Provide Granular User Controls:** Instead of a simple "take a break" notification, platforms could offer users insights into their own usage patterns, similar to our cluster profiles. A dashboard could highlight if a user's behavior is shifting towards a high-risk pattern and offer tailored suggestions based on that profile.
- **Support Research and Data Transparency:** Policymakers should encourage or mandate that social media companies provide privacy-preserving access to anonymized data for independent research. This would allow for more robust, objective, and longitudinal studies to be conducted, moving beyond the limitations of self-reported data.

6.3. For Educators and Mental Health Professionals

- **Integrate Digital Literacy into Curricula:** Educational institutions should incorporate digital literacy programs that teach students not just about online safety, but also about the psychological impact of social media. The concept of different user "types" or profiles can be a powerful and relatable teaching tool.
- **Promote Positive Role Models:** Highlighting the habits of "Balanced" users (like Cluster 2) can provide a positive, achievable model for students, demonstrating that it is possible to engage with social media in a healthy and moderated way.
- **Personalize Clinical Advice:** Mental health professionals can use the findings from this type of research to offer more personalized advice. Instead of generic recommendations, they can ask more specific questions to understand a client's usage profile and tailor interventions accordingly, such as exploring the quality of breaks for an anxious user or time-management strategies for a high-usage one.

7. Conclusion

This study successfully leveraged unsupervised machine learning to move beyond aggregated statistics and offer a nuanced understanding of the interplay between social media usage and mental well-being. While the findings are insightful, they should be interpreted in light of certain limitations, including the reliance on a cross-sectional, self-reported dataset from a predominantly young-adult sample. These factors limit the generalizability of the results and prevent causal inference.

Despite these constraints, our primary achievement lies in the data-driven segmentation of users into six distinct profiles, each with unique behavioral and psychological footprints. The identification of non-obvious segments—such as ‘Anxious Student Users’ who report high anxiety despite frequent breaks, or the resilient ‘Low-Break Working Males’—highlights that the psychological impact of social media is not monolithic. It varies significantly across these groups, with factors like age, gender, usage intensity, and break-taking patterns playing differential roles. This research underscores the potential of machine learning to pinpoint vulnerable populations with greater precision. The distinct profiles provide a critical foundation for developing the targeted and personalized digital wellness strategies outlined in our recommendations, paving the way for more effective interventions designed to mitigate the psychological risks of social media in our increasingly connected world.

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