The difference in mediated effect between cyberbullying and cybervictimisation under the influence of problematic social media use

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Abstract

The influence between cyberbullying (CB) and cybervictimisation (CV) is known to be two-way, but the prominence of the two directions remains unclear especially under the influence of another factor. Uncovering the mystery helps policy makers decide how to allocate the limited resource between interventions against children CB and CV. Since social media becomes increasingly relevant to children cyberaggression, this study utilises two independent mediation models to examine how problematic social media use (PSMU) potentially influence CB-induced-CV (Model 1) and CV-induced-CB (Model 2) and the difference in the proportions of mediated effect between models. As a part of Health Behaviour in School-aged Children (HBSC) study, this study included a total of 11178 children (2643 from Hong Kong and 8535 from Netherland). Results showed that the paths in the models did not differ between culture. In Model 1, CB was a significant partial mediator between PSMU and CV, $\beta_{indirect} = .08$, $p < .001$, and CV was a significant partial mediator between PSMU and CB in Model 2, $\beta_{indirect} = .06$, $p < .001$. However, CB mediated 52.78% whilst CV mediated only 28.06% of the total effect from PSMU in respective models. The ratio of mediated effect proportions between models is 1.88:1, indicating that under the influence of PSMU, CB-induced-CV is nearly twice as prominent as CV-induced-CB in a relative sense. Implications on cyberaggression research assumptions are discussed.

Keywords: cyberbullying, cybervictimisation, problematic social media use, school-aged children, HBSC

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Given cyberbullying (CB) and cybervictimisation (CV) are intercorrelated strongly (e.g., between .23 and .43; Baldry et al., 2015; Chu et al., 2018; Lozano-Blasco et al., 2020), people may cyberbully others because they are cybervictimised first, or the other way around. However, only limited resources are available and policy makers struggle in a dilemma, if any, of choosing between reducing the number of people perpetrating cyber aggressive acts so that they are less likely to become cybervictims, or reducing the number of people experiencing (at least subjectively) those aggressions so that they are less likely to retaliate (e.g., Gaffney et al., 2019). But more realistically, they must at least decide how much resources should be allocated relatively more to one side over another. The decision necessitates evidence of whether CB-induced-CV or CV-induced-CB is more prominent, especially when they are fuelled by another variable.

In general, CB refers to a collection of repeated behaviours which are intended to inflict harm on others via electronic means whereas the experience of receiving CB defines CV (e.g., Li, 2007; Gao et al., 2016; Tokunaga, 2010; Zych et al., 2019). Extensive research in CB and CV has been conducted to understand their, including but not limited to, differences from traditional bullying and victimisation (e.g., Smith et al., 2012), prevalence in different countries (e.g., Li, 2008), associations with demographics such as gender, age, and socioeconomic status (e.g., Erdur-Baker, 2010; Wang et al., 2009; Wang et al., 2019), personalities such as empathy, agreeableness, and sadism (e.g., Ang & Goh, 2010; van Geel et al., 2017), mental health such as depression and suicidal thoughts (e.g., Bottino et al., 2015; Fahy et al., 2016), situational factors such as those of schools and parents (e.g., Vale et al., 2018; Yang et al., 2020), and technological use such as internet and social media use (e.g., Craig et al., 2020; Smith et al., 2008). However, the directionality of influence between CB and CV powered by a single variable has not been studied as extensive.

From Cybervictimisation to Cyberbullying

Most studies that address the direction focus on the one from CV to CB. In fact, previously experiencing CV is argued to be the strongest predictor of engagement in CB (Kowalski et al., 2014; Kwan & Skoric, 2013; Quintana-Orts & Rey, 2018). For example, after controlling for social anxiety, and traditional bullying and victimisation, a cross-lagged structural equation model revealed that CV significantly predicted CB after six months in a sample with more than 2000 adolescents, but the effect was small (Pabian & Vandebosch, 2016). In another study across three time points, CV at a given time point marginally predicted CB at a subsequent time point (Chu et al., 2018). Results from hierarchic regression analysis and cross-lagged panel model also showed the significant prediction of CV at time 1 on CB at time 2 (Akgül & Artar, 2020). Despite the weak effects, these longitudinal findings provide some support to the directional effect from CV to CB.

Such direction is usually illustrated with reactive factors such as negative affect and desire for retaliation because they show significant predictions of the role transformation from a cybervictim to a cyberbully (König et al., 2010; Peets et al., 2013; Safaria et al., 2016; Watson et al., 2015). General strain theory (GST) posits that some negative relationships with others create strains and subsequently give raise to anger that arouses retaliation (Agnew, 1992; Ortega et al., 2009). Those who experience the strain of CV (e.g., being boycotted, threatened, or defamed on social media) were found to have more anger and perpetrated more CB behaviours, such as delivering ruthless messages and posting embarrassing pictures (Law et al., 2012; Lianos & McGrath, 2018). These CB behaviours would be further facilitated when combined with the strains from negative parental and peer relationships (e.g., Burton et al., 2013; Paez, 2018).

The transformation from a victim to a bully, however, may not take place if individuals engage in positive and adaptive emotion expression and regulation strategies (e.g., Garner & Hinton, 2010; Kokkinos & Voulgaridou, 2017). It echoes with GST since the negative affects resulted from strains could be effectively managed through, for example, positive reappraisal and positive refocusing (Kelly et al, 2008). Moreover, high forgiveness may offer a buffer against the aggressive tendency resulting from victimisation and the triggering threshold of negative reactions towards external aggressive behaviour (van Rensburg & Raubenheimer, 2015; Watson et al., 2015).

In the most cited critical review and meta-analysis in the field of CB and CV to date, Kowalski et al. (2014) built upon the general aggression model (GAM; Anderson & Bushman, 2002) and proposed a version that accounts for the roles of various personal and situational factors play in CB and CV. More importantly, GAM focuses more on the direction from CV to CB. It argues that the exposure of CB during CV functions as a form of social learning (i.e., observational learning) that helps victims transform into cyberbullies. According to the Barlett Gentile cyberbullying model (2012), the transformed cyberbullies likely remain cyberbullies because they acquire a positive attitude towards perpetrating CB anonymously (i.e., positive reinforcement).

From Cyberbullying to Cybervictimisation

Less research, however, has investigated the direction from CB to CV. To name a few, Li (2007) found that CB was the best predictor of CV. In Pabian and Vandebosch (2016), CB at time 1 significantly associated with CV at time 2. But the effect became marginal after controlling for traditional bullying and victimisation, and social anxiety in a cross-lagged structural equation model. In Chu et al. (2018), CB at time 1 moderately associated with CV at time 2 and time 3; CB at time 2 also moderately associated with CV at time 3. But results from a structural equation model across three time points showed that CB at a given time point marginally predicted CV at a subsequent time point. In Akgül and Artar (2020), CB at time 1 also significantly associated with CV at time 2 but the effect was not significant after controlling for CV at time 1 in both hierarchic regression model and cross-lagged panel model. Similar to the findings for the effect of CV on CB, although not all findings provide clear causal evidence, most demonstrated that CV is longitudinally associated with prior CB.

The process of a cyberbully becoming victimised could involve the process of another cyber victim becoming a cyberbully because the CV of the original bully necessitates the CB from others. In other words, one’s CB perpetration could victimise others who may then become aroused and retaliate as cyberbullies, victimising the original CB perpetrator. This mechanism could explain why findings that support the CV-to-CB direction would appear relatively more prominent than those of CB-to-CV direction since the former direction is more direct than the latter.

Thus, explanations for the CB-to-CV direction usually emphasise the proactivity that leads to CB and consequently CV. Contrary to those who are reactively motivated, proactive cyberbullies can be more invested in the behaviour, such as spending more time developing hostile websites (Law et al., 2012). Potential motivators for the proactivity include showing off technological proficiencies, empowerment, anger, and moral disengagement (Gradinger et al., 2012; Kowalski et al., 2014; Pornari & Wood, 2010). In fact, studies based on GST suggested that in addition to negative emotions such as anger, the causes of CB also include strains from parents, peers, and school (e.g., Jang et al., 2014; Paez, 2018).

Some social psychological theories provide more insights in the motivators of the proactivity. For example, in the social processing model, when the anonymity offered by communication technologies becomes a cue of social stimuli, it may weaken one's self-control because of social cues absence (Derks et al., 2008; Runions et al., 2013). In turn, when given an opportunity, people with low self-control are more likely to cyberbully or aggress (Guo, 2016; Holt et al., 2010; Marcum et al., 2014). Furthermore, instead of intrinsic factors, external influence can also attribute to the proactivity. Through observational learning and operant conditioning, CB can be acquired by imitating abnormal models and receiving positive reinforcements (Akers, 1998; Skinner & Fream, 1997). Subsequently, CB behaviours expose cyberbullies to the vulnerability of becoming victimised and likely invite retaliations from the cyberbullied.

Problematic Social Media Use

In both directions, there are a range of variable simultaneously influencing both CB and CV, and one of them is problematic social media use (PSMU). Research in social media use has received much attention in the last decade. Whilst some argued against a policy change despite the evident link between technological usage and well-being, the threats PSMU poses to adolescents, such as defective social interactions and social disengagements, have urged refinements in educational programmes (Jiang et al., 2018; Orben & Przybylski, 2019; Valkenburg & Peter, 2011). Studying how PSMU contributes to cyberaggression in both directions is thus vital for targeted prevention and intervention programmes.

PSMU refers to the addiction to social media and is measured by addiction-like symptoms (van den Eijnden et al., 2016). Craig et al. (2020) surveyed nearly 17 thousand adolescents and found that PSMU strongly and consistently associates with both CB and CV. These links are supported by research with both cross-sectional (e.g., Erreygers et al., 2019; Rice et al., 2015) and longitudinal designs (e.g., Barlett et al., 2018).

GST has crucial implications for how PSMU may lead to CV and CB. As mentioned above, negative interpersonal relationships act as strains that contribute to cyberaggression. Some of those relationships are listed as symptoms of PSMU (van den Eijnden et al., 2016). For example, they include frequent arguments with others over social media use, frequent deception to parents or friends about the amount of time spent on social media, and frequent serious conflict with family members over social media use. Furthermore, the PSMU symptoms of dissatisfaction of insufficient social media usage, negative emotion when social media is inaccessible, and failure to spend less time on social media correspond more or less to a primary source of strain: the prohibition of achieving positively valued goals. In short, PSMU houses the strains that link to cyberaggression.

On one hand, people experiencing these strains have another PSMU symptom of using social media to escape negative feelings such as anxiety, distress, and depression (Cappadocia et al., 2013; Hinduja & Patchin, 2010). They cope by spending more time online and by interacting with others on social media platforms (Boniel-Nissim & Sasson, 2018; Gámez-Guadix et al., 2012). Consequently, PSMU steers them to lower well-being (Boer et al., 2020), lower life satisfaction (Walsh et al., 2020), and more depression and anxiety (Kelleci & Ìnal, 2010). It may facilitate the exposure and interactions on social media platforms and lead to a higher vulnerability in CV (Boer et al., 2021).

On the other hand, PSMU could lead to CB by extensive online exposure also. Specifically, being exposed to online aggression repeatedly may enhance the acceptability of CB and the likelihood of imitating CB, especially when positive outcomes outnumber negative ones (Bandura, 1986; Olweus, 1994). Increased in social status, as an example of positive outcomes, could be perceived as the social reward of engaging in CB and reinforces the behaviour under the group conforming tendency during adolescence (Blakemore & Mills, 2014). It is, however, not to state that the negative outcomes such as victims' emotional breakdowns or suicidal attempts are absent. Cues to these consequences are more difficult to be perceived online than face-to-face, leading to higher recurrence in CB (Barlett & Gentile, 2012).

PSMU differs from intense social media use (ISMU) although the latter was also found to associate with cyberaggression (e.g., Jiang et al., 2018; Kowalski et al., 2014). The intensity of social media usage does not necessarily entail that the usage per se produces interpersonal and intrapersonal difficulties. Intensive users could enjoy interacting social media without the abovementioned strains if there are better, for example, supports from peer and parents and time management skills. However, they could still suffer from CV and/or be prone to perpetrate CB because of the exposure of more, potentially aggressive, online interactions (Underwood & Ehrenreich, 2017). But when the strains are in play amongst problematic users, their susceptibility to CV and CB exacerbates. Craig et al. (2020) recently reported that across 42 nations, PSMU was a stronger risk factor for both CV and CB than ISMU in both males and females after controlling for multiple confounding variables (e.g., age). More importantly, the results suggested that PSMU contributes higher risk to CB than it does to CV and PSMU has more possible influence on CB than on CV.

Cultural Individualism and Cyberaggression

Our examination on the adjusted risk ratios for the relationship between PSMU and CB reported in Craig et al. (2020) against the country-level individualism documented on Hofstede's website (2022) revealed that there could be a strong positive correlation. Particularly, the risk ratios appeared be higher in countries with higher individualism.

To our knowledge there are only two studies that have specifically investigated cultural variation in the *process* of cyberaggression. Barlett et al. (2014) found that US participants were more likely to engage in CB compared to Japanese participants. In both cultures, those with low individualism had less engagement in CB. Barlett et al. (2021) conducted another study with seven countries (i.e., US, Australia, Brazil, China, Germany, Japan, and Singapore) and showed that the path from positive attitude towards CB to CB perpetration was stronger in individualistic countries than in collectivistic countries. The findings support a positive correlation between country-level individualism and CB.

However, the difference in technological and internet accessibility between WEIRD and non-WEIRD (or partially WEIRD) countries could confound the categorisation of individualistic (i.e., US, Australia, and Germany) and collectivistic countries (i.e., Brazil, China, Japan, and Singapore) in those studies. According to a recent report by Organisation for Economic Co-operation and Development (OECD; 2021) with the latest data collected in 2018 (Table B 2.2), the three individualistic countries on average had consistently more 15-year-old children with internet access at home (Δ 2.62%), a computer for schoolwork at home (Δ 21.68%), and both (Δ 21.46%) than the three collectivistic countries (no China data included). Students who had access to both the interest and a computer but studied in disadvantaged schools in the three individualistic countries on average outnumbered those in the three collectivistic countries (Δ 26.85%; Table B 2.3). In general, it is possible that instead of individualism, the relatively high accessibility could explain the strong connection between cyberaggression and its key correlates in specific group of countries or cultures.

The present study is part of the Health Behaviour in School-aged Children study (HBSC) initiated by World Health Organisation since 1983 to monitor the health behaviours of children aged 11, 13, and 15 across the globe. To minimise the differences in the accessibility, this study focuses on school-aged children from Hong Kong (HK) and Netherland (NL) surveyed via HBSC. Although NL also consistently had more students with home internet access (Δ 1.33%), computer access (Δ 7.12%), and both (Δ 6.94%) than HK, the differences were relatively smaller. It was also the same for students in disadvantaged schools (Δ 9.66%). More importantly, given the accessibility has more direct relevance to cyberaggression than the country-level individualism has, the study does not expect that the processes amongst PSMU, CB, and CV differ between HK and NL because of their extremely high technological and internet accessibility despite the radical difference in individualism (Hofstede, 2022; OECD; 2021).

Present Study

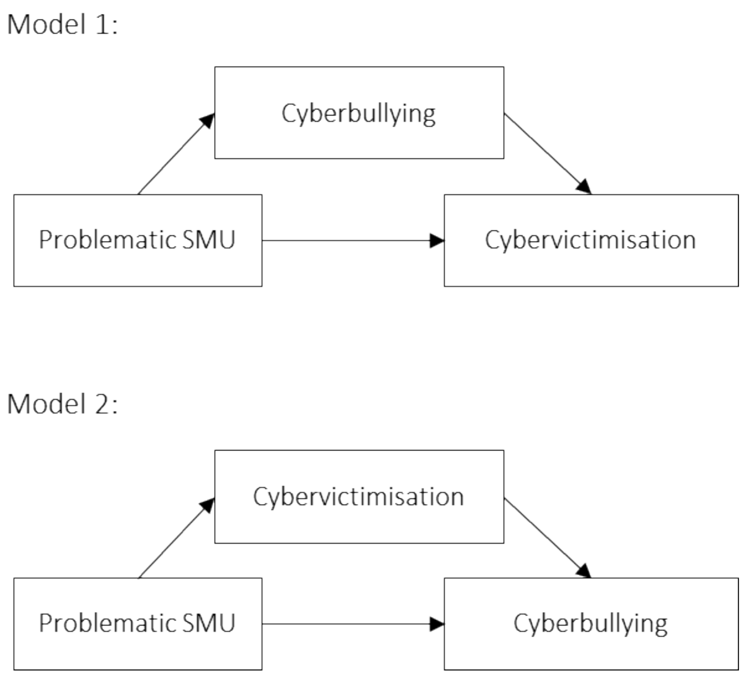
It is evident that both directions reasonably exist. But the question of whether one direction of influence is more prominent remains unanswered. Longitudinal designs with advanced statistical models (e.g., Pabian & Vandebosch, 2016) are good attempts to locate a rather definite causal direction between CB and CV, but it is *not* the aim and scope of this paper. This study does *not* directly investigate or estimate the definite causal effects between CB and CV. Instead, we acknowledge the two-way directionality between CB and CV and aim to study whether one direction would be relatively more prominent than the other when PSMU is the source of cyberaggression, based on the temporal ordering summarised in the literature.

An appropriate approach is a nonrecursive mediation model that involves a feedback path between CB and CV (Berry, 1984). But it requires two other variables specified as instrumental, in which one of them predicts CB and not CV whilst another predicts CV and not CB. The instrumental variables are also required to be the least correlated with each other and other exogenous variables, such as PSMU in this study (Cohen et al., 2003; Martens & Haase, 2006). However, no literature to date has suggested variables that are causal only to either CB or CV and have little association with each other and PSMU.

Due to the methodological limitation, we utilise a simpler approach and study the directions independently in two mediation models which the assumed independent causal direction between CB and CV differs (see Figure 1). Model 1 assumes that CV is the effect of CB without exerting a reverse causal effect back on CB, and vice versa in Model 2. Although we could not employ an ideal nonrecursive model with proper instrumental variables, studying the mediation models independently allows observation of differences in results due to changes in the assumed causal relationship. So, even it does not approximate how nonrecursive model estimates the bidirectional causal relationship, comparing results between models can reveal which direction is more prominent.

Figure 1

Proposed Path Mediation Models of Cyberbullying Mediating the Effect of Problematic Social Media Use on Cybervictimisation (Model 1) and of Cybervictimisation Mediating the Effect of Problematic Social Media Use on Cyberbullying (Model 2)



Note. Problematic SMU = problematic social media use.

In Model 1, we hypothesise that there is a significant indirect effect from PSMU to CV via CB in the combined (H1a), HK (H1b), and NL (H1c) samples and the indirect effect does not differ between HK and NL samples (null H2). In Model 2, there is a significant indirect effect from PSMU to CB via CV in the combined (H3a), HK (H3b), and NL (H3c) samples and the indirect effect does not differ between HK and NL samples (null H4). H5a to null H8 are consistent with the same hypotheses above but with ISMU controlled for. H9a to null H12 are also the same hypotheses but with common cyberaggression correlates controlled for, including age, gender, life satisfaction, and ISMU.

To answer which direction is more prominent, the study operationalises the prominence of a direction as the proportion of the mediated total effect. It should reflect how much of the PSMU effect is channelled via each direction when both CB and CV are under the influence of PSMU. Because there is no known statistical analysis to reveal the significance of the difference in the proportions in two models, this study reports a ratio between the proportions to reveal how prominent is a direction relative to another. For example, when the ratio of the proportion in Model 1 to that in Model 2 equals 1:1, neither direction appears to be more prominent under the influence of PSMU. When the ratio of Model 1 to Model 2 is higher, it indicates that the direction from CB to CV is more prominent whereas when the ratio is smaller, the direction from CV to CB is more prominent.

Methods

Participants

The present study used the 2017/2018 data collected in HK and NL via the HBSC research protocol (Robert et al., 2009). A total of 11691 children participated in the survey. After removing missing data and outliers in the separate samples, the valid sample size was 11178, consisting of 2643 Hong Kong children and 8535 Dutch children. The total sample comprised 51.7% of females and 81.5% of the total sample studied at secondary schools[1]. They aged 13.58 (SD = 1.89) years on average (M_{HK} = 13.25, SD_{HK} = 1.81; M_{NL} = 13.68, SD_{NL} = 1.91). Voluntary consent from school administrators, parents, and adolescents were secured prior to study participation and data collection.

Measurements

The questionnaire of HBSC project has different languages but the one of traditional Chinese was absent for the HK participants. Adhering to the standardised protocol, the questionnaire was translated from English to traditional Chinese and back-translated into English for validation and adjustments. Not all scales in the questionnaire were used and reported in the present study.

Cyberbullying and Cybervictimisation

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[1] The HK and NL samples consisted of 51.2% and 51.8% of females respectively. The HK and NL samples consisted of 74.3% and 83.7% of females respectively.

Adapted and revised from Olweus (1994), two items measured respectively the frequency of cyberbullying perpetration and cybervictimisation in the past couple of months, on a 5-point Likert scale from not at all (1) to several times a week (5). The questions accompany concrete examples of CB and CV to aid participants' understanding and enhance the measurement validity[2].

Problematic Social Media Use

A total of nine items from the Social Media Disorder Scale measured PSMU on a dichotomous scale (i.e., yes or no; van den Eijnden et al., 2016). Each item was developed based on the diagnostic criteria of Internet gaming disorder, which was thought to share the same overarching construct with social media disorder. They include cognitive preoccupation, stimulation tolerance, negative emotion from withdrawal, persistent use, neglecting other activities, arguments with others, deception, displacing negative affect, and serious family conflict. Participants responding yes to six or more items were categorised as having PSMU. The scale had good internal consistency in the present study ($\alpha_{combined} = .72$; $\alpha_{HK} = .79$; $\alpha_{NL} = .70$). The analyses were based on the total number of symptoms (i.e., the number of "yes").

Control Variables

Participants recorded their age and gender (female = 1; male = 0) in the demographic section of the questionnaire.

The Cantril Ladder of Life scale was used to measure life satisfaction (Cantril, 1963). Participants were asked to rate their position when imagining a ladder of life that ranges 11 levels, from the bottom indicating the worst possible life (0) to the top indicating the best possible life (10). The item has shown good convergent validity and reliability (e.g., Levin & Currie, 2014).

A total of four items adapted from the EU Kids Online Survey were included to measure ISMU on a 5-point Likert scale (Mascheroni & Ólafsson; 2014). The items

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[2] The question for cyberbullying is that "*In the past couple of months how often have you taken part in cyberbullying (e.g., sent mean instant messages, email or text messages; wall postings; created a website making fun of someone; posted unflattering or inappropriate pictures online without permission or shared them with others)?*" The question for cybervictimisation is that "*In the past couple of months how often have you been cyberbullied (e.g., someone sent mean instant messages, email or text messages about you; wall postings; created a website making fun of you; posted unflattering or inappropriate pictures of you online without permission or shared them with others)?*"

represent the people whom the participants have online contact with, including close friend(s), friends from a larger friend group, friends that the participant got to know through the internet but did not know before, and other people than friends. Participants were asked to rate the frequency of contact from "Never/Almost never" (1) to "Almost all the time" (5). The items had good internal consistency in the present study, capturing the general intensity of SMU ($\alpha_{combined}$ = .67; α_{HK} = .73; α_{NL} = .65). The analyses were based on the average score after omitting the "Don't know/NA" response.

Procedure

In Hong Kong, 10 randomly selected secondary and 10 randomly selected primary schools agreed to participate after invitations were sent. In the Netherlands, 85 of 232 randomly selected secondary schools and 72 of 187 randomly selected primary schools agreed to participate in the study after invitations were sent. To adhere to the age criteria for HBSC, invitations were limited to students studying in the fifth year (HK system) or group eight (NL system) of primary school (i.e., 11-year-old) and the first and third year (HK system) or classes one to four (NL system) of secondary school (i.e., 13- and 15-year-old). Data were collected between March and May 2018 in HK and between October and November 2017 in NL.

Data Analysis

Whereas the absolute value of 2 for skewness and 3 for kurtosis indicated all three primary variables except the frequency of cyberbullying perpetration (skewness = 6.64; kurtosis = 50.52) and victimisation (skewness = 5.58; kurtosis = 35.97) were within the acceptable margin of normality[3], histograms and tests of normality (i.e., Kolmogorov-Smirnov & Shapiro-Wilk tests) showed that the variables were not normally distributed. Additionally, PSMU, CB, and CV did not suffer from multicollinearity because their correlations were lower than .90. Differences in prevalence of PSMU, CB, and CV between cultures were examined by chi-square difference test.

The correlations amongst the variables were therefore based on Spearman's rho. Difference in the correlations between cultures was examined by Fisher's z (1925) and Zou's (2007) confidence intervals. This procedure is usually applied to comparisons between Pearson's correlations, but it is also applicable to Spearman's when the

[3] In both cultures, the skewness and kurtosis of CB and CV exceeded the cutoffs substantially.

sample size is larger than 10 and the rho is less than .90 (Sheshkin, 2004; Zar, 1999).

Because of the ordinal and non-normal data of this study, the widely used normal theory-based maximum likelihood (ML) is not an ideal estimation in this study (Mîndrilă, 2010)[4]. "Robust" variants are proposed to alleviate the problems, such as robust corrections-ML. But Li (2016a, 2016b), amongst other researchers, suggested that diagonally weighted least squares (DWLS) with robust corrections (or weighted least squares—mean and variance adjusted; WLSMV) can provide more accurate estimation in factor loadings, interfactor correlations, and structural coefficients when data are ordinal and asymmetric. Although under some conditions DWLS may perform better than WLSMV, the large sample size of this study keeps the negative impact minimal (DiStefano & Morgan, 2014). Despite our focus on the path coefficients instead of a full SEM model, the analysis employs WLSMV estimation for the rigour of structural coefficients because of the data type and distributions.

The two models were first analysed without covariates. Then ISMU entered the models predicting CB and CV whilst covarying with PSMU. Lastly, age, gender, and life satisfaction joined ISMU in the models to predict CB and CV and covary with PSMU. Standardised beta, 95% confidence intervals, standard errors, and *z*-values were reported. The difference in standardised betas between cultures was also reported.

[4] The study utilised LISERL and used the term "DWLS (i.e, diagonally weighted least squares)" instead of WLSMV. But they equivalently refer to the DWLS with robust correction because it is termed DWLS in LISERL and WLSMV in Mplus and lavaan.

Results

Prevalence of and Correlations amongst PSMU, CB, and CV

As shown in Table 1, chi-square independence tests revealed that consistently there are proportionally more adolescents categorised as problematic social media users, perpetrated CB, and suffering from CV in HK than in NL.

Table 1

Means, standard deviations, proportions, and chi-square independence tests of the difference in the proportion of problematic social media users, cyberbullies, and cyberbullying victims between Hong Kong and Netherland samples

	Combined (N = 11178)	HK (n = 2643)	NL (n = 8535)	Difference between HK and NL
Variable	M(SD) / %	M(SD) / %	M(SD) / %	$\chi 2$
PSMU	1.47 (1.83)	1.56 (2.07)	1.45 (1.74)	
Equals to or more than six items	4.02%	6.24%	3.33%	44.49***
CB	1.08 (.40)	1.14 (.54)	1.06 (.35)	
At least once	5.10%	8.82%	3.95%	98.79***
CV	1.11 (.47)	1.18 (.60)	1.09 (.43)	
At least once	7.34%	11.92%	5.93%	106.39***
Roles				153.05***
Non-participants	89.90%	83.88%	91.76%	
Cyberbullies	2.76%	4.20%	2.31%	
Cybervictims	5.00%	7.30%	4.29%	
Both	2.34%	4.62%	1.64%	

Note. HK = Hong Kong; NL = Netherland; PSMU = problematic social media use; CB = cyberbullying; CV = cybervictimization.
*** $p < .001$

The number of four roles involved in cyberaggression also differ between cultures in which there are proportionally more cyberbullies, cybervictims, and those involved in both in HK than in NL.

Table 2

Spearman's Correlations Amongst Problematic Social Media Use, Cyberbullying, and Cybervistimisation in Hong Kong and Netherland Samples, and z-values and 95% Confidence Intervals of the Differences in the Correlations

	r_s		Δr_s	
Variable pair	HK	NL	z	95% CI
PSMU <-> CB	.22***	.14***	3.66***	[.04, .12]
PSMU <-> CV	.19***	.14***	2.42*	[.01, .09]
CB <-> CV	.40***	.31***	4.35***	[.05, .12]

Note. HK = Hong Kong; NL = Netherland; PSMU = problematic social media use; CB = cyberbullying; CV = cybervictimization. 95% CI = 95% confidence interval.
*** $p < .001$, * $p < .05$

Correlations between PSMU and CB ($r_s = .22, p < .001$), between PSMU and CV ($r_s = .19, p < .001$), and between CB and CV ($r_s = .40, p < .001$) are all positive and significant in the combined sample. Correlations in each culture and the cross-cultural difference in the correlations are shown in Table 2. Results indicated that although the directions of correlations in each pair of variables are culturally consistent, the strength of correlations is significantly stronger in HK than in NL.

Prominence of CB-induced-CV and CV-induced-CV

No Control Variables

In Model 1 (see Table 3), results from the combined sample indicated that PSMU directly predicts CB and CV, and CB directly predicts CV. The indirect effect from PSMU to CV via CB is positively significant at a moderate level, constituting 52.78% of the total effect from PSMU to CV. The direction and magnitude of these effects are similar in individual culture and have no significant differences. There is also no cultural difference in the mediated effect proportion, Δ proportion = 1.46% [-21.36%, 24.28%], $p = .900$.

In Model 2, results from the combined sample indicated that PSMU directly predicts CV and CB, and CV directly predicts CB. The indirect effect from PSMU to CB via CV is positively significant at a marginal to moderate level, constituting 28.06% of the total effect from PSMU to CB. The direction and magnitude of these effects are also similar in individual culture and have no significant differences. There is also no cultural difference in the mediated effect proportion, Δ proportion = -1.53% [-15.32%, 12.27%], $p = .828$.

In the combined sample, the proportion of mediated total effect in Model 1 and 2 indicates a ratio of 1.88:1 (i.e., 52.78%:28.06%), suggesting that for every 10% PSMU contributes to CV-induced-CB, there will be 18.8% PSMU contributes to CB-induced-CV when the causal relationship between CB and CV is assumed independent and opposite. The ratios are largely consistent between cultures (HK = 2.03:1; NL = 1.85:1).

Table 3

Standardised Estimates of Path Coefficients, Differences in Path Coefficients between Cultures, Standard Errors, z-values, 95% Confidence Intervals, and Proportions of Mediated Effects in Total Effects of Model 1 and 2 in Combined, Hong Kong, and Netherland Samples

	Combined sample (*N* = 11178)			HK (*n* = 2643)			NL (*n* = 8535)			Difference between HK and NL			
Effect	β [95% CI]	*SE*	*z*	β [95% CI]	*SE*	*z*	β [95% CI]	*SE*	*z*	Δβ [95% CI]	*SE*	*z*	*p*
Model 1													
Direct													
PSMU→CB	.20 [.17, .23]	.02	13.22	.22 [.17, .27]	.03	8.44	.18 [.15, .22]	.02	10.06	.04 [-.03, .10]	.03	1.16	.248
CB→CV	.39 [.34, .44]	.03	14.39	.38 [.30, .46]	.04	9.02	.39 [.32, .46]	.04	10.84	.00 [-.11, .11]	.06	-.07	.947
PSMU→CV	.07 [.05, .09]	.01	5.99	.07 [.03, .12] *	.02	3.25	.07 [.04, .09]	.01	5.08	.01 [-.04, .06]	.03	.31	.760
Indirect													
PSMU→CV (via CB)	.08 [.06, .09]	.01	9.81	.08 [.06, .11]	.01	6.20	.07 [.05, .09]	.01	7.46	.01 [-.02, .05]	.02	.81	.420
Total													
PSMU→CV	.14 [.12, .17]	.01	11.99	.16 [.11, .20]	.02	6.96	.14 [.11, .16]	.01	9.64	.02 [-.03, .07]	.03	.80	.425
Proportion of mediated effect	52.78%			53.50%			51.47%						
Model 2													
Direct													
PSMU→CV	.14 [.12, .17]	.01	11.99	.16 [.11, .20]	.02	6.96	.14 [.11, .16]	.01	9.64	.02 [-.03, .07]	.03	.80	.425
CV→CB	.38 [.33, .43]	.03	14.22	.37 [.29, .45]	.04	8.91	.38 [.31, .45]	.04	10.72	-.01 [-.11, .10]	.06	-.13	.898
PSMU→CB	.14 [.11, .17]	.02	9.64	.16 [.11, .21]	.03	6.14	.13 [.10, .17]	.02	7.40	.03 [-.03, .09]	.03	.94	.349
Indirect													
PSMU→CB (via CV)	.06 [.04, .07]	.01	8.52	.06 [.04, .08]	.01	5.19	.05 [.04, .07]	.01	6.59	.01 [-.02, .03]	.01	.51	.612
Total													
PSMU→CB	.20 [.17, .23]	.02	13.22	.22 [.17, .27]	.03	8.44	.18 [.15, .22]	.02	10.06	.04 [-.03, .10]	.03	1.16	.248
Proportion of mediated effect	28.06%			26.36%			27.87%						

Note. HK = Hong Kong; NL = Netherland; PSMU = problematic social media use; CB = cyberbullying; CV = cybervictimization; 95% CI = 95% confidence interval. Estimations utilised diagonally weighted least squares. Standard errors and test statistics were based on robust corrections (or weighted least squares—mean and variance adjusted).
All paths are significant at $p < .001$ unless specified otherwise.
* $p = .001$

Controlling for ISMU

Results largely mirror the above even after controlling for the effect of ISUM in both models (see Table 4). The proportion of mediated effect drops to 50.17% in Model 1. No cultural difference is found in the mediated effect proportion, Δ proportion = 1.10% [-22.14%, 24.34%], p = .926. Moreover, ISMU does not predict CV across the combined (β = -.01 [-.03, .01], p = .309), HK (β = .02 [-.02, .05], p = .332), and NL (β = -.02 [-.04, .01], p = .175) samples. Although it predicts CB in the combined (β = .02 [.00, .05], p = .019) and HK sample (β = .05 [.01, .09], p = .011), the prediction is not significant in the NL sample (β = .02 [.00, .05], p = .068). All predictions are extremely weak.

In Model 2, the proportion of mediated effect rises to 29.55%. No cultural difference is found in the mediated effect proportion, Δ proportion = -1.29% [-16.21%, 13.63%], p = .866. ISMU similarly does not predict CV across the combined (β = .00 [-.02, .02], p = .992), HK (β = .04 [.00, .08], p = .058), and NL (β = -.01 [-.03, .02], p = .595) samples. But it predicts CB across the samples ($\beta_{combined}$ = .02 [.01, .04], p = .012; β_{HK} = .04 [.00, .08], p = .044; β_{NL} = .03 [.00, .05], p = .030). Though, the effects are also very weak.

In the combined sample, the proportion of mediated total effect in Model 1 and 2 indicates a ratio of 1.70:1 (i.e., 50.17%:29.55%), suggesting that for every 10% PSMU contributes to CV-induced-CB, there will be 17% PSMU contributes to CB-induced-CV. The ratios are largely consistent between cultures (HK = 1.81:1; NL = 1.69:1).

Table 4

Standardised Estimates of Path Coefficients, Differences in Path Coefficients between Cultures, Standard Errors, z-values, 95% Confidence Intervals, and Proportions of Mediated Effects in Total Effects of Model 1 and 2 in Combined, Hong Kong, and Netherland Samples after Controlling for Intense Social Media Use

	Combined sample (*N* = 10658)			HK (*n* = 2400)			NL (*n* = 8258)			Difference between HK and NL			
Effect	β [95% CI]	*SE*	*z*	β [95% CI]	*SE*	*z*	β [95% CI]	*SE*	*z*	Δβ [95% CI]	*SE*	*z*	*p*
Model 1													
Direct													
PSMU→CB	.19 [.16, .22]	.02	12.67	.21 [.15, .26]	.03	7.75	.18 [.14, .22]	.02	9.68	.03 [-.04, .09]	.03	.77	.440
CB→CV	.39 [.33, .44]	.03	14.05	.38 [.30, .47]	.04	8.68	.39 [.31, .46]	.04	10.66	.00 [-.11, .11]	.06	-.05	.957
PSMU→CV	.07 [.05, .10]	.01	6.36	.08 [.03, .12] *	.02	3.23	.07 [.04, .10]	.01	5.39	.01 [-.05, .06]	.03	.21	.833
Indirect													
PSMU→CV (via CB)	.07 [.06, .09]	.01	9.40	.08 [.05, .11]	.01	5.75	.07 [.05, .09]	.01	7.19	.01 [-.02, .04]	.02	.54	.590
Total													
PSMU→CV	.15 [.13, .17]	.01	12.20	.16 [.11, .20]	.02	6.64	.14 [.11, .17]	.01	9.82	.01 [-.04, .07]	.03	.54	.590
Proportion of mediated effect	50.17%			50.82%			49.72%						
Model 2													
Direct													
PSMU→CV	.15 [.13, .17]	.01	12.20	.16 [.11, .20]	.02	6.64	.14 [.11, .17]	.01	9.82	.01 [-.04, .07]	.03	.54	.590
CV→CB	.38 [.33, .44]	.03	13.89	.37 [.29, .46]	.04	8.61	.38 [.31, .45]	.04	10.53	-.01 [-.12, .10]	.06	-.10	.921
PSMU→CB	.14 [.11, .17]	.02	9.04	.15 [.10, .20]	.03	5.54	.13 [.09, .16]	.02	6.98	.02 [-.04, .08]	.03	.63	.530
Indirect													
PSMU→CB (via CV)	.06 [.04, .07]	.01	8.55	.06 [.04, .08]	.01	5.05	.05 [.04, .07]	.01	6.60	.00 [-.02, .03]	.01	.34	.737
Total													
PSMU→CB	.19 [.16, .22]	.02	12.67	.21 [.15, .26]	.03	7.75	.18 [.14, .22]	.02	9.68	.03 [-.04, .09]	.03	.77	.440
Proportion of mediated effect	29.55%			28.10%			29.39%						

Note. HK = Hong Kong; NL = Netherland; PSMU = problematic social media use; CB = cyberbullying; CV = cybervictimization; 95% CI = 95% confidence interval. Estimations utilised diagonally weighted least squares. Standard errors and test statistics were based on robust corrections (or weighted least squares—mean and variance adjusted).
All paths are significant at $p < .001$ unless specified otherwise.
* $p = .001$

Controlling for Gender, Age, Life Satisfaction, and ISMU

After gender, age, life satisfaction, and ISMU are controlled for, the results maintain high consistency to those without any control variables (see Table 5). In Model 1, the proportion of mediated effect climbs to 58.94%. No cultural difference is found in the mediated effect proportion, Δ proportion = -12.99% [-41.34%, 15.36%], $p = .369$. Being a male (vs. female) predicts CB across samples ($\beta_{combined}$ = -.09 [-.11, -.08], $p < .001$; β_{HK} = -.12 [-.15, -.08], $p < .001$; β_{NL} = -.08 [-.10, -.06], $p < .001$) and CV only in the HK sample ($\beta_{combined}$ = -.01 [-.03, .01], $p = .357$; β_{HK} = -.05 [-.09, -.02], $p = .003$; β_{NL} = .01 [-.01, .03], $p = .323$). Age does not predict CB across samples ($\beta_{combined}$ = .00 [-.02, .02], $p = .982$; β_{HK} = .01 [-.03, .06], $p = .539$; β_{NL} = .01 [-.01, .03], $p = .409$) but predicts CV except the HK sample ($\beta_{combined}$ = -.05 [-.07, -.03], $p < .001$; β_{HK} = -.01 [-.05, .02], $p = .474$; β_{NL} = -.06 [-.09, -.04], $p < .001$). Low life satisfaction predicts CV in all samples ($\beta_{combined}$ = -.12 [-.15, -.09], $p < .001$; β_{HK} = -.07 [-.12, -.03], $p = .002$; β_{NL} = -.14 [-.17, -.10], $p < .001$) and CB except the NL sample ($\beta_{combined}$ = -.07 [-.10, -.04], $p < .001$; β_{HK} = -.08 [-.14, -.03], $p = .004$; β_{NL} = -.03 [-.06, .01], $p = .101$). Across samples, ISMU predicts CB ($\beta_{combined}$ = .03 [.01, .05], $p = .002$; β_{HK} = .06 [.02, .10], $p = .003$; β_{NL} = .03 [.00, .05], $p = .027$) but not CV ($\beta_{combined}$ = .00 [-.02, .02], $p = .716$; β_{HK} = .03 [-.01, .06], $p = .160$; β_{NL} = .00 [-.03, .02], $p = .657$). Other than some cases for gender and life satisfaction, the effects are generally weak.

In Model 2, the proportion of mediated effect falls to 24.49%. No cultural difference is found in the mediated effect proportion, Δ proportion = 2.90% [-11.70%, 17.50%], $p = .697$. Being a male (vs. female) predicts CB in all samples ($\beta_{combined}$ = -.08 [-.09, -.06], $p < .001$; β_{HK} = -.08 [-.11, -.05], $p < .001$; β_{NL} = -.07 [-.09, -.05], $p < .001$) and CV except the NL sample ($\beta_{combined}$ = -.04 [-.06, -.03], $p < .001$; β_{HK} = -.09 [-.13, -.06], $p < .001$; β_{NL} = -.02 [-.04, .00], $p = .074$). Except the HK sample, age predicts both CB ($\beta_{combined}$ = .02 [.00, .04], $p = .022$; β_{HK} = .02 [-.02, .06], $p = .403$; β_{NL} = .03 [.01, .05], $p < .001$) and CV ($\beta_{combined}$ = -.05 [-.07, -.03], $p < .001$; β_{HK} = -.01 [-.05, .03], $p = .689$; β_{NL} = -.06 [-.08, -.04], $p < .001$). Across samples, low life satisfaction predicts CV ($\beta_{combined}$ = -.15 [-.18, -.12], $p < .001$; β_{HK} = -.10 [-.15, -.05], $p < .001$; β_{NL} = -.15 [-.18, -.11], $p < .001$) but not CB ($\beta_{combined}$ = -.01 [-.04, .02], $p = .419$; β_{HK} = -.04 [-.10, .01], $p = .096$; β_{NL} = .03 [-.01, .06], $p = .107$). ISMU predicts CB in all samples ($\beta_{combined}$ = .03 [.01, .05], $p = .006$; β_{HK} = .04 [.01, .08], $p = .026$; β_{NL} = .03 [.00, .05], $p = .029$) but not CV except the HK sample ($\beta_{combined}$ = .02 [.00, .04], $p = .113$; β_{HK} = .05 [.01, .09], $p = .014$; β_{NL} = .01 [-.02, .03], $p = .638$).

Table 5

Standardised Estimates of Path Coefficients, Differences in Path Coefficients between Cultures, Standard Errors, z-values, 95% Confidence Intervals, and Proportions of Mediated Effects in Total Effects of Model 1 and 2 in Combined, Hong Kong, and Netherland Samples after Controlling for Gender, Age, Life Satisfaction, and Intense Social Media Use

	Combined sample (*N* = 10640)			HK (*n* = 2394)			NL (*n* = 8246)			Difference between HK and NL			
Effect	β [95% CI]	*SE*	*z*	β [95% CI]	*SE*	*z*	β [95% CI]	*SE*	*z*	Δβ [95% CI]	*SE*	*z*	*p*
Model 1													
Direct													
PSMU→CB	.18 [.15, .21]	.02	11.92	.19 [.14, .24]	.03	7.06	.18 [.14, .22]	.02	9.48	.01 [-.06, .07]	.03	.25	.799
CB→CV	.38 [.33, .44]	.03	13.64	.37 [.28, .46]	.04	8.26	.38 [.31, .46]	.04	10.63	-.02 [-.13, .10]	.06	-.27	.786
PSMU→CV	.05 [.03, .07]	.01	4.13	.07 [.02, .11] *	.02	2.77	.04 [.01, .06] **	.01	2.85	.03 [-.03, .08]	.03	1.01	.314
Indirect													
PSMU→CV (via CB)	.07 [.05, .08]	.01	8.99	.07 [.04, .10]	.01	5.38	.07 [.05, .09]	.01	7.14	.00 [-.03, .03]	.02	.02	.987
Total													
PSMU→CV	.12 [.09, .14]	.01	9.31	.14 [.09, .18]	.02	5.78	.11 [.08, .14]	.02	6.95	.03 [-.03, .08]	.03	.99	.324
Proportion of mediated effect	58.94%			51.51%			64.50%						
Model 2													
Direct													
PSMU→CV	.12 [.09, .14]	.01	9.31	.14 [.09, .18]	.02	5.78	.11 [.08, .14]	.02	6.95	.03 [-.03, .08]	.03	.99	.324
CV→CB	.38 [.32, .43]	.03	13.58	.36 [.27, .45]	.04	8.19	.38 [.31, .45]	.04	10.60	-.02 [-.14, .09]	.06	-.42	.675
PSMU→CB	.14 [.11, .17]	.01	9.27	.14 [.09, .19]	.03	5.21	.14 [.10, .17]	.02	7.67	.00 [-.06, .06]	.03	.03	.976
Indirect													
PSMU→CB (via CV)	.04 [.03, .06]	.01	7.11	.05 [.03, .07]	.01	4.57	.04 [.03, .06]	.01	5.29	.01 [-.02, .03]	.01	.56	.576
Total													
PSMU→CB	.18 [.15, .21]	.02	11.92	.19 [.14, .24]	.03	7.06	.18 [.14, .22]	.02	9.48	.01 [-.06, .07]	.03	.25	.799
Proportion of mediated effect	24.49%			25.79%			22.89%						

Note. HK = Hong Kong; NL = Netherland; PSMU = problematic social media use; CB = cyberbullying; CV = cybervictimization; 95% CI = 95% confidence interval. Estimations utilised diagonally weighted least squares. Standard errors and test statistics were based on robust corrections (or weighted least squares—mean and variance adjusted).
All paths are significant at $p < .001$ unless specified otherwise.
** $p = .004$; * $p = .006$

In the combined sample, the proportion of mediated total effect in Model 1 and 2 indicates a ratio of 2.41:1 (i.e., 58.94%:24.49%), suggesting that for every 10% PSMU contributes to CV-induced-CB, there will be 24.1% PSMU contributes to CB-induced-CV. Despite the seemingly different ratios between cultures (HK = 2.00:1; NL = 2.82:1), because the mediated effect proportions do not differ between cultures in both models, the ratios should also not statistically differ between cultures.

Discussion

The purpose of this study was to gain better understanding of whether CB-induced-CV or CV-induced-CB is more prominent when under the influence of PSMU. To this end, the study examined two mediation models that respectively built upon the assumption that CB is the cause of CV (i.e., Model 1) or CV is the cause of CB (i.e., Model 2), without using a methodologically constrained model to account for the bidirectional effect between CB and CV. There are some key findings. First, CB and CV are significant partial mediators in their respective models (i.e., H1, H3, H5, H7, H9, and H11). Second, in addition to the direct effects, the indirect effects are consistent across HK and NL (i.e., null H2, H4, H6, H8, H10, H12). Third, the effects are still present after controlling for the common cyberaggression correlates. Lastly, CB-induced-CV is consistently more prominent than CV-induced-CB when PSMU is in effect.

In Mode 1, 52.78% of the influence from PSMU to CV is explained by CB. It suggests that at least half of the reason why PSMU leads children to be victimised online is because PSMU gives rise to more frequent behavioural aggression online, exposing themselves to higher risk of victimisation. However, in Model 2, CV only explains 28.06% of the influence from PSMU to CB. It indicates that suffering from PSMU brings children more victimisation experience online and thereby inducing stronger behavioural tendency to bully others online; this process accounts for at least a quarter of the variance of how PSMU leads to behavioural aggression online. It is clear that PSMU is associated with both CB and CV, but PSMU contributes more to CB-induced-CV than it does to CV-induced-CB at a ratio of 1.88:1.

Findings from controlling the covariates carry helpful implications for the relationship between PSMU and ISMU and the uniqueness of PSMU in the cyberaggression context. Whereas PSMU could substantially predict variations in CB and CV, ISMU could hardly, if not weakly, predict CB and CV in models that it was controlled for. It suggests that although ISMU alone is relevant to cyberaggression (e.g., Jiang et al., 2018), such relevance could in fact be powered by PSMU because ISMU is a manifestation of PSMU. Such findings extend those in Craig et al. (2020). That is, the reason ISMU being a relatively weaker risk factor than PSMU could be that the variance of PSMU consists of the variance of ISMU and other unique variance accountable to the variance of cyberaggression. This is also why PSMU possesses the unique variance to predict CB and CV when ISMU has only little when both are accounted for in the present study.

The uniqueness of PSMU further stood out when more covariates (at least those in this study) entered the models. The rigorous relationships between PSMU and cyberaggression prevent the magnitude of paths from radical deviation when the covariates are in play. In fact, after accounting for the effects of age, gender, life satisfaction, and ISMU, the proportion of mediated effects increased in Model 1 but decreased in Model 2. The prominence ratio consequently surged from 1.88:1 to 2.41:1 (i.e., 58.94%:24.49%), indicating that for every 10% of effect PSMU channels through CV to CB, there would be 24.1% of effect PSMU channels through CB to CV. The findings collectively implicate that the potential CB-induced-CV is consistently more prominent than CV-induced-CB when PSMU is the reason for cyberaggression, and the prominence would be even stronger when other reasons for cyberaggression are accounted for.

These results challenge the common retaliation assumption in cyberaggression research in which people bully others online because they are bullied first (e.g., Kowalski et al., 2014; Pabian & Vandebosch, 2016). It is not to say that the assumption is wrong. In fact, findings from Model 2 support this assumption that children with PSMU avenge the violence they receive from the Internet probably because they reactively want to displace and resolve negative emotions, such as distress, anger, and anxiety induced from the aggression (e.g., Safaria et al., 2016; Watson et al., 2015). On the other hand, results from Model 1 support another assumption that PSMU fuels the proactivity of bullying others online and thus brings risks of being victimised, probably from those who are bullied according to the retaliation assumption. However, the results from this study offer more evidence for the proactivity assumption than the retaliation assumption.

The proactivity assumption receives more empirical support could be attributed to the characteristics of PSMU measured by the scale (van den Eijnden et al., 2016). It includes items that reflect negative affects (e.g., felt dissatisfied because you wanted to spend more time on social media; felt bad when you could not use social media; used social media to escape from negative feelings), anger arousal (e.g., regularly had arguments with others because of your social media use; had serious conflict with your parents/brother(s)/sister(s) because of your social media use), and low self-control (e.g., regularly found that you can't think of anything else but the moment that you will be able to use social media again; tried to spend less time on social media, but failed; regularly neglected other activities because you wanted to use social media). These three are some of many factors that can cultivate the proactivity of CB (Marcum et al., 2014; Kowalski et al., 2014; Pornari & Wood, 2010; Runions et al., 2013).

A primary implication here is that studying the directionality between CB and CV by treating them as exogenous variables may not be sufficient (e.g., at Time 1 in Pabian & Vandebosch, 2016). It is because the direct source of CB and CV may have more effect on one but less on another. In turn, the selection of which cause to include in the study could moderate the ratio of total effect explained by indirect effects between CB-induced-CV model and CV-induced-CB model. For example, when unforgiveness replaces PSMU as the predictor, the empirical results would likely support the retribution assumption because unforgiveness has more to do with CV-induced-CB. It is possible that the stronger the general unforgiving attitude children have, the more likely they would engage in CB after being victimised online because of the vengeance tendency.

The implication also signals that even if a study could account for all possible causes of CB and CV, that absolute ratio of effects between the CB-induced-CV model and CV-induced-CB model could not become informative enough for designing effective policies or interventions because of extreme generalisability. Causes and mechanisms of cyberaggression differs as the contexts change. For example, in one region, children who are bullied at school could become cyberbullies towards the school bullies. In another region, children cyberbully and then are cybervictimised because of social skills difficulties. An ultimate ratio could not be used to produce a programme effective for both cases. Instead, we suggest conducting systematic research with each possible causes treated as the only predictor in the mediation models (or two to three predictors if resources allow). Then governments or agencies could analyse each case individually and identify the most influential causes for that case. Referring back to findings of the ratios relevant to the identified causes could suggest how much resources should be weighted between CB-focused and CV-focused programmes.

The consistent findings between HK and NL revealed that the accessibility to the Internet and technological devices could be a confounding variable of individualism in some of the previous studies that focused on the process of cyberaggression (e.g., Barlett et al., 2014, 2021). The current study selected two regions with very different levels of individualism but similar levels of accessibility. It showed that the processes of how PSMU potentially influences and thus is channelled through CB and CV were not stronger in the individualistic region. In other words, as long as there is high accessibility, children suffering from PSMU in collectivistic regions could also undergo the same process with the same tendencies as their individualistic counterparts. This implication is inconsistent with those reported in Barlett et al. (2021), where the path between CB attitude and CB perpetration was stronger in the individualistic regions. Although PSMU and CB attitude differs conceptually, they could both be affected by the accessibility in which its variability could assist or restrict the potential growth of PSMU and CB attitude.

Limitations and Further Research

It leads to the first limitation. Findings cannot be generalised to other predictors of CB and CV. Although this study reveals that PSMU is prone to produce CB-induced-CV more than CV-induced-CB at a ratio of 1.88:1, other predictors that affiliate more with the proactivity assumption may not show a similar ratio. Consequently, the proportion of resources allocating between CB-focused and CV-focused programmes would vary across the predictors identified even they operate under the same assumption. It necessitates a systematic study on possible predictors of CB and CV to unveil the ratios for informed and effective resources allocation in programmes development.

The other limitations are methodological. First, the present study utilised only samples in HK and NL. Although the findings of the mediation models are highly consistent between cultures, future replication studies are required in more countries with various cultures to enhance generalisability. Specifically, the study did not systematically control the variability in the accessibility and only included two regions with high accessibility. It is possible that individualism could moderate processes in the models when in regions with low accessibility, given the relatively higher cyberaggression motivation amongst the individualistic regions. We would like to call for replications of the present study and the studies by Barlett et al. (2014, 2021) with the accessibility accounted for.

The present study did not employ an ideal nonrecursive mediation model that was methodologically constrained. We call for more research to identify adequate instrumental variables for CB and CV to fulfil the required assumptions for using the nonrecursive mediation model.

The analyses were based on cross-sectional data. Importantly, literature showed that CB and CV are moderately correlated with themselves across different time points (e.g., Akgül & Artar, 2020; Chu et al., 2018). The cross-sectional measurements of CB and CV could therefore serve as their proxies at different time points, partially fulfilling the criterion of the temporal order of variables for causal analysis. However, even a large amount of cyberaggression studies were based on cross-sectional data without explicitly highlighting the definite causality between CB and CV (Zych et al., 2015), we acknowledge that the findings in the present study should be tentative and replicated longitudinally.

Findings from mediation models may not completely support causal claims. Some suggested that the findings for causal relationships are not conclusive although mediation model implies a causal structure amongst variables and a mediation hypothesis is a causal hypothesis (Imai et al., 2010; James & Brett, 1984). They argued that the statistical models for testing mediation are not fundamentally causal and the coefficients from the models are correlational in nature (Fairchild & McDaniel, 2017; Sobel, 2008). The resulting findings at most support possible, but not definite, causal explanations in the mediation models (Agler & Boeck, 2017). Although these criticisms are fair and reasonable, we believe that the literature and theories have established theoretically valid, but indefinite, causal links amongst PSMU, CB, and CV. We call for research using more advanced statistical models to conduct a conceptual or theoretical replication of the present study.

Lastly, because the data was collected in 2018, some might consider the findings a bit outdated despite only four years has passed. But it made the data and findings more valuable since they are free from the COVID-19 influence. During the pandemic, many schooltime has been moved online and students were asked to stay home, facilitating more online interpersonal interactions. The increased time spent on social media has exposed children to higher risks of CB, CV, and more importantly, PSMU. Although the pandemic may affect the applicability of our findings, however, the current study certainly offers a reference point if further research focuses on how much the pandemic affects the directionality between CB and CV as it potentially worsens PSMU amongst children.

Conclusion

The bidirectional effect between CB and CV causes difficulty for better resource allocation on intervention or prevention programmes. One solution requires understanding which direction is more prominent and deserves relatively more resources. Instead of a methodologically demanding statistical analysis that might suggest a net effect in one direction, findings of the present study are based on two simple mediation models based on the assumptions of two respective directions between CB and CV. When PSMU is the source for CB and CV, the proportion of mediated total effects in the model assuming CB causes CV is about twice as much as that in the model assuming CV causes CB. Moreover, these findings are largely consistent across samples in HK and NL. The findings imply not only the development of CB intervention (vs. CV prevention) programmes targeting PSMU deserve relatively more efforts and resources, but they also suggest that the relative prominence between CB and CV may depend on the strength of their associations with the fuelling variable and add value to previous research that is heavily based on the retribution direction from CV and CB. More research replicating our findings, extending the usage of the proportion ratio, and preparing the usage of the nonrecursive mediation model is warranted. These endeavours can advance our understanding of the relative prominence within the bidirectional effect between CB and CV and help make informed decisions in developing programmes that tackle cyberaggression.

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