Perceived-Social Isolation and Cyberbullying Involvement:
The Role of Online Social Interaction

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ABSTRACT

Although perceived social isolation (i.e., feelings of loneliness and a perceived lack of social support) has been shown to be associated with the involvement in cyberbullying behaviors, little is known about the mediating mechanisms underlying this relationship. This study tested the mediating role of a preference for online social interaction in the association between perceived social isolation and cyberbullying involvement. Our findings demonstrated that increasing levels of perceived social isolation were associated with enhanced levels of preference for online social interaction, which in turn were associated with a higher probability of being involved in cyberbullying. These findings contribute significantly to the literature on both cyberbullying involvement and problematic internet use, and provide suggestions for practical applications.

KEYWORDS

Bystander, Cyberbullying, Loneliness, Online social interaction, Perceived social support, Perpetrator, Victim

1. INTRODUCTION

Cyberbullying is defined as aggressive behaviors (e.g., threats and intimidation), acted by an individual or a group of individuals, carried out over time and through the use of electronic communication technologies (e.g., texting, email, social networks; Camerini et al., 2020; Giumetti & Kowalski, 2022; Vismara et al., 2022). Cyberbullying has been established as a very common phenomenon that occurs globally, as shown, for example, by the analyses of the prevalence of cyberbullying in the USA, Canada, China, and Italy (for a review see Broachado et al., 2017; Piccoli et al., 2020). Prevalence analyses typically assess the frequency of cyberbullying by considering the role of the victim of cyberbullying as well as the perpetrators and bystanders. Specifically, Brochado, Soares, and Fraga

(2017) demonstrated across a review of 159 studies that cyberbullying perpetration prevalence rates ranged from 1.0% to 61.1%, whereas cyberbullying victimization rates ranged from 3.0% to 39.0% (see also Patchin, 2016). Moreover, other studies have shown that between 50 and 80% of individuals who participated in the study, reported witnessing at least one episode of cyberbullying (Olenik-Shemesh et al., 2017; Valdés-Cuervo et al., 2021; Zhu et al., 2022). In the Italian context, which is the country in which this research was carried out, 34.2% of adolescent participants in the study were victims of cyberbullying behaviors, 38.3% responded that they cyberbully others, and that 77.1% reported that they had witnessed cyberbullying behaviors (Piccoli et al., 2020).

The analysis of cyberbullying prevalence testifies to the high frequency of such a phenomenon across countries, and also provides information regarding a constituent facet of the cyberbullying phenomenon. Indeed, cyberbullying appears to be a multicomponent process which involves three distinct roles, namely victim, perpetrator, and bystander (Piccoli et al., 2020; Pozzoli & Gini, 2020; for a review see Kowalski et al., 2014). Such roles are strongly intertwined and, at least in certain cases, interchangeable. Being a victim of cyberbullying is associated with a high probability of also being a cyberbullying perpetrator as well as a bystander of cyberbullying, and vice versa (Piccoli et al., 2020; Pozzoli & Gini, 2020; Walrave & Heirman, 2011); being a bystander of cyberbullying is associated with a high probability of also being a cyberbullying perpetrator, and vice versa (Barlińska et al., 2013; Bastiaensens et al., 2016; Giumetti & Kowalski, 2022; Piccoli et al., 2020). Hence, assessing cyberbullying from the perspective of perpetrator, victim, and bystander is mandatory in order to gain an accurate representation of cyberbullying involvement in a given context.

Several studies have aimed to better understand the situational and interpersonal factors that may foster or prevent individuals from being involved in cyberbullying. Among the situational variables, social influence processes were found to play a crucial role in fostering cyberbullying involvement (Bullo & Schulz, 2022; Dang & Liu, 2020; Piccoli et al., 2020). Within the individual variables, empirical research (for a review see Chen et al., 2017) have shown that self-esteem (Martínez et al., 2020; Pyżalski, 2012; Wachs et al., 2020), moral disengagement (Gao et al., 2020; Lo Cricchio et al., 2021), narcissism (Schade et al., 2021), depression (Zhang et al., 2020), and perceived social isolation (Al Qudah et al., 2020; Arató et al., 2020; Brighi et al., 2013; Chu et al., 2021; Eden et al., 2014; Fanti et al., 2012; Olenik-Shemesh et al., 2012; Olenik- Shemesh et al., 2015; Şahin; 2012) are associated with a higher probability of being involved in cyberbullying.

In this research, we focused on perceived social isolation to better understand *how* this interpersonal factor might be associated with cyberbullying involvement. Perceived social isolation is defined as feelings related to a sense of loneliness and a perceived lack of social support (Cacioppo et al., 2006; Cornwell & Waite, 2009, p 2). Evidence suggests that perceived social isolation is a predictor of being a cyberbullying perpetrator (Al Qudah et al., 2020; Eden et al., 2014), of being a victim of cyberbullying (Brighi et al., 2012; Kowalski et al., 2019) and of being a cyberbullying bystander (Olenik- Shemesh et al., 2015). In addition, research has tried to understand the underlying process that accounts for perceived social isolation and association with cyberbullying involvement. Specifically, two variables can account for the relationship in question: rejection by peers (Brewer & Kerslake, 2015; Mueller-Coyne et al., 2022) and problematic internet use (Chu et al., 2021).

Research that has focused on peer rejection suggests that cyberbullying involvement is a compensatory reaction of individuals in response to isolation resulting from rejection by peers (Brewer & Kerslake, 2015; Mueller-Coyne et al., 2022). Studies addressing the relationship between problematic internet use and cyberbullying involvement have almost exclusively operationalized problematic internet use in terms of internet addiction, namely as an excessive and dysfunctional use of the Internet (Chu et al., 2021; Zhang et al., 2018). Internet addiction has been found to mediate the relationship between perceived social isolation and cyberbullying involvement (Chu et al., 2021; Gül et al., 2019; Kwok et al., 2017; Martínez-Ferrer et al., 2018). Notwithstanding the importance of such studies, this strand of research has limited its investigation to internet addiction as the operationalization of problematic internet use, while such a construct is multicomponent by definition and further involves individuals' preference for online over offline social interactions (Beard & Wolf, 2001, p. 378). In the current study, we fill this lacuna by testing whether the preference for online social interaction can be an additional social and psychological factor that mediates the relationship between perceived social isolation and cyberbullying involvement.

A preference for online social interaction is defined as a "cognitive individual-difference construct characterized by beliefs that one is safer, more efficacious, more confident, and more comfortable with online interpersonal interactions and relationships than with traditional face-to-face social activities" (Caplan, 2003, p. 629). The hypothesis that a preference for online social interaction may mediate the perceived social isolation - cyberbullying involvement link is guided by two main theoretical observations. First, individuals with high levels of perceived social isolation showed a high preference for online interactions compared to offline interactions (Caplan, 2003; Kim et al., 2009; Morahan-Martin & Schumacher, 2003; Mueller-Coyne et al., 2022), because those individuals find a certain degree of anonymity on the Internet (Morahan-Martin & Schumacher, 2003; Mueller-Coyne et al., 2022) and also find opportunities to experiment with several identities (Leung, 2011; Nowland et al., 2018). Online anonymity (Caplan, 2003; Kim et al., 2009; Morahan-Martin & Schumacher, 2003; Mueller-Coyne et al., 2022) and fluid identity (Leung, 2011; Nowland et al., 2018) are two aspects of the preference for online interaction and have also been found to be precursors to involvement in cyberbullying (Barlett & Gentile, 2012; Barlett, 2015; Kowalski et al., 2014; Mueller-Coyne et al., 2022; Schade et al., 2021; Walrave & Heirman, 2011). Indeed, anonymity and fluid identity can disinhibit cyberbullying involvement by increasing the sense of de-responsibility in both those who perpetrate and those who witness cyberbullying behaviors (for a review see Kowalski et al., 2014; Wang et al., 2020). Furthermore, these constituent aspects of the preference for online social interaction might increase a sense of powerlessness in cyberbullying victims, as the possibility of identifying the perpetrator of such aggression is diminished (for a review see Giumetti & Kowalski, 2022).

Based on this rationale, we predicted that individuals who showed high levels of perceived social isolation also showed a high preference for online social interaction (*Hypothesis 1*). Moreover, we hypothesized that individuals who showed high levels of preference for online social interaction also showed high levels of probability of being involved in cyberbullying behaviors *(Hypothesis 2).* Finally, we predicted that the preference for online social interaction mediated the relationship between perceived social isolation and cyberbullying involvement *(Hypothesis 3*).

2. METHOD

2.1 Participants and Procedure

We recruited three hundred and four participants (n = 202 female, n = 86 male participants, n = 3 participants self-identified as 'other', and n = 13 not reporting) who voluntarily took part in the research. Participants' age ranged from 18 to 35 (M = 22.09, SD = 3.77; n = 37 not reporting). Two hundred and fifty-eight participants were Italian, and thirty-three participants were not Italian citizens (n = 13 not reporting).

The research was approved by the University Ethics Committee. All the data were obtained via an anonymous self-report questionnaire through a web survey (i.e., SurveyMonkey). The survey was published on social networks such as Facebook and Instagram. The advertisement for the survey and the self-report questionnaire were in Italian. Participants were asked to complete the survey individually after providing their informed written consent. The questionnaire took approximately fifteen minutes to be fill out.

2.2 Measures

We operationalized *perceived social isolation* as suggested by Cacioppo and colleagues (2006) namely via the loneliness and perceived social support constructs.

Loneliness. The UCLA Loneliness Scale contains 20 items assessing the subjective feelings of loneliness and social isolation (e.g., "How often do you feel alone?"; Russell et al., 1978; for the Italian version see Boffo et al., 2015). Participants rated their answers on a 4-point scale ranging from 1 (*never*) to 4 (*always*).

Perceived social support. Perceived social support was measured using the Multidimensional Scale of Perceived Social Support (MSPSS; Zimet, et al.,1988; for the Italian version see Sestito et al., 2008), and it was comprised of 12 items (e.g., "I feel that there is no one I can share my most private worries and fears with"). Participants provided their answers on a 7-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

Preference for online social interaction. Preference for online social interaction was measured using 11 items (e.g., "I am more comfortable with computers than people") from the Generalized Problematic Internet Use Scale (i.e., GPIUS; Caplan, 2002; 2003; Chung, 2013). This scale was translated into Italian by the authors. Participants provided their answers on a 7-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

Cyberbullying involvement. Participants' involvement in cyberbullying behaviors was assessed using a 15-item scale (Piccoli et al., 2020) measuring: (1) *perpetrator* (five items; e.g., How often in the last year, via Smartphone (e.g., SMS, WhatsApp), email (e.g., mailing list) and social networks (e.g., Facebook, Instagram, Snapchat) have you sent offensive and/or vulgar messages to somebody?); (2) *victim* (five items; e.g., How often in the last year, via Smartphone (e.g., SMS, WhatsApp), email (e.g., mailing list) and social networks (e.g., Facebook, Instagram, Snapchat) have you received offensive and/or vulgar messages from someone?); *bystander* (five items; e.g., How often in the last year, via Smartphone (e.g., SMS, WhatsApp), email (e.g., mailing list) and social networks (e.g., Facebook, Instagram, Snapchat) have you read offensive and/or vulgar messages addressed to someone other than you?). The scale in question is available in Italian. Participants rated their answers on a five-point Likert scale ranging from 1 (*never*) to 5 (*always*).

At the end of the questionnaire, participants were asked to indicate their gender, age, nationality, and native language. Finally, they were debriefed and thanked.

3. RESULTS

3.1 Descriptive Results

Means, standard deviations, Cronbach's alpha, and correlations between the measures employed in the current study are provided in Table 1.

3.2 Participants' Cyberbullying Involvement

As regards participants' cyberbullying involvement, 40.8% of the participants responded that they had bullied another person at some time in the last year, 37.8% of participants responded that they

Table 1. Means, standard deviations, Cronbach's alpha, and correlations of the measures

Measures	Mean *(SD)*	α (alpha Cronbach)	1.	2.	3.	4.	5.
1. Loneliness	2.25 (0.53)	.93					
2. Perceived social support	5.66 (1.08)	.90	-.65**				
3. Preference for online social interaction	2.04 (0.65)	.82	.24**	-.27**			
4. Perpetrator of cyberbullying	1.53 (0.53)	.62	.009	.02	.19**		
5. Victim of cyberbullying	1.53 (0.56)	.70	.23**	-.15**	.26**	.48**	
6. Bystander of cyberbullying	2.70 (0.91)	.82	.11*	-.09	.27**	.44**	.47**

Note. *$p < .05$, **$p < .01$

were bullied at some time in the last year, and 85.9% of participants reported that they had witnessed cyberbullying behaviors at some time in the last year.

3.3 Statistical Approach

In order to generate perceived social isolation profiles, a two-step cluster analysis was conducted. The two-step clustering analysis is a fitting exploratory technique used to detect natural clusters (Bacher et al., 2004; Benassi et al., 2020; Hsu, 2020). In order to generate perceived social isolation profiles, a two-step cluster analysis was conducted. The two-step clustering analysis is a fitting exploratory technique used to detect natural clusters (Bacher et al., 2004; Benassi et al., 2020; Hsu, 2020). In comparison to more traditional techniques (e.g., arbitrary choice), it has the advantage of determining the number of clusters based on a statistical measure of fit, namely the Bayesian information criterion – BIC – index (the best model is the one with the lowest BIC value), rather than on an arbitrary decision (e.g., hierarchical, or k-means cluster analysis). Furthermore, comparative studies found that two-step cluster analysis was one of the most reliable techniques to identify the number of subgroups (see Benassi et al., 2020).

Specifically, the two-step cluster is an analysis which first uses a distance measure to separate groups and then a probabilistic approach to select the optimal subgroup model (Gelbard et al., 2007; Kent et al., 2014). The same analysis was performed to identify cyberbullying involvement profiles (for similar procedure see Traijtenberg et al., 2021).

3.4 Cluster Analysis

Perceived social isolation. Loneliness and perceived social support measures were analyzed via a cluster analysis. This analysis identified a three-cluster solution based on a lower BIC value of 219.635 and a higher ratio of the distance of measures with a value of 2.966. The quality of the cluster solution can be characterized as "good" based on a silhouette measure of cohesion and separation close to 0.6. Additionally, two-step clustering examined the order of importance of each variable as a predictor of the clusters. In this analysis, the most relevant predictor for the cluster solution was perceived social support followed by loneliness. In particular, this result indicated that the clusters were primarily created on the basis of perceived social support. Clustering analysis resulted in three groups: high levels of perceived social isolation (cluster 1; $n = 53$) *vs.* medium levels of perceived social isolation (cluster 2; $n = 118$) *vs.* low levels of perceived social isolation (cluster 3; $n = 125$). Cluster 1 comprised participants who showed higher levels of loneliness and lower levels of perceived social isolation than participants in cluster 2 and participants in cluster 3 ($ps < .001$). Moreover, participants in cluster 2 showed higher levels of loneliness and lower levels of perceived social isolation than participants in cluster 3 ($ps < .001$). Table 2 contains means and standard deviations for loneliness and perceived social support measures separately for the three perceived social isolation clusters.

Cyberbullying involvement. The same clustering analysis was performed for the three roles (i.e., perpetrator, victim, and bystander) of cyberbullying involvement. The analysis suggested a three-cluster

Table 2. Means and standard deviations of perceived social isolation clusters separately for perceived social support and loneliness

	Perceived social support		**Loneliness**	
	M	*SD*	*M*	*SD*
Perceived social isolation				
1 = High levels	3.82	.68	2.91	.27
2 = Medium levels	5.60	.57	2.47	.33
3 = Low levels	6.48	.42	1.77	.28

solution based on a lower BIC value of 435.89 and a higher ratio of the distance of measures with a value of 2.267. The quality of the cluster solution can be characterized as "fair" based on a silhouette measure of cohesion and separation close to 0.5. The most relevant predictor for the cluster solution was the victim of cyberbullying involvement, followed by the bystander of cyberbullying involvement, and then the perpetrator of cyberbullying involvement. Specifically, this result suggested that the clusters were created mainly based on the victim of cyberbullying involvement. Clustering analysis generated three groups: high levels of cyberbullying involvement (cluster 1; $n = 74$) *vs*. medium levels of cyberbullying involvement (cluster 2; $n = 129$) *vs.* low levels of cyberbullying involvement (cluster 3; $n = 95$). Importantly, cluster 1 comprised participants who showed higher levels of perpetrator, victim and bystander of cyberbullying involvement compared to those participants in cluster 2 ($ps < .001$) and in cluster 3 ($ps < .001$). Moreover, participants in cluster 2 showed higher levels of perpetrator, victim, and bystander of cyberbullying involvement compared to those participants in cluster 3 ($ps < .001$). Table 3 contains means and standard deviations for perpetrator, victim, and bystander separately for the three cyberbullying involvement clusters.

3.5 Mediation Analysis

The mediation model represents a chain of events in which the predictor X influences the outcome variable Y indirectly via the mediator variable M. This model assumes that X has an effect on M (a path), which then propagates to Y (b path). The process by which X transmits its effect to Y is represented in the indirect effect. In particular, the product of coefficients method involves the product of a and b paths to form the mediated or indirect effect, namely ab coefficient. According to this paradigm, X can also have a direct effect (c') on Y regardless of X influence on M. Formally, the path diagram for a mediation model with a single mediator M through which X has an impact on Y can be described by two linear equations:

$$M = i_1 + aX + e_M$$

$$Y = i_2 + c'X + bM + e_y$$

The total effect of X on Y can be computed as the sum of X's direct and indirect effect on Y, formally c = c' + ab."

Data were analyzed by means of the R package *lavaan* (R Core Team, 2021; Rosseel, 2012): X = perceived social isolation (1 = high *vs.* 2 = medium *vs.* 3 = low), M = preference for online social interaction, Y = cyberbullying involvement (1= high *vs.* 2 = medium *vs.* 3 = low). Specifically, since the perceived social isolation levels can be ranked, we entered the variable in the analysis by means of two dummy variables coding two unweighted contrasts (e.g., Hayes & Preacher, 2014): one corresponding to the low condition relative to high and medium conditions averaged together ($D_{hm.l}$), and the second comparing high vs. medium perceived social isolation ($D_{h.m}$). When calculating the

Table 3. Means and standard deviations of perpetrator, victim, and bystander, separately for three clusters of cyberbullying involvement

	Perpetrator		**Victim**		**Bystander**	
	M	*SD*	*M*	*SD*	*M*	*SD*
Cyberbullying involvement						
1 = High levels	2.07	.60	2.29	.49	3.43	.69
2 = Medium levels	1.53	.38	1.36	.29	3.02	.56
3 = Low levels	1.14	.20	1.14	.17	1.69	.47

mediation model with *lavaan*, we treated cyberbullying involvement as an ordinal outcome activating the WLSMV (weighted least square mean and variance adjusted) robust estimation method which provides the best option for modelling ordinal data. The estimated model was represented in path diagram form in Figure 1. Using the dummy coding for X defined above, the mediation model was then parameterized by these two linear equations:

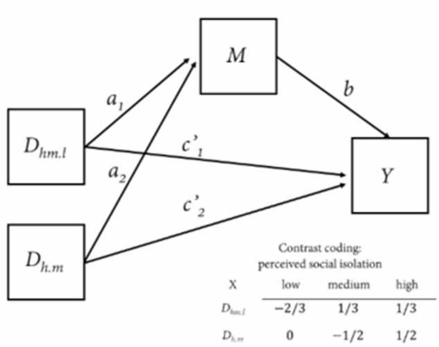
$$M = i_1 + a_1 D_{hm.l} + a_2 D_{h.m} + e_M$$
$$Y = i_2 + c'_1 D_{hm.l} + c'_2 D_{h.m} + bM + e_y$$

The relative total effects of the two dummy variables coding groups contrasts on Y can be computed as the sum of corresponding direct and indirect effect, formally $c_1 = c'_1 + a_1 b$ and $c_2 = c'_2 + a_2 b$.

Results showed that both $D_{hm.l}$ and $D_{h.m}$ variables coding specific contrasts among perceived social isolation levels were positively associated with a preference for online social interaction. In particular, medium to high levels of perceived social isolation yielded a higher preference for online social interaction relative to low levels of perceived social isolation (a_1 path: $B = .31$, $SE = .08$, $p < .001$). Furthermore, high levels of perceived social isolation yielded a higher preference for online social interaction relative to medium levels of perceived social isolation (a_2 path: $B = 0.32$, $SE = 0.10$, $p = .001$). These results indicate that the higher the levels of perceived social isolation, the higher the levels of preference for online social interaction *(Hypothesis 1)*. Moreover, and in line with *Hypothesis 2*, a preference for online social interaction was positively associated with cyberbullying involvement (*b* path: $B = 0.49$, $SE = 0.09$, $p < .001$). This result indicates that the higher the preference for online social interaction, the higher the levels of being involved in cyberbullying behaviors. As suggested by Hayes and Preacher (2014), we also tested for non-uniqueness of b path for both contrast coding variable $D_{hm.l}$ and $D_{h.m}$ (i.e., between-group heterogeneity hypothesis in the effect of M on Y), by inserting the following interaction terms into the Y equation to set up a new (moderated) mediation model:

$$M = i_1 + a_1 D_{hm.l} + a_2 D_{h.m} + e_M$$
$$Y = i_2 + c'_1 D_{hm.l} + c'_2 D_{h.m} + b_1 M D_{hm.l} + b_2 M D_{h.m} + b_3 M + e_y$$

Figure 1. Preference for online social interaction as a mediator (M) in the relationship between perceived social isolation (whose levels are represented by contrast coding variables $D_{hm.l}$ and $D_{h.m}$) and cyberbullying involvement (Y)



Results were not statistically significant ($\div^2$ (2, N = 295) = 4.18, p = .124), when the moderated mediation model was compared to a constrained model in which the two interaction terms were constrained to be zero ($b_1 = b_2 = 0$), thus indicating that the assumption of between-group homogeneity in the effect of M on Y was not violated."

As for the relative direct effects, adjusting for group differences in preference for online social interaction, participants who reported medium to high perceived social isolation were more likely to be involved in cyberbullying behaviors relative to those who reported low levels of perceived social isolation, but the test fell short of significance (c'_2 path: $B = 0.25$, $SE = 0.14$, $p = .064$). No difference emerged in cyberbullying involvement between participants who reported high relative to medium levels of perceived social isolation ($c'2$ path: $B = -0.03$, $SE = 0.18$, $p = .875$).

Finally, and in line with our main hypothesis (*Hypothesis 3*), both relative indirect effects of contrast coding variable $D_{hm.l}$ and $D_{h.m}$ on involvement in cyberbullying behaviors through a preference for online social interaction were positive and statistically significant (a_1b path: $B = 0.15$, $SE = 0.05$, $p = .001$; a_2b path: $B = 0.16$, $SE = 0.06$, $p = .004$). These results indicate that individuals who show high levels of perceived social isolation also show a high preference for online social interaction, and that the stronger the preference for online social interaction, the higher the involvement in cyberbullying behaviors. In other words, a preference for online social interaction is a significant mediator of the relationship between perceived social isolation and cyberbullying involvement.

The post-hoc Monte Carlo power analysis for mediation models (Schoemann et al., 2017) was used to determine whether sufficient power was achieved given the size of the current sample. The power analysis indicated that our sample achieved sufficient power: .90 based on conventional power values (power = .80; Cohen, 1988).

4. DISCUSSION

In this study, we investigated the mediating role of a preference for online interaction in the relationship between perceived social isolation and cyberbullying involvement. As expected and consistent with previous studies (Caplan, 2003; Kim et al., 2009; Morahan- Martin & Schumacher, 2003; Mueller-Coyne et al., 2022) perceived social isolation is associated with a preference for online social interaction (*Hypothesis 1*). This result may suggest that participants with high levels of perceived social isolation may cope with a lack of offline interactions by compensating with enhanced value placed on online social interactions, (Kardefelt-Winther, 2014; Tosuntaº et al., 2020). Furthermore, individuals who showed a high preference for social online interaction also reported high levels of cyberbullying involvement (*Hypothesis 2*). These results suggest that those constituent characteristics that both a preference for online social interaction and cyberbullying involvement have in common, such as for instance the user's anonymity and fluidity in terms of online identity, may contribute to binding the two processes under analysis (Leung, 2011; Nowland et al., 2018).

Finally, and according to our main hypothesis (*Hypothesis 3*), the relationship between perceived social isolation and cyberbullying involvement was mediated by a preference for online social interaction. Our research contributes to the literature regarding problematic internet use in general by showing that not only clinical conditions such as those represented by internet addiction, but also non-pathological conditions such as those indicated by a preference for online social interaction, might be considered risk factors for the involvement in cyberbullying dynamics.

However, we failed to find a significant direct effect between perceived social isolation and cyberbullying involvement. Previous research which analyzed the relationship between perceived social isolation and cyberbullying behaviors has produced mixed results. Indeed, some studies have not found a significant relationship between the two variables in question (Brewer & Kerslake, 2015; Kokkinos et al., 2019; Sahin, 2012; Varghese & Pistole, 2017). In contrast, other research has found a significant and positive association between perceived social isolation and involvement in cyberbullying behaviors (Al Quadah et al., 2020; Arató et al., 2020; Brighi et al., 2012; Fanti et al., 2012; Olenik- Shemesh et al., 2012; Olenik-Shemesh & Heiman, 2014). Such a discrepancy might be accounted for by the manner in which the constructs of interests were assessed, given that some studies relied on loneliness (Brewer et al., 2015; Brighi et al., 2012; Kokkinos et al., 2019; Sahin, 2012; Varghese & Pistole, 2017) and perceived social support measures (Aratò et al., 2020; Fanti et al., 2012; Williams & Guerra, 2007) separately, and other studies assessed only a few and not all the roles involved in cyberbullying involvement (i.e., perpetrator, victim, and bystander; Al Qudah et al., 2020; Arató et al., 2020; Brighi et al., 2013; Chu et al., 2021; Eden et al., 2014; Fanti et al., 2012; Olenik-Shemesh et al., 2012; Olenik-Shemesh & Heiman, 2014; Olenik- Shemesh et al., 2015; Şahı̂n; 2012; Williams & Guerra, 2007). The current study contributes to the debate on the association between perceived social isolation and involvement in cyberbullying by testing such an association with a more encompassing assessment of these constructs and suggests that such association is highly likely to work in an indirect mediated fashion (Preacher & Hayes, 2004; Preacher & Hayes, 2008).

Despite these findings, some limitations of this study must be considered. First, the cross-sectional nature of the data does not enlighten us as to the causal relationship between the variables. Thus, future studies using experimental and longitudinal research designs are needed in order to understand the causal mechanisms behind the association of perceived social isolation on cyberbullying involvement through the mediating role of the preference for online social interaction over time. Second, the present research relied on a convenience sample of undergraduate students. Future studies should be carried out on different samples of the population, such as those represented by individuals of different ages to improve the external validity of our results.

Notwithstanding the above-mentioned limitations, some applied implications can be derived from our findings. First, increasing offline social interactions for individuals with high levels of loneliness and low levels of perceived social support may be a plausible route for interventions aimed at reducing cyberbullying involvement. Second, online social interactions might also enhance healthy social connections when individuals are able to use them appropriately (Clark & Green, 2018; Lieberman & Schroeder, 2020). Indeed, online social interactions might provide individuals with social support when offline interactions are poor or impractical (Lieberman & Schroeder, 2020), as is the case of the recent Covid-19 pandemic. This indicated that Internet use may not necessarily be problematic and associated with social isolation. Indeed, relationships formed online can later continue offline or both online and offline. Online interactions can also complement and strengthen existing offline relationships (Clark et al., 2018; Nowland et al., 2018). Hence, education regarding how to safely engage in online interactions, as well as to improve the quality of offline relationships together with expanding one’s network may buffer the sense of perceived social isolation as well as discourage cyberbullying involvement.

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