The Social Media Grasp: Understanding Its Mediating Relationship to Social Media Use

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Social media anxiety has become a focal point explaining continued use of social media despite aggressive social content. Using structural equation modeling, we examine a conceptual model explaining social media use that includes the constructs of social interactive anxiety, social media anxiety, and antisocial online behavior, which is divided into aggressive and non-aggressive antisocial cyber content. Our sample includes respondents of multiple age-groups that is representative of the actual social media population. We have surveyed users of six popular social media platforms including Facebook, Twitter, Instagram, Snapchat, Linked-In, and Pinterest. Results show that social anxious individuals participate more actively in social media when social media anxiety is present. Thus, despite increased social media anxiety, social anxious individuals remain online using social media platforms. We also see evidence that exposure to nonaggressive antisocial content leads to exposure to aggressive antisocial content. This aggressive antisocial content increases social media anxiety.

Keywords: social media, social media anxiety, aggressive antisocial content

INTRODUCTION

Asserting itself as one of the most prevalent social activities on a worldwide scale, both the number of participants and the time spent on social media outlets is on the rise. The number of social media users in 2022 in the USA surpassed 2.98 billon and 4.65 billion active social media users worldwide (Statista, 2022a). According to the same source, social media users in the USA accessed social media for 2.05 hours per day (Statista, 2022b). The statistics indicate that social media is an increasingly relevant method by which to exert social influence. Amongst the social media platforms, Facebook Inc., renamed as Meta in 2021 is now the parent company of Facebook, Instagram, Facebook Messenger and WhatsApp, together being known as Metaverse. Although other sites remain popular, Facebook remains the leading social media platform in terms of social media site visits. In 2021, Facebook accounted for 71.8 percent of all social media visits in 2021, with the number of daily active users on Facebook reaching 1.93 billion (Statista, 2022c). Ranking in second place was Pinterest with 12.4 percent of all social media visits, followed by Twitter and Instagram, with 9.15 percent and 3.82 percent, respectively. Most preferred among millennials and younger users are video sharing platforms, specifically Snapchat, TikTok and YouTube. The biggest web publisher on Facebook, dailywire.com, gathered 36.59 million Facebook interactions, using the common features of likes, shares and comments (Statista, 2022c).

Consequently, an increasing amount of research focuses on the implications of social media use, and all the more so, social media addiction. Though much of the literature is dedicated to prosocial positive content and its effects, negative antisocial content also exists in the Internet and deserves attention (Liu & Yu, 2013; Brooks, 2015). Antisocial behavior has serious social implications that can incur legal and financial consequences. Antisocial online behavior (AOB), is a term for any malicious behavior that can be found in the textual content on online communications platforms. Because AOB has spread at alarming rates, social media platforms are called upon to detect behavior that violate their own codes of conduct. All antisocial offensive and harmful behavior is now flagged (Zinovyeva et al., 2020).

In order to fill the gap in academic research on AOB, our study investigates the relationship between antisocial content and social media participation. We measure social media participation by asking for the number of minutes the respondent participates in social media on a daily basis. We propose a model that reflects the typical social media network dynamics where social interactions are enabled by technology and user generated content. Specifically, we examine the interrelations among face-to-face social interaction anxiety, social media anxiety, and exposure to antisocial content categorized as either nonaggressive or aggressive cyber content. We examine the intersection of face-to-face social interaction with the virtual social interaction by providing empirical evidence supporting the relationship between these types of communication. We find that social media use is reduced to a statistically significant degree by aggressive violent content and reduced to a lesser degree, in terms of effect size, degree by nonaggressive violent content. However, exposure to nonaggressive AOB leads to exposure to aggressive AOB We also confirm that social media anxiety increases social media use and acts as a mediator between individual who are fearful of face-to-face social interactions and social media use.

In the following sections, we review related literature, present a theoretical model and a series of hypotheses. We then report on our methodology and discuss our findings, implications, limitations and directions for future work.

THEORETICAL DEVELOPMENT

Social Interaction Anxiety

The social interaction anxiety (SIA) construct assesses fears of all face-to-face social interactions. Mattick & Clarke (1998), define SIA as the anguish experienced while in conversations with others, and feeling a sense of unease of not being liked because of their perceived inability to sound appealing or interesting. According to The National Institute of Mental Health website (2022), social anxiety disorder is an intense, persistent fear of being watched and judged by others. People with social anxiety disorder may experience, among other symptoms, feelings of self-consciousness or a persistent fear that people will judge them negatively. This is an unrelenting fear of social situations in which the person is exposed to unfamiliar people or to possible scrutiny by others (Zalinska & Agopian, 2022). In particular, studies addressing this phenomenon have found links to social irregularities in real life.

Social Media Anxiety

While SIA is results in the mental state of auto-criticism and an expectation that others will have the same negative perception of themselves and fear of social humiliation (Levitan, 2017), social media anxiety (SMA) may result from fears of humiliation and/or negative evaluations by other social media users in an online setting. Indeed, SIA and SMA are documented as two distinct constructs which are significant predictors of each other (Farquhar & Davidson 2014). According to Brailowvskaia &Margraf (2016), there are significant differences between Facebook and non-Facebook users regarding the association of personality traits and mental health variables, including depression, anxiety and stress symptoms. In particular, shyness and withholding traits typify individuals with low self-esteem and they rarely initiate face-to-face social interactions. Accordingly, non-Facebook users exhibited higher values of depression symptoms than Facebook users. Ndasauka et al. (2016) propose a scale to measure excessive use of the microblog, Twitter. They found a negative relationship between social interaction in the physical or "real" world and excessive use of Twitter, yet the relationship is positive when mediated by the loneliness construct. Furthermore, Satici, et al. (2014) examined the role of social competence and psychological vulnerability as determinants of controlling and limiting the time spent on Facebook. As such, we hypothesize:

H1: *Higher levels of social interaction anxiety result in higher levels of social media anxiety.*

Within the context of social media use, Lee-Won et al. (2015) found support to the claim that socially anxious individuals are more likely to become addicted to Facebook. Because of the absence of face-to-face interactions, social anxious individuals typically invest attention, time and effort in online socializing. In general, social media outlets such as Facebook are perceived as more controllable and less threatening as compared to the face-to-face interaction. More recently, Vannucci, et al. (2017) examined the relationship between time spent on social media and anxiety among emerging adults. They found a positive relationship between time spent and symptoms of anxiety. Lastly, Honnekeri & de Souza (2017) administered a self-report questionnaire to a sample of college students in India. They found that higher social phobia scores were associated with tendencies to spend more time on Facebook, inability to reduce Facebook use, impulses toward increasing use, and negative reactions to limiting its use. Consistent with previous studies, Honnekeri & de Souza (2017) deduced that Facebook (and other social platforms) are a coping mechanism for socially anxious users. Consistent with recent work, the study has found social media use has a positive effect on individuals alleviating anxiety from social exclusion.

Lin et al. (2017) conducted an experimental study on the effects of social media participation in alleviating negative feelings of social exclusion. They found that individuals scoring high in social anxiety felt less belonging satisfaction and inclusion when experiencing a condition of exclusion than individuals scoring low in social anxiety. After inclusion, individuals feeling high social anxiety felt higher meaningful existence than their counterparts. In other words, individuals experiencing higher levels of anxiety might be susceptible to higher social capital gains from social networking in order to recover from social exclusion. In a related study, Leung (2013) found narcissistic personalities were more likely to actively participate in social media outlets. He also found specific outlets such as Facebook and blogs were more prone to be selected to satisfy social and affective needs, whereas forums were the preferred outlet to vent anger or discontentment. Based on the assumption that social media outlets would promote affiliation, we expect that social anxious individuals would pursue a positive state-of-being by being more enthusiastic toward social media participation, even though they are experiencing social media anxiety.

Because social media use serves as a mechanism to facilitate and nurture social interactions without face-to-face interactions and subsequently this anonymity may serve to alleviate fears of evaluation by other users, we expect there is a positive relationship between SMA as a mediator between SIA and social media usage. During the COVID-19 pandemic, social media became a vehicle for maintaining interpersonal connectivity (Islam et al., 2022). Because everyone was forced into quarantines and lockdowns, and because face-to-face contact was prohibited and inhibited by mask-wearing, people became isolated and social media became a coping mechanism. However, researchers observed that this coping strategy can have negative consequences because it can also lead to misinformation and increased anxiety (Islam et al., 2022). This led to even more activity online. Therefore, based on the assumption that social anxious individuals would seek frequent and extended social media use as a coping mechanism when exhibiting SIA, we hypothesize:

H2: *Higher levels of social media anxiety from individuals will result in higher social media use.*

Effects of Antisocial Cyber Content

All social media platforms benefit from increased social media usage, and through hit and mis discover which elements act as motivators and which inhibit social media use. Academic researchers have developed many theoretical models to explain social media use in its many forms. Both practitioners and researchers have come to realize the duality of these models which depend on the context of social media post-adoption use (Sullivan & Ko, 2019). The context may be prosocial benefiting society but it can also be antisocial and aggressive which may lead to negative antisocial consequences.

Antisocial behavior are acts that run contrary to society, and its norms of conduct and the opposite of prosocial norms. Antisocial online behavior is present online in a variety of forms and intensity. Therefore, in this study, we adopt a taxonomy for antisocial cyber content that can be classified into two categories: aggressive antisocial cyber content (AACC) and non-aggressive antisocial cyber content (NACC), as is supported in the literature (Vitaro et al., 2015; den Hamer et al., 2017), a distinction that is necessary to distinguish amongst range of emotional responses. Accordingly, aggressive antisocial behaviors may encompass expressions of violence whereas non-aggressive behaviors may include cyberbullying or trolling, a more modern term where a person actively harasses another without actually knowing the other person (Zezulka & Seigfried-Spellar, 2016). Cyberbullying is an umbrella term that is used to encompasses repetitively harassing and threatening someone, sharing false information about someone, recording a session while a person is being bullied for circulation purpose, and denigration of someone's character (Balakrishnan et al., 2020).

With regard to nonaggressive antisocial behavior, two research streams have explored its effects, particularly among youth. One stream of research has focused on the effect of antisocial non-aggressive verbal content on predicting cyberbullying (den Hamer et al., 2014). Bullying is defined an aggression using verbal or physical means to inflicts pain (Baruch 2005; Fernandez et al., 2017), while cyberbullying refers to odious, aggressive behaviors that are displayed through electronic means to intimidate and harm a target (Cruz & Noronha 2013). All electronic devices from computers to cell phones can be used for cyberbullying in a ubiquitous manner (Fernandes et al. 2017). Sparsely studied in the literature is adult cyberbullying in the workplace, or elsewhere, but not involving children or young adolescents. Baruch (2005) who investigated workplace cyberbullying via email concluded that the electronic medium could vary, but the feelings inflicted on individuals were as real as if the bullying were conducted face-to-face. Targets of cyberbullying showed dire consequences, such as increased absenteeism, reduced job satisfaction and lowered work performance. Cruz and Noronha (2013) add psychological effects to cyberbullying including among others: "low self-esteem, sleep problems, anxiety, anger, depression, suspicion, bitterness, chronic fatigue and even suicidal thoughts" (p. 326). More recently, another study conducted by Peluchette et al. (2015) explored the effects of a number of social media practices and personality traits on cyberbullying. They found that having many friends who posted indiscreet/negative content would encourage and predict cyberbullying. Lim and Teo (2009) use the term cyber uncivility to distinguish a verbal aggression as one that violates the norms of mutual respect, but is not referring to physically violent behavior.

A second research stream focused on social media content advocating risky behavior, which have been recently studied among anorexics (Park et al., 2017), sexual conduct (Vandenbosh et al., 2015), and alcohol-use (Moraes et al., 2014) which leads to an increased tendency to watch violent content. By extension, we hypothesize:

H3a: *Higher exposure to non-aggressive antisocial cyber content will increase exposure to aggressive antisocial cyber content.*

Mood management theory states individuals are motivated to select media content that supports a positive mood state and consequently, suggests the avoidance of affective states that are not positive (Stevens & Dillman Carpentier, 2017). Because the expanding diversity of social media content, we expect that exposure to content perceived as aggressive would negatively influence the impressions and emotions of users, and consequently would lessen the user motivations to engage in social media. According to Kunimatsu and Marsee (2012), anxiety coexists more frequently with perceived social threats, particularly with certain types of relational aggressions.

H3b: *Higher exposure to aggressive antisocial cyber content will increase social media anxiety.*

On the other hand, there are users who may not experience social media anxiety who will reduce their willingness to participate in social media because extended exposure to aggressive content. Thus, we hypothesize:

H3c: *Higher exposure to aggressive antisocial cyber content will decrease social media use.*

RESEARCH METHODOLOGY

Research Model

A graphical summary of the hypotheses shown in Figure 1 below represent each of the proposed relationships as can be seen with the arrows and the plus or negative sign will indicate a proposed positive or inverse relationship. The various paths form our conceptual model which was tested using structural equation modeling in AMOS 27.

Participants

To test the proposed model, we conducted a cross-sectional design using an anonymous web-based survey method for data collection. A pretested online survey questionnaire was administered in the US using the Qualtrics survey administration platform. The initial set of respondents was composed of university students attending two universities located in Texas. Subsequently, respondents of this study were instructed to use a snowball method to recruit more participants. A total of 447 complete questionnaires were returned. Sample demographics are shown in Table 1. Our sample is 59% female vs. 41% male, and more than half of the respondents have never married. With regard to education, the respondents represented an ample range from high school to doctoral degrees; 50.2%, the largest sector, had a four-year college degree. Though age is a continuous variable, for reporting purposes, social media usage was cross-tabulated in age ranges, as shown in Table 2. The median age of our sample is 29 years of age. We have also summarized the number of friends and followers of those respondents who answered this question the largest sector of Facebook users are the 20-25 year-old respondents with an average of 726 friends; 26-30 year-olds have an average of 535 friends, almost the same average as the 36-49 year old's, who hold an average of 500 friends in Facebook. This may be a bit misleading in that having friends does not necessarily mean active use of Facebook. The largest percentage of Twitter following is the 20 to 25-year old's with an average of 1177 followers, a distant second are the 26-30 year old's with an average of 400 followers. Instagram and Snapchat are mostly used by the respondents who are 25 years of age or younger. LinkedIn and Pinterest, on the other hand, are used more frequently by the 36-49 age group. In addition to number of followers, we were most interested to gather the amount of time spent on social media and we decided to ask for it in terms of minutes per day. We found that the younger generations spend the most time on social media, as was expected, yet we have a very interesting mix of respondents within all age groups as shown in Table 3. The mean for the complete sample is two hours of daily use.

TABLE 1
SAMPLE DEMOGRAPHICS

Categories	Percentage
Gender	
Male	40.9%
Female	58.9%
Marital Status	
Married	35.8%
Never married	58.7%
Other	5.6%
Education	
Less than high school	*1.1%*
High school graduate	*2.9%*
Some college	*16.1%*
2-year degree	*15.6%*
4-year degree	*50.2%*
Master degree	*12.9%*
Doctoral degree	*1.1%*

TABLE 2
MINUTES ONLINE BY AGE

Age	*N*	*Mean*	*Std. dev.*
Less than 20	12	125.83	109.19
20-25	184	172.02	195.47
26-30	59	91.46	109.02
31-35	53	63.40	58.23
36-49	58	62.79	65.52
50+	21	58.57	95.36
Total	387	120.90	156.05

TABLE 3
NUMBER OF FRIENDS OR FOLLOWERS BY SOCIAL MEDIA PLATFORM

Platform	*Age*	*N*	*Mean*	*Std. dev.*
Facebook	Less than 20	12	331.58	151.08
	20-25	179	726.71	664.69
	26-30	63	559.32	535.07
	31-35	52	421.62	500.745
	36-49	60	358.43	409.708
	50+	17	49.88	52.084
	Total	383	557.64	589.694
Twitter	Less than 20	7	170.71	258.23
	20-25	155	352.70	1177.25
	26-30	43	137.51	400.32
	31-35	39	27.38	108.59
	36-49	38	32.66	62.10
	50+	10	0.90	2.85
	Total	292	219.50	884.10

Instagram	*Less than 20*	*12*	*417.42*	*362.55*
	20-25	*178*	*511.86*	*628.77*
	26-30	*54*	*197.59*	*226.17*
	31-35	*43*	*89.56*	*140.26*
	36-49	*38*	*80.00*	*159.88*
	50+	*11*	*4.55*	*7.89*
	Total	*336*	*338.49*	*514.95*
Snapchat	Less than 20	10	115.80	60.62
	20-25	173	111.65	144.86
	26-30	52	52.98	87.58
	31-35	43	20.00	31.39
	36-49	38	15.18	38.18
	50+	12	2.25	5.75
	Total	328	75.28	120.31
LinkedIn	Less than 20	7	2.86	4.88
	20-25	139	55.99	120.66
	26-30	48	105.17	125.95
	31-35	46	155.35	248.19
	36-49	50	248.14	343.73
	50+	13	67.31	176.31
	Total	303	109.83	209.45
Pinterest	Less than 20	7	80.00	193.82
	20-25	137	33.66	122.33
	26-30	45	31.62	57.33
	31-35	40	26.93	81.68
	36-49	31	78.16	269.77
	50+	10	5.00	10.80
	Total	270	37.57	135.41

Measures

Participants responded to the survey including four multiple-item scales for SIA (Mattick and Clarke 1998), SMA (Venkatesh et al., 2003), NACC, and AACC using the original scale proposed by den Hamer et al. (2014). In a later study, den Hamer et al. (2017) used factor analysis to create constructs and their findings are similar to ours. The original CME scale used in den Hamer et al. (2014) contains 14 items measuring how often the respondent watches depictions of antisocial behavior (e.g., drug abuse, fighting, etc.). The original scale includes two reversed items reflecting prosocial behavior and one neutral behavior (e.g., watching news) which we felt ran contrary to our research purpose. After performing a factor analysis on the remaining items, two additional questions were eliminated because the items cross-loaded heavily into the two constructs. The two components explain 82.876 of the variance and were rotated using the Varimax method. The excluded questions included people enticed to commit violent acts and people fighting from AACC

To improve the measurement model's overall fit measures and decreasing the degrees of freedom, the original SIA scale containing 19 items has been adapted and simplified to 8 items for this study. The scale's reliability was not compromised and it remained high at [.926] as shown in Table 5. The SMA scale from Venkatesh et al. (2003) was adapted to social media participation. For example, the original item "The system is somewhat intimidating to me" was replaced by "Social media is somewhat intimidating to me." The scale items and corresponding Cronbach's Alphas are listed in Table 5. The scales' reliability are all above the [.70] benchmark (Hair et al., 2010) and remained consistent when compared to the reliabilities from the pilot test which consisted of 138 responses. For the first two scales, SIA and SMA, participants were asked to respond to each item by using a 5-point Likert scale (1= totally disagree to 5= totally agree).

For the cyber content scales, a 5-point Likert scale (1=never; 2=incidentally; 3=several times; 4=often; 5=very often) was used.

Following the factor analysis and scale improvements, a confirmatory factor analysis of the model's four latent variables was done using AMOS 27. The model fit statistics were very good (Chi-square 1.742; Comparative Fit Index CFI .965; Incremental Fit Index IFI .965; Chi-Square 2.348; and Root mean square error of approximation RMSEA .055). The measurement model was then tested to establish the path relationships.

TABLE 4
PATTERN MATRIX FACTOR ANALYSIS

Variable	NACC	AACC
People destroying someone else's belongings?		.840
People shooting another person?		.878
People stealing?		.883
People destroying someone else's reputation?	.850	
People exposing someone else's behavior?	.859	
People using derogatory/racist/sexist/classicist language?	.835	
People making fun of a person?	.850	

TABLE 5
CONSTRUCTS

Construct	*Measured by Questions 5-point Scales*	*Cronbach's Alpha*
Social Interactive Anxiety (SIA)	I become tense if I have to talk about myself or my feelings	.926
	When mixing socially, I am uncomfortable.	
	I have difficulty talking with other people.	
	I worry about expressing myself in case I appear awkward.	
	I find myself worrying that I won't know what to say in social situations.	
	I am nervous mixing with people I don't know well.	
	I feel I'll say something embarrassing when talking.	
	I feel apprehensive about using social media.	
Social Media Anxiety (SMA)	It scares me to think that I could lose or disclose a lot of information using social media by hitting the wrong command.	.803
	I feel apprehensive about using social media.	
	I hesitate to use social media for fear of making mistakes I cannot correct.	
	Social media is somewhat intimidating to me.	

Nonaggressive Antisocial Cyber Content (NACC)	*On social media how often do you watch…* *people destroying someone else's reputation?*	*.922*
	people exposing someone else's behavior?	
	people using derogatory/racist/sexist/classicist language?	
	people making fun of a person?	
	people shooting another person?	.905
	people stealing?	
	people fighting?	

TABLE 6
RELIABILITIES, CORRELATIONS AND AVE

Construct	*Internal Composite Reliability*	*AVE*	*Correlation of Constructs* *SIA*	*SMA*	*NAAC*	*AACC*
SIA	.918	.585	.765			
SMA	.824	.548	.353	.740		
NACC	.917	.734	.078	.135	.857	
AACC	.901	.753	.082	.169	.682	.868

a. The diagonal element of the correlation of constructs is the square root of the average variance extracted.
b. To be discriminant, the off-diagonal elements should be lower than the square root of the average variance extracted.

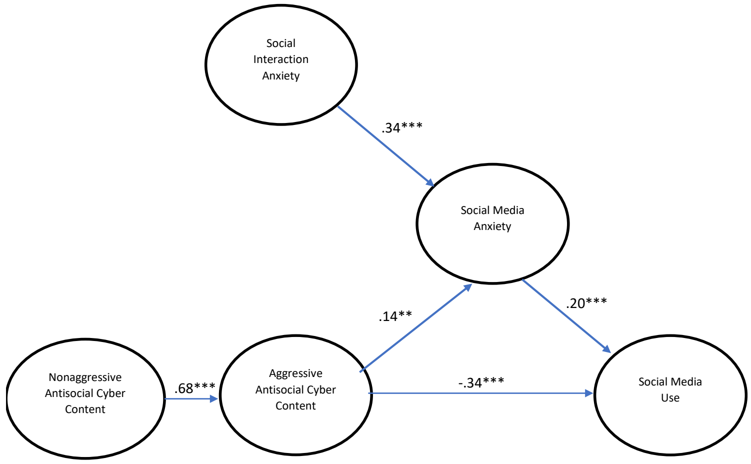
DATA ANALYSIS AND RESULTS

The constructs and measures included in the model were evaluated for internal consistency, convergent validity and discriminate validity as prescribed by Bagozzi and Yi (1989). All scales showed excellent levels of reliability (SIA α=.926; SMA α=.803; NACC α=.922; AACC=.905). We also calculated the Internal Composite Reliability as shown in Table 6. Discriminant validity was assured by comparing the square root of the Average Variance Extracted (AVE) to the correlation amongst the construct (Table 6).

The phenomenon is known as common method variance, can have a significant impact on the relationships between measures of different constructs due to fatigue or loss of concentration a respondent may feel while answering a questionnaire (Podsakoff et al., 2003). Common method variance was tested by using the Harman's single factor test. This is a simple test that ensures that no one factor accounts for the majority of variance in a Factor Analysis with one factor. The eigenvalue of this factor was 23.7, well below the 50% limit, and therefore indicating no common method variance (Podsakoff et al., 2003).

To test our hypotheses, we ran the measurement Structural Equation Model analysis. We examined the fit indexes, path coefficients and their significance level. The fit indices showed: chi-square per degrees of freedom X2/df=2.241 (p<.01); CFI=.942; IFI = .942; Chi-Square=2.640; and RMSEA=.061; suggesting the model fits the data at a good level. Thus, we proceeded to test the hypotheses. The results for the standardized path coefficients are presented in Figure 1.

FIGURE 1
MEASUREMENT MODEL



The first hypothesis (H1) predicting that SIA would result in higher incidence of SMA was supported. The effect was positive, and the p-value was .000 and therefore statistically significant (b=.34, p <.001). Similarly, the relation between SIA and SMA was statistically significant and positive (b=.20, p < .001), providing support for H2. Thus, a higher level of SIA is more likely to lead to increased SMA. Consistent with recent research findings (Ndasauka et al. 2016), the hypotheses support the notion that individuals with SMA participate more actively in social media, possibly to alleviate their anxiety resulting from face-to-face interactions.

Furthermore, the predicted positive relationship NACC and AACC as stipulated as H3a was supported with a positive and statistically significant path (b=.66, p < .001).. Hypothesis 3b stated that exposure to AACC would add to social media anxiety. The results were moderate in terms of effect size (Cohen 1988), statistically significant (b= -.19, p < .01), therefore, H3b was supported. Further, H3c predicted that exposure to AACC would have have a negative effect on social media use. The effect was found negative, and also found to be significant (b=-.33, p < .01). These results were consistent with Leung (2013), indicating that the presence of aggressive content extends to any social media outlet and extended exposure does affect social media participation. Collectively, exposure to antisocial content reduces participation in social media. Finally, the study included a couple of control variables, age and education. This study finds that individuals use less social media the more education they have and the older they are. The relationship is statistically significant (b=-.15, p < .01) and (b=-.16, p < .001), respectively.

To validate the quantitative portion of our study, we analyzed the qualitative questions and found congruence. The respondents made comments such as: “I believe Social Media is getting out of hand.” “Social media, although fun, can be dangerous.” “I have learned to unfollow dangerous people.” “Social media is toxic.” “I closed Facebook 5 years ago.” Various respondents recognized the dichotomy of social media, admitting they feel it is at the same time “good” and “bad” i.e., both “productive” and “destructive.” As one participant noted, “It all depends on the user’s intentions.” In addition we tested the model in the 3 waves of data collection which were separated in time for about a year per wave. The model was confirmed each time giving us positive robustness checks.

DISCUSSION

Our findings suggest that the proposed model is a useful tool to determine social that explains social media use and how it is affected by SMA and negative antisocial content. Overall, our study provides evidence that different sources of anxiety play a role on social media participation. It was particularly interesting to find that our proposed model also revealed distinct degrees of antisocial content on social media participation. This content distinction has been scarcely examined in the social media literature. Our study includes a wide range of participants composed of users of all ages and with varying amounts of education.

Our study makes several important contributions to the literature on social media by simultaneously exposing elements that increase and reduce its use. First, it contributes to the Social Interaction Anxiety literature by assessing the effects of anxiety on social media usage. The literature is inconclusive and our study findings support a strong relationship between social media use, SMA and SIA. The second contribution relates to the negative effect of antisocial content on social media use. Previous studies have found positive persuasive content (e.g., philanthropic content) are key to effective engagement (Lee et al., 2015). However, the effects of AOB requires increased attention. Our findings indicate this distinction is key to predict social media use. Theoretically, mood management theory states individuals are motivated to select media content that supports a positive mood state (Zillmann, 1988) and consequently, suggests the avoidance of affective states that are not positive (Stevens & Dillman Carpentier, 2017). This is in tune with Gearhard and Weiwu's (2015) study concluding that in the political arena when social media users encounter agreeable content, they will speak out, while disagreeable content suppresses the expression of opinion. Because of the expanding diversity of social media content, we expected that exposure to content perceived as antisocial would negatively influence the impressions and emotions of users, and consequently lessen the user motivations to engage in social media. In fact, a recent study that has focused on the precise sources of social media anxiety conducted by Alkiset al. (2017), developed a scale to measure social anxiety among Turkish college students. A four-dimensional structure emerged, including shared content anxiety, privacy concern anxiety, interaction anxiety and self-evaluation anxiety. Our findings, however, imply that focusing solely on effects of antisocial content in general is insufficient. A more granular inspection of content, such as finding the degree of aggression, is needed.

CONCLUSION

The findings from the current study highlight the complex nature of the relationship between social interaction anxiety, social media anxiety and exposure to aggressive and nonaggressive antisocial content. There are a number of implications for practice in both the market and workplace environments. Social media participation is an important process for marketers, as they attempt to disseminate information, as well as, foster dialogs with potential and current consumers (Neier & Tuncay 2015). Its implications for digital marketing are profound. While some consumers are turned off by AOB, there are those who will remain hooked if SMA is produced. This means that AOB, especially AACC, has the capacity to engage consumers. We can explain this phenomenon by comparing it to movie goers who pay entrance fees to see movies with aggressive content, especially those who have expressed fear to go in the first place.

On the other hand, practical implications of our model may occur in the workplace (Rueda et al., 2017). As organizations are increasingly promoting the use of social media features in business processes, they may explore strategies to reduce sources of AOB, because of the intense effect on users who may develop SMA. For instance, organizations may offer tutorials on dealing with antisocial, aggressive and non-aggressive content posted by customers in social networks. In helping to reduce or eliminate sources of antisocial content, individuals might have fewer concerns about exposure to others' opinions, and thus become more open to social media and enjoy the flow of it as proposed by Pelet et al. (2017). "The flow concept is operationalized with five dimensions: concentration, enjoyment, control, challenge, and curiosity (p. 116). These dimensions are "sufficiently parsimonious to capture the entire experience of flow in this context (116)." Alternatively, organizations may offer training to employees on how to become comfortable with new features of social media outlets.

Limitations and Future Research

While there are many reasons that users participate in social media, the investigation into AOB and its effects are underdeveloped. Other than aggressive and non-aggressive antisocial content, future work can assess other issues that can cause social media addiction and its consequences. For example, social media burnout is defined as the degree to which the user feels exhausted when using social media (Han, 2018). The literature indicates that social media burnout can reflect emotional exhaustion, which refers to the degree to which the user regard that their resources such as time and effort were depleted by the usage of social media (Han, 2018). Previous investigations have shed some light on the mechanism underlying how social media burnout develops from a perspective of overload (Liu & Ma, 2020).

Mood management theory has been challenged by gender preferences to exposure to negative content (Knobloch-Westerwick, 2007), and more research is needed to explain this preference. Finally, future studies may want to segment social media users by age or education to see if these segments respond differently to the same stimuli. Our qualitative study revealed that users may be attracted to aggressive violent content and this deserves further investigation. Could it be that the attraction is limited and will be reduced when they feel threatened or become the target of such content? Future research can employ a qualitative analysis of social media anxiety (e.g. sentiment analysis) in order to add to the existing literature that discover and confirm the determinants of social media use.

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