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Instagram Abuse and Deficient Emotion Facial Recognition Explain Young Adults' Affective Depressive Symptoms

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ABSTRACT

Objective: Extant research suggests that women report higher levels of depression than men, and affective symptoms of depression (ASD) increases as self-esteem decreases. Some data also suggest that ASD grows with age into the 20's. Besides replicating such findings, this study sought to determine whether self-reported abusive consumption of Instagram and objective emotion facial recognition deficit in Gen Z Young adults might explain the variance of ASD above and beyond that accounted for by demographic factors and self-esteem alone.

Methods and Materials: Forty-eight students in a Midwest university volunteered to participate. Participants completed a demographic form, the Rosenberg Self-Esteem Scale, an adapted version of Andreassen et al.'s (2012) Bergen Facebook Addiction Scale, two sub-scales of Soto and John's Big Five Inventory-2 (2017), and an objective recognition task of 20 pre-selected facial expressions of basic emotions taken from Ekman and Friesen's (2003) validated sample.

Findings: As predicted, multiple regressions initially replicated earlier correlation reports of biological sex, age, and self-esteem in predicted directions. After adding all factors in the full model, R2 significantly increased to 41%.

Conclusion: The results suggest that both self-perceived Instagram abuse and deficient objective emotion facial recognition play a critical role in young adults' ASD. A three-pronged recommendation is made for effective prevention of depression in this age group.

Keywords: *Depression prevention; Generation Z; Instagram abuse; emotion facial recognition; social media co-regulation.*

1. Introduction

Relative to prior generations, the current iGen (or, Generation Z), born between the late 1990s and early 2010s (Twenge & Campbell, 2018), has been experiencing a significant increase in major depressive disorder (MDD), according to national Gallup data (Tang et al., 2025; Witters, 2023), but often symptoms remain under the diagnostic radar. A series of studies of depressive symptomatology in community samples using age-period-cohort (APC) analysis detected millennial-Gen Z cohort differences for college-age adults after controlling for both age and time effects for over a decade prior to Covid-19 (Udupa et al., 2023). Persistent negative emotionality such as pessimism and sadness has been shown to interfere with college students' academic performance (Strack et al., 1985) and engagement (Tang & He, 2023). When combined with emotional volatility expressed through irritability and mood swings, they can also detrimentally impact social interactions and quality of life, or even flag a history of suicidal attempts (Balbuena et al., 2016; Fava et al., 2010). It is therefore very important to determine which specific factors are associated with these affective symptoms of depression that may direct preventative efforts for non-clinical samples transitioning into adulthood.

One social demographic factor in depression and its symptoms that has been well established is sex. Specifically, from puberty through the 20's, women across many nations around the globe have been found to present an incidence of diagnosed MDD fluctuating around twofold that of men at the same age (Albert, 2015; Labaka et al., 2018; Nolen-Hoeksema, 2001; Salk et al., 2017), but when looking into depressive symptomatology below the diagnostic threshold, Salk et al. (2017) reported a lower but still significant odds ratio favoring women (Salk et al., 2017). Albert (2015) believes that the generalizability of this male-female difference across nationalities suggests a more preponderant role for biological forces in depressive symptoms linked to sex than for culture, race, or education (Albert, 2015). Moreover, in a recent systematic review, Labaka et al. (2018) suggested that levels of neurotrophic, inflammatory, and serotonergic markers of depression tend to be higher in women than in men, which may also explain why women usually show a stronger correlation between levels of certain inflammatory and neurotrophic factors and severity of depressive symptoms than men (Labaka et al., 2018). Therefore, in the present study we used biological sex as a covariate in our model to explain individual differences in symptoms of depression. Specifically, we hypothesized that women would report higher affective symptoms of depression (i.e., negative affect, emotional volatility) than men.

Age is another demographic factor explored in research on the trajectory of depressive symptoms. Some data (Kwong et al., 2019) show a significant rate increase for depressive symptoms during adolescence followed by a plateau in the 20's, and then a decline, but others (Klein et al., 2013) have found mixed evidence on such changes and recommended caution about not all studies properly accounting for subtypes of depression, or distinguishing between diagnosed mood disorders and nonpathological dysphoria or subthreshold symptoms in young samples. We therefore added the age of participants as a second demographic covariate in our model and predicted a mild but significant increase in affective symptoms of depression with age.

Another well-established factor in the depressive symptomatology of college-age individuals is self-esteem. A number of studies (Abramson et al., 1978; Franck et al., 2007; Orth & Robins, 2013; Orth et al., 2008; Sowislo & Orth, 2013) have reported that self-esteem explains a significant portion of the variability in depressive symptomatology, so that the lower the self-esteem, the higher the self-reported depressive symptomatology. Yet, some researchers claim that how self-esteem is measured (e.g., implicit vs. explicit; or, global vs. domain/context-specific) can make a difference in its prediction of depressive symptoms (Franck et al., 2007). So, we also included global self-esteem as a third covariate in our model of affective symptoms of depression. We expected that participants would report higher rates of negative affect and emotional volatility as their self-esteem rates diminished.

Less studied than sex, age, or self-esteem are the abusive consumption of social media and the diminished recognition of emotional facial expressions as potential explanatory factors in the affective symptoms of depression. College-age adults are in a developmental phase which, among other traits, is characterized by seeking to gain financial as well as decision-making independence, which are essential for self-responsibility, especially in individualistic cultural contexts such as the USA (Arnett, 2004). Technology (social media use in particular) is one domain for responsible decision-making explored in research. To date, studies on social media use and abuse have heavily relied on the Facebook app, combined with smartphone abuse and virtual matchmaking as part of a broader problematic Internet use,

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which has been linked to depression (Sayeed et al., 2023). As Facebook use becomes heavier and more problematic, more time is spent on upward social comparisons, which have been reported to play a role in increased symptoms of depression (e.g., (Alfasi, 2019)). However, as Gonzales and Hilcock's (2011) data suggested, if users devote their attention to editing their profile instead of just browsing their feed, state self-esteem may rise, which may protect against depressive symptomatology (Gonzales & Hancock, 2011). Furthermore, recent Pew Research Center data suggest that among iGeners (ages 18-29; today's young adults), Instagram is the most preferred platform (i.e., about 78%), well above the rates for both Snapchat (65%) and TikTok (62%) (Gottfried, 2024). Research exploring the potential implications for affective symptoms of depression as young adults' Instagram use grows heavier and more problematic is still scarce (e.g., (Nimbalkar et al., 2025)). Therefore, in the present study we focus on young adults' levels of Instagram abuse as an important explanatory factor in affective depressive symptomatology; we predicted that such symptoms would increase as a function of more abusive self-reported Instagram consumption.

Finally, in recent years researchers have sought to specify social cognitive deficits which may contribute to individuals' social isolation, a common factor in the onset and maintenance of depressive symptoms (Cheeta et al., 2021) as well as in the increased abuse of social media by young adults (Primack et al., 2017). In particular, and most relevant to the present study, the recognition of emotions in facial expressions has been reported to significantly differentiate between research participants who are healthy and those with a diagnosis of MDD. In fact, a recent meta-analysis including 23 studies in English with 516 dysthymic/depressed participants and 614 euthymic controls led researchers to conclude that multiple studies "support the existence of a broad facial emotion recognition deficit in individuals suffering from unipolar depression" (Krause et al., 2021). Yet, the authors qualified their conclusion in that the facial emotion recognition deficit was significantly more pronounced in the more severely depressed patients than in those with mild or moderate levels of depressive symptoms, and especially more so among inpatients than outpatients. Evidence for a negative relation between objective facial emotion recognition and self-reported affective symptoms of depression in community samples of young adults still awaits empirical support, as far as we know.

Furthermore, Monferrer et al. (2023) reported that the deficient facial emotion recognition of depressive patients was worse the younger their age at the MDD diagnosis, such that those diagnosed between ages 20-39 years had more difficulty recognizing basic emotions than those diagnosed either at middle age (40-59) or older (60+). Furthermore, the authors reported greater recognition deficits in the MDD group relative to the healthy group for specific emotions such as fear, sadness, and disgust, as compared to other basic emotions (Monferrer et al., 2023). Therefore, in the present study, we added deficient recognition of facial emotion expressions as another key factor in our model for explaining affective symptomatology of depression in young adults, and we also explored how fear, sadness, and disgust might have a differential negative relation with levels of affective symptoms of depression.

In summary, based on the reviewed literature, the following specific hypotheses are tested in the present study with young adults:

1. Biological sex will significantly relate to self-reported affective symptoms of depression (negative affect, emotional volatility) so that being a woman will be associated with higher symptom levels than being a man.
2. Age of young adult participants will relate positively with self-reported affective symptoms of depression.
3. Global self-esteem will negatively relate to affective depression symptoms, so that the lower the self-reported self-esteem the higher the affective symptoms of depression.
4. As participants' Instagram consumption grows more abusive, so will their affective symptoms of depression.
5. In general, facial emotion recognition will relate negatively with affective symptoms of depression, more so for the sub-set of fear, sadness, and disgust.

2. Methods and Materials

2.1. Sample

The study protocols were approved by the Research Participant Protection Program/Institutional Review Board of the institution of higher education to which the authors were affiliated; the methods followed the APA standards for research. Recruitment of participants was done via e-mail and word of mouth; those who agreed to participate signed an Informed Consent Form and had their names entered in a draw for a $ 25 gift card. Preliminary G*Power statistics (Faul et al., 2007) indicated that a minimal sample size of 73

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was required for 90% statistical power in a multiple regression test with α at .05 and 5 predictors to detect a significant increase in R^2. However, only 48 participants volunteered to be in this study, with 28 identified as Women and 20 as Men; no participant identified as having "Other" sex. We attribute the somewhat low response rate to time constraints and to the fact that instructors turned down our request for academic credit as an incentive for research participation.

All participants attended a private liberal arts college in the Midwest and volunteered to participate in this study in response to an email invitation from their instructors (i.e., cluster sampling, cf. (Cozby & Bates, 2024)). Participants reported their age to be from 18 to 28 years, with a mean of 18.9 (*SD* = 1.72). Sampled participants reported their race to be 85.4% White, 4.2% Black, 2.1% Asian, and 8.2% mixed (see Table 1). Both fathers and mothers of participants were reported to have a modal (54.2% and 62.5%, respectively) completed college or higher level of education, as shown in Table 1.

Table 1

Demographic Characteristics of Participants(N=48)

Characteristic		*N*	%	*M*	*SD*
Sex					
	Male	20	41.7		
	Female	28	58.3		
	Other	0	0.00		
Race					
	White	41	85.4		
	Black	2	4.2		
	Asian	1	2.1		
	Mixed	4	8.2		
Father's completed education					
	Elementary or Middle School	2	4.2		
	High School	20	41.6		
	College or Higher	26	54.2		
Mother's completed education					
	Elementary or Middle School	1	2.1		
	High School	17	35.4		
	College or Higher	30	62.5		
Age in years				18.90	1.72
Number of years in school				13.59	1.00

2.2. Measures

In addition to providing paper-and-pencil demographic information (biological sex, age, years in school, parental education, etc.), participants used a Google Form on a laptop to report on their global self-esteem, Instagram use, and affective symptoms of depression. Their accuracy of recognition of emotion facial expression was objectively measured using standard, previously validated photographs of both men's and women's faces displaying various basic emotional expressions. The order of the scales was digitally shuffled at two points during the data collection, except that demographics were always collected first. Participants' emotional expressions while using Instagram were also collected via video recording, but they are not included in the present study. Average scores were used for missing data.

2.2.1. Self-Esteem

Participants completed the widely used Rosenberg Self-Esteem Scale (RSES, (Rosenberg, 1979)) as a measure of their global self-esteem. A 4-point Likert scale (1 = strongly agree; 4 = strongly disagree), the RSE contains 10 statements tapping a single factor on the respondent's self-perceived confidence or satisfaction with themselves as a person, as well as with their ability to do things. Sample items are: "At

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times, I think I am no good at all" (reversed) and "I am able to do things as well as most other people" (Rosenberg, 1979). Although conceptualized as a Guttman scale with a guided scoring procedure, the author also encourages the alternative simple totaling of all item scores, after the required reversal of some of them, which was the adopted procedure in this study. In the original scale the higher the scores, the lower the level of self-esteem, but in the present study, items were multiplied by -1 so that higher rates denoted higher self-esteem.

The Cronbach's α for this sample was very good at .89, which is at the upper end of those reported in other studies done in the USA, which range from .72 to .88 (Gray-Little et al., 1997). In terms of criterion validity, the RSE measure correlates moderately with the Single Item Self-Esteem scale (SISE, r values between .72-.76; (Robins et al., 2001)) and with the Coopersmith Self-Esteem Inventory (CSEI, $r = .52$; (Francis & Wilcox, 1995)). The latter is not impressive, but Francis and Wilcox (1995) believe that the reason lies in that the RSE taps *global* self-esteem, whereas the CSEI measures attitudes toward the self in *specific contexts* such as the family, peers, school, etc (Francis & Wilcox, 1995).

2.2.2. *Instagram Abuse*

The Bergen Facebook Addiction Scale (Andreassen et al., 2012) was adapted by simply replacing Facebook with its sister app, Instagram in each item. In both forms, this scale contains only 6 items, each one tapping one of the six core dimensions of addiction (or abuse) put forth by Brown (1993) and Griffiths (1996), as cited by the authors (Brown, 1993; Griffiths, 1996): 1) Salience – the extent to which a behavior dominates one's thinking and activities; 2) Mood Change – the extent to which the behavior in question improves one's subjective mood; 3) Tolerance – the extent to which raising the frequency of the behavior becomes necessary to produce previous effects; 4) Withdrawal – when the behavior is suddenly reduced or stopped, how much unpleasant feelings tend to occur; 5) Conflict – the extent to which the behavior generates conflict in relationships, work, or education; and 6) Relapse – the extent to which one tends to revert to earlier behavioral patterns after abstinence or some degree of control (Brown, 1993). The items involve 5-point Likert-type response options, with anchors of 1 = Very rarely, and 5 = Very often (Andreassen et al., 2012). Sample items in this study with Instagram read as follows: "How often during the last year have you felt an urge to use Instagram more and more?" and: "How often during the last year have you become restless or troubled if you have been prohibited from using Instagram?"

Andreassen et al. (2012) reported a Cronbach's α of .83 and a three-week test-retest reliability of .82, along with data supporting a single factor solution for the scores on the BFAS; they also reported good concurrent validity, as evidenced by a correlation of (Andreassen et al., 2012).69 with the Addictive Tendencies Scale by (Wilson et al., 2010). In the present sample, the Cronbach's α for the Instagram Abuse Scale (IAS) standardized items was a bit lower, at .76, but still above the "acceptable" cutoff point of .70, especially considering how short this scale is (Cortina, 1993).

2.2.3. *Facial Emotion Recognition*

Facial emotion recognition was objectively measured through 20 black-and-white photographs selected from Ekman and Friesen's Chapter 10 of *Unmasking the face: A guide to recognizing emotions from facial expressions* (2003), with model men and women displaying facial expressions for the basic emotions of happiness/joy, anger, fear, surprise, sadness, neutrality, and disgust. The authors standardized and validated all images of facial emotion expressions in their book. In the present study, the images were degraded through a filter for reduced visual contrast by 25% so that the recognition task would get a little more difficult and produce better variability of scores, after Andric et al.'s (2016) similar procedure. Participants were given a multiple-choice test asking them to identify the emotion in each one of the 20 faces (Andric et al., 2016). Possible scores ranged from zero to 20 accurate answers; the present sample scored from a lowest of 9 to a highest of 18, with a mean of 13.8, $SD = 1.99$.

2.2.4. *Affective Symptoms of Depression (ASD)*

Two sub-scales from Soto and John's Big Five Inventory-2 (2017) were used in combination to measure the participants' affective symptoms of depression: Depression and Emotional Volatility. Along with another sub-scale, Anxiety, these two are conceptualized by the authors as facets that load on one of the "big five" factors of personality, namely Negative Emotionality. Each sub-scale contains 4 items involving short clauses that complete the sentence presented at the top of the scale: "I am someone who…." Participants answer with a Likert scale from 1 (= Disagree strongly) to 5 (= Agree strongly) applied to items such as: "…often feels sad" (Depression sub-scale); and:

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"…keeps their emotions under control" (reversed, Emotional Volatility sub-scale). The authors report an excellent Cronbach's α of .90 for the entire Negative Emotionality scale with 12 items. The present sample yielded Cronbach's α of .74 and .69 for the Emotional Volatility and Depression sub-scales, respectively. The two sub-scales correlated significantly at r = .66 (p < .001), which justified combining the scores. The longer scale for Affective Symptoms of Depression with 8 items had a Cronbach's α of .82 in this sample. Soto and John (2017) also provide data supporting both domain-level and facet-level convergence with other Big Five measures, such as their original BFI and the NEO-FFI and PI-R (Soto & John, 2017).

2.3. Design and Data Analyses

This study used a non-experimental, cross-sectional design (Cozby & Bates, 2024). A series of hierarchical regression analyses was used in order not only to replicate previous reports of demographic and Self-Esteem effects on the participants' ASD, but also and mainly to determine how much more Instagram Abuse and deficiencies in Facial Emotion Recognition would add to these covariate effects. Model 1 comprised the three covariates in the regression model: Biological Sex (dummy coded as Male = 0, Female = 1), Age in years, and Self-Esteem (RSE scale). It tested Hypotheses 1-3. Model 2 tested Hypothesis 4 by entering the measure of Instagram Abuse (IAS) to the regression equation, and Model 3 tested Hypothesis 5 by entering the Facial Emotion Recognition Test (FERT) to the regression equation. Hypothesis 5 was further tested through examining the bivariate correlations of ASD with the FERT scores involving images for fear, sadness, and disgust, relative to other basic emotions. Each one of three participants left an item blank in their FERT; they were marked as zero, like in any achievement test with only one acceptable answer when a respondent omits a question. Missed responses in the RSE and IAS (Likert scales) were filled in with average scores.

3. Findings and Results

3.1. Model 1: Covariates

The initial model in the hierarchical regressions was statistically significant, $F_{(3, 44)} = 5.93$, $p = .002$ and explained 29% of the variance in participants' self-reported ASD (see Table 2). Table 2 also shows that each explanatory variable had a significant unique effect in the predicted direction of Hypotheses 1-3. Specifically, Sex had a β weight of .29, p = .029, so that women reported significantly higher levels of ASD than men; Age had a β weight of .28, reflecting a modest but significant increase in ASD with age, p = .036. After multiplying RSES scores by -1 (so that higher scores would reflect higher self-esteem), RSES had a negative effect on ASD, with a β weight of -.29, p = .027. Therefore, this initial model replicates previously reported effects of these factors related to the ASD of American young adults.

Table 2

Multiple Regression Analysis (N=48)

Model	Variable	B	SE B	β	p	F	df1	df2	R²
Model 1	Constant	–0.802	—	—	.684	25.927	3	44	.29
	Sex	0.790	.351	.29	*.029				
	Age	0.219	.102	.28	*.036				
	RSET	–0.661	.290	–.29	*.027				
Model 2	Constant	–2.158	—	—	.299	5.495*	4	43	.34
	Sex	0.658	.349	.24	.067				
	Age	0.241	.100	.30	*.020				
	RSET	–0.667	.282	–.30	*.023				
	IAS	0.436	.241	.23	.077				
Model 3	Constant	2.319	—	—	.410	5.842*	5	42	.41
	Sex	0.935	.356	.34	*.012				
	Age	0.152	.103	.19	.148				
	RSET	–0.606	.271	–.27	*.031				
	IAS	0.475	.231	.25	*.046				
	FEERT	–0.212	.094	–.31	*.029				

Note. RSET = Rosenberg Self-Esteem Test; IAS = Instagram Abuse Scale; FERT = Facial Emotional Recognition Test

$^{*}p < .05$, $^{**}p < .01$, $^{***}p \leq .001$

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3.2. Model 2: IAS

Hypothesis 4 predicted that as participants' self-reported use of Instagram grew heavier and more problematic, their ASD rates would also increase. The addition of the IAS scores to the regression equation produced an R^2 of .34 (R^2_{Adj} = .28), with $F_{(4, 43)} = 5.5$, $p = .001$. However, the change in R^2 was but marginal with a p value of .077, and the unique effect for IAS likewise was marginal, β = .23, $p = .077$, as shown in Table 2. So, Model 2 data did not significantly support Hypothesis 4. Interestingly, in this model, Sex effect dropped to a non-significant level, suggesting some suppressor effect for IAS on Sex in the explanation of individual differences in ASD (Watson et al., 2013).

3.3. Model 3: FERT

Hypothesis 5 predicted that participants' self-reported ASD scores would grow as a function of objective deficiencies in facial emotion recognition, as measured through the FERT. In fact, like the two previous models, Model 3 was also statistically significant, $F_{(5, 42)} = 5.84$, $p = .000$, and accounted for 41% of the variance in ASD, as shown in Table 2. Furthermore, unlike in Model 2, the increase in R^2 for Model 3 was statistically significant, $F_{(1, 42)} = 5.12$, $p = .029$, and FERT had a significant unique effect in the predicted direction, with β = -.31, $p = .029$. Sex had a β of .34, $p = .01$. Also importantly, in the Full Model, IAS unique effect grew to a statistically significant level (β = .252, $p = .046$); indeed, all explanatory variables except for Age had a significant unique effect on ASD in the directions hypothesized in this study (see Table 2).

3.4. Fear, Sadness, and Disgust

Table 3 summarizes the participants' objective accuracy scores (Means and *SD*s) for facial emotion recognition involving each basic emotion that was measured, as well as the zero-order correlations between ASD and recognition accuracy of each emotion. Consistent with the second part of Hypothesis 5, the negative correlation between ASD and Disgust was statistically significant, suggesting that deficient recognition of disgust relates to increased ASD. However, recognition deficit of neither Fear nor Sadness had any statistically significant correlation with ASD, contrary to our prediction.

Table 3

Descriptive Statistics and Correlations for Each Basic Emotion Facial Expression Recognition and ASD (N=48).

Variable	*M*	SD	1	2	3	4	5	6	7	8
Happiness	.990	.072	—							
Anger	.743	.241	-.16	—						
Fear	.549	.296	-.06	-.14	—					
Surprise	.840	.228	-.10	.18	-.01	—				
Sadness	.576	.236	-.06	.50***	-.05	.21	—			
Neutral	.865	.225	-.09	-.00	.34*	-.02	-.24	—		
Disgust	.516	.239	-.15	.10	.20	-.02	.15	.14	—	
ASD	5.104	1.362	0.11	-.07	-.20	.04	-.01	-.05	-.35**	—

Note: ASD = Affective Symptoms of Depression.
*$p = .017$, **$p = .016$, ***$p = .000$

4. Discussion and Conclusion

Because data from clinical samples may underestimate the real picture of US college students' wellbeing, the American College Health Association's National College Health Assessment has examined depressive symptomatology in community samples, revealing that "68% of students reported they 'felt very sad' at some time within the last 12 months" and "41% reported they 'felt so depressed that it was difficult to function' at some time within the last 12 months" (Quinn et al., 2023). The present study sought not only to replicate earlier findings that Age, Biological Sex, and Global Self-Esteem contribute to Affective Symptoms of Depression (ASD – i.e., persistent negative affect and emotional volatility) in young adults, but also to determine whether and to what extent Instagram Abuse and diminished Facial Emotion Recognition explain individual differences in ASD above and beyond that accounted for by demographics and self-esteem alone. We hoped that these findings would illuminate preventative efforts with young adults in the USA.

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4.1. The Role of Demographics and Self-Esteem

The hierarchical regression results for Model 1 corroborated prior reports that women develop higher levels of depressive symptoms than men (Nolen-Hoeksema, 2001; Salk et al., 2017)), and that such symptoms tend to grow with age up to the early 20's (e.g., Kwong et al., 2019). Corroborative sex difference data on ASD are important, given that Sarks, Hyde, and Abramson (2017) found just a modest women-men difference for individuals with sub-clinical levels of dysthymia, contrary to the much stronger sex difference often reported for clinical samples (Abramson et al., 1978). Likewise, the finding on the growth of ASD with age important because it addresses Babajide et al.'s (2020) concern that often depression studies focus on either adolescents (ending at about age 18) or adults within a very wide age range, but seldom do they look into young adults (i.e., 18-late 20's), as done in this study (Babajide et al., 2020).

In addition, Model 1 data also supported earlier reports (e.g., (Abramson et al., 1978; Orth et al., 2008)) that the lower participants rate their self-esteem, the higher their ASD scores tend to be. Together, the three factors (Sex, Age, and Global Self-Esteem) in Model 1 accounted for 29% of the variance in ASD and supported Hypotheses 1-3.

4.2. The Role of Instagram Abuse

The data suggested that the role of self-reported Instagram Abuse in ASD is a little more nuanced. Model 2 was statistically significant but did not yield a significant increase in R^2 after the inclusion of IAS in the regression equation. Also, IAS had but a marginal effect on ASD. However, in the full model with all factors included, the effect of IAS rose to a significant level, suggesting that as participants' self-perceived abuse of Instagram increases by one standard deviation, their ASD rates grow significantly by .252 (Model 3 in Table 2). This finding supported our Hypothesis 4, and we think that two mechanisms highlighted by Boers et al. (2019) may be involved (Boers et al., 2019). First, as with the Facebook app (Alfasi, 2019), Instagram abusers may spend much time browsing their feed, which allows much of their attention to focus on featured images that make others seem to have perfect bodies and material possessions, or idealized lifestyles, thereby making them wonder, through social comparison, whether they are falling behind. In this way, upward comparison may be deflating Instagram abusers' self-esteem and fostering in them negative emotions which tend to persist and disrupt their emotional regulation (i.e., the ASD pattern in this study), as their abuse intensifies.

Second, "reinforcing spirals" may be formed between media selectivity and media effects that impact on Instagram abusers' screen time behavior and personal traits (Slater, 2007). As Boers et al. (2019) proposed, algorithm-based content feeding, such as that used by Youtube, Netflix and other video streaming service providers, is also present in Instagram, forming a "closed system" (or, filter bubble) that keeps suggesting new content that abusers are likely to be interested in, based on prior searches and selections (Boers et al., 2019). And the more Instagram abusers consume the newly suggested media, the more addicted they become to a particular genre of media that reinforces their social identity. In this way, young adults with ASD tendencies may be drawn to Instagram, and as their content selection keeps on reinforcing their ASD, the more time they tend to spend on Instagram. This pattern seems consistent with Boers et al.'s report of increased depressive symptoms in adolescents for each 1-hour increase in their abuse of a variety of social media.

Regardless of whether either social comparison or reinforcing spirals, or both of these mechanisms are in effect, recent Pew Research data (Anderson, 2024) suggest that 51% of US Americans wish that social platforms were regulated by an official, government-appointed body, and their reason seems to be grounded on the concentration of power in the hands of big technological companies that may be influencing the political direction in this nation. While this may be an important reason, the present study adds a concern about young adults' wellbeing and mental health as another very important reason. From a developmental standpoint, in the context of a democratic, free society, we think that the control of Instagram use needs to be reasonably shared among individual young adult users (or abusers) and a government-appointed body, if one is ever going to be in place. These two should be able to coexist, as in fact it is already the case with other addictive behaviors in the transition from adolescence to adulthood.

4.3. The Role of Facial Emotion Recognition (FERT)

Model 3 in this study extends earlier findings with clinical samples on a link between depressive symptoms and objectively deficient facial emotion recognition to a community sample of US young adults. As predicted in Hypothesis 5, as recognition accuracy of emotional expressions in faces decreases, young adults' ASD rates rise significantly. Indeed, this finding seems to complement that for IAS (Hypothesis 4) in this study: As young adults' facial emotion recognition diminished by one standard deviation, their ASD rates grew by .31 unit; and as their abuse of Instagram increased by one standard deviation, their ASD rates grew by .252. These results are intriguing as Models 2 and 3 yielded contrasting results for IAS. Specifically, the rise of the IAS unique effect after the inclusion of the participants' FERT scores in the regression equation is indicative that the effect of the former may be exacerbated at participants' different levels of FERT. By contrast, the drop in age effects to a non-significant level in the final model leads us to conclude that the explanatory factors used in this study do not seem to depend on varying participants' age.

4.4. *Differential Basic Emotion Effects*

Monferrer et al.'s (2023) recent report of greater objective deficit in facial emotion recognition for fear, sadness, and disgust than for other basic emotions in MDD patients was only partially corroborated by the present study with non-clinical participants (Monferrer et al., 2023). Specifically, our results suggested that ASD rates increased significantly as objective recognition of disgust in human faces diminished, but similar correlations were not statistically significant for fear, sadness, or any other measured emotion. Regardless of the mental health of participants, facial expressions for disgust have been notoriously more difficult to recognize than for any other basic emotion (e.g., (Ekman & Friesen, 2003)), and therefore we should not be surprised with the present results.

Based on the results, we believe that social isolation may be involved in the higher affective depressive symptoms of Gen Z young adults to the extent that Instagram abuse may be robbing them of essential three-dimensional, in-person interactions with others which are necessary for the recognition of emotional expressions in human faces. Given that FERT is an important element for both intrapersonal and interpersonal understanding and effective social functioning at school, work, and many other contexts (Kafetsios & Hess, 2023), preventative efforts should also target direct training in the reading of one's own and others' emotion facial expressions. Incorporated into a more comprehensive social skill training program to Gen Z young adults, as ASD declines, facilitation of "soft skills" can also take place for more effective communication, interactional skills, and professional navigation in complex social situations in the workplace that would meet prospective employers' expectations (Zilber, 2024).

Rather than vilifying Instagram or social media, however, we propose that it is only when technology-mediated interactions replace or weaken direct, face-to-face experiences that this study's FERT and IAT data pattern relative to ASD will be manifested. The results seem to endorse the wisdom of moderation, which ASD preventative interventions should emphasize. Young adults are encouraged to be savvy consumers of social media who avoid both the high salience of these platforms in their daily lives and their frequent overuse, thereby releasing time for direct social interaction with others at school, work, and other contexts.

5. Limitations and Future Directions

This study had some limitations, two of which need to be addressed in future studies. First, it was our intention to have a larger sample, but time and other practical constraints led to a limited pool of 48 participants, thereby limiting statistical power. Despite the limited statistical power, however, it is noteworthy that most statistical tests still came out significant providing important information on the risk for ASD increase associated with self-perceived Instagram abuse and an objective measure of deficient emotion facial recognition. Future studies with a similar number of explanatory factors as those in our full model should consider having a larger sample for better estimated parameters in the population. In addition, future research with a larger sample should be able to explore how Instagram abuse may interact with the diminished ability of participants to recognize emotional expressions in faces and possibly also consider the role of social isolation and decline in the maintenance of key human connections, characteristics which have grown much more pronounced in those growing up in a digital age, such as Gen Z (see the (Report, 2023)).

This study is a significant step toward explaining affective depressive symptoms in non-clinical young adults in the USA as a function of both self-reported abusive Instagram consumption and objective deficit in recognition of emotional expressions in faces, above and beyond participants' demographic characteristics and self-esteem. We think the results have three practical implications in the prevention of affective depressive symptoms of Gen Z young adults.

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First, clinical mental health counselors, instructors and others working with young adults may design preventative programs that encourage higher levels of three-dimensional, in-person interactions among them. Although further studies would be needed to support this notion, we think that more in-person, direct interactions with others would take time away from abusing Instagram, and in turn result in lower rates of depressive symptoms while fostering social skills. Secondly, we think that increased frequency of purposeful, meaningful direct social interactions with peers and others might give young adults more opportunities to hone their ability to read other people's emotional expressions, which in this study was an important factor uniquely contributing to higher depressive symptoms. Finally, given the addictive nature of social media such as Instagram, we support the contemporary initiative of several states to hold Big Tech accountable, to some extent, for enticing young people to become addicted through its content and consumption-based algorithms (Boers et al., 2019; Pierson, 2024). To be sure, these companies have provided some control features in their apps that may help consumers avoid problematic use, but we believe that much more can be done especially when it comes to content presentation and notification systems.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Declaration

None.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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