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Social Media Use and Depression and Anxiety Symptoms: A Cluster Analysis

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Abstract

Objectives—Individuals use social media with varying quantity, emotional, and behavioral attachment that may have differential associations with mental health outcomes. In this study, we sought to identify distinct patterns of social media use (SMU) and to assess associations between those patterns and depression and anxiety symptoms.

Methods—In October 2014, a nationally-representative sample of 1730 US adults ages 19 to 32 completed an online survey. Cluster analysis was used to identify patterns of SMU. Depression and anxiety were measured using respective 4-item Patient-Reported Outcome Measurement Information System (PROMIS) scales. Multivariable logistic regression models were used to assess associations between cluster membership and depression and anxiety.

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Human Subjects Statement
The University of Pittsburgh Institutional Review Board (IRB # PRO12010572) reviewed and approved this study.

Conflict of Interest Statement
The authors have no conflicts of interest to declare.

Results—Cluster analysis yielded a 5-cluster solution. Participants were characterized as "Wired," "Connected," "Diffuse Dabblers," "Concentrated Dabblers," and "Unplugged." Membership in 2 clusters – "Wired" and "Connected" – increased the odds of elevated depression and anxiety symptoms (AOR = 2.7, 95% CI = 1.5–4.7; AOR = 3.7, 95% CI = 2.1–6.5, respectively, and AOR = 2.0, 95% CI = 1.3–3.2; AOR = 2.0, 95% CI = 1.3–3.1, respectively).

Conclusions—SMU pattern characterization of a large population suggests 2 patterns are associated with risk for depression and anxiety. Developing educational interventions that address use patterns rather than single aspects of SMU (eg, quantity) would likely be useful.

Keywords

cluster analysis; social media; depression; anxiety; PROMIS

Each year, approximately 7% and 18% of adults in the United States (US) are affected by depression and anxiety, respectively.[1] Individuals with anxiety disorders are approximately 4 times more likely to visit a doctor or be hospitalized for a psychiatric disorder compared to those without this condition. Whereas anxiety disorders are the most common manifestations of mental illness in the US, depression carries the heaviest burden of disability among mental and behavioral disorders.[1,2] It has been estimated that in the US alone, the economic burden of depression is $210 billion, the majority of costs of which are attributable to reduced workplace productivity, suicide, and comorbidities.[3] Rates for both depression and anxiety are disproportionally high among women, individuals of low socio-economic status, and emerging adults.[4–6] For young adults in particular, depression and anxiety are associated with increased risk of substance abuse, poor academic performance, and suicide.[7–10]

Social media have been defined as computer-mediated technology that allows one to create and share information and other forms of expression though virtual communities (eg, Facebook, Twitter, and Instagram).[11,12] Volume of social media use (SMU), encompassing metrics of quantity, has been associated with increased risk for both depression and anxiety among young adults. Numerous studies found that greater daily time spent on social media, increased frequency of SMU, and multiple platform use were associated with both depression and anxiety.[13–17] Research suggests that increased social media consumption may lead to negative online experiences, fewer in-person social interactions, and decreased ability to sustain attention.[18,19]

Other research has demonstrated that the association between SMU and depression and anxiety may be more indicative of personal experience than volume of SMU. In other words, how one feels about or experiences social media may be a more salient indicator of the effect of social media on an individual than simply the quantity of consumption or exposure to social media. For example, several studies found that users may develop addictive or problematic levels of SMU, which have been associated with increased anxiety and depression.[20–22] These associations may be attributable to the increased likelihood of individuals who experience depression and anxiety also developing addictive behaviors.[23,24] Alternatively, negative consequences of problematic SMU, such as neglecting one's "real-life" responsibilities and relationships, may lead to depression and anxiety. Similarly, individuals who feel more emotionally connected to social media may be more susceptible to negative social interactions and feedback, and subsequently, at higher risk for depression.[25]

However, there is conflicting research on the association between SMU and depression and anxiety. For example, several studies have found no association between increased daily time spent on Facebook and depression.[26,27] There is also evidence that being emotionally connected to SMU is not associated with depression and anxiety and in some cases, may provide social capital, and increased life satisfaction, which may be protective against depression and anxiety sympomology.[14,27–29] These mixed findings contribute to the difficulty understanding the relationship between SMU and negative mental health outcomes such as depression and anxiety.

The nature of the association between individual SMU characteristics and depression and anxiety may be tenuous because SMU is multifaceted, not characterized simply by a measure of quantity, for example. It may be more reflective of actual use to examine how SMU characteristics co-occur. Prior research has utilized clustering techniques to identify distinct groups and patterns of media use.[30–32] However, to our knowledge, this is the first study to explore distinct patterns of SMU characteristics, both volume and personal experience, and how they are associated with depression and anxiety symptomology. Additionally, most research on SMU and depression and anxiety has been platform-specific or conducted using college students.[14,26,33–36] Although this vein of research has value for elucidating the effect of a particular platform such as Facebook for this particular population, it does not account for the rapidly changing popularity of platforms, a broader population of young adults, and their use of multiple platforms.[37] Therefore, the purposes of this study were to: (1) classify distinct SMU patterns in a nationally-representative sample of US young adults using cluster analysis; and (2) assess the differential associations between these distinct patterns of SMU and elevated depression and anxiety symptomology. Social network and social support theories would suggest that individuals who are most engaged with social media have more positive outcomes.[38–40] However, given the mixed results in the literature concerning SMU and depression and anxiety outlined above, and because cluster analysis is an exploratory, hypothesis-generating technique, we had no specific *a priori* hypotheses.

METHODS

Participants and Procedures

This study was conducted using an online survey of a nationally-representative sample of US adults ages 19 to 32. Participants were recruited from a probability-based online non-volunteer access panel maintained by Growth from Knowledge (GfK). This panel, populated through both address-based sampling and random digit dialing, covers approximately 97% of US households and consists of approximately 55,000 members.[41] GfK provides Internet access and a computer to those households without prior access to maintain representation of the off-line population. To achieve a nationally-representative panel and subsequent study sample, GfK utilizes a comprehensive weighting protocol. First, a statistical weighting adjustment is calculated and applied to the base weight to offset any known selection deviations from a pure equal probability sample design that may have resulted from any recruitment efforts incorporated to improve efficiency. Second, to reduce the effects of any potential sources of survey error such as non-coverage, non-response, and attrition in the overall panel prior to drawing the study sample, GfK applies a panel post-stratification adjustment on demographic distributions from the most recent Current Population Survey (CPS) data. Finally, after the sample has been drawn and study data collected, another post-stratification weight is computed to adjust for potential sources of error such as non-response, non-coverage, or under- and over-sampling resulting from the study-specific sample design. Both sets of post stratification weights account for household Internet access and are benchmarked using the most recent special CPS survey measuring Internet access.[41]

In October 2014, as the second wave of a longitudinal study of young adult tobacco-related health behaviors and perceptions, GfK sent a survey including items on mental health and social media use (SMU), to 3048 panel members who had completed a baseline survey 18 months earlier. is current study was based upon secondary, exploratory analyses and utilized data only from the follow-up wave, as the baseline survey did not include the study variables. To assure good data quality, GfK employed several strategies such as screening for a high proportion of skipped responses or other patterns suggesting poor effort. Participants were given no time limit for completing the survey. Although the entire survey contained approximately 140 items, most participants were presented with fewer items due to skip patterns. Median time for completion was 15 minutes, and individuals received a $15 cash-equivalent incentive for participation.

Measures

We used 5 variables (time, frequency, multiple platform use, problematic social media use, and social media intensity) to identify distinct patterns of SMU. Because a primary goal of cluster analysis is to identify a meaningful and interpretable solution,[42] we categorized each clustering variable for analysis into *low* and *high* categories, which helped achieve this goal. Criteria for categories included their being: (1) conceptually reasonable estimates; (2) supported by literature suggesting their relevance; and (3) based upon the distribution of the data to compare below- and above-average endorsement.

Social Media Use (Clustering Variables)

Time—Participants were asked to report (in hours and minutes), approximately how much time per day they spent on social media for personal, non-work-related use. Responses ranged from 0 to 1440 minutes. Responses were divided into low or high groups based upon findings that spending more than 60 minutes per day on social media was associated with decreased life satisfaction.[43] The low category contained individuals who reported spending 60 minutes or less per day on social media (49.9%), whereas the high category contained individuals who spent greater than 60 minutes per day on social media (50.1%).

Frequency—Participants were asked to indicate how often they visited each of the 11 most popular social media platforms at the time of the survey (Facebook, Twitter, Google+, YouTube, LinkedIn, Instagram, Pinterest, Tumblr, Vine, Snapchat, and Reddit). Response categories were based on the Pew Research Center's SMU assessment and included the following response options: "*I don't use this platform*," "*less than once a week*," "*1–2 days a week*," "*3–6 days a week*," "*about once a day*," "*2–4 times a day*," and "*5 or more times a day*." Responses were converted into conservative estimates of average weekly site checks ranging from 0 to 35. For example, "*less than once a week*" was recoded as 0 site checks per week, "*1–2 days a week*" was recoded as 1.5 site checks per week, "*2–4 times a day*" was recoded as 21 site checks per week, and "*5 or more times a day*" was recoded as 35 site checks per week. To calculate participants' weekly site checks across platforms, a composite score was created by totaling responses for all 11 platforms. The resultant frequency scale ranged from 0 to 385 (maximum weekly value of 35 × 11 platforms) and responses were divided into either low or high frequency. The low category contained individuals who reported visiting social media sites fewer than 30 times per week (49.5%), whereas the high category contained individuals who visited these sites 30 or more times per week (50.5%). Because there is no established cut-point in the literature associated with this measure, we based categories on conceptually reasonable cut-points and distribution.

Multiple platform use—Using the frequency items detailed above, responses of "*I don't use this platform"* were assigned 0 and all other responses were assigned 1 for each social media platform. Responses were totaled across all 11 platforms to produce a summary score ranging from 0 to 11. Individuals' multiple platform usage were categorized as low if they reported using 3 platforms or less (44.0%), and high if they reported using 4 or more (56.0%). is cut-point represents a conservative estimate of the number of platforms *actively* used by the average Internet user and reflected by our dataset.[44] is variable was derived from the same set of items used to calculate frequency and the 2 variables were positively correlated (r = .54). However, this association suggests that, although related, some individuals frequently check their social media but only use 1 or 2 platforms. Conversely, individuals may use many different platforms but check them infrequently.

Problematic social media use—Problematic social media use (PSMU) was measured with 6 items adapted from the Bergen Facebook Addiction Scale (BFAS). [45] Whereas original items specified "Face-book," this study modified the original items to encompass more general SMU, similar to prior work.[46] Rooted in addiction theory, each item represented 1 of 6 core elements of addiction (salience, mood modification, tolerance, withdrawal, conflict, and relapse) and asked participants to rate their agreement on a 5-point Likert-type response scale (*very rarely, rarely, sometimes, often, or very often*) based upon past year use.[45] We performed factor analysis using principal component analysis (PCA), a viable method of factor extraction to identify and compute a composite score, rather than perform a theoretical analysis.[47–49] Visual inspection of a scree plot and the PCA revealed a one-factor solution with an initial eigenvalue of 3.88, and explaining 65% of the variance. All items were retained, with factor loadings ranging from 0.76 to 0.84. Internal consistency reliability in the present sample, calculated using Cronbach's alpha, was .89. The resulting composite scale ranged from 0 to 24. Individuals with scores of 0–11 were categorized as low (86%) and individuals with scores of 12 or more were categorized as high (14%). These categories represent a monothetic scoring approach (cutoff score ≥ 2 on all 6 items) suggested by the developers of the BFAS and used in prior research.[45,50] We chose this more conservative cut-point because although the PSMU scale is an indicator of problematic or addictive use, it is not considered a diagnostic tool or PSMU a formal diagnosis.[51]

Social media intensity—Social media intensity (SMI) was measured using 6 items adapted from the Facebook Intensity Scale (FIS).[38] is scale was developed to measure one's emotional connection to Facebook and its integration into one's daily activities. Whereas original items specified "Facebook," this study modified the scale to encompass more general SMU, like prior work adapting the FIS to address broader SMU.[52,53] Additionally, this study did not include 2 Facebook-specific items assessing number of friends or time spent on Facebook, nor did it specify a time frame. Visual inspection of a scree plot and the PCA revealed a single-factor solution (eigenvalue = 4.3) explaining 72% of the shared variance. All items were retained with factor loadings ranged from 0.80 to 0.90. Internal consistency in the present sample, measured using Cronbach's alpha, was 0.92. Items were averaged, and the resulting composite scale ranged from 1 to 5. Individuals were categorized as low if they received a score of 3 or below (53.0%) and high for scores greater than 3 (47.0%). Because there is no established cut-point associated with this measure, we based categories on conceptually reasonable cut-points and distribution.

Depression and anxiety symptoms (dependent variables)—Depression and anxiety were measured using the Patient-Reported Outcomes Measurement Information System (PROMIS) 4-item short forms. The PROMIS depression scale has been correlated with several well-established depression instruments, such as the Center for Epidemiological Studies Depression scale (CESD) and the Patient Health Questionnaire (PHQ-9), providing a source of validity evidence for the measure.[54,55] The 4-item scale asks participants how frequently over the past 7 days they felt hopeless, worthless, helpless, or depressed.[56] Items were scored using a 5-point Likert-type scale with corresponding responses of *Never* (1), *Rarely* (2), *Sometimes* (3), *Often* (4), and *Always* (5). The internal consistency reliability of items in the present sample, calculated using Cronbach's alpha, was 0.93. A composite scale was calculated, with raw scores ranging from 4 to 20, and greater scores indicating increased severity of symptoms.[57]

The PROMIS anxiety scale has been correlated with several other commonly used anxiety instruments, such as the Generalized Anxiety Disorder 7-item Scale (GAD-7), the Mood and Anxiety Symptom Questionnaire (MASQ), and the Positive and Negative Affect Schedule (PANAS), providing a source of validity evidence for the measure.[58] The 4-item PROMIS anxiety scale asks participants how frequently over the past 7 days they experienced the following: "I felt fearful," "I felt it was hard to focus on anything other than my anxiety," "My worries over-whelmed me," and "I felt uneasy."[56] Response choices were identical to those for the depression scale noted above. The internal consistency reliability of scale items in the present sample, calculated using Cronbach's alpha, was 0.90. A composite scale was calculated, with raw scores ranging from 4 to 20, and greater scores indicating increased severity of symptoms.[59]

Visual inspection of the depression and anxiety symptoms scales suggested deviations from univariate normality, with the distribution of scores for both scales skewed right and a preponderance of individuals endorsing no symptoms. The skewness and kurtosis test for normality[60,61] revealed that for both depression and anxiety symptoms, there was a significant departure from normality (skewness = 1.11, kurtosis = 3.42, $p < .001$ and skewness = 1.05, kurtosis = 3.42, $p < .001$, respectively). Kernel density and Q-Q plots of the standardized residuals in addition to the Shapiro-Wilk test also indicated a departure from multivariate normality for models using depression and anxiety symptoms as the dependent variable ($p < .001$, respectively). Attempts to transform the scales using the Box-Cox technique, however, were unsuccessful, rendering use of these scales as continuous variables unfavorable. Therefore, we categorized scales based upon recommended guidelines for interpreting PROM-IS scores.[62] The depressive symptoms and anxiety symptoms scales were collapsed into 3 categories, *None, Mild,* and *Moderate to Severe*, classifying 41%, 41%, and 18%, and 33%, 48%, and 19% of our sample, respectively. These categories serve to classify severity of symptoms associated with depression or anxiety, not as diagnostic criteria.

Socio-demographic characteristics (covariates)—GfK provided information on participants including age, sex, race/ethnicity, education, and household income. Relationship status (Single/Engaged or in a committed dating relationship/Married or with a domestic partner/Separated, divorced, or widowed) and living situation (Parent or guardian/ Significant other/Friends or acquaintances/By myself) were obtained via self-report from participants. We planned *a priori* to control for these variables, in multivariable models, due to their association with depression and/or anxiety.[63,64] We collapsed categories with responses of less than 5% for model stability.

Data Analysis

We examined patterns of missing data, and included only individuals with complete data on all 5 clustering variables in the final sample. Additionally, we omitted individuals who reported no endorsement of any of the 5 clustering variables, as the purpose of this study was to characterize patterns of use, not to differentiate between users and non-users. Best practices for cluster analysis recommend assessing clustering variables for collinearity and suggest correlations above .90 are problematic.[42] Therefore, we examined the 5 clustering variables for multi-collinearity by computing the bivariate correlation matrix and calculating the variance inflation factor (VIF) with the variables in their original scales. Next, we performed cluster analysis using the 2-step cluster algorithm and log-likelihood distance measure.[42,65,66] The minimum number of solutions was set at 3 and maximum number at 15 to avoid overly trivial or complex solutions. The algorithm provides a table of fit indices using either the Akaike's Information Criterion (AIC) or Schwarz's Bayesian Criterion (BIC). The optimal number of clusters is indicated by the largest ratio of distance measures provided by the AIC and BIC.[65] The most viable solution was chosen based on these measures of model fit as well as a conceptually sound interpretation.

The stability of the chosen solution was assessed using several recommended techniques.[67] First, the cluster analysis was repeated using the hierarchical method, examining the agglomeration schedule coefficients for substantial changes between coefficients. Additionally, the final solution was cross-validated by repeating the same analysis 10 times using a random sample of 50% of individuals. We then compared the cluster membership between each subsample and the whole sample. We assessed face validity of the resulting solution by examining the overall distribution and individual composition of clusters. Having found a satisfactory solution, the cluster-solution was interpreted, labeling each cluster accordingly (Table 1).[42]

We used Stata statistical software version 14.1[68] to perform descriptive statistics and examine associations of cluster group membership with socio-demographic variables and depression and anxiety symptoms. We used chi-square tests and ANOVA to assess bivariable associations between socio-demographic covariates and cluster membership. After examining the distributions of our dependent variables and testing the assumptions of linear regression, we considered alternative regression models to fit our data better. After confirming that each model met the proportional odds assumption, that the relationship between each pair of groups in the dependent variable is the same,[69] we used ordered logistic regression to assess bivariable and multivariable associations between cluster membership and depression and anxiety, including all socio-demographic covariates in multivariable models. These analyses also helped evaluate the criterion-related validity of the cluster solution.[42] Design-specific survey weights, which were provided from GfK, and adjusted for any under- or over-sampling, non-response, or non-coverage, were incorporated into these bivariable and multivariable analyses.[70] Two-tailed p values $< .05$ were considered statistically significant.

RESULTS

Participants

Of the 1796 individuals who completed the survey, the final sample consisted of 1730 (96.3%) individuals with complete data on the 5 clustering variables and endorsement of some level of SMU. There were no statistically significant differences between individuals with and without complete data in terms of socio-demographic characteristics and depressive and anxiety symptoms (p values ranging from .08 to .98). Because there was no evident pattern of missing data, and it was a relatively small proportion of individuals (N = 33, 1.8%), we used casewise deletion.[47] Additionally, we omitted from analyses 33 (1.8%) individuals who endorsed no SMU on any of the 5 clustering variables. There was no evidence of multicollinearity among the clustering variables, with pairwise correlations ranging from .19 to .54 and a mean variance inflation factor of 1.5. Sample socio-demographic characteristics are presented in Table 2.

Description of Clusters

The AIC and BIC indices were nearly identical, and both indicated the best fit was achieved with a 5-cluster solution. is solution was confirmed using the hierarchical clustering method. Cross-validation using 10 random subsamples provided good evidence of cluster stability. On average, 75% of individuals classified into the same cluster compared with the complete sample. The distribution of the 5-cluster solution was both substantial and parsimonious, with the largest cluster containing 32% of individuals and the smallest containing 14%. Each cluster had at least one SMU characteristic for which either 0% or 100% of the group had high levels, suggesting good face validity. The 5-cluster solution was comprehensible and interpretable in terms of SMU characteristics.

Based upon the SMU composition, clusters 1 through 5 were assigned the following monikers: Unplugged; Concentrated Dabblers; Diffuse Dabblers; Connected; and Wired. Cluster membership was classified by percent of individuals endorsing high levels of each SMU characteristic. Cluster 1, Unplugged, reported no high levels of any of the 5 clustering variables. Cluster 2, Concentrated Dabblers, reported no high multiple platform use or PSMU, but the majority reported high time, frequency, and SMI. Cluster 3, Diffuse Dabblers, all reported high multiple platform use and none reported high PSMU, although some (but not the majority) reported high time, frequency, and SMI. Cluster 4, Connected, all reported high time, frequency, multiple platform use, and SMI, but none reported high PSMU. Cluster 5, Wired, all reported high PSMU and the majority reported high time, frequency, multiple platform use, and SMI (Table 1).

Bivariable Associations of Cluster Membership and Socio-demographic Characteristics

Age, sex, education, and household income were significantly associated with cluster membership ($p < .001$, $p = .02$, $p < .001$, and $p < .001$, respectively) (Table 2). In terms of these 3 “cluster” characteristics, the Connected cluster was the youngest cluster (mean age of 23.8 years) and had the greatest proportion of women (60%). The Diffuse Dabbler cluster was the most educated (36% reported having at least a Bachelor’s degree) and economically advantaged cluster (48% reported a household income of $75,000 or above). Table 2 presents additional socio-demographic composition for all clusters.

Bivariable and Multivariable Associations of Cluster Membership with Depression and Anxiety Symptoms

The Unplugged cluster served as the reference group in regression models due to the uniformly low endorsement across all 5 SMU characteristics, such that we were able to assess any change in risk of elevated depression and/or anxiety symptomology relative to Unplugged membership. In bivariable models, not including socio-demographic covariates, membership in 2 clusters—Wired and Connected—was associated with significantly increased odds of elevated depression symptoms (OR = 3.1, 95% CI = 1.8–5.6, and OR = 1.9, 95% CI = 1.2–2.9, respectively); moreover, membership in 3 clusters—Wired, Connected, and Diffuse Dabblers—was significantly associated with increased odds of elevated anxiety symptoms (OR = 4.5, 95% CI = 2.5–8.0, OR = 2.2, 95% CI = 1.4–3.3, and OR = 1.5, 95% CI = 1.0–2.3, respectively; Table 3). In multivariable models controlling for socio-demographic covariates, the Wired cluster had the greatest odds of moderate to severe symptoms of depression (AOR = 2.7, 95% CI = 1.5–4.7), followed by the Connected cluster (AOR = 2.0, 95% CI = 1.3–3.0). Neither the Diffuse Dabblers nor the Concentrated Dabblers clusters were significantly associated with elevated depression symptoms. In models using anxiety as the dependent variable, relative to the Unplugged cluster, the Wired cluster had the greatest odds of moderate to severe anxiety symptoms (AOR = 3.7, 95% CI = 2.1–6.5), followed by the Connected cluster (AOR = 2.0, 95% CI = 1.3–3.1). Diffuse Dabblers and Concentrated Dabblers cluster membership was not significantly associated with elevated anxiety symptoms (Table 3).

DISCUSSION

This cluster analysis from a nationally-representative sample of 19-to-32 year-olds yielded 5 distinct patterns based upon their social media use (SMU). Clusters were characterized in terms of high (as opposed to low) time on social media per day, frequency of site visits per week, multiple platform use, problematic social media use (PSMU), and social media intensity (SMI). Two specific SMU patterns—Wired and Connected—were associated with the most risk of depression and anxiety. The 3 remaining clusters, although representing different patterns of use, were not associated with depression or anxiety.

Membership in the Wired cluster was most strongly associated with elevated symptoms of both depression and anxiety. This finding suggests that high volume SMU occurring in tandem with high levels of problematic use and high emotional connection to social media is most concerning. It may be that this particular pattern of SMU is indicative of a preoccupation with, and hyper-vigilant surveillance of, one's social media.[71] For example, Wired individuals may routinely engage in attention seeking behaviors, reflected in high volume SMU, such as frequent status updates and subsequent checking for "likes."[72,73] is preoccupation may lead to depression if the individual does not receive the desired feedback from his or her social media audience.[73] Similarly, "fear of missing out" (FOMO), characterized by the desire to stay continually connected, and "Snapstreaks," metrics of consecutive daily "Snaps" between friends on Snapchat, may contribute to a hyper-vigilant social media surveillance.[74] These social media-derived behaviors may mimic and contribute to symptoms of anxiety.[21,75]

The Connected cluster also was associated with elevated symptoms of depression and anxiety, but to a lesser degree than Wired membership. Characterized by 100% endorsement of high levels of all SMU characteristics except PSMU, the Connected cluster represents high volume, highly emotionally connected, yet low problematic users. is finding suggests that feeling emotionally connected to one's social media community, in combination with high volume SMU, may be deleterious to one's well-being, even in the absence of any problematic use. It may be that these individuals seek connectedness through SMU due to absence of real-life connectedness.[76] However, the strong association between Connected membership and depression and anxiety suggests this pattern of SMU may not be an effective means for procuring sustaining feelings of connectedness. is potential displacement of time and attention away from in-person connection and toward SMU also may result in decreased mental health benefits associated with in-person relationships.[77–81]

There were several differences between the Connected and Wired clusters worth noting. First, the Connected cluster was more homogenous than the Wired cluster in terms of composition of SMU characteristics. Specifically, 100% of individuals in the Connected cluster reported high levels of time, frequency, multiple platform use, and SMI, whereas the majority (ranging from 61% to 79%) of individuals in the Wired cluster reported high levels among these same SMU variables. This is particularly interesting because Connected membership was not as strongly associated with depression or anxiety symptom levels as Wired membership despite having higher levels of SMU. is suggests that it is not simply high-volume SMU that is associated with depression and anxiety, but more likely, a pattern of use demonstrated by the Wired cluster. Second, Wired membership was more strongly associated with anxiety than depression, whereas Connected membership was similarly associated with both outcomes. is difference may be attributable to the ubiquitously high PSMU in the Wired cluster (100%) as opposed to that in the Connected cluster (0%). Indeed, it is plausible that PSMU is more closely related with anxiety than depression.[21]

An alternative explanation for the association between Wired and Connected membership and increased risk of depression and anxiety is that these distinct patterns are mileposts along a continuum of problematic SMU. For the Wired cluster, of which 100% of members reported high PSMU, perhaps the lower volume (compared with the Connected cluster), reflects attempts to disengage or cut-back on SMU. It may be that individuals in the Connected cluster have not yet experienced any indications of PSMU, ie, the pervasive high-volume use and emotional connectedness. Identifying individuals for whom SMU resembles that of the Connected cluster may be an important point of intervention along a continuum toward a more problematic pattern of SMU and subsequent increased risk of depression and anxiety, as demonstrated by the Wired cluster.

Three clusters—Unplugged, Concentrated Dabblers, and Diffuse Dabblers—were not associated with depression or anxiety. is finding supports the notion that moderate media consumption may not be associated with mental health risks for some individuals.[82,83] It may be that for individuals in these clusters, social media are simply tools for maintaining and building relationships, rather than replacing in-person relationships.[84] Additionally, these individuals may be benefitting from self-expression and identity development via social media, which supports a more youth-normative perspective of SMU.[85,86]

This study had several limitations, many of which relate to measurement issues. First, the dichotomization of variables may result in loss of information about individual differences. It should be noted that the goal of cluster analysis is not necessarily to assess individual differences, but rather, to identify distinct and interpretable patterns or groups.[42] Second, we used 2 scales modified from their original versions without conducting extensive validation work. Third, whereas we categorized depression and anxiety symptoms according to recommended guidelines, future studies of the non-clinical, young adult population may benefit from use of scales more likely to result in normal distributions. Additionally, the 5 SMU characteristics included are likely neither exhaustive nor representative of all SMU characteristics. It may be valuable for future research to assess patterns of SMU using a more extensive and theoretically grounded set of items. For example, this study did not assess users' reaction to social media. It may be that how one feels in response to social media (ie, Instagram's image-based or LinkedIn's professional content) may cause dissatisfaction with oneself and subsequent depressive symptoms.[36,87–91]

Other limitations of this study pertained to design. For example, data were self-reported survey responses and may not accurately reflect behavior. Additionally, these data were collected in 2014. Increasing SMU trends suggest these data may be conservative estimates of current rates of use.[92] The cross-sectional nature of these data limits inferences about the direction or causal nature of associations. The relationships of depression, anxiety, and SMU patterns may, in fact, be bidirectional, which cannot be determined using cross-sectional data. Future work utilizing longitudinal data will be useful in that regard. Although GfK attempts to represent off-line households, as described in the methods section, it is possible that individuals who participate in online studies may be more likely to use social media, adding a potential source of bias to this study. Finally, because of having data from only one point in time, we were unable to examine the stability of membership in the 5 SMU clusters over time.

Findings from this study may help inform future educational and clinical interventions. For example, depression and anxiety prevention and management tools may include recommendations for SMU. Such recommendations should note the importance of not only how much social media one uses, but also how emotionally and behaviorally attached an individual is to social media. Similarly, if young adult individuals are experiencing elevated depression and/or anxiety symptoms, it may be useful for health practitioners to assess their SMU patterns, not simply focus on volume of use. However, these findings also should be interpreted with caution, given the exploratory nature of the analyses and limitations noted above.

In conclusion, cluster analysis yielded 5 distinct SMU patterns in a large sample of US young adults. Groups differed from each other in terms of key SMU characteristics, socio-demographic variables, and associations with depression and anxiety symptoms. Two specific patterns of use are associated with the most risk of elevated symptom levels of depression and anxiety. Three groups, representing differing patterns of moderate use, were not associated with elevated depression or anxiety symptoms. Patterns of use, rather than individual characteristics, may be more reflective of real-world SMU, and therefore, valuable in elucidating associations between SMU and depression and anxiety symptom levels. Finally, SMU patterns may be useful in developing educational and clinical interventions for those individuals at highest risk for depression and anxiety.

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Table 1

Composition of Clusters by Social Media Use Characteristics

Cluster Label	Whole Sample N (%)	Time[a,b]	Frequency[a,c]	Multiple Platform Use[a,d]	PSMU[a,e]	SMI[a,f]
Cluster 1: **Unplugged**	326 (18.8)	0.0	0.0	0.0	0.0	0.0
Cluster 2: **Concentrated Dabblers**	340 (19.7)	67.7	52.4	0.0	0.0	56.8
Cluster 3: **Diffuse Dabblers**	549 (31.7)	34.2	44.4	100.0	0.0	38.4
Cluster 4: **Connected**	274 (15.8)	100.0	100.0	100.0	0.0	100.0
Cluster 5: **Wired**	241 (13.9)	78.8	73.9	68.9	100.0	61.4

Note

[a]Percent of individuals classified as “high” as opposed to low

[b]Minutes per day, non-work-related, spent on social media

[c]Number of social media site checks per week

[d]Number of social media platforms used

[e]Problematic social media use scale

[f]Social media intensity scale

Table 2

Socio-demographic Composition of Whole Sample and Individual Clusters

Socio-Demographic Characteristic	Whole Sample N = 1730	Unplugged	Concentrated Dabblers	Diffuse Dabblers	Connected	Wired	p[a]
	%	%	%	%	%	%	
Age, years (M, SD)	**25.5 (3.8)**	**26.4 (3.5)**	**25.9 (3.7)**	**25.5 (3.9)**	**23.8 (3.7)**	**25.5 (3.8)**	< .001
Sex							.02
Women	50.8	39.6	51.7	50.0	59.7	57.5	
Race/Ethnicity							.32
White, Non-Hispanic	57.1	58.2	55.8	60.8	55.3	51.6	
Black, Non-Hispanic	13.2	17.1	14.1	7.9	18.1	12.8	
Hispanic	20.5	16.2	23.1	20.4	20.4	22.9	
Other[b]	9.1	8.4	7.1	10.9	6.2	12.6	
Relationship Status							.15
Single	44.3	36.8	45.2	44.7	53.1	43.2	
Living Situation							.07
Friends	17.6	9.9	17.2	19.9	22.8	18.2	
Significant Other	35.6	42.6	36.0	36.0	23.5	37.2	
Parent/Guardian	33.6	31.5	35.7	30.3	37.4	36.4	
Alone	13.2	16.0	11.1	13.8	16.2	8.2	
Education							<.001
High School or Less	34.9	32.7	48.0	23.6	30.3	46.6	
Some College	38.9	41.6	34.6	40.2	44.5	33.2	
Bachelor's Degree or Higher	26.2	25.7	17.4	36.2	25.2	20.2	
Household Income							<.001

Socio-Demographic Characteristic	Whole Sample N = 1730	Unplugged	Concentrated Dabblers	Diffuse Dabblers	Connected	Wired	P[a]
	%	%	%	%	%	%	
Low (< $30,000)	22.9	21.8	32.3	16.9	16.0	30.0	
Medium ($30,000–$74,999)	38.1	36.9	46.8	35.1	39.2	30.8	
High (≥$75,000)	39.0	41.3	20.9	48.1	44.9	39.2	

Note.

[a] p value derived using Chi-square tests for independence comparing categorical socio-demographic characteristics and cluster membership and analysis of variance (ANOVA) for comparing age across clusters.

[b] Included multi-racial

Table 3

Bivariable and Multivariable Associations between Cluster Membership and Depression and Anxiety

Cluster	Depression		Anxiety	
	OR (95% CI)	AOR[a] (95% CI)	OR (95% CI)	AOR[a] (95% CI)
Unplugged	Reference	Reference	Reference	Reference
Concentrated Dabblers	1.08 (0.68–1.70)	0.86 (0.53–1.39)	1.11(0.70–1.75)	0.86 (0.55–1.37)
Diffuse Dabblers	1.28 (0.87–1.88)	1.34 (0.92–1.97)	**1.54 (1.04–2.30)**	1.45 (0.99–2.14)
Connected	**1.89 (1.22–2.93)**	**2.03 (1.29–3.21)**	**2.18 (1.44–3.32)**	**2.00 (1.31–3.07)**
Wired	**3.13 (1.76–5.56)**	**2.68 (1.53–4.72)**	**4.49 (2.52–8.00)**	**3.68 (2.09–6.50)**

Note.

OR = odds ratio; AOR = adjusted odds ratio; CI = confidence interval. Bolded values indicate significance

[a]Associated odds ratios represent the odds of moderate to severe depression or anxiety adjusting for age, sex, race/ethnicity, relationships status, living situation, education, and household income.