Humanities, Arts and Social Sciences Studies

Research Article

Humanities, Arts and Social Sciences Studies
https://so02.tci-thaijo.org/index.php/hasss
ISSN (Online): 2630-0079

PERSPECTIVES ON LATE ADOLESCENT CYBERBULLYING VICTIMIZATION: GENDER DIFFERENCES IN BEHAVIORAL HEALTH EFFECTS

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ABSTRACT

Even though information technology has brought great benefits to its users, its growing popularity has also increased the risk of cyberbullying. This research fills an empirical gap by exploring both the perceptions of late adolescent victims and gender differences in the behavioral health effects of online bullying. It presents a perspective on changing health behavior that aligns with the conceptual framework of social cognitive theory (SCT). The sample comprised 578 undergraduate students (286 males and 292 females) from three university campuses in Thailand that were selected by using a multistage random sampling technique. The causal relationships between factors in the model were analyzed using partial least squares structural equation modeling (PLS-SEM). The results indicated that social media addiction and self-disclosures on social media are key environmental factors, for both males and females, leading to victimization by cyberbullying. In particular, late adolescents who compare themselves with others (i.e., social comparison) are more severely affected by cyberbullying. In addition, these findings reveal a new relationship between victimization and sleep disorders: For both men and women, social comparison mediates the relationship between cyberbullying victimization and sleep disorders. This study's results clarify how health behaviors are affected by the environment and the personal behavior of victims of online bullying.

Keywords: Cyberbullying; late adolescent victimization; behavioral health; gender differences; social cognitive theory; social media

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Received: *27 July 2021*
Revised: *13 January 2022*
Accepted: *13 January 2022*
Published: *18 April 2023*

Citation:
Jattamart, A. and Kwangsawad, A. (2023). Perspectives on late adolescent cyberbullying victimization: Gender differences in behavioural health effects. Humanities, Arts and Social Sciences Studies 23(1): 180–194.

1. INTRODUCTION

Interpersonal communication has developed rapidly as a result of advancements in technology. This is particularly the case with regard to social networking services, as they provide platforms to build relationships between users worldwide via the Internet. This global reach allows users to share information without time, and place constraints (Cho et al., 2017) and exchange both academic and health-related information (Korda and Itani, 2013). Previous research has investigated the impact of social media use, reporting that excessive use can cause mental health problems and that such risks have been heightened during

the COVID-19 pandemic. Studies suggest that taking breaks from social media may help promote well-being and reduce the risk of harming people's mental health (Zhong et al., 2021). Recently, cyberbullying has become a growing concern, especially regarding its impact on public health (Mishna et al., 2016) as vulnerable patients are encouraged to access the Internet and online media to support behavioral modification (Jattamart and Leelasantitham, 2019).

Cyberbullying is behavior that was defined as bullying or harassing others when communicating by using technology (Livazović and Ham, 2019). Chang et al. (2013) reported that Taiwanese children at middle and high school levels were the most affected by cyberbullying. In the West, more than 25% of young people have experienced cyberbullying, while college undergraduates have also reported its occurrence (Watts et al., 2017). A study of 3,767 high school students by Kowalski and Limber (2007) found that cyberbullying was more common among females than males, with at least 11% of schoolchildren experiencing cyberbullying at least once in a 2 month period. Smith et al. (2019) also found that females are more likely to be victims of cyberbullying than males. These situations can lead to inappropriate behavior that can be passed on to adolescents and adults.

Furthermore, previous research has shown that young people who experience cyberbullying are likely to report problems such as poor academic performance, anxiety, stress, social shutdown, interpersonal issue, and psychological distress and depression that led to a higher chance of suicide when compared to adults (Hinduja and Patchin, 2010). Cyberbullying is also an important contributor to school violence, which has both emotional, mental, and physical effects (Gumpel and Sutherland, 2010). These findings indicate that being a victim of cyberbullying has a strong correlation to mood, behavior, and mental health problems, and affects people of any age and in any occupation. Therefore, it is important to examine cyberbullying's impacts and analyze its risk factors regarding demographics, personal factors, and environment to address bullying on the internet.

This study fills the existing research gap by focusing on the perceptions of late adolescent victims and identifying gender differences in the behavioral health effects of online bullying. It determines the impact of health behavior modification on being bullied on social media. Understanding the attitudes of late adolescent victims towards social media bullying will help those involved in academic institutions, families, and healthcare professionals caring for late adolescents to develop ways to prevent long-term negative effects. This study's research questions explore these issues sequentially: (a) does the environment influence the incidence of becoming a cyberbullying victim? (b) how does being a victim of cyberbullying affect one's inner personality? and (c) how does being a victim of cyberbullying affect health behaviors?

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

According to global social media usage statistics, social media has become increasingly popular as a means of communication, especially Facebook, the most popular social media platform in 2019 (Kemp, 2019). As a result, a large amount of content is created and shared through social media. In recent years, the impact of negative social media content has been linked to effects on the mental health of social media users (Jattamart and Leelasantitham, 2020).

2.1 Cyberbullying on social media

Livazović and Ham (2019) define online bullying (cyberbullying) as the bullying or harassment of others through negative online channels such as harassing transmission of content, unauthorized access to other people's personal information that convinced others to feel disgusted with or excluded from society and impersonating people to create content on online media. Cyberbullying comprises four elements: (a) intentional aggressive behavior, (b) repeated occurrence, (c) power disparities between perpetrator and victim, and (d) use of technology (Kowalski and Limber, 2007). Willard (2007) classifies seven types of cyberbullying: (a) flaming, (b) harassment, (c) outing and trickery, (d) exclusion, (e) impersonation, (f) cyber-stalking, and (g) sexting.

2.2 Cyberbullying victimization and behavioral health

Although young people can benefit significantly from information technology, its increasing popularity renders them vulnerable to cyberbullying. Moreover, several studies have found the prevalence of cyberbullying to be growing, especially among teenagers. Therefore, studies of the effects of online bullying on victims are of substantial interest, especially regarding their impact on mental health (Parris et al., 2012). Previous research has reported that teenagers are exposed to online bullying experience social anxiety, stress, and shutdown. It also causes depression and an increased risk of suicide in comparison with adults (Hinduja and Patchin, 2010). In particular, female victims of online bullying are at an increased risk of both adverse mental health effects and substance abuse (Kim et al., 2019). This is consistent with the

results of a long-term study by Liu et al. (2020) who found that cyberbullying has a direct effect on depression and that can lead to post-traumatic stress symptoms. These effects are causally implicated in school violence (Gumpel and Sutherland, 2010), which itself results in harmful emotional, mental, and physical outcomes for students.

Research has also examined individual differences among cyberbullying victims. For instance, females were more likely to be victims of online bullying than males (Kowalski and Limber, 2007; Tsitsika et al., 2015). Aizenkot (2020) also identified similar gender differences among students. Additionally, males were found to exhibit more violent online threats than females (Makri-Botsari and Karagianni, 2014). Other studies, however, have found no significant associations between sex and cyberbullying (Kowalski et al., 2014). In light of such suggestive but inconclusive findings, the relationship between personal factors and cyberbullying must be studied from a variety of perspectives to better understand the multi-dimensional nature of the phenomenon.

2.3 Social media addiction

Social networking sites (SNS) such as Facebook, Twitter, Google+ and Instagram are popular with a multitude of users. Cannarella and Spechler (2014) reported that in 2014 the total number of Facebook users peaked and began to decline. According to a survey by Rainie et al. (2013), approximately 20% of respondents voluntarily quit Facebook due to gossip-related messages and repeatedly have to view information unrelated to Facebook. Notably, problematic technology use (e.g., too much time spent on smartphones, decreased focus on other activities, decreased learning efficiency) correlated with the likelihood of being a victim of teenage cyberbullying (Peláez-Fernández et al., 2021).

At the same time, the popularity of social networking has resulted in some users exhibiting symptoms of social media addiction due to an excessive interest in and overuse of social media. Consequently, working, studying, living a normal life, and interacting are detrimentally affected, especially among adolescents who may be most at risk of addiction (Sirola et al., 2019). Indeed, Longobardi et al. (2020) reported that teenagers on the popular platform Instagram are at increased risk of both social media addiction and becoming victims of bullying. In addition, Giordano et al. (2021) found that spending more time on online media is associated with higher levels of social media addiction, especially for males who may be at higher risk of cyberbullying. Such findings suggest that long-term prevention of these risks requires a renewed focus on the factors and causal relationships associated with being a late adolescent cyberbullying victim.

2.4 Online self-disclosure

Self-disclosure is one of the main activities users engage in when connecting and interacting with a large number of people on social networks. Previous research has indicated that personal posting details on social networking profiles and active self-disclosure are linked to an increased risk of victimization (Aizenkot, 2020). Edwards et al. (2020) also found a significant correlation between the amount and type of information disclosed on social networking profiles and cyberbullying. Although previous research has explored the impact of self-exposure on the likelihood of falling victim to cyberbullying, no studies have examined the impact of social media self-disclosure on behavioral modification among victims, particularly health behaviors. This study will help generate guidelines for defining user security measures (USM) and website security measures (WSM) that can reduce the perceived vulnerability (PV) of those who are repeat victims of cyberbullying.

3. RESEARCH MODEL AND HYPOTHESES

3.1 Research model

Social cognitive theory (SCT) is a widely used framework that describes the behavioral changes arising from environmental and personal factors (Bandura, 1986; Cao et al., 2019). This study utilized SCT as a framework explaining the causal factors underpinning a person's behavior in terms of the following three processes:

1. Environment: self-disclosures on social media and social media addiction that could lead to victimization through online bullying.
2. Personal: loneliness, negative emotions, and social comparison.
3. Health Behavior: anxiety, depression, self-esteem, and sleep disorders, as shown in Figure 1.

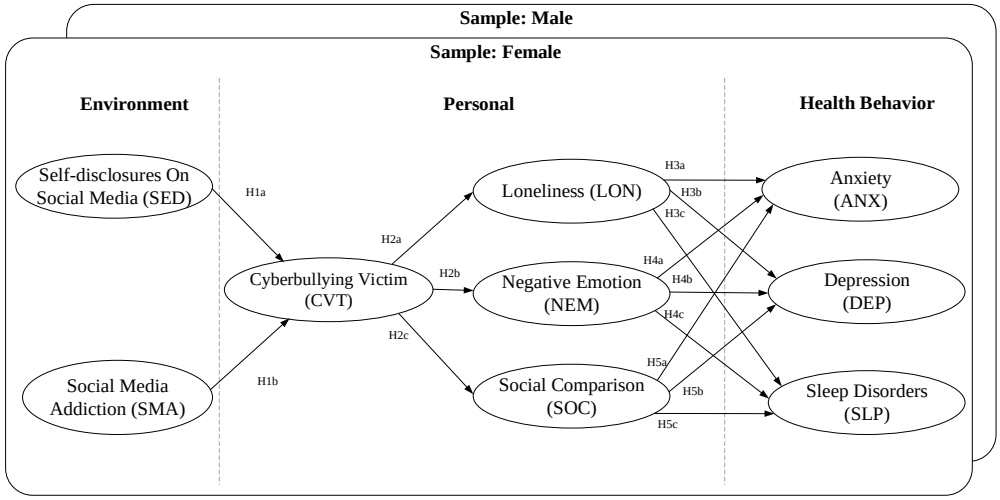

Figure 1: Proposed Research Model for Behavioral Health Effects of Cyberbullying Victim

3.2 Hypotheses

The hypotheses related to the causal factors are as follows:

Self-exposure and individual differences in social networking profiles can lead to an increased risk of becoming a victim of cyberbullying (Aizenkot, 2020; Peluchette et al., 2015; Won and Seo, 2017). The following hypothesis was therefore proposed:

H1a: Self-disclosures on social media (SED) increase the likelihood of becoming a late adolescent cyberbullying victim (CVT).

Peláez-Fernández et al. (2021) explained that problematic technology used among late adolescents is associated with an increased risk of becoming a victim of cyberbullying, especially if more time is spent on online media. Furthermore, the occurrence of social media addiction leads to a higher chance of falling victim to bullying. Therefore, the following hypothesis was proposed:

H1b: Social media addiction (SMA) among late adolescents is associated with becoming a cyberbullying victim (CVT).

Victims of cyberbullying have difficulty adjusting to their environment and shut themselves off from society (Hinduja and Patchin, 2010). Fang et al. (2020) reported that becoming a victim of cyberbullying was significantly and positively correlated with loneliness. This is because lonely people were more likely to use mobile phones and the Internet, which are tools for separating oneself from society (Şahin, 2012). Therefore, this study also examined the relationship between loneliness, negative emotion, and becoming a victim of cyberbullying. Attention was also paid to social comparison which Appel et al. (2016) found to be positively associated with Facebook use. The following hypotheses were therefore proposed:

H2a: Becoming a cyberbullying victim (CVT) is associated with loneliness (LON) among late adolescents.

H2b: Becoming a cyberbullying victim (CVT) is associated with negative emotions (NEM) among late adolescents.

H2c: Becoming a cyberbullying victim (CVT) is associated with social comparison (SOC) among late adolescents.

The health implications of being a victim of online bullying have garnered great attention. Victims of cyberbullying are reported to be anxious, stressed, socially shut down, and depressed, leading to a higher likelihood of suicide than adults (Hinduja and Patchin, 2010; Liu et al., 2020). In addition, it is also linked to a shorter amount of sleep (Sladek et al., 2020). In order to examine the relationship between individual differences and health effects after cyberbullying, the following hypotheses were proposed:

H3a: Loneliness (LON) is associated with anxiety (ANX) among late adolescents.

H3b: Loneliness (LON) is associated with depression (DEP) among late adolescents.

H3c: Loneliness (LON) is associated with sleep disorders (SLP) among late adolescents.

H4a: Negative emotion (NEM) is associated with anxiety (ANX) among late adolescents.

H4b: Negative emotion (NEM) is associated with depression (DEP) among late adolescents.

H4c: Negative emotion (NEM) is associated with sleep disorders (SLP) among late adolescents.

H5a: Social comparison (SOC) is associated with anxiety (ANX) among late adolescents.

H5b: Social comparison (SOC) is associated with depression (DEP) among late adolescents.

H5c: Social comparison (SOC) is associated with sleep disorders (SLP) among late adolescents.

4. RESEARCH METHOD

4.1 Participants

The study employed a cross-sectional design. The population comprised 1,155 undergraduate students from a university in Thailand. The sample was randomized by using a multistage sampling technique. The first step was choosing a field of study; the Faculty of Business Administration was selected across three campuses. Next, students were considered from 3 courses, each employing are the same teaching model across all three campuses: Management, Accounting, and Business Information Technology. The next step employee had a simple random sampling technique where all students had an equal chance of being selected. The researchers used Google Form to design an online questionnaire and share it via university email to all students who meet the criteria of the population studied. Respondents were aged between 18–23 years old. Data were also collected by administering an online questionnaire on Facebook for a period of 6 months. Respondents submitted the completed questionnaire through the Line application and Facebook platforms.

The research process was carried out in line with the ethical principles for conducting human research. The research team had all participated in the Human Research Ethics Training for Social Sciences, Class 1/2020 of Mahidol University, Thailand. All participation was voluntary and participants were informed of the study objectives prior to completing the questionnaire. Responses did not identify by respondents or revealed any personal information, and all information disclosed remained confidential (Jattamart and Kwangsawad, 2020).

4.2 Measurement Instrument

The online questionnaire was divided into 4 parts.

Part 1 provided a self-report measure of the frequency of Facebook bullying over the past 6 months. This was a short version adapted from the victimization subscale of the Cyberbullying Questionnaire (Gámez-Guadix et al., 2014; Oksanen et al., 2020; Santos et al., 2020) and comprised 9 questions in total (see Table 1). The list of questions relates to seven types of cyberbullying drawn from Willard (2007), and responses were given on the following five-point scale: 1 (never), 2 (1–3 times), 3 (4–6 times), 4 (7 or more times) and 5 (almost daily). This scale has good inter-item reliability ($\alpha = 0.76$).

Table 1: Nine-Item Modified Scale Based on the Cyberbullying Behavior Questionnaire

Items
1. You have been gossiped about or insulted online.
2. You have been harassed or threatened online.
3. You have had confidential pictures or videos disclosed on social media.
4. You have been framed by creating rumors or false information and shamed on social media.
5. You have been impersonated and your name / identity used to harass others on social media.
6. You have been intimidated through social media.
7. You have been excluded or blocked from social media groups to cause discomfort or pain.
8. You have been assaulted by other people and had pictures or videos of this published on social media.
9. You have been asked by an acquaintance to send hot photos or videos of yourself and these have been published on social media.

Part 2 involved demographic questions eliciting information on gender, age, current living accommodations, and hours of internet use per day. Part 3 comprised 40 questions about the health impact of becoming a victim of Facebook bullying, focusing on 10 areas: (a) Self-disclosures on social media, (b) Cyberbullying victim, (c) Social media addiction, (d) Loneliness, (e) Negative emotion, (f) Social comparison, (g) Anxiety, (h) Depression, (i) Self-esteem, and (j) Sleep disorders, and Part 4 was for Proposal. To facilitate the data analysis, responses were given on a 5-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree), as shown in Table 2.

Table 2: Measurement Items

Construct	Items	Survey Items	Sources
Self-disclosures On Social Media (SED)	SED1	Excessive commenting on Facebook leads to the risk of cyberbullying.	Adapted from Aizenkot (2020) Peluchette et al. (2015); Won and Seo (2017)
	SED2	Posting personal information on your Facebook profile leads to an increased risk of cyberbullying.	
	SED3	Posting private photos on your Facebook profile leads to an increased risk of cyberbullying.	
	SED4	In general, you think disclosure of personal information on your Facebook profile leads to the risk of cyberbullying.	
Social Media Addiction (SMA)	SMA1	Excessive time spent on Facebook leads to an increased risk of cyberbullying.	Adapted from Giordano et al. (2021); Longobardi et al. (2020)
	SMA2	Spending more time on Facebook activities than other activities leads to an increased risk of cyberbullying.	
	SMA3	Interacting with Facebook friends leads to an increased risk of cyberbullying.	

Table 2: Measurement Items (Continued)

Construct	Items	Survey Items	Sources
Cyberbullying Victim (CVT)	SMA4	Overall, you think social media addiction leads to an increased risk of cyberbullying.	Adapted from Giordano et al. (2021); Longobardi et al. (2020)
	CVT2	Being a victim of cyberbullying makes you feel like you are separated from society.	
	CVT3	Being a victim of cyberbullying can have a negative impact on your emotions.	
	CVT4	Being a victim of online bullying has led to a feeling of comparing yourself to your Facebook friends.	
Loneliness (LON)	LON1	The feeling of isolation after being a victim affects your health.	Adapted from Fang et al. (2020) Şahin (2012)
	LON2	The feeling of loneliness after being a victim leads to a feeling of distress.	
	LON3	A feeling of separation from society after being a victim leads to a feeling of distress.	
	LON4	The feeling of loneliness after being a victim contributes to stress.	
Negative Emotion (NEM)	NEM1	The negative emotions you feel after being a victim make you feel bored.	Adapted from Fang et al. (2020); Şahin (2012)
	NEM2	The negative emotions you feel after being a victim leads to a depressive mood.	
	NEM3	The negative emotions you feel after being a victim can cause feelings of distress.	
	NEM4	Overall, you think online bullying can cause negative emotions.	
Social Comparison (SOC)	SOC1	Being a victim creates a feeling of being compared to your Facebook friends.	Adapted from Appel et al. (2016)
	SOC2	Being a victim creates a greater sense of being compared to others.	
	SOC3	The feeling of comparing yourself with your Facebook friends makes you feel anxious when you carry out activities on Facebook.	
	SOC4	The feeling of comparing oneself with others makes you feel depressed when you use Facebook.	
Anxiety (ANX)	ANX1	Being a victim can make you anxious when it comes to using online media.	Adapted from Hinduja and Patchin (2010); Liu et al. (2020)
	ANX2	Being a victim can make you feel anxious when it comes to expressing opinions online.	
	ANX3	Being a victim can make you feel anxious when it comes to being exposed online.	
	ANX4	Overall, you think online bullying causes anxiety when it comes to online activities.	
Depression (DEP)	DEP1	Online bullying can lead to depressive moods such as irritability and anger	Adapted from Hinduja and Patchin (2010); Liu et al. (2020)
	DEP2	The feeling of loneliness after being a victim leads to a depressive mood.	
	DEP3	The negative mood you feel after being a victim leads to a depressive mood.	
	DEP4	The feeling of comparing yourself with your Facebook friends causes a depressed mood.	
Sleep Disorders (SLP)	SLP1	Cyberbullying leads to poor sleep.	Adapted from Jattamart and Kwangsawad (2020); Sladek et al. (2020)
	SLP2	Cyberbullying makes it difficult to sleep.	
	SLP3	Cyberbullying affects the amount of time it takes to go to bed.	
	SLP4	Overall, you think cyberbullying affects sleep.	

4.3 Data Analysis

Partial least squares structural equation modeling (PLS-SEM) with a basal variance analysis model was employed to analyse causal relationships. As a test of concept for each factor, variance-based structural equation modeling (variance-based SEM) was employed by using SmartPLS version 3.3.2 software (Ringle et al., 2015). This is because (a) PLS-SEM in SmartPLS software does not operate under restrictive assumptions regarding data distribution as it is non-parametric (Ringle et al., 2015); (b) PLS-SEM is effective at predicting related components to be used for theoretical testing of research, and is thus extremely popular among research groups studying social media behavior (Jattamart and Leelasantitham, 2020), health behavior from the perspective of disease prevention (Jattamart and Leelasantitham, 2019), and to test variables associated with smart cities which affect the quality of life for tourists (Keawsomnuk, 2021); (c) PLS-SEM is able to simultaneously analyze the results of both measurement and structural model; and (d) content validity and discriminant validity tests can be performed. For these reasons, PLS-SEM is the most suitable method for this study.

The data analysis process was divided into (a) basic information data, in which demographic data and data on the frequency of victims of Facebook bullying over the past 6 months were used to analyze the data

(number and percentage) and (b) two-step model evaluation via PLS-SEM. The first step involves checking the quality of variables assessed for internal consistency, reliability, and convergent validity with loading, Cronbach's α, composite reliability, and average variance extracted. The second step involves verifying the model fit (SRMR, chi-square, NFI, and GoF) and testing the structural equation model with path coefficients that meet the criteria (Hair et al., 2019; Sarstedt and Cheah, 2019).

5. RESULTS

5.1 Basic information data

Of the 1,155 undergraduate students who completed the online survey, 578 people had been victimized by social media bullying in the past six months: 286 males and 292 females. The largest cohorts were aged 21–23 years (66.1%), had studied for a bachelor's degree (57.6%), lived in a house / dormitory (57.7%), used the internet for 7–8 hours (41.6%), and all had been a victim of social media bullying (100%), Tables 3, 4 and 5 indicate that most Facebook bullying over the past 6 months was in the form of online gossip or insults (males = 41.3% and females = 47.6%).

Table 3: Baseline Demographic Characteristics of Participants

Characteristics	Number		Percentage	
	Male (N = 286)	Female (N = 292)	Male (N = 59.5)	Female (N = 50.5)
Age				
18–20 years	97	136	33.9	46.6
21–23 years	189	156	66.1	53.4
Current places to stay				
Private house	121	118	42.3	40.4
House for rent / dormitory	165	173	57.7	59.3
Condo	0	1	0.0	0.3
How many hours of internet use per day?				
1–2 hours	2	3	0.7	1.0
3–4 hours	13	12	4.6	4.1
5–6 hours	61	113	21.3	38.7
7–8 hours	119	93	41.6	31.9
9–10 hours	86	26	30.1	8.9
11 hours or more	5	45	1.7	15.4

Table 4: Experiences of Victims of Facebook Bullying over the Past 6 Months of Male Sample

Experience	Never	1–3 times	4–6 times	7 or more times	Almost every day
1. You have been gossiped about or insulted online.	17	57	72	118	22
	5.9%	19.9%	25.2%	41.3%	7.7%
2. You have been harassed or threatened online.	56	83	97	46	4
	27.2%	24.6%	38.7%	7.9%	1.6%
3. You have had confidential pictures or videos disclosed on social media.	154	32	56	43	1
	53.8%	11.2%	19.6%	15.0%	0.3%
4. You have been framed by creating rumors or false information and shamed on social media.	132	46	71	37	0
	46.2%	16.1%	24.8%	12.9%	0.0%
5. You have been impersonated and your name / identity was used to harass others on social media.	114	68	70	34	0
	39.9%	23.8%	24.5%	11.9%	0.0%
6. You have been intimidated through social media.	101	53	79	49	4
	35.3%	18.5%	27.6%	17.1%	1.4%
7. You have been excluded or blocked from social media groups to cause discomfort or pain.	114	45	84	36	7
	39.9%	15.7%	29.4%	12.6%	2.4%
8. You have been assaulted by other people and had pictures or videos of this published on social media.	174	69	36	7	0
	60.8%	24.1%	12.6%	2.4%	0.0%
9. You have been asked by an acquaintance to send hot photos or videos of yourself and these have been published on social media.	122	27	46	79	12
	42.7%	9.4%	16.1%	27.6%	4.2%

Table 5: Experiences of Victims of Facebook Bullying over the Past 6 Months of Female Sample

Experience	Never	1–3 times	4–6 times	7 or more times	Almost every day
1. You have been gossiped about or insulted online.	1	77	42	33	139
	0.3%	26.4%	14.4%	11.3%	47.6%
2. You have been harassed or threatened online.	111	88	40	51	2
	38.0%	30.1%	13.7%	17.5%	0.7%
3. You have had confidential pictures or videos disclosed on social media.	186	51	34	18	3
	63.7%	17.5%	11.6%	6.2%	1.0%
4. You have been framed by creating rumors or false information and shamed on social media.	165	63	37	22	5
	56.5%	21.6%	12.7%	7.5%	1.7%
5. You have been impersonated and your name / identity was used to harass others on social media.	170	54	36	29	3
	58.2%	18.5%	12.3%	9.9%	1.0%
6. You have been intimidated through social media.	163	62	31	31	5
	55.8%	21.2%	10.6%	10.6%	1.7%
7. You have been excluded or blocked from social media groups to cause discomfort or pain.	146	76	34	34	2
	50.0%	26.0%	11.6%	11.6%	0.7%
8. You have been assaulted by other people and had pictures or videos of this published on social media.	196	39	44	11	2
	67.1%	13.4%	15.1%	3.8%	0.7%
9. You have been asked by an acquaintance to send hot photos or videos of yourself and these have been published on social media.	181	47	24	37	3
	62.0%	16.1%	8.2%	12.7%	1.0%

Tables 4 and 5 explain that the victim experience Facebook bullying over the past 6 months. The majority of the male and female sample was bullied in the form of online gossip or insults (Male = 41.3% and female = 47.6%).

5.2 Validity and relationship test

The model tested the quality of the variables in accordance with Hair Jr et al. (2016). The Cronbach's α was between 0.755–0.882 for the male sample and 0.850–0.936 for the female sample, above the minimum requirement of 0.70 in both cases. The composite reliability (CR) of each component was also higher than the 0.70 thresholds, ranging between 0.893–0.919 for the male sample and 0.899–0.954 for the female sample. The Average Variance Extracted (AVE) test for each element was above the 0.50 threshold, ranging between 0.671–0.739 for the male sample and 0.690–0.838 for the female sample. In addition, the load value of each component (loading) was no lower than 0.70, indicating that the variables in each component were well-correlated and explained the measurement model in the component, as shown in Table 6.

Table 6: Measures of Internal Consistency Reliability, and Convergent Validity

Construct	Items	Loading (> 0.70)		Cronbach's α (> 0.70)		Composite reliability (> 0.70)		AVE (> 0.50)	
		Male	Female	Male	Female	Male	Female	Male	Female
Self-disclosures on Social Media (SED)	SED1	0.846	0.897	0.861	0.914	0.906	0.939	0.706	0.795
	SED2	0.865	0.895						
	SED3	0.862	0.901						
	SED4	0.784	0.873						
Social media addiction (SMA)	SMA1	0.894	0.876	0.882	0.921	0.919	0.944	0.739	0.809
	SMA2	0.876	0.899						
	SMA3	0.812	0.911						
	SMA4	0.854	0.912						
Cyberbullying Victim (CVT)	CVT1	0.852	0.869	0.840	0.908	0.893	0.935	0.678	0.783
	CVT2	0.746	0.860						
	CVT3	0.846	0.910						
	CVT4	0.844	0.899						
Loneliness (LON)	LON1	0.839	0.870	0.755	0.866	0.860	0.918	0.671	0.789
	LON2	0.820	0.907						
	LON4	0.799	0.888						
Negative Emotion (NEM)	NEM2	0.871	0.875	0.821	0.830	0.893	0.898	0.736	0.746
	NEM3	0.868	0.885						
	NEM4	0.834	0.831						
Social Comparison (SOC)	SOC1	0.888	0.906	0.876	0.936	0.915	0.954	0.730	0.838
	SOC2	0.880	0.925						
	SOC3	0.794	0.915						
	SOC4	0.853	0.916						
Anxiety (ANX)	ANX1	0.867	0.907	0.844	0.933	0.895	0.952	0.682	0.833
	ANX2	0.834	0.910						
	ANX3	0.769	0.922						
	ANX4	0.830	0.912						

Table 6: Measures of Internal Consistency Reliability, and Convergent Validity (Continued)

Construct	Items	Loading (> 0.70)		Cronbach's α (> 0.70)		Composite reliability (> 0.70)		AVE (> 0.50)	
		Male	Female	Male	Female	Male	Female	Male	Female
Depression (DEP)	DEP1	0.812	0.876	0.865	0.917	0.908	0.942	0.712	0.802
	DEP2	0.872	0.912						
	DEP3	0.855	0.905						
	DEP4	0.836	0.888						
Sleep Disorders (SLP)	SLP1	0.874	0.916	0.886	0.919	0.921	0.943	0.744	0.806
	SLP2	0.848	0.920						
	SLP3	0.861	0.841						
	SLP4	0.867	0.911						

Table 7: Discriminant Validity of the Measurement Model of Male

Construct	Correlation Matrix								
	CVT	SED	SMA	LON	NEM	SOC	ANX	DEP	SLP
Cyberbullying Victim (CVT)	**0.823**								
Self-disclosures on Social Media (SED)	0.796	**0.840**							
Social media addiction (SMA)	0.853	0.853	**0.860**						
Loneliness (LON)	0.519	0.657	0.566	**0.819**					
Negative Emotion (NEM)	0.583	0.657	0.611	0.725	**0.858**				
Social Comparison (SOC)	0.664	0.706	0.650	0.628	0.727	**0.855**			
Anxiety (ANX)	0.497	0.535	0.527	0.726	0.715	0.628	**0.826**		
Depression (DEP)	0.524	0.640	0.578	0.743	0.834	0.667	0.779	**0.844**	
Sleep Disorders (SLP)	0.560	0.691	0.586	0.638	0.709	0.602	0.591	0.732	**0.863**

Table 8: Discriminant Validity of the Measurement Model of Female

Construct	Correlation Matrix								
	CVT	SED	SMA	LON	NEM	SOC	ANX	DEP	SLP
Cyberbullying Victim (CVT)	**0.885**								
Self-disclosures on Social Media (SED)	0.772	**0.892**							
Social media addiction (SMA)	0.837	0.836	**0.900**						
Loneliness (LON)	0.462	0.488	0.482	**0.888**					
Negative Emotion (NEM)	0.528	0.609	0.572	0.770	**0.864**				
Social Comparison (SOC)	0.602	0.669	0.637	0.759	0.766	**0.916**			
Anxiety (ANX)	0.464	0.505	0.470	0.770	0.758	0.749	**0.913**		
Depression (DEP)	0.406	0.467	0.428	0.782	0.764	0.746	0.857	**0.895**	
Sleep Disorders (SLP)	0.492	0.508	0.538	0.898	0.538	0.537	0.598	0.591	**0.898**

As presented in Tables 7 and 8, Fornell and Larcker (1981) were employed to assess the relationship between variables in the form of a diagonal matrix. As shown, the square roots of AVEs in each element (bold characters) are greater than the values in the corresponding horizontal and vertical rows, indicating discriminant validity and confirming they can be analyzed in the structural model.

5.3 Structural model test

Verification of the model fit prior to testing the criterion path coefficient significance of Hair et al. (2019); Henseler et al. (2016). The Stone-Geisser Q^2 blindfolding method was evaluated, which showed results greater than 0. This indicated that the constructs were associated with the predictive relevance of the model. The model was fitted in SmartPLS 3.3.2 by performing the PLS-SEM Algorithm. The model fit indices included standardized root mean square residual (SRMR), chi-square, and normed fit indexes (NFI). The SRMR values were lower than 0.08, with 0.068 for the male model and 0.051 for the female model. The chi-square was equal to 1560.523 for the male model and 1905.038 for the female model. Finally, the NFI value was equal to 0.756 for the male model and 0.799 for the female model, which is close to the suggested threshold values of NFI > 0.50 (Dash and Paul, 2021; Hair et al., 2010; Nunnally, 1994). These values indicate that the model has a good fit for PLS-SEM. The consistency of the model with the data has been tested in terms of goodness-of-fit (GoF). GoF values of 0.1, 0.25, and 0.36 indicate small, moderate, and large model fits, respectively (Tenenhaus et al., 2005; Wetzels et al., 2009). The GoF value is 0.60 (large) in the male model, and is 0.59 (large) in the female model, which suggests high applicability.

The structural equation model was tested with 5,000 bootstraps to increase confidence in the correlation between elements. Furthermore, multicollinearity was examined with VIF, which demonstrated that the causal variable had a low correlation of 3.3. The path coefficients, p-value, and t-value were evaluated

using t-value thresholds greater than 1.96 (significance level = 5%), 2.58 (significance level = 1%), and 3.29 (significance level = 0.1%). As presented in Tables 9 and 10, the H4c, H5a, and H5b hypotheses were not supported in the male sample while the H3c, H4c, and H5b hypotheses were not supported in the female sample.

Table 9: Hypothesis Testing of Male

Hypotheses	Relationship	Male (n = 286)				Supported
		β	t-Value	p-Value	VIF	
H1a	SED → CVT	0.796	24.073	0.000***	1.000	Supported
H1b	SMA→ SMA	0.853	30.143	0.000***	1.000	Supported
H2a	CVT → LON	0.519	7.518	0.000***	1.000	Supported
H2b	CVT → NEM	0.583	8.418	0.000***	1.000	Supported
H2c	CVT → SOC	0.664	11.650	0.000***	1.000	Supported
H3a	LON → ANX	0.407	4.935	0.000***	2.207	Supported
H3b	LON → DEP	0.277	3.590	0.000***	2.207	Supported
H3c	LON → SLP	0.292	2.632	0.000**	2.207	Supported
H4a	NEM → ANX	0.317	2.666	0.000**	2.832	Supported
H4b	NEM → DEP	0.583	7.231	0.000***	2.832	Supported
H4c	NEM → SLP	-0.055	0.522	0.601	2.832	Not Supported
H5a	SOC →ANX	0.142	1.491	0.136	2.220	Not Supported
H5b	SOC → DEP	0.069	0.953	0.340	2.220	Not Supported
H5c	SOC → SLP	0.549	8.694	0.000***	2.220	Supported

Table 10: Hypothesis Testing of Female

Hypotheses	Relationship	Female (n = 292)				Supported
		β	t-Value	p-Value	VIF	
H1a	SED → CVT	0.772	17.545	0.000***	1.000	Supported
H1b	SMA → SMA	0.837	31.070	0.000***	1.000	Supported
H2a	CVT → LON	0.462	6.563	0.000***	1.000	Supported
H2b	CVT → NEM	0.528	8.044	0.000***	1.000	Supported
H2c	CVT → SOC	0.602	8.336	0.000***	1.000	Supported
H3a	LON → ANX	0.346	3.364	0.000**	2.967	Supported
H3b	LON -> DEP	0.378	3.899	0.000***	2.967	Supported
H3c	LON → SLP	0.041	0.352	0.725	2.967	Not Supported
H4a	NEM → ANX	0.288	3.130	0.000**	3.036	Supported
H4b	NEM → DEP	0.294	3.882	0.000***	3.036	Supported
H4c	NEM → SLP	0.106	1.007	0.314	3.036	Not Supported
H5a	SOC → ANX	0.265	2.181	0.000*	2.915	Supported
H5b	SOC → DEP	0.234	1.896	0.058	2.915	Not Supported
H5c	SOC → SLP	0.563	5.614	0.000***	2.915	Supported

Note: * = p < 0.05, ** = p < 0.01, *** = p < 0.001, β = Path Coefficients, CVT = Cyberbullying Victim, SED = Self-disclosures On Social Media, SMA = Social media addiction, LON = Loneliness, NEM = Negative Emotion, SOC = Social Comparison, ANX = Anxiety, DEP = Depression and SLP = Sleep Disorders

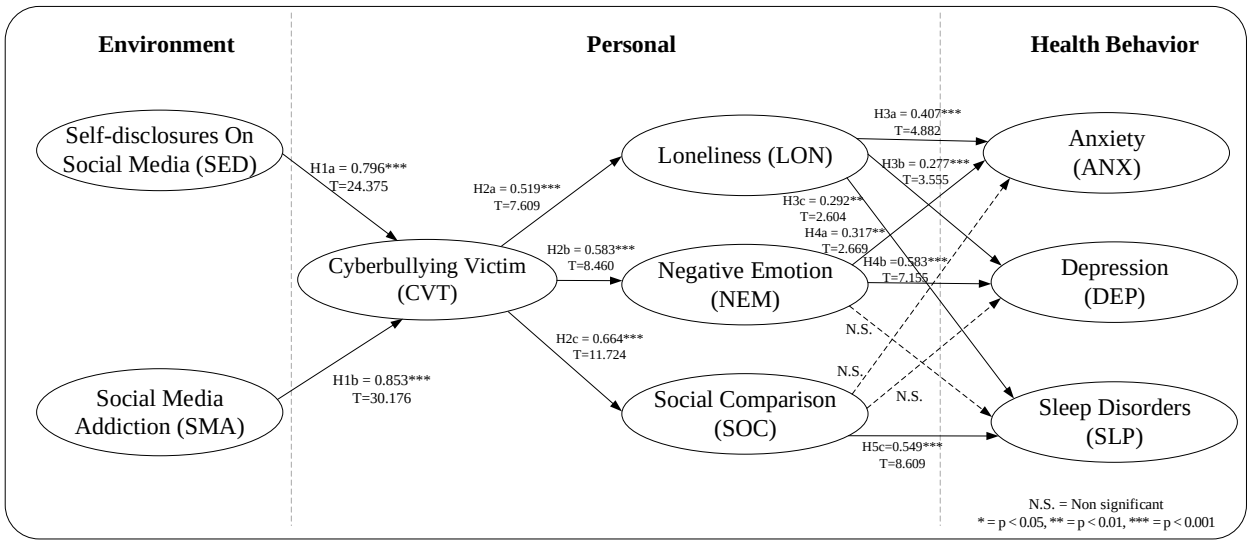

Figure 2: Structural Model Results of Male

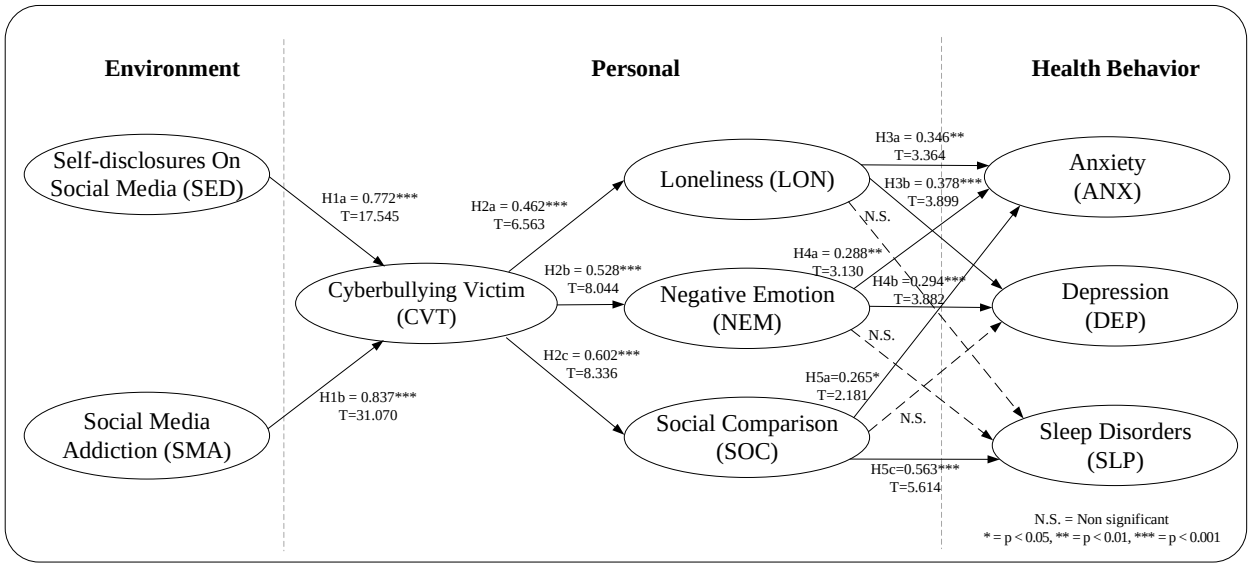

Figure 3: Structural Model Results of Female

6. DISCUSSION

This study examined the perceptions of late adolescent victims of online bullying and gender differences in health behavior modification by presenting the results of a behavioral modification analysis for each respective process. This study's results, as displayed in Tables 7–8 and Figures 2–3, are explained below.

6.1 Self-report

In terms of processes operating through the environment, self-disclosures on social media (SED) and social media addiction (SMA) contribute to an increased chance of becoming a victim of cyberbullying. Social media addiction (SMA) correlated strongly with being a male (β = 0.853) and female (β = 0.837) victim of cyberbullying. This indicated that victims are aware of the social media addiction risk of being exposed to cyberbullying. Self-disclosures on social media (SED) correlated strongly with being a male (β = 0.796) and female (β = 0.772) victim of cyberbullying. This indicates that victims are aware that self-disclosures on social media can increase the risk of cyberbullying (Aizenkot, 2020; Peluchette et al., 2015; Won and Seo, 2017). Therefore, campaigning for and preventing victims from disclosing personal information online and spending time using online media will reduce their perceived vulnerability to becoming a victim of online bullying in the future.

Important associations were also apparent in the area of personal processes. Suffering online bullying displayed the strongest association with social comparative feelings for both men (β = 0.664) and women (β = 0.602), followed by negative emotions that impact victimization for both males (β = 0.583) and females (β = 0.528). This association between victimization and social comparison indicates that individuals who compare themselves to others may suffer more from being victimized. It also highlighted the negative emotional impact of online bullying. These findings can play a crucial role in informing healthcare professionals caring for late adolescents on how to best advise victims to address their problems and manage their emotions.

Finally, in the area of processes related to health behavior, negative emotion had a direct influence on anxiety (β = 0.583) and social comparison had a direct influence on sleep disorders (β = 0.549). This indicates that the negative emotions and social comparison reported by victims of online bullying can affect health behaviors, including anxiety and sleep disorders. This is consistent with the results of Sladek et al. (2020), who reported that stress or negative feelings can affect sleep disorders. In women, the social comparison was found to have a direct effect on sleep disorders (β = 0.563), and there was a less direct effect of loneliness on depression (β = 0.378). It thus appears that the social comparison and loneliness of victims of online bullying has an impact on health behaviors, including depression and sleep disorders. This newly discovered association extends the findings of a study by Vhaduri and Poellabauer (2018) and Thompson and Lougheed (2012) who found that using phones leads to poor sleep quality, women are more likely to fall asleep after using Facebook, and the long-term effects to sleep problems can lead to an increased risk of developing chronic illnesses (Owens et al., 2017).

6.2 Practical implications

Further research on the effects on health behaviors and sleep disorders, especially among victims of cyberbullying, should be conducted. This will enable stakeholders such as medical personnel, educational institutions, families, and victims to jointly assess the impact and develop guidelines for preventing online bullying of teenagers. Specifically, the issue of relationships and family communication will help teenagers reduce their time on social media and can lead to a reduction in the chances of becoming victims (Jattamart and Kwangsawad, 2021). Education and advice on the use of social media should be provided in a timely manner so as not to affect late adolescents' daily activities. It is particularly important to advise them on how to enact behaviors that will reduce the risk of becoming a victim of bullying, such as being more cautious when accepting new friend requests on social media and not posting excessive amounts of personal information to a social network profile (SNS). From the perspective of the social networking service provider, user security measures (USM) and website security measures (WSM) should be addressed to reduce the perceived vulnerability (PV) of late adolescents to becoming a victim of cyberbullying.

6.3 Limitations and future research

This study has several limitations that need to be addressed. Firstly, the sample lacked demographic diversity as it consisted of undergraduate adolescents from only one university. As a result, the study results cannot be considered representative of every student group. Secondly, this study only explored victims' experiences of bullying on Facebook. Future studies could focus on examining whether social media use on other platforms affects victims differently. Thirdly, this study relied on self-disclosures on social media and social media addiction, which limited the analysis of relevant causal factors. Future studies could focus on other relevant environmental influences, such as parenting styles or family relationships that may be linked to the likelihood of being a victim of cyberbullying. Finally, this study only explored behavioral health effects in three areas (anxiety, depression, and sleep disorders). Future studies could examine the effects of cyberbullying on substance use behavior among late adolescents, as previous research has reported links to such behavior (Kim et al., 2019). Such efforts would illuminate a wider range of impacts on victims' health behaviors. Finally, the data were obtained via self-report, which raises the possibility of response bias.

7. CONCLUSION

This study examined the perspectives of victims and gender differences in behavioral health effects of online bullying among late adolescents. It employed Social Cognitive Theory (SCT) as a conceptual framework to examine causal relationships between cyberbullying and individual behavior occurring across three processes. The results indicated that social media addiction and self-disclosures on social media contribute to the likelihood of being victimized by cyberbullying, and this applied to both men and women. In particular, late adolescents who compare themselves with others (social comparison) were affected more severely. In addition, social comparison mediates the relationship between victimization and sleep disorders that affect health behaviors among both men and women. Thus, a new relationship has been identified between being a cyberbullying victim and sleep disorders. The results of this study provide fresh insight into the way that health behaviors are affected by the environment and personal behavior of cyberbullying victims.

ACKNOWLEDGEMENT

The researchers also do appreciate and would like to thank the Rajamangala University of Technology Rattanakosin for supporting the research process of this article.

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