Received: 15 April 2023 | Accepted: 31 May 2024

DOI: 10.1002/jad.12362

RESEARCH ARTICLE

Foundation for PSA WILEY

Who's most at risk? A person-centered approach to understanding the long-term relationship between early social media use and later depression across adolescence

W. Justin Dyer[1] | Sarah M. Coyne[2] | Megan Gale[2] | J. Andan Sheppard[2]

[1]Religious Education, Brigham Young University, Provo, Utah, USA

[2]School of Family Life, Brigham Young University, Provo, Utah, USA

Correspondence
W. Justin Dyer, Religious Education, Brigham Young University, JSB 270B Provo, UT 84602, USA.
Email: justindyer@byu.edu

Abstract

Introduction: Person-centered analyses examined the relationship between social media use and depression over an 8-year period. The purpose was to examine the varying ways early social media use was associated with the development of depressive symptoms with a hypothesis that social media would not have a uniform association with depressive symptoms across adolescents.

Methods: Participants included 488 adolescents (52% female), living in the United States, who were surveyed once a year for 8 years (beginning in 2010 when the average age for participants was 13.33 years old).

Results: Longitudinal mixture regression was used to identify classes of adolescents representing unique ways their early social media use was related to the development of depressive symptoms over an 8-year period. Five classes were found representing unique ways social media use was related to depression. Findings suggest social media use does not impact all adolescents in the same way. Social media use was related to increased depression for adolescents with greater parental hostility, peer bullying, anxiety, reactivity to stressors, and lower parental media monitoring. In other instances, social media use was related to less depression or was unrelated to depression.

Conclusions: By identifying which adolescents may be most at risk from social media use, health providers, schools, and caregivers can tailor interventions to fit the needs of each adolescent.

KEYWORDS
adolescence, depression, longitudinal, mixture modeling, social media

Over the past several years, rates of depression and anxiety have steadily increased among adolescents (Bitsko et al., 2018; Pew Research Center & Davis, 2019) with reports in 2021 recording that 42% of adolescents felt sad or hopeless and 29% experienced poor mental health (Centers for Disease Control and Prevention [CDC], 2023). Adolescent mental health challenges are often associated with other health and behavioral risks and problems which carry into adulthood (CDC, 2023); thus, it is important to understand what might play a role in adolescent mental health. Social media use has been implicated in the increase in mental health challenges (American Academy of Child and Adolescent Psychiatry, 2018; Pew Research Center, 2018). Research findings are mixed with some studies finding a relationship between poorer mental health and social media use (Hunt et al., 2018; Twenge et al., 2018) and others finding no relationship (Appel et al., 2020; Berryman et al., 2018; Meier & Reinecke, 2020). It is important to note that these findings may not be contradictory because multiple theories posit the effect of any process (e.g., social media use) may differ given various circumstances (Dyer et al., 2012; Nesi et al., 2022). For example, some strands of resiliency theory (see McCubbin et al., 1995) argue that, depending on the circumstances,

Approval was obtained from the Institutional Review Board at Brigham Young University. Participants were treated in accordance with the APA's Code of Conduct, Ethical Principles & Guidelines and gave consent to participate in this study.

stressors may lead to bon-adaptation (i.e., constructive change) to increase, or maladaptation (i.e., disorganization) to decrease functioning. Haggerty and Sherrod (1995) note that there are variations in the effects of stressors, and that it is important to identify variation in the effects of stressors, arguing that "variability must be given equal attention, and not treated as error variation" (p. xviii).

Bronfenbrenner's general bioecological model may be particularly useful in conceptualizing the ways in which social media may influence the development of mental health problems (Bronfenbrenner, 1999). In the bioecological model, the nexus of development is the proximal process. While we view social media use as a proximal process in this study, other literature (see Navarro and Tudge's *Neo-Ecological Theory*, 2022) suggests that media could also be examined as being part of one's microsystem (virtual space) and macrosystem (media influencing culture).

Bronfenbrenner's first proposition defines proximal processes as regularly occurring processes that occur within the immediate environment of the developing individual (Bronfenbrenner, 1999). These can include interactions between the developing person and other individuals (e.g., parent-child activities) or between the developing person and objects and/or symbols (e.g., child reading, studying, engaging in solitary play). Bronfenbrenner's second proposition states that the power and direction of proximal process's effects on the developing person vary systematically as a joint function of the characteristics of the developing person, as well as the environment, and the historical period within which the person lives (Bronfenbrenner, 1999). In other words, social media use is a proximal process, and under certain conditions, social media use may: 1) be related to worse mental health, 2) have no relationship with mental health, or 3) be related to better mental health. The present study examines various personal and environmental factors that may influence the effect of social media use (a proximal process) on mental health. In this way, we can better understand the circumstances under which social media may be particularly problematic or beneficial, enabling identification of those most at risk.

Research has identified several personal and environmental characteristics that may influence the effect of social media use on adolescent mental health. The current study considers characteristics such as gender, race, self-regulation, and physiologic sensitivity to the environment. Prior research has found girls' mental health may be more susceptible to the influence of social media use (Coyne et al., 2021; Crockett et al., 2020), perhaps given females, on average, have greater sensitivity to events within their social network (Kessler & McLeod, 1984)—social networks being a distinguishing feature of social media. Recent reports have indicated that girls who already struggle with mental health are at risk for negative experiences with social media, yet may also find resources, communities, and support systems on social media (Nesi et al., 2022). Two-thirds of girls of color report ever coming across racist content on social media, and one in five reports coming across it at least daily (Nesi et al., 2022). In general, minorities may be at particular risk for social media having a negative effect given research finding that "minority status may increase the likelihood of negative online experiences thereby activating more negative affect during active social media use" (Nereim et al., 2020).

Adolescent self-regulation may also factor into social media's effects. The experiential avoidance model suggests that long term effects of negative emotions in the face of negative experiences (such as those within social media) may be interrupted by adolescents being able to regulate their emotions (Chapman et al., 2006). In addition to emotions, the current study posits that regulation of behaviors and cognitions will help regulate and likely diminish the effect of experiences online.

Adolescent reactivity to environmental stimuli (Porges, 2011) may also relate to the differential effects of social media use (Porges, 2011). Ellis and Boyce (2011) use the term *differential susceptibility to the environment* to describe how individual differences in physiologic reactivity to the environment predicts variation in how individuals are affected by their environment. In other words, a single stimuli may create, within some, substantial reactions whereas, in others, there may be little to no reaction. This variation in reaction to the same stimuli influences the impact of that stimuli on the individual. Regarding social media use, individuals whose stress system becomes more engaged in the presence of negative social media (e.g., bullying) may have worse outcomes than those whose stress system is not particularly engaged in the context of negative social media. Highly reactive adolescents may experience more intense positive or negative emotions when receiving feedback on social media (Lu et al., 2010). One index of susceptibility to the environment is the reactivity of the autonomic nervous system (ANS) measured by responses in Respiratory Sinus Arrhythmia (RSA; vagal tone) and Galvanic Skin Conductance (SCL).

RSA measures the activity of the "rest and digest" functions of the autonomic nervous system (i.e., the parasympathetic branch of the ANS). When this system is activated, heart rate is slowed, enables rest, and enhances the ability to engage in socially nuanced ways (e.g., ability to perceive nuanced social cues). SCL measures the inhibitory function of the ANS which produces fear and anxiety, increasing the individual's motivation to remove themselves from a situation perceived as dangerous (i.e., the sympathetic branch of the ANS). When RSA and SCL activation are reciprocal (one increases while the other decreases) individuals are likely more sensitive to context (Abaied et al., 2018) given that this reciprocal activation produces the most change in the body, either towards rest and digest or towards inhibition (compared to when only RSA or SCL changes or when they change in the same direction). When environments are supportive, greater reactivity can be beneficial given they are more able to "soak up" the positive aspects of the environment. However, in harsh environments, highly reactive individuals may flounder as they are more sensitive to the harshness (Ellis & Boyce, 2011). Adolescents who are more reactive (e.g., have greater anxious responses to negative events) may be more influenced by social media use (Lu et al., 2010), for good or for ill, depending on the type of online engagement.

Environmental factors that may affect the relationship between social media and mental health include parenting style, parental media monitoring, and adolescents being bullied. More parental warmth and less parental hostility positively influence adolescent mental health (Gorostiaga et al., 2019; Padilla-Walker et al., 2018) and may provide a buffer against negative online interactions. Parents who monitor their adolescents' media use may direct their children towards more positive and less negative uses of social media and help their children understand the media they are consuming, steering them away from or buffering against potential negative social media interactions (Padilla-Walker et al., 2018). Further, adolescents who are bullied may often have that bullying follow them online (or have bulling occur exclusively online), creating more negative experiences of social media use that lead to mental health difficulties (Landstedt & Persson, 2014; Macalli et al., 2021).

Given the number of potential moderators of the relationship between social media use and mental health, person-centered analyses are particularly useful in identifying first, the varying ways in which social media is related to mental health and second, what significantly predicts the ways in which social media is related to mental health. To date, most research has used cross-sectional and variable-centered designs, not allowing for variation within individuals and typically assuming a single set of parameters for the entire sample (Coyne et al., 2022). A longitudinal, person-centered approach provides greater flexibility to understand how processes function across various subpopulations within a sample.

1 | CURRENT STUDY

Using mixture regression (Dyer et al., 2012), we examined how various levels of social media use related to growth in depression from adolescence into emerging adulthood. In mixture regression, various groups or "classes" of individuals are identified based on differences in how one or more independent variable relates to one or more dependent variables across time. Given prior research, we hypothesized classes in which social media would be: 1) related to greater depression, 2) unrelated to depression, and 3) related to less depression. Characteristics used to predict the various classes included: personal (gender, race, self-regulation, neurophysiologic sensitivity) and environmental (parenting, media monitoring, being bullied). We hypothesized that adolescents with greater personal and environmental risk factors would more likely be in a class where social media use was related to greater depression. Adolescents with greater personal and environmental protective factors were hypothesized to be in a class where social media use was related to less depression or unrelated to depression.

Mixture regression is particularly useful when the primary research regards whether the relationship between an independent and dependent variable varies—not simply whether it varies *as a function of third variables* (or a combination of additional 'third' variables). Whether the relationship between an independent and dependent variable varies is often examined by multiplying the independent variable by a hypothesized moderator. However, detecting varying effects depends on whether the moderator does, in fact, moderate the relationship as well as the degree of measurement error in the moderator. Indeed, we are at risk not identifying varying effects due to measurement error in the moderator. With mixture regression, we *first* identify the varying ways social media is related to depression growth and *then* examine what variables relate to the ways social media relates to depression growth. This is particularly useful as there may be a complex combination of moderators that would be needed to identify varying ways the independent variable relates to the dependent variable. Thus, mixture regression can more effectively test higher order and multiple interactions than typical methods (see Dyer et al., 2012 for a more detailed discussion of the benefits of mixture over typical interaction and multiple group analyses).

We examined the development of depression over 8 years, through adolescence into emerging adulthood (approximately ages 13 through 20). This time period is crucial to consider as prior research has found substantial increases in depression from early to late adolescence with the increase often tapering off in emerging adulthood (Rawana & Morgan, 2014; Salk et al., 2016). Examining the trajectories of depression as well as the varying effects of social media use provides a more nuanced understanding of what interventions may be needed during this highly sensitive time of depression development.

2 | METHODS

2.1 | Sample

Data come from Waves 3–10 of the Flourishing Families Project, a longitudinal study exploring adolescent development (Wave 3 was the first wave social media data were collected). Each Wave was 1 year from the previous. At Wave 3 (in 2009) 488 families participated (child age $M = 13.33$, $SD = 1.06$; child gender 52% female; child race 67% White, 13% Black, 20%

Multi-racial/Other). Participants lived in a large urban center in the Northwest United States and were recruited from a national database mirroring local socioeconomic and racial stratification. IRB approval was obtained, and parents gave consent for parental and child participation.

2.2 | Measures

Measure items can be found in the Supporting Information S1: Appendix A1. All measures from Wave 3 are used in analyses with depression assessed at each time point (Wave 3 to Wave 10).

2.2.1 | Social media use

Adolescents self-reported time spent on social media by a single item question, "How much time do you spend on social media in a typical day?" Responses were categorized as 1 = none, 2 = 1 hor less, 3 = 1–2 h, 4 = 2–3 h, and 5 = 3 + hours. Self-report measures of time use are relatively basic but correlate moderately well (due to the relative stability over time; Scharkow 2019) with actual measures of time use. More recent measures such as passive sensing apps may have higher reliability, these were not available when data collection began (Lin et al., 2021). Wave 3 social media (the first wave when social media use was captured) was used to predict depression growth parameters. This variable was treated as an unordered categorical variable in the analyses. It may be that each category of social media use in this measure is uniquely related to depression. Treating this variable as an unordered category provides maximum possibilities for the "shape" of the relationship (i.e., linear, quadratic, cubic, etc.) between social media use and depression development in each of the classes. In other words, rather than treating the variable as continuous or ordinal, analyses are able to compare each category of media use to all other categories. This allows for additional complexity in how social media use may be related to depression.

2.2.2 | Depression

Adolescent depression at each wave was assessed using the 20-item self-report Center for Epidemiological Studies Depression Scale for Children (Weissman, 1996). Participants rated the degree to which they experienced symptoms in the past week, ranging from 1 = *not at all* to 4 = *a lot*. Reliability was acceptable ($\alpha = 0.90$). This scale has also been found to have good validity, particularly for adolescents ages 12–18 (Fendrich et al., 1990).

2.2.3 | Warmth and hostility

Maternal warmth and hostility were assessed using adolescent reports of the Parenting Styles and Dimensions Questionnaire-Short Version (Robinson et al., 2001). Responses ranged from 1 = *never* to 5 = *always*. This scale appears to have face validity (as originated by Robinson et al. based on Baumrind's work). Five items assessed warmth ($\alpha = 0.91$) and four items assessed hostility ($\alpha = 0.82$).

2.2.4 | Media monitoring

Maternal reports of parental monitoring of children's media exposure were used with a modified 7-item scale (Nikken & Jansz, 2006; Warren et al., 2002). Mothers rated how often they engaged in monitoring behaviors such as forbidding certain kinds of media and helping the child understand what they see in the media (1 = *never* to 5 = *very often*). Reliability was acceptable ($\alpha = 0.92$). The original scales, where items were adapted, were found to have good validity. For example, Nikken & Jansz found parental mediation to be prevalent among parents and perceived by their children, suggesting high validity (2006). Although a second caregiver (primarily the father) was also asked these questions, given the number of single mother households in the sample, there was substantial missing data from the other caregiver and so their report is not included.

2.2.5 | Being bullied

Perception of being bullied was assessed using seven items (modified from Moore & Lippman, 2005), with adolescents reporting how often instances of bullying occurred (1 = *never* to 4 = *very often*; sample items: *How often are you bullied by* *classmates or neighborhood kids? How often does someone try to isolate you from the rest of your peer group by telling others not to hang out with you?*). Cyberbullying was not assessed as part of this measure, rather a more holistic measure of bullying is used, which was found to be valid in the original measure. Reliability in this sample was acceptable ($\alpha = .97$).

2.2.6 | Self-regulation

Adolescents' self-regulation was measured with the revised 3-scale self-regulation measure (Novak & Clayton, 2001; i.e., regulate emotions, cognitions, and behaviors). Responses ranged from 1 = *never true* to 4 = *always true*. Novak and Clayton created the three scales from other existing valid measures (2001). Reliability in this sample was good for each subscale ($\alpha = 0.96$, 0.93, and 0.98 respectively) which were comparable to Novak and Clayton's reliabilities: $\alpha = 0.95$, 0.96, and 0.94.

2.2.7 | Autonomic nervous system

Two components of adolescents' Autonomic Nervous System (ANS) were assessed: RSA and SCL (Porges, 2011). The following were used as frequency bands for RSA: very low frequency [0.003–0.040], low frequency [0.040–0.120], and high frequency/RSA [0.120–0.400]. Respiration, a potential confound to RSA measurement, was measured by the impedance signal and examined for its potentially confounding influence. SCL relates to the body's "fight or flight" response with high baseline levels and high increases to challenges being associated with high anxiety and fear. RSA and SCL were collected during a variety of 3–5-min tasks with baselines measured between tasks. The first task was a 3-min resting period (baseline) to know how adolescents are autonomically configured without stressful stimuli. The second task was a cognitively challenging Rubik's Cube to simulate what is experienced when performing a difficult and unfamiliar task, followed by a 3-min resting period measured as a second baseline. Following the second baseline, adolescents conversed with parents for 3 min (task three) followed by another 3-min resting period (baseline three). The levels of RSA and SCL are in and of themselves important, however their *reactivity* is also critical. Reactivity is RSA and SCL change from the prior baseline. The greater RSA and SCL values, the greater the engagement of their respective systems.

2.3 | Analysis plan

Depression from Waves 3–10 was specified as a latent growth curve in Mplus 8.5 (Muthén & Muthén, 2017). It was examined whether growth was linear or quadratic. The intercept and slope(s) were saved, exported, and used in a mixture regression model specified in LatentGold 6.0 (Vermunt & Magidson, 2021). Social media use predicted growth parameters with the relationship between social media use and growth parameters allowed to vary by class. The constants of regressions, variances of growth parameters, and the correlations between growth parameters were permitted to vary across class. Predictors of class membership were child gender, child race, child self-regulation (emotional, behavioral, cognitive), RSA and SCL baseline and reactivity, mother warmth, mother hostility, mother media monitoring, and the child being bullied. Figure 1 provides the conceptual model for the mixture regression. Socioeconomic status may confound the relationships in the model. For example, it may be that adolescents who are more affluent have more access to social media and may be able to use it more often. Family income was therefore included as a control. The analytic model as outlined in Figure 1 was specified a priori.

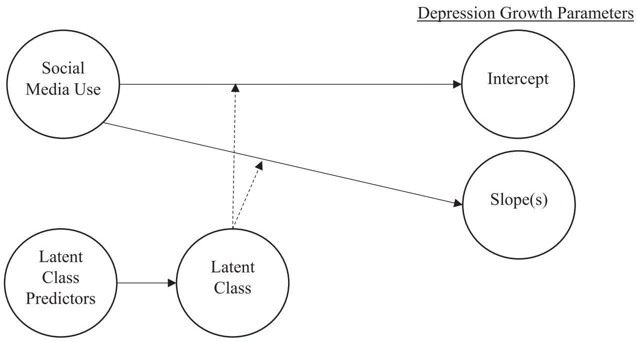

FIGURE 1 Conceptual Model of Mixture Regression. Dashed arrows from Latent Class to the solid arrows indicate the latent classes are determined by the varying ways social media use is related to depression growth parameters.

What was not specified a priori were the number of classes and whether there would be a quadratic slope in the growth of depression. These were determined during the analytic phase based on statistical criteria as indicated in the results section.

The retention rate over the 10-year course of the study was high at 88%. Retention strategies for this study included:

1) Researchers made home visits. There was no need for the respondents to travel and researchers would build relationships with the family.
2) Families were made to feel part of the research project by receiving regular project updates and reaching out with cards such as "Happy Holidays!"
3) Family members were paid $75 for their participation. This was sufficient to encourage continued participation.

There were some differences in those who left the study and those who stayed in the study. Those who stayed were more likely to: be white, have high maternal warmth and low maternal hostility, have higher income, experience less bullying, and have higher cognitive self-regulation. These were differences found in the variables used in the analyses. Given we were able to predict whether or not a person was not in the study at Wave 10, the missingness can be categorized as missing at random (MAR; i.e., when the missing data mechanism is partially known) rather than missing completely at random (i.e., missingness is truly random). Because variables that predict missingness are included in the analyses (i.e., race, parenting, income, bullying, and cognitive self-regulation) and because full information maximum likelihood (FIML) is used to handle missing data, parameter estimates should be unbiased in the face of attrition (see Little, 2024), particularly because the attrition is relatively small.

3 | RESULTS

Table 1 contains correlations and means of variables.

3.1 | Growth curve

A linear growth curve of depression was compared to a quadratic growth curve. When adding the quadratic term, the chi-square significantly improved ($\Delta\chi^2(df)$=9.75(4), $p = 0.04$). The CFI improved from 0.969 to 0.973. The mean of the quadratic parameter was −0.049 ($p = 0.084$). Its variance was 0.058 ($p = 0.060$). With the increase in model fit and the mean and variance significant at $p < 0.10$, the quadratic slope was retained. The means of the intercept, linear slope, and quadratic slope were exported for use in mixture regression.

The mixture regression was specified for one to six classes. Previous mixture regression research finds the AIC3 the optimal information criteria in determining the number of classes. It has the highest success rate and lowest bias (Andrews & Currim, 2003). AIC3 suggested the three and five-class models fit the data best with a bootstrap log-likelihood difference test suggesting the five-class model fit better than the three-class model. In the five-class solution, cases were well classified with an entropy of 0.89.

3.2 | Class descriptions

Classes are numbered based on size, with Class 1 the largest (29.66% of the sample), followed by Class 2 (26.15%), Class 3 (24.09%), Class 4 (13.18%), and Class 5 (6.92%). Figure 2 displays depression growth trajectories for each class. Classes were labeled according to their relative risk of depression over time. Though, the two classes highest in depression were similar in their trajectory and were also designated by their predominant gender (although both genders are represented in both classes, the majority gender in each class was used to define the overall class characteristics). Thus, Class 1 is "High Risk Female" (81% female), Class 3 is "High Risk Male" (62% male), Class 5 is "Moderate Risk", Class 2 is "Low Risk", and Class 4 is "Very Low Risk". Table 2 contains the relationship between social media use and growth parameters and Table 3 contains significant differences in class predictors using effects coding. Below, classes will be described as having higher and lower rates of class predictors. These designations are in reference to the other classes. Class pairwise comparisons are found in Table 3.

Table 4 contains amount of social media use across classes. It should be noted that latent classes *were not created based on the different trajectories*. Identification of classes were based on the various relationships between social media use and the growth parameters. Depression trajectories within these classes also differ (though some differ very little). It was not by these differences that latent classes were identified (in contrast to, e.g., growth mixture modeling).

TABLE 1 Correlations and Descriptives ($n = 488$).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Intercept	1.00																	
2. Linear Slope	0.45*	1.00																
3. Quadratic Slope	−0.47*	−0.68*	1.00															
4. Social Media	0.15*	0.04	−0.11*	1.00														
5. ^{M}Warmth	−0.15*	0.00	0.06	−0.15*	1.00													
6. ^{M}Hostility	0.24*	0.01	−0.06	0.05	−0.47*	1.00												
7. ^{M}Media Monitor	−0.02	0.02	0.04	0.00	0.10*	−0.04	1.00											
8. Bullied	0.37*	0.00	−0.03	0.16*	−0.24*	0.24*	−0.05	1.00										
9. Emotional SR	0.13*	0.11*	−0.07	0.07	−0.17*	0.18*	0.00	0.17*	1.00									
10. Behavioral SR	0.09	0.03	−0.03	0.06	−0.21*	0.14*	−0.07	0.16*	0.70*	1.00								
11. Cognitive SR	−0.06	0.01	0.01	−0.06	0.21*	−0.12*	0.09	−0.14*	−0.55*	−0.98*	1.00							
12. RSA Baseline	−0.10	−0.04	0.07	−0.09	0.02	0.01	0.07	−0.05	−0.04	−0.09	0.10*	1.00						
13. RSA Reactivity	0.04	0.03	−0.08	−0.04	−0.14*	0.12*	−0.04	0.02	0.08	0.08	−0.07	−0.26*	1.00					
14. SCL Baseline	0.05	0.16*	−0.13*	−0.09	0.01	0.12*	0.01	−0.09	−0.04	−0.06	0.06	0.01	0.07	1.00				
15. SCL Reactivity	0.00	0.00	−0.03	0.11*	0.04	−0.07	−0.07	−0.01	0.04	0.04	−0.04	−0.02	−0.06	−0.15*	1.00			
16. Male	−0.26*	−0.21*	0.15*	−0.09	−0.10*	−0.05	0.01	−0.10*	0.02	0.20*	−0.22*	0.07	0.05	0.12*	−0.09	1.00		
17. White	−0.10*	−0.04	0.02	−0.10*	0.13*	−0.15*	−0.02	−0.09	−0.07	−0.12*	0.12*	0.03	0.03	0.11*	0.03	0.05	1.00	
18. Income	−0.04	−0.02	0.02	−0.08	0.12*	−0.16*	−0.02	−0.05	−0.14*	−0.19*	0.18*	0.02	−0.05	0.04	−0.03	0.04	0.36*	1.00
Mean	37.52	0.78	−0.05	2.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.80	−0.87	4.68	1.48	0.48	0.67	8.41
SD	4.93	0.85	0.11	1.24	0.60	0.73	0.39	0.21	0.66	0.41	0.49	1.03	0.81	2.99	1.56	0.50	0.47	0.76

Note: Male (0 = female; 1 = male), White (0 = other, 1 = White).

Abbreviations: M, Mother's; SR, Self-Regulation.

*$p < 0.05$.

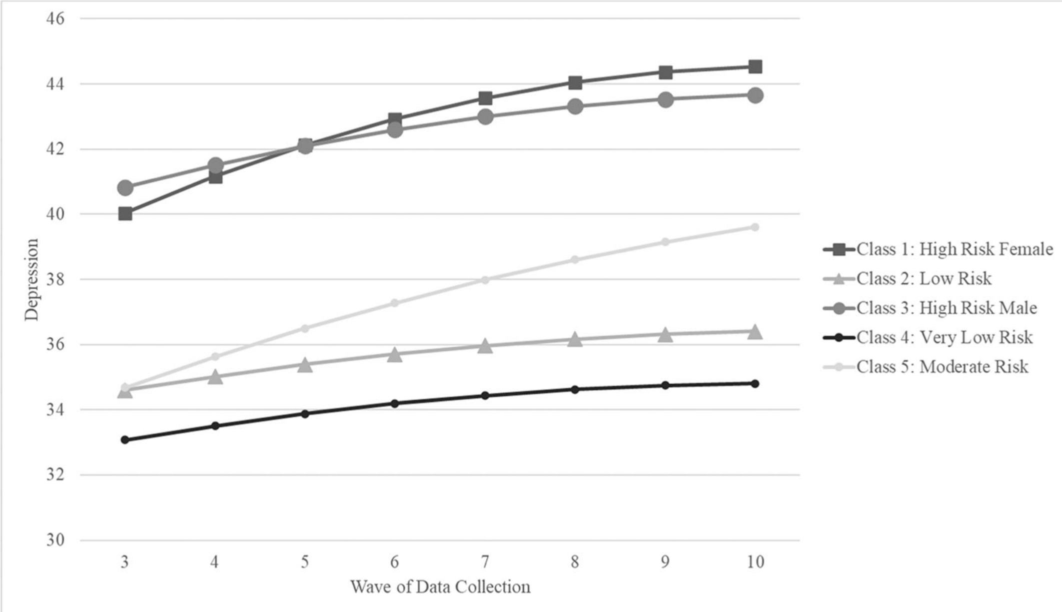

FIGURE 2 Depression by class across waves of data collection ($n = 488$).

For all but the Low Risk class, using social media between 2 and 3 h *or* 3 + hours was related to an increase in depression over time (i.e., social media use was positively related to the linear slope), though these effects were to varying degrees. For the Very Low Risk class, social media use between 2 and 3 h was related to less depression over time with 3 + hours related to increased depression.

The two high risk classes are similar in that at higher social media use (between 2 and 3 h for the High Risk Female class and 3 + hours for the High Risk Male class) was related to a more rapid increase in depression. For the High Risk Female class, 3+ hours was related to a higher initial level of depression as was 1–2 h for the High Risk Male class. For the High Risk Male class, these higher initial values are somewhat compensated for by a slower increase in depression when using 1–2 h. Although similar in trajectory and in relationship with social media, these high-risk classes differ substantially in their characteristics.

The High Risk Female class was predominantly female with the highest percentage of those who used social media 3 + hours a day (12.7%). They reported relatively good emotional and behavioral regulation, but their state anxiety (SCL Baseline) was high. This class also had warmer parents but the least parental media monitoring. In contrast, the High Risk Male class was predominantly male with the second highest percentage of those who used *no* social media (47.2%). Those in the High Risk Male class had high RSA reactivity and low RSA baseline indicating higher physiologic sensitivity. They were more likely to be bullied and to experience parental hostility.

The Moderate Risk class began at lower depression risk but increased rapidly. The relationship between 3+ hours of social media use and change in depression over time was the highest in this class. Less social media (none or 1–2 h) was associated with less depression over time. In this class, no social media use was associated with a lower intercept. Regarding class characteristics, the moderate risk class was more likely to be female and nonwhite with lower behavioral self-regulation and higher cognitive regulation. Though their physiologic profile was somewhat mixed, it suggests sensitivity to context, having low RSA reactivity, high SCL reactivity, and low SCL baseline. This class experienced low parental warmth, high parental media monitoring, and lower parental hostility.

Similar to Moderate Risk class, the Low Risk class had low initial levels of depression, but rather than rising quickly, this class's depression levels remained relatively steady. No social media use was related to a more negative (downward) trajectory of depression across time. High use was not a risk factor. This class was more likely to be white males with low emotion regulation but high cognitive regulation. Their RSA being average with greater RSA reactivity and lower SCL reactivity suggested low physiologic sensitivity. This class experienced low parent media monitoring, greater parental hostility, but less bullying.

In the Very Low Risk class, 3 + hours of social media use was associated with a more rapid increase in depression over time. This is the only Class where 2–3 h of social media use was related to less depression. This class was approximately 50%/50% male/female. Suggesting high reactivity, this class had low RSA baseline, high SCL baseline, and the highest SCL reactivity. They experienced high levels of parental warmth and media monitoring and were less likely to be bullied.

TABLE 2 Time on social media and growth parameters for adolescent depression.

	Class 1 High Risk Female (30%) b(se)	Class 2 Low Risk (26%) b(se)	Class 3 High Risk Male (24%) b(se)	Class 4 Very Low Risk (13%) b(se)	Class 5 Moderate Risk (7%) b(se)
Intercept					
None					−5.51 (1.16)*** β = −1.12
1 h or less					
1–2 h			3.27 (1.51)* β = .66		
2–3 h					
3+ hours	3.26 (1.03)** β = .66				
Linear Slope					
None					−0.44 (0.19)* β = −0.52
1 h or less					
1–2 h			−0.48 (0.24)* β = −0.57		−1.06 (0.36)** β = −1.25
2–3 h	1.25 (0.56)* β = 1.47			−0.58 (0.19)** β = −0.68	
3+ hours			0.84 (0.27)** β = .99	0.58 (0.15)*** β = .68	1.54 (0.36)*** β = 1.82
Quadratic Slope					
None	0.06 (0.03)* β = .56	−0.03 (0.01)** β = −0.28		0.04 (0.02)** β = .38	
1 h or less					0.09 (0.02)*** β = .85
1–2 h					
2–3 h					
3+ hours				−0.07 (0.02)** β = −0.66	−0.10 (0.04)* β = −0.94

Note: Parameters represent the relationship between the amount of social media use on the intercept, linear slope, and quadratic slope. β indicates the standardized coefficient (i.e., the effect divided by the standard deviation of the growth parameter).

*$p < 0.05$,; **$p < 0.01$,; ***$p < 0.001$, only significant values reported, *b*(*se*)*.

When significant, effect sizes for social media use on growth parameters were typically medium to large (see Table 2). Large effect sizes (even those about 1.00) are unsurprising given mixture regression creates classes based on the various relationships between the independent and dependent variables estimated within the sample. Although the correlation between social media use and the intercept, linear slope, and quadratic slope are relatively small (0.15, 0.04, and −0.11) in creating classes we identify those for whom the relationship is particularly strong or weak.

4 | DISCUSSION

Using mixture regression, this study examined the relationship between early social media use and development of depressive symptoms from adolescence to emerging adulthood. Findings are consistent with the bioecological model which suggests the effect of processes may differ based on personal and environmental factors. Indeed, this study found five classes, each differing in how self-reported social media use duration related to depressive symptoms. Although high amounts of reported social media use was often related to larger increases in depressive symptoms, this was not universal and the size of the effect varied substantially. Further, personal and environmental characteristics predicted the various ways in which early social

TABLE 3 Mean of class predictors within each class, significant differences across class indicated.

Class Predictors	Class 1 High Risk Female (30%)	Class 2 Low Risk (26%)	Class 3 High Risk Male (24%)	Class 4 Very Low Risk (13%)	Class 5 Moderate Risk (7%)
Mother warmth	0.19^{235}	0.02^{145}	-0.27^{145}	0.23^{235}	-0.37^{1234}
Mother hostility	-0.09^{235}	-0.07^{1345}	0.45^{1245}	-0.35^{235}	-0.28^{1234}
Mother media monitor	-0.06^{45}	-0.02^{5}	-0.01^{5}	0.06^{15}	0.26^{1234}
Bullied	-0.02^{345}	-0.07^{345}	0.19^{1245}	-0.13^{123}	-0.08^{123}
Emotional self-reg.	0.13	−0.27	0.13	0.06	−0.11
Behavioral self-reg.	0.02^{45}	-0.12^{345}	0.10^{25}	0.03^{12}	-0.06^{123}
Cognitive self-reg.	-0.01^{45}	0.10^{345}	-0.11^{25}	-0.02^{125}	0.08^{1234}
RSA baseline	6.89^{4}	7.0^{134}	6.57^{2}	6.50^{125}	6.98^{4}
RSA reactivity	-1.02^{23}	-0.82^{145}	-0.64^{145}	-0.89^{235}	-1.22^{234}
SCL baseline	4.79^{23}	4.55^{14}	4.66^{14}	5.00^{23}	4.14
SCL reactivity	1.72^{235}	1.31^{145}	1.14^{145}	1.81^{235}	1.71^{1234}
Male	0.19^{234}	0.69^{145}	0.62^{14}	0.51^{123}	0.44^{23}
White	0.59^{235}	0.91^{145}	0.68^{145}	0.64^{235}	0.18^{1234}
Income	8.36^{3}	8.56^{345}	8.48^{1245}	8.32^{23}	8.01^{23}

Note: Parameters represent the level of class predictors for each class.
$\text{mean}^{\text{SignificantClassDifference}}$. E.g., the level of mother warmth in Class 1 was 0.19 which was significantly higher (by at least $p < 0.05$) than Classes 2, 3, and 5.

TABLE 4 Distribution of time on social media by class.

Social media time	Class 1 High Risk Female (30%)	Class 2 Low Risk (26%)	Class 3 High Risk Male (24%)	Class 4 Very Low Risk (13%)	Class 5 Moderate Risk (7%)
None	23.8%[b]	50.89%[a]	47.19%[a]	22.03%[b]	17.70%
1 h or less	38.71%	25.84%[b]	20.85%[b]	38.24%	55.89%[a]
1–2 h	12.65%	6.27%	6.52%	23.36%[a]	2.96%
2-3 h	1.44%[b]	3.67%[b]	13.88%	4.65%[b]	20.49%[a]
3+ hours	12.74%[a]	5.9%[a]	4.30%	9.29%[a]	2.96%[b]

Note: Percentages come from individual class and not from overall sample.
[a]Higher percentage than grand mean.
[b]Lower than grand mean.

media use related to depression over time. Results were consistent with previous research and theory, though a highly nuanced picture emerged.

In the High Risk Female and High Risk Male classes, social media use was a risk factor, though it may be so for different reasons. The High Risk Female class did have some protective factors (compared to the High Risk Male class), including a warm relationship with their mother and good self-regulation. However, this class also had risk factors including low parental media monitoring, meaning their parents rarely discussed media content or provided boundaries around media, making it less likely they learned positive media consumption skills (Collier et al., 2016), increasing the likelihood that the time spent on social media may have been harmful. One intervention for the High Risk Female class would be helping parents learn to engage with their children to become healthy media consumers. This may be particularly important given adolescents in this class are higher in state anxiety and may be more susceptible when interacting with social media in negative ways. For this more anxious class, even fewer or infrequent negative social media incidents may have an outsized impact, causing them to ruminate on negative events for longer periods of time.

The High Risk Male class had similar high levels of depression. However, in contrast to the High Risk Female class, this class experienced parental hostility and were bullied by peers, both of which are related to negative mental health (Franck & Buehler, 2007; Macalli et al., 2021). Additionally, this group had a highly reactive physiological profile—meaning their bodies have stronger reactions to stressors. For this class with several risk factors, spending a moderate amount of time on social media might increase connection with others (Mitev et al., 2021), especially if they do not get positive connection from their parents or peers. Some social media might have been a respite from the stress these individuals experienced, especially if they had positive interactions online (Naslund et al., 2016). However, spending a high amount of time on social media might be maladaptive.

The other three classes had much lower depression trajectories over time. However, they are each unique in terms of social media and other predictors. The reactive physiologic profile (greater sensitivity to context) coupled with a supportive environment of the Very Low Risk class (Class 4) would, as was found, be hypothesized to be associated with better outcomes. Further, having positive relationships with parents and being more critical consumers of media may have mitigated media effects and/or enabled them to tune into the supportive environment, benefiting substantially from it. This was the only group where 2–3 h of use was related to a reduced trajectory of depression over time. Some research indicates that a moderate use of digital technology may not be inherently harmful but instead help adolescents in a digitally connected world (Przybylski & Weinstein, 2017). Given greater media use monitoring (which includes directing that use) from warm parents, these adolescents' social media use may have been more positive and therefore greater use may have been related to less depression. Since victimization is low, it may be they are had more positive interactions online that strengthened connections and led to positive mental health (though this would need to be examined in future research).

The Low Risk and Moderate Risk classes had similar depression levels at Wave 3, though the Moderate Risk class increased more rapidly. There were other marked differences in characteristics of these classes. For the Moderate Risk class, using 3 + hours of social media was related to the strongest increases in depression over time. In other words, this group was the most susceptible. This may be due to lower levels of behavioral self-regulation which may decrease the likelihood they would disconnect from negative social media interactions. They were also more physiologically reactive, suggesting social media stressors may have uniquely impacted this group, perhaps explaining the rapid depression increase. The additional risk factor of low parental warmth may also have combined with this more physiologically reactive group to influence greater depression. Again, greater physiologic sensitivity can be a protective factor in positive environments, but a risk factor in negative ones.

Finally, in the Low Risk class, using high levels of social media was not related to growth of depression and using no social media was associated with a less steep trajectory. Despite somewhat higher parental hostility, social media use having had little effect may be due to the several personal protective factors such as having a physiologic profile indicating good regulation, good cognitive regulation skills, and less bullying.

This study has a number of implications for individuals, parents, schools, and medical professionals. Social media does not impact all adolescents the same way, especially over time. This study found social media use for young adolescents (average age being 13 years old), influencing differing depression trajectories as they age over a 7-year period. Similar research has found that early social media, and other media use, does not have the same effect on adolescents' mental well-being (including suicidality), into emerging adulthood (Coyne et al., 2021). Thus, it is important to understand the possible long-term mental health implications for early social media use, especially as adolescents start using social media at young ages.

Hence, simply encouraging adolescents to reduce screen time will likely be ineffective as there are significant differential effects. Indeed, a moderate amount of social media use was *protective* against depression, even for some of the riskier groups. This may help explain the mixed findings in literature which sometimes finds no, or little effects of time spent using social media (Coyne et al., 2021; Cunningham et al., 2021). Time spent on social media significantly negatively affects some individuals (High Risk Female class), but may be protective for others, essentially washing out or diminishing an "overall" effect. A person-centered approach identifying those most susceptible to media will likely elucidate the relationship between social media and mental health.

Individuals working with adolescents might take a holistic view when thinking about mental health and social media. Medical professionals may discuss screen time in well-child checkups and might consider a person's general neurophysiologic profile and how that might interact with screen time. For example, highly reactive individuals are more likely to develop pathological relationships with media (Coyne et al., 2015). Thus, an understanding of existing physiologic states will help medical professionals treat individuals better in the context of media and mental health. They could also discuss parenting or peer relationships to determine how and when social media might be risky compared to protective. Schools often provide digital literacy programs which may benefit from including discussions of self-regulation in the use of digital media. Finally, parents have many decisions to make in terms of helping their child become a healthy media consumer. It would be helpful to understand their child's personal risk and protective factors to encourage critical thinking around media and choose what level to engage with social media in general. Understanding physiology may also help, particularly for children who are highly reactive as there are exercises that can decrease sympathetic reactivity (Grossman & Taylor, 2007), such as meditation or mindfulness. These could be implemented by adolescents (and encouraged by parents, schools, and medical professionals) to improve stress management, particularly in the context of social media.

The development of depression in the four classes mirrors some prior research. Similar to the current study, Rawana and Morgan (2014) found depression substantially increased from age 13 until approximately age 18.5 with depression leveling off in these later years (see also Hankin et al., 2015). However, they also found depression then decreased into the early 20's. It may be, had our sample been older at the later waves, this later decrease would have been identified.

Limitations of this study included not examining social media context (these data were not available). Future research should examine the context of social media over time as related to longitudinal growth of depression. Additionally, social media use was a single item self-reported measure. Though self-reports tend to be moderately reliable (Andrews et al., 2015), there is likely some misestimation (with some adolescents underestimating, including those with greater social desirability; and others overestimating, including those with higher levels of depression) of social media time (Ivie et al., 2020; Seabrook et al., 2016). Recent research is beginning to use passive sensing apps to more accurately capture screen time on various apps—however, this technology did not exist when the study began. Future longitudinal research should utilize this technology to build on this study.

This study also must be seen within its historical context. When the question of social media use was initially asked, there were few options for social media (although more options became available over the years) and much of it was accessed on a desktop computer—smartphone ownership being more rare (compared to 9 in 10 adolescents owning a smartphone in 2021; Rideout et al., 2022). Further, average social media use has increased over time (Rideout et al., 2022) and there may now be more individuals in the higher categories of use. For example, 1 year into COVID-19, there was a 7% increase in the number of adolescents who had social media and a 5% increase in reports of using it daily (Rideout et al., 2022). Since the context of the pandemic has shifted how people communicate and connect (Saud et al., 2020), it may be more normative for more adolescents to use social media and at higher rates. According to the digital goldilocks hypothesis, adolescent social media use is a normal part of them navigating and participating in the digital world, which can help them socially and psychologically adapt (Przybylski & Weinstein, 2017) so they do not experience the fear of missing out (Zhang et al., 2021). The current study provides direction for future research by demonstrating social media use is longitudinally related to mental health and identifying protective and risk factors but could be further assessed using more current social media platforms and trends of use.

This study should also be seen within the developmental period covered: mid-adolescence to emerging adulthood, a period of rapid changes. The relationship between social media and mental health should also be examined during more stable developmental periods. Similarly, it may be that the relationship between social media use and depression changes over time and has reciprocal effects. Cross-lagged panel models would be particularly useful to determine this. This would also address the issue of the changing nature of social media over time. The effect of social media may differ as social media continues to evolve.

A final limitation is the sample size. Mixture modeling often requires large samples with some research suggesting that for mixture regression, over 1000 is ideal (Jaki et al., 2019), though other research appears to indicate 300 may be sufficient (Andrews & Currim, 2003). A primary concern is identifying spurious classes. However, given we used numerous predictors of class that significantly differed across class, this risk is attenuated. Further, class characteristics are conceptually in line with other research making it less likely we have identified a spurious class. Still, larger samples sizes would be important in replicating results.

Despite these limitations, our person-centered approach provides a unique examination of early social media use and depression across adolescence and into emerging adulthood. Each individual has a differential susceptibility to social media use. This study helped elucidate what factors might play into certain profiles to make social media more risky or protective. Social media is one of many potential risk factors to the development of significant depression over time. This study may provide direction in using social media, even from young ages, in the most protective ways depending on personal characteristics, potentially leading to better mental health collectively.

ACKNOWLEDGMENTS

We thank the Family Studies Center at BYU, the School of Family Life, and the College of Family, Home, and Social Sciences at BYU, and recognize the generous support of the many private donors who provided assistance for this project. We also thank those families who were willing to spend valuable hours with our team in interviews and the many students who assisted in conducting the interviews.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Sarah M. Coyne http://orcid.org/0000-0002-1403-8726
Megan Gale http://orcid.org/0000-0002-0253-0481

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Dyer, W. J., Coyne, S. M., Gale, M., & Sheppard, J. A. (2024). Who's most at risk? A person-centered approach to understanding the long-term relationship between early social media use and later depression across adolescence. *Journal of Adolescence*, *96*, 1555–1568. https://doi.org/10.1002/jad.12362