

ASSESSING RISKY ONLINE BEHAVIOR IN NZ UNIVERSITY STUDENTS

Abstract

This study examines the relationship between two types of cyberabuse: cyberharassment and cyberstalking, and constructs from the lifestyle-routine activity approach relating to the *visibility* and *accessibility* of victims (targets) online. Data were collected from 185 university students in New Zealand via an online survey. Descriptive statistics show cyberabuse victimization experiences in the previous year were common, but respondents only reported associated feelings of fear or distress for half of these experiences. Findings indicated using dating apps is associated with an increased risk of cyberharassment and including details of other social network accounts in a user profile is associated with an increased risk of cyberstalking. Interestingly, demographic characteristics did not correlate with victimization. Overall, this research underscores the importance of differentiating between cyberharassment and cyberstalking to inform prevention activities.

Keywords: target visibility, target accessibility, online routine activities, victimology, fear

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**Assessing risky online behavior for cyberharassment and cyberstalking among
university students in New Zealand**

The rapid growth of communication technologies in the 21st century has significantly expanded opportunities for cyberabuse. While scholarly attention on cyberstalking has kept pace with its rising prevalence (Kaur et al., 2021), much of the research is based on U.S. samples, and findings on cyberstalking victimization correlates vary across studies (Marcum & Higgins, 2021). This inconsistency underscores the need to test victimization correlates across diverse socio-political contexts (Kabiri et al., 2022). This study addresses this gap by examining risky online behavior linked to two forms of cyberabuse—cyberharassment and cyberstalking—among a high-risk population; university students in New Zealand.

Cyberabuse manifests in several forms. Of direct relevance to this study, cyberharassment involves threats or unwanted advances via digital platforms (Brown et al., 2017). Cyberstalking refers to intentional, repeated, and unwanted pursuit behaviors via technology that instill fear, distress, or significant disruption to a victim's¹ daily life (Reyns et al., 2012). Cyberstalking tactics include unwanted contact, data theft, unsolicited sexual content, and monitoring behaviors. However, the operationalization of cyberstalking varies across studies. Some require a pattern of repeated, unwanted behavior causing fear (e.g., Akinduko et al., 2017; Leukfeldt & Yar, 2016), while others include only some of these elements (e.g., Reyns, 2010; Sheridan & Grant, 2007). A key debate remains whether victimization status hinges on fear or if other negative emotions, such as anxiety and depression, should be factored into legal definitions (Fissel, 2022).

These definitional variations complicate efforts to synthesize research findings and obscure estimates of cyberstalking prevalence. A scoping review found prevalence rates in

¹ There are divergent opinions on how to refer to victims in the literature. Here, for the sake of simplicity, we use the term victim, but we acknowledge that some people prefer the term victim-survivor.

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the general population ranging from 0.7% to 85.2%, similar to findings in university samples (Wilson et al., 2023). This wide range suggests both the phenomenon and the way it is studied differ considerably. With social media facilitating interpersonal contact (Maple et al., 2011), cyberstalking continues to evolve alongside the digital landscape (Reyns et al., 2012), and research must adapt to these changes.

Cyberstalking can lead to serious psychological, social, economic, and physiological harm (Jerath et al., 2022; Stevens et al., 2010; Worsley et al., 2017). University students may be particularly vulnerable due to the social nature of this lifestage and their need to navigate new environments both online and offline. As Pereira & Matos (2016) note, evolving communication technologies have shifted social norms, especially in dating, creating opportunities for exploitation. The extensive time students spend interacting online, especially during the pandemic (Silveira et al., 2022), may further increase their risk.

Student cyberstalking victims may face unique harms, including academic difficulties such as poor concentration, low grades, and failure to complete studies (Fissel & Reyns, McNamara & Marsil, 2012; 2020; Stevens et al., 2010). Cyberstalking may also exacerbate trauma in individuals with prior experiences of abuse, which is disproportionately common among minority groups, such as those with disabilities or from ethnic and rainbow² communities (Wolfe, 2018).

Despite the frequent focus on university students in cyberstalking research, it remains unclear how online behavior correlates with victimization risk across different time periods and contexts. Identifying these behaviors is critical for developing prevention strategies. This paper begins by outlining how lifestyle-routine activity theory (L-RAT) has been used to study cyberabuse and explores known behaviors that increase victimization risk. We then

² Rainbow communities is the preferred term in New Zealand for LGBTQI+ and represents minority groups on the dimensions of sexual identity and gender.

describe our methods and present the statistical findings, concluding with a discussion of their implications for both theory and practice.

L-RAT Applied to Cyberabuse

Most empirical research on cyberabuse applies the Lifestyle-Routine Activities Theory (L-RAT), which integrates two major perspectives on victimization risk (Cohen et al., 1981). The routine activity approach (Cohen & Felson, 1979) identifies three key elements in crime occurrence: a likely offender, a suitable target (including human victims), and the absence of a capable guardian. Routine activities shape how and when offenders and victims intersect. Hence, crime opportunities are the product of victims and offenders converging in optimal conditions.

Lifestyle exposure theory (Hindelang et al., 1978) expands this by explaining differential victimization risk through individuals' lifestyles, which expose them to potential offenders and risky situations. Both theories emphasize that victim attributes, activities, and lifestyles increase exposure to crime, especially in unguarded public or semi-public spaces. L-RAT posits that routine activities leading to risky situations elevate victim exposure to offenders, while target suitability and the absence of guardians further facilitate victimization.

Research applying L-RAT to cyberabuse focuses on identifying risky online behaviors, as these drive offender-target convergence. However, findings have been inconsistent (Vakhitova et al., 2016), likely due to varying definitions of cyberabuse (e.g., cyberharassment, cyberbullying, cyberstalking) and the dynamic nature of cyberspace, where mediums and functionalities evolve over time.

Recent studies have examined online lifestyle choices that increase victimization risk. Kabiri et al. (2022) found that social media engagement and time spent on social networks were positively associated with cyberstalking among Iranian university students. Marcum and Higgins (2021) found a similar correlation with multiple social media accounts (Marcum et

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al., 2017; Reynolds et al., 2011, 2016). Online gaming, another popular activity, has shown mixed results, with some studies linking it to cyberabuse (Vakhitova et al., 2019) and others finding no association (Ngo et al., 2020).

Deviant online behaviors are also hypothesized to elevate risk. Studies have found associations between cyberstalking victimization and having deviant online peers (Reynolds et al., 2011), viewing pornography (Novo et al., 2014), possessing pirated media (Back, 2016), and hacking (Holt & Bossler, 2008). Overall, individuals actively engaging online—through frequent updates, posting personal photos, or sharing information—are at heightened risk (Kabiri et al., 2022). Increased visibility to offenders, particularly through personal information disclosure, may directly correlate with cyberstalking risk (Welsh & Lavoie, 2012). Hence, relatively innocuous activities that increase one's social network reach or evoke attention may increase visibility to potential offenders.

Visibility is one element of the VIVA framework (value, inertia, visibility, accessibility) from routine activity theory (Cohen & Felson, 1979), describing factors that make targets suitable to offenders. Despite its relevance, VIVA has been underutilized in cyberabuse studies (Leukfeldt & Yar, 2016). Target 'value' in cyberabuse is harder to assess than in theft, as it often involves symbolic or individualized worth, such as attachments to the victim (Wilson et al., 2023). Inertia, initially describing physical resistance, may translate online as a target's ability to resist or deter offenses (Yar, 2005). Visibility, the most studied VIVA factor, refers to the exposure of targets to offenders. Accessibility, distinct from visibility, refers to the ease with which offenders can reach a target, such as through accepting unknown contacts online. Research shows that lower accessibility correlates with reduced cyberstalking risk (Reynolds et al., 2016; van Ouytsel et al., 2018). Target hardening—self-protective behaviors by victims—can reduce accessibility and may be seen as a form of self-(cyber)guardianship within the L-RAT framework (Butler et al., 2021).

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In brief, despite the extensive use of L-RAT in cyberabuse research, our understanding of risky online behaviors that increase visibility and accessibility to offenders remains limited. This dearth of understanding of two important characteristics of targets stymies efforts to protect victims and prevent the proliferation of cyberabuse. For this reason, it is practically meaningful to study target suitability characteristics for different forms of cyberabuse.

The Present Study

This study extends prior research in two important ways. First, using survey methods, we examine whether the visibility and accessibility constructs of the VIVA framework are associated with two distinct forms of cyberabuse: cyberharassment (without victim fear/distress) and cyberstalking (with fear/distress). Few studies differentiate between these categories, making this comparison a novel contribution to understanding the correlates of each. Second, our research takes place in New Zealand, offering a unique socio-political context. Unlike many non-US studies (e.g., Acquadro Maran & Begotti, 2019; Kabiri et al., 2022), New Zealand's post-colonial setting features a significant and growing Indigenous population (17% in 2021; Stats New Zealand, 2021) and a focus on biculturalism. Additionally, stalking is not yet criminalized under New Zealand law, setting it apart from other jurisdictions. Socialization patterns in New Zealand universities also differ from those in the US, with less emphasis on formal university groups (e.g., no fraternity or sorority houses), providing further contextual variation.

Method

Data

Data for this study were collected through a self-report online survey on the Qualtrics platform. Due to Covid-19 restrictions recently introduced at the time of data collection, recruitment was conducted via social media (e.g., Facebook, Twitter), resulting in a non-

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probabilistic sample. The survey was open for five weeks (November–December 2021), and eligible participants were domestic and international students enrolled at any New Zealand university, provided they were in the country. Students abroad were excluded due to the country's closed borders at the time.

Given that prior cyberstalking research predominantly includes white women, we aimed to increase sample diversity. Following Reynolds et al. (2011), we tailored social media posts to attract different student groups and collaborated with minority student associations to promote recruitment. To enhance accessibility and response rates, we used a video format to convey key information about the survey and employed clear, lay language to explain cyberstalking behaviors and ethical concerns around consent (see Stern et al., 2020). The survey questions were piloted with current students to ensure clarity and ease of understanding. Consent was obtained via an initial screening question confirming participants were over 18, university students in New Zealand, and had agreed to the criteria outlined in the video. To protect anonymity, participants could enter a prize draw via a separate, discrete survey at the end. The survey took an average of 5.5 minutes to complete, yielding 222 responses, of which 185 were complete, unique, and non-fraudulent³.

Measures

A detailed description of all survey questions and their coding can be found in Appendix A.

Dependent Variable

To measure cyberharassment and cyberstalking victimization, we adapted questions from Reynolds et al. (2011). We combined three survey items where participants reported receiving unwanted electronic communications from a single individual on more than one

³ Qualtrics prevented multiple submissions and flagged suspicious responses (e.g., from other countries, unusually quick and that looked like bots) and we excluded these from the sample.

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occasion in the previous 12 months that: a) persistently harassed or annoyed them⁴, b) contained unsolicited sexual content, or c) contained threats or violent content. These were combined into a single dichotomous measure of "any cyberharassment." Respondents who answered "yes" to any of the three experiences were classified as cyberharassment victims. Unlike Reynolds et al. (2011), we did not require participants to have asked the aggressor to stop, as social media controls like 'block' or 'mute' have rendered this criterion less relevant. Participants who reported any of the behaviors a)-c) above and answered "yes" to feeling worried, threatened, or fearful as a result were classified as experiencing cyberstalking (in line with the 'fear standard' in the literature, see Reynolds et al., 2018). Otherwise, their experiences were categorized as cyberharassment. These two outcomes served as mutually exclusive dependent variables.

Independent Variables

The independent variables were drawn from two key VIVA criteria for target suitability: visibility and accessibility.

Target visibility reflected online behaviors that could expose participants to potential offenders. Participants were asked how frequently they engaged in online activities that might bring them into contact with deviant peers, including gaming, chat rooms, dating platforms, pornographic websites, and torrent websites (for downloading pirated content). Online activities theoretically expected to be inert (e.g., emails, reading blogs) were included for completeness but not reported in the models. Visibility was further assessed by the number of social networks used, the number of contacts, frequency of updates, and number of photos uploaded.

⁴ This included passive behaviour (see Kaur et al., 2021) such as 'likes' on social media.

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Target accessibility captured the ease with which potential offenders could connect with participants. Questions focused on whether participants allowed strangers to become contacts, used privacy settings to restrict access, and included social media account details in their profiles. Absence of these protective measures indicated greater accessibility.

Control variables. L-RAT posits that exposure to offenders is driven by risky activities, not demographic characteristics. However, these demographics may influence the types of activities individuals engage in and could serve as confounding factors. Therefore, similar to other studies (e.g., Nobles et al., 2014), we controlled for age, gender, and ethnicity in the models.

Hypotheses and Analytic Strategy

Guided by prior research, and the tenets of L-RAT, we hypothesized:

H₁: Higher target visibility would be positively associated with both cyberharassment and cyberstalking victimization.

H₂: Higher target accessibility would be positively associated with both cyberharassment and cyberstalking victimization.

Since the relationship between these cyberabuse types has been understudied, we lacked empirical guidance on which specific visibility or accessibility measures might predict each type.

We conducted analyses using R (v4.4.0, R Core Team, 2023). First, we produced descriptive statistics to summarize the sample and variables. Second, we performed chi-square tests to examine the relationship between each independent variable and the two dependent variables. Given the uncertainty about which VIVA constructs had the strongest predictive power, we tested each construct separately in logistic regression models, both with and without control variables. We then combined the constructs into a full theoretical model

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and evaluated predictive improvement using Nagelkerke R^2 (Menard, 2010). In total, we ran six logistic regression models for each dependent variable, excluding cases with missing data.

Due to non-significant results when control variables were included, we only present models without control variables. Additionally, to address large parameter estimates from data sparseness, we collapsed independent variable categories where appropriate (Tabachnick & Fidell, 2016). For example, frequency of risky online activities was recoded into ‘infrequent’ (Unsure/Not applicable; Less than once a week) and ‘once a week or more’ (Once or twice a week; 3-6 times a week; Everyday). The reference category for each independent variable was the one expected to have the weakest correlation with victimization (e.g., infrequent online activities).

Observations (e.g., participants) with missing values were removed from the analyses. Since bivariate correlations between independent variables were all below .33 and variance inflation factors were uniformly below 1.5 in each model, the threat of multicollinearity to the modelling strategy was considered acceptable (Fox, 2008).

Results

Sample Characteristics

Of the 185 participants, most were women under 25, with 7.5% ($n = 14$) identifying as gender diverse. While the majority self-identified as white, the proportion of indigenous Māori participants was consistent with national population estimates (Stats New Zealand, 2021). Other ethnic groups, including Asian and Pacific Peoples, were underrepresented. Over a quarter of participants identified as part of the rainbow community. Nearly all were domestic students living off-campus, and few reported membership in university clubs or societies.

In terms of online behavior, most participants spent 4–10 hours online daily, with 86.3% ($n = 126$) reporting increased online activity during Covid-19 lockdowns. Their daily

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activities included social media, messaging, and email use. About half of the participants used 4–6 social media platforms, though most did not post daily. Roughly half had fewer than 500 followers across all platforms, and nearly all had set their profiles to 'private.'

Participants were evenly split on whether they accepted contact requests from strangers.

Descriptive and Bivariate Statistics

As shown in Table 1, nearly one-third of participants reported some form of cyberharassment in the past 12 months. The most frequent behavior was unwanted sexual advances, followed by repeated unwanted contact. Threats of violence were relatively common. Victimization types were not mutually exclusive, with many experiencing multiple forms of harassment. When applying the "fear standard" to classify cyberstalking, approximately a quarter of participants reported victimization, with unwanted sexual advances again being the most common, followed by repeated contact and threats. While these figures do not represent prevalence rates due to the non-probabilistic sample, they suggest that harassing online behavior is common.

Most offenders were strangers, with this being more frequent in cyberharassment cases (68.4%, $n = 39$) than cyberstalking (40.8%, $n = 20$). In contrast, acquaintances were more common offenders in cyberstalking (24.5%, $n = 12$) than cyberharassment (5.2%, $n = 3$). A small number of offenders were partners or ex-partners for both crime types (10.5%, $n = 6$; 16.3%, $n = 8$, respectively). A minority of participants reported that the abusive behavior intensified during the Covid-19 lockdown (8.8%, $n = 5$ for cyberharassment; 16.3%, $n = 8$ for cyberstalking).

Chi-square tests revealed a significant association between cyberharassment and using dating apps ($\chi^2 = 5.7$, d.f. = 1, $p = 0.017$). Cyberstalking was significantly associated with displaying social network account details in an online profile ($\chi^2 = 14.2$, d.f. = 1, $p < 0.001$).

<INSERT TABLE 1 ABOUT HERE>

Multivariate Statistics

Only the target visibility model and the full theoretical model were statistically significant for cyberharassment, while the target accessibility model was not (Table 2). In the target visibility model, using dating apps was the sole significant predictor, associated with a more than threefold increase in victimization risk. This association remained significant in the full model, with an even higher odds ratio (5.58, CI: 1.60–21.57, $p = 0.01$). The full model, incorporating both visibility and accessibility constructs, showed an improved fit based on the pseudo R^2 value. Allowing strangers to become contacts, which was not significant in the accessibility model, emerged as a risk factor in the full model, suggesting it was previously masking the effect of another variable. Surprisingly, displaying other social media account details in one's profile was linked to a reduced risk of cyberharassment in the full model. Although there is no consensus on strong pseudo R^2 thresholds, a value over 0.20, as seen in the full cyberharassment model, is considered good (McFadden, 1974).

A contrasting pattern emerged for cyberstalking (Table 3). Here, the target visibility model was non-significant, while the target accessibility and full theoretical models were significant, though with lower pseudo R^2 values than the cyberharassment models. The only significant finding was that displaying social network account details increased the risk of cyberstalking fivefold, an effect that persisted in the full model.

Interestingly, none of the control variables produced significant results⁵, indicating that demographic characteristics did not predict cyberharassment or cyberstalking in this sample. In conclusion, there was limited support for both hypotheses, leading to their rejection.

⁵ Analyses available on request.

<INSERT TABLES 2 AND 3 ABOUT HERE>

Discussion

This study surveyed 185 university students to examine whether target visibility and accessibility constructs are associated with cyberharassment and cyberstalking victimization. This is the first study to use a New Zealand sample—where stalking is not yet criminalized—within this framework. It differs from existing research in three key ways: 1) it differentiates between cyberharassment and cyberstalking, 2) it extends the understanding of target accessibility from the VIVA framework (value, inertia, visibility, and accessibility) by Cohen & Felson (1979), and 3) it provides insights into cyberabuse correlates using a non-US sample.

Studies focusing on cyberabuse victimization rarely delineate cyberharassment and cyberstalking, which are typically defined by the victim's response (e.g., the absence or presence of fear or distress) are rare. This study makes two empirical contributions: first, in this sample, fear or distress was reported in only about half of victimization experiences. As prior work suggests, initial online communications may not seem threatening until they escalate (Nobles et al., 2014). The remote nature of online interactions likely minimizes psychological proximity (Mellberg et al., 2022), particularly since most cyberharassment offenders were strangers (68.4%, $n = 39$). However, a substantial portion of cyberstalking offenders were also strangers (40.8%, $n = 20$), consistent with Reyns et al. (2012), showing that strangers can still evoke fear despite psychological distance being unknown.

Second, few online activities were linked to cyberabuse victimization. This in itself is interesting; and could point to the unsuitability of L-RAT to assess target risk for these types of crime, or it could be weaknesses in our survey design (see below). Nevertheless, it is important to publish null results, to avoid publication bias when research topics are synthesized (Tompson & Belur, 2015). A notable exception was the use of dating apps,

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which was significantly associated with cyberharassment in both bivariate and multivariate analyses (Tables 1 and 2). Dating apps plausibly increase target visibility by facilitating interactions between strangers, often in unregulated environments lacking social guardianship (e.g., place managers), creating permissive spaces where the abusive behaviour of emboldened offenders may go unchallenged.

For cyberstalking, no target visibility factors were significant, while only one target accessibility factor—displaying other social network accounts—was associated with victimization in both bivariate and regression analyses (Tables 1 and 3). It was surprising that accepting strangers as contacts was not significantly related to cyberstalking, as found in prior studies (Kabiri et al., 2022; Reynolds et al., 2011). This could be due to the widespread use of ‘blocking’ functions, which can prevent unwanted behavior. However, after initial contact is blocked, displaying other social network details could enable continued harassment. More social network platforms provide more avenues for contact, and different platforms may reveal personal or professional information, allowing harassment to take a more intimate tone and induce fear. Further research could explore this relationship, especially given its inverse association with cyberharassment (Table 3c).

Echoing other studies (Leukfeldt & Yar, 2016; Reynolds et al., 2018), control variables were not significantly associated with victimization. This suggests that victim characteristics may be less relevant than how the victim came to the offender's attention or what they symbolically represent. In cyberstalking, the 'value' of the target (Cohen & Felson, 1979) may mirror offline stalking, where the real or perceived relationship between the stalker and victim is key (Sheridan & Grant, 2007), and not easily. However, Wilson et al. (2023) highlight the need for further study into how cultural and sexual orientation factors may influence victimization risk, suggesting some target characteristics warrant further exploration.

Implications for Practice: Prevention and Support Services

Cyberharassment and cyberstalking, like offline stalking, are believed to stem from diverse motives (Wilson et al., 2023), complicating the development of targeted prevention strategies for various social groups. Given that much cyberstalking is perpetrated by strangers (Reyns et al., 2012), raising awareness about precautionary measures can help mitigate the risks associated with these crimes.

With high victimization rates in this sample and a significant proportion of offenders being strangers, relying solely on conventional criminal justice sanctions is impractical. Instead, prevention efforts should target both pre-victimization and post-victimization phases. Preemptively, increasing awareness of cyberabuse and its subtypes can empower individuals to adopt safer online practices. For example, individuals might refrain from disclosing details about other social networks in their social media profiles and exercise caution when using dating platforms.

Furthermore, university students would benefit from training programs designed to identify unacceptable online behavior. Many offenders in this study were strangers, and victims may not recognize trivial behavior as a precursor to more serious incidents until it escalates (Nobles et al., 2014). By equipping individuals to identify and challenge abusive online behavior, we can promote capable guardianship within the framework of L-RAT, enhancing community resilience against cyber abuse.

Limitations

Our predominantly null findings may be attributed to several factors. First, our sample size may be underpowered, leading to potential type II errors. Similar to other studies (Strawhun et al., 2013; White & Carmody, 2018), our sample was modest, with a gender distribution skewed towards women (Kircaburun et al., 2018; Reyns et al., 2012).

Additionally, the reintroduction of Covid-19 restrictions limited our ability to collect a non-

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probabilistic sample, and response rates remain unavailable. Participants may have been motivated to complete the survey due to personal experiences with cyberstalking, introducing potential self-selection bias. Consequently, our findings should be viewed as indicative rather than definitive.

Nevertheless, our sample included a reasonable proportion of minoritized groups often considered "hard-to-reach," which may have captured cultural differences in online behaviors that are typically overlooked (Akinduko et al., 2017). This heterogeneity could explain why expected relationships between risky online behavior and victimization risk were not observed, as online activities in our sample may be too varied and individualized for statistical modeling. The limited sample size also restricted our ability to examine potential moderators.

Another limitation lies in our conceptualization and operationalization of target suitability constructs. While we advocate for expanding empirical investigation into the relevance of VIVA qualities in understanding target vulnerabilities, the lack of precedence in measuring constructs other than visibility in extant research meant that we may have omitted confounding variables. Our operationalization of target accessibility may also be underdeveloped; for example, we classified target hardening measures as part of accessibility, whereas others might categorize them as inertia (i.e., resistance to offender efforts). Moreover, the original VIVA framework did not account for the specific motivations behind predatory crimes (Clarke & Webb, 1999). The heterogeneous motives for cyberharassment and cyberstalking (Wilson et al., 2023) may lead to varying pathways for identifying and pursuing targets online, suggesting that psychological theories such as Target Congruence Theory (Finkelhor and Asdigian, 1996) may be more relevant than ecological theories like L-RAT.

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Lastly, our survey, like many, was cross-sectional by design (Reyns et al., 2011), capturing only a single point in time and failing to account for time-varying perceptions of victimization. Victims may initially perceive repeated contact as irritating, becoming fearful only as the situation escalates in seriousness or frequency (Noble et al., 2014). Thus, surveys represent only a snapshot of a broader process and may not accurately reflect changes over time. While we sought to mitigate temporal variables through careful question wording, causal inferences between cyber activities and behavior may still confound time ordering with the dependent variable.

Future Research

Addressing the limitations identified can enhance the design of future research. First, while probabilistic random sampling is ideal, it can be challenging to implement effectively. Researchers should design optimal strategies for accessing university students as a sampling frame, ensuring compliance with data privacy requirements and ethical considerations, such as avoiding the mandating of survey participation as part of class activities (Midzinski, 2010).

Second, due to the absence of standardized estimates of correlates in the existing literature (Reyns et al., 2018), there is a need to work towards consensus of how to measure L-RAT constructs. Previous research has conflated various control forms, such as target hardening and cyber guardianship, in cybercrime studies (Vakhitova et al., 2021). Further discourse is needed to standardize measurement approaches for these constructs in survey designs. Consistent testing would allow for a more robust assessment of the validity of the L-RAT framework in explaining cyberabuse victimization risk.

Moreover, it is crucial to test VIVA constructs consistently across diverse contexts to understand how target behaviors may influence victimization risk. Identifying contextual variations will illuminate which types of online behavior are universally relevant and how they contribute to elevating victimization risk. Currently, much of the evidence comes from

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the Global North, highlighting the need for a more diverse evidence base to enhance the external validity of correlates related to cyberabuse victimization.

A significant gap in the literature is the lack of longitudinal research examining how victim behavior influences changes in cyberstalking victimization risk (Kaur et al., 2021; Marcum & Higgins, 2021). Additionally, qualitative methods are necessary to explore the causal processes regarding cyberstalking initiation, continuation, and desistence. Such methods are better suited for informing nuanced awareness campaigns and tailored victim support services.

In conclusion, this study demonstrates the value of a comparative approach to cyberharassment and cyberstalking, revealing distinct correlates of victimization risk for these two outcomes in our New Zealand sample. Our limited findings suggest that while target visibility significantly influences cyberharassment risk, target accessibility plays a more critical role in cyberstalking. These insights can guide local support services in minimizing the harm associated with victimization.

References

- Acquadro Maran, D, & Begotti, T. (2019). Prevalence of cyberstalking and previous offline victimization in a sample of Italian university students. *Social Sciences*, 8(1).
<https://doi.org/10.3390/socsci8010030>
- Agresti, A., & Finlay, B. (1997). Statistical models for the social sciences. *Journal of the American Medical Association*, 269, 2642-2646.
- Akinduko, A., Ariwa, E., & Gibson, M. *A cross cultural investigation into adoption of user controls in cyberstalking protection: A case study of Nigeria and the United Kingdom*. 2017 Seventh International Conference on Innovative Computing Technology, Luton, United Kingdom. <https://ieeexplore.ieee.org/document/8102443>
- Back, S. (2016). *Empirical Assessment of Cyber Harassment Victimization via Cyber-Routine Activities Theory*. [Masters thesis, Bridgewater State University]. Item 30.
<https://vc.bridgew.edu/theses/30>
- Bossler, A. M., & Holt, T. J. (2009). On-line activities, guardianship, and malware infection: An examination of Routine Activities Theory. *International Journal of Cyber Criminology*, 3(1).
- Brown, A., Gibson, M., & Short, E. (2017). Modes of cyberstalking and cyberharassment: Measuring the negative effects in the lives of victims in the UK. *Annual Review of Cyber Therapy and Telemedicine*, 15, 57–63.
- Butler, L. C., Graham, A., Fisher, B. S., Henson, B., & Reynolds, B. W. (2022). Examining the effect of perceived responsibility on online bystander intervention, target hardening, and inaction. *Journal of Interpersonal Violence*, 37(21-22), NP20847–NP20872.
<https://doi.org/10.1177/08862605211055088>
- Clarke, R. V. G., & Webb, B. (1999). *Hot products: Understanding, anticipating and reducing demand for stolen goods* (Vol. 112). London: Home Office, Policing and Reducing

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Crime Unit, Research, Development and Statistics Directorate.

https://popcenter.asu.edu/sites/default/files/hot_products_understanding_anticipating_and_reducing_demand_for_stolen_goods_clarke_1999.pdf

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, *44*(4), 588–608.

<https://doi.org/10.2307/2094589>

Cohen, L. E., Kluegel, J. R., & Land, K. C. (1981). Social inequality and predatory criminal victimization: An exposition and test of a formal theory. *American Sociological Review*, *46*(5), 505–524. <https://doi.org/10.2307/2094935>

Dietz, N. A., & Martin, P. Y. (2007). Women who Are stalked: Questioning the fear standard. *Violence Against Women*, *13*(7), 750–776.

<https://doi.org/10.1177/1077801207302698>

Elvey, K., Reyns, B. W., & McNeeley, S. (2018). Stalking on campus: A gendered perspective on target congruence and opportunity. *Criminal Justice and Behavior*, *45*(8), 1308–1327. <https://doi.org/10.1177/0093854818773792>

Finkelhor, D., & Asdigian, N. L. (1996). Risk Factors for Youth Victimization: Beyond a Lifestyles/Routine Activities Theory Approach. *Violence and Victims*, *11*(1), 3–19.

<https://doi.org/10.1891/0886-6708.11.1.3>Fissel, E. R. (2022). Victims' perceptions of cyberstalking: an examination of perceived offender motivation. *American Journal of Criminal Justice*, *47*(2), 161–175. <https://doi.org/10.1007/s12103-021-09608-x>

Fissel, E. R., & Reyns, B. W. (2020). The aftermath of cyberstalking: School, work, social, and health costs of victimization. *American Journal of Criminal Justice*, *45*(1), 70–87. <https://doi.org/10.1007/s12103-019-09489-1>

Fox, J. (2008). *Applied regression analysis and generalized linear models* (2nd ed.). Sage Publications, Inc.

ASSESSING RISKY ONLINE BEHAVIOR IN NZ UNIVERSITY STUDENTS

Hindelang, M. J., Gottfredson, M. R., & Garofalo, J. (1978). *Victims of personal crime: An empirical foundation for a theory of personal victimization*. Ballinger.

Holt, T. J., & Bossler, A. M. (2009). Examining the applicability of lifestyle-routine activities theory for cybercrime victimization. *Deviant Behavior*, *30*(1), 1–25.

<https://doi.org/10.1080/01639620701876577>

Jerath, K., Tompson, L., & Belur, J. (2022). Risk Management in Stalking Victims: A Multi-Agency Approach to Victim Advocacy. *Journal of Interpersonal Violence*, *37*(11-12), NP8989-NP9015. <https://doi.org/10.1177/0886260520980402>

Kaakinen, M., Koivula, A., Savolainen, I., Sirola, A., Mikkola, M., Zych, I., Paek, H., & Oksanen, A. (2021). Online dating applications and risk of youth victimization: A lifestyle exposure perspective. *Aggressive Behavior*, *47*(5), 530–543. <https://doi.org/10.1002/ab.21968>

Kabiri, S., Choi, J., Shadmanfaat, S. M. (Shamila), & Lee, J. (2022). Cyberstalking victimization: An empirical assessment of RAT among female Iranian college students. *Journal of Interpersonal Violence*, *37*(9-10), NP8088–NP8114.

<https://doi.org/10.1177/0886260520975826>

Kaur, P., Dhir, A., Tandon, A., Alzeiby, E. A., & Abohassan, A. A. (2021). A systematic literature review on cyberstalking. An analysis of past achievements and future promises. *Technological Forecasting & Social Change*, *163*.

<https://doi.org/10.1016/j.techfore.2020.120426>

Kircaburun, K., Jonason, P. K., & Griffiths, M. D. (2018). The Dark Tetrad traits and problematic social media use: The mediating role of cyberbullying and cyberstalking. *Personality and Individual Differences*, *135*, 264–269.

<https://doi.org/10.1016/j.paid.2018.07.034>

ASSESSING RISKY ONLINE BEHAVIOR IN NZ UNIVERSITY STUDENTS

Leukfeldt, E. R., & Yar, M. (2016). Applying Routine Activity Theory to cybercrime: A theoretical and empirical analysis. *Deviant Behavior*, 37(3), 263–280.

<https://doi.org/10.1080/01639625.2015.1012409>

Maple, C., Short, E., & Brown, A. (2011). *Cyberstalking in the United Kingdom: An analysis of the ECHO pilot survey*. University of Bedfordshire.

Marcum, C. D., Higgins, G. E., & Nicholson, J. (2017). I'm watching you: Cyberstalking behaviors of university students in romantic relationships. *American Journal of Criminal Justice*, 42(2), 373–388. <https://doi.org/10.1007/s12103-016-9358-2>

Marcum, C. D., & Higgins, G. E. (2021). A systematic review of cyberstalking victimization and offending behaviors. *American Journal of Criminal Justice*, 46(6), 882–910. <https://doi.org/10.1007/s12103-021-09653-6>

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In F. Zabembka (Ed.), *Frontiers in econometrics* (pp. 105–142). Academic Press.

Mellberg, J., Chataway, M. L., Ball, M. J., & Miles-Johnson, T (2022). Psychological distance and fear of crime: Towards a new understanding of risk perception formation. *Journal of Criminology* (2021), 55(3), 377–399.

<https://doi.org/10.1177/26338076221105899>

Menard, K. S., & Cox, A. K. (2016). Stalking victimization, labeling, and reporting: Findings from the NCVS stalking victimization supplement. *Violence against women*, 22(6), 671–691.

Midzinski, A, L. (2010). *Students' perceptions of coercion in research*. [Master's thesis, Utah State University]. Digital Commons at USU.

<https://digitalcommons.usu.edu/etd/583>

Miró Llinares, F., & Johnson, S. D. (2018). Cybercrime and place: Applying environmental criminology to crimes in cyberspace. In *The Oxford Handbook of*

ASSESSING RISKY ONLINE BEHAVIOR IN NZ UNIVERSITY STUDENTS

Environmental Criminology (pp. 883–906). Oxford University Press.

<https://doi.org/10.1093/oxfordhb/9780190279707.013.39>

Ngo, F. T., & Paternoster, R. (2011). Cybercrime victimization: An examination of individual and situational level factors. *International Journal of Cyber Criminology*, 5(1).

Ngo, F. T., Piquero, A. R., LaPrade, J., & Duong, B. (2020). Victimization in cyberspace: Is it how long we spend online, what we do online, or what we post online? *Criminal Justice Review*, 45(4), 430–451. <https://doi.org/10.1177/0734016820934175>

Nobles, M. R., Reynolds, B. W., Fox, K. A., & Fisher, B. S. (2014). Protection against pursuit: A conceptual and empirical comparison of cyberstalking and stalking victimization among a national sample. *Justice Quarterly*, 31(6), 986–1014.

<https://doi.org/10.1080/07418825.2012.723030>

Novo, F., Pereira, F., & Matos, M. (2014). Cyber-aggression among Portuguese adolescents: A study on perpetration, victim offender overlap and parental supervision. *International Journal of Cyber Criminology*, 8(2).

Pereira, F., & Matos, M. (2016). Cyber-stalking victimization: What predicts fear among Portuguese adolescents? *European Journal on Criminal Policy and Research*, 22(2), 253–270. <https://doi.org/10.1007/s10610-015-9285-7>

R Core Team (2023). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org>

Reynolds, B. W. (2010). A situational crime prevention approach to cyberstalking victimization: Preventive tactics for internet users and online place managers. *Crime Prevention and Community Safety*, 12(2), 99–118. <https://doi.org/10.1057/cpcs.2009.22>

Reynolds, B. W., Fisher, B. S., & Randa, R. (2018). Explaining cyberstalking victimization against college women using a multitheoretical approach: Self-control,

ASSESSING RISKY ONLINE BEHAVIOR IN NZ UNIVERSITY STUDENTS

opportunity, and control balance. *Crime and Delinquency*, 64(13), 1742–1764.

<https://doi.org/10.1177/0011128717753116>

Reyns, B. W., Henson, B., & Fisher, B. S. (2011). Being pursued online: Applying cyberlifestyle–Routine Activities Theory to cyberstalking victimization. *Criminal Justice and Behavior*, 38(11), 1149–1169. <https://doi.org/10.1177/0093854811421448>

Reyns, B. W., Henson, B., & Fisher, B. S. (2012). Stalking in the twilight zone: Extent of cyberstalking victimization and offending among college students. *Deviant Behavior*, 33(1), 1–25. <https://doi.org/10.1080/01639625.2010.538364>

Reyns, B. W., Henson, B., & Fisher, B. S. (2016). Guardians of the cyber galaxy: An empirical and theoretical analysis of the guardianship concept from Routine Activity Theory as it applies to online forms of victimization. *Journal of Contemporary Criminal Justice*, 32(2), 148–168. <https://doi.org/10.1177/1043986215621378>

Sheridan, L. P., & Grant, T. (2007). Is cyberstalking different? *Psychology, Crime & Law*, 13(6), 627–640. <https://doi.org/10.1080/10683160701340528>

Short, E., Guppy, A., Hart, J.A., & Barnes, J. (2015). The impact of cyberstalking. *Studies in Media and Communication*, 3, 23-37.

Silveira, P., Morais, R., & Petrella, S. (2022). A Communication Study of Young Adults and Online Dependency during the COVID-19 Pandemic. *Societies*, 12(4), Article 4. <https://doi.org/10.3390/soc12040109>

Stern, M. J., Fordyce, E., Hansen, C., Heim Viox, M., Michaels, S., Schlissel, A., Avripas, S., Harper, C., Johns, M., & Dunville, R. (2020). Social media recruitment for a web survey of sexual and gender minority youth: An evaluation of methods used and resulting sample diversity. *LGBT Health*, 7(8), 448–456. <https://doi.org/10.1089/lgbt.2019.0311>

Stevens, F., Nurse, J. R. C., & Arief, B. (2021). Cyber stalking, cyber harassment, and adult mental health: A systematic review. *Cyberpsychology, Behavior and Social Networking*, 24(6), 367–376. <https://doi.org/10.1089/cyber.2020.0253>

ASSESSING RISKY ONLINE BEHAVIOR IN NZ UNIVERSITY STUDENTS

Strawhun, J., Adams, N., & Huss, M. T. (2013). The assessment of cyberstalking: An expanded examination including social networking, attachment, jealousy, and anger in relation to violence and abuse. *Violence and Victims, 28*(4), 715–730.

<https://doi.org/10.1891/0886-6708.11-00145>

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Pearson Education.

Tompson, L., & Belur, J. (2016). Information retrieval in systematic reviews: a case study of the crime prevention literature. *Journal of Experimental Criminology, 12*, 187-207.

Van Ouytsel, J., Ponnet, K., & Walrave, M. (2018). Cyber dating abuse victimization among secondary school students from a lifestyle-routine activities theory perspective. *Journal of Interpersonal Violence, 33*(17), 2767–2776.

Vakhitova, Z. I., Alston-Knox, C. L., Reynald, D. M., Townsley, M. K., & Webster, J. L. (2019). Lifestyles and routine activities: Do they enable different types of cyber abuse? *Computers in Human Behavior, 101*, 225–237.

<https://doi.org/10.1016/j.chb.2019.07.012>

Vakhitova, Z. I., Go, A., & Alston-Knox, C. L. (2023). Guardians against cyber abuse: Who are they and why do they intervene? *American Journal of Criminal Justice, 48*(1), 96–122. <https://doi.org/10.1007/s12103-021-09641-w>

Vakhitova, Z. I., Reynald, D. M., & Townsley, M. (2016). Toward the adaptation of Routine Activity and Lifestyle Exposure Theories to account for cyber abuse victimization. *Journal of Contemporary Criminal Justice, 32*(2), 169–188.

<https://doi.org/10.1177/1043986215621379>

Welsh, A., & Lavoie, J. A. A. (2012). Risky eBusiness: An examination of risk-taking, online disclosiveness, and cyberstalking victimization. *Cyberpsychology, 6*(1).

<https://doi.org/10.5817/CP2012-1-4>

ASSESSING RISKY ONLINE BEHAVIOR IN NZ UNIVERSITY STUDENTS

Wilson, C., Sheridan, L., & Garratt-Reed, D. (2023). Examining cyberstalking perpetration and victimization: A scoping review. *Trauma, Violence & Abuse, 24*(3), 2019–2033. <https://doi.org/10.1177/15248380221082937>

White, W. E., & Carmody, D. (2018). Preventing online victimization: College students' views on intervention and prevention. *Journal of Interpersonal Violence, 33*(14), 2291–2307. <https://doi.org/10.1177/0886260515625501>

Wolfe, D. A. (2018). Why polyvictimization matters. *Journal of Interpersonal Violence, 33*(5), 832–837. <https://doi.org/10.1177/0886260517752215>

Worsley, J. D., Wheatcroft, J. M., Short, E., & Corcoran, R. (2017). Victims' voices: Understanding the emotional impact of cyberstalking and individuals' coping responses. *SAGE Open, 7*(2). <https://doi.org/10.1177/2158244017710292>

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Table 1

Descriptive and Bivariate Statistics for Key Variables

	n	%	Cyber-harassment		Cyber-stalking	
			χ^2	<i>p</i>	χ^2	<i>p</i>
<i>Target Visibility</i>						
Online games	185	29.2	1.83	.18	0.65	.42
Chatrooms	184	20.7	0.18	.67	0.06	.80
Dating apps	184	9.2	7.12	.01	0.72	.56
Porn sites	184	20.1	0.09	.76	0.02	.88
Pirate sites	184	14.0	0.07	.79	0.08	.78
N social networks	185	-	5.97	.05	3.64	.16
Posts daily	184	26.6	3.68	.05	0.03	.86
>500 photos on social networks	183	21.3	0.28	.60	3.07	.08
>500 social network contacts	184	50.0	2.54	.11	2.78	.09
<i>Target accessibility</i>						
Strangers as contacts	181	47.5	2.45	.11	0.08	.78
No privacy settings	185	7.6	2.91	.09	0.05	.83
Displays social network details	179	18.4	0.12	.73	14.17	<.01
<i>Control Variables</i>						
Gender	185	-	0.43	.81	1.54	.47
Men	-	21.6	-	-	-	-
Women	-	70.8	-	-	-	-
Gender diverse	-	7.6	-	-	-	-
Age (years)	183	-	0.92	.93	0.50	.98
18-19	-	26.2	-	-	-	-
20-24	-	39.9	-	-	-	-
25-29	-	14.2	-	-	-	-
30-39	-	12.6	-	-	-	-
40+	-	7.1	-	-	-	-
Primary ethnicity	183	-	1.75	.42	2.65	.27
European	-	62.8	-	-	-	-
Māori	-	17.5	-	-	-	-
Alternative	-	19.7	-	-	-	-
<i>Outcome Variables</i>						
Any cyberharassment victimization	185	30.8	-	-	-	-
Unwanted repeat contact	184	17.3	-	-	-	-
Unwanted sexual advances	183	21.1	-	-	-	-
Threats of violence	184	5.9	-	-	-	-
Any cyberstalking victimization	185	26.5	-	-	-	-
Unwanted repeat contact (with fear)	184	21.2	-	-	-	-
Unwanted sexual advances (with fear)	183	16.9	-	-	-	-
Threats of violence (with fear)	184	13.6	-	-	-	-

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Table 2

Multivariate Logistic Regression Analyses using Target Visibility Variables (Model A), Target Accessibility Variables (Model B), and All Variables (Model C) to Predict Cyberharassment

Variable	Model A ^a			Model B ^b			Model C ^c		
	OR	95% CI	p	OR	95% CI	p	OR	95% CI	p
Constant	0.15		<.001	0.33		<.001	0.14		<.001
Porn sites	0.59	0.23 – 1.42	0.26	-	-	-	0.52	0.19 – 1.30	0.18
Pirate sites	1.27	0.46 - 3.32	0.63	-	-	-	1.51	0.52 – 4.20	0.44
Dating apps	3.28	1.08 - 10.48	0.04	-	-	-	5.58	1.60 – 21.57	0.01
Chatrooms	0.81	0.32 - 1.99	0.66	-	-	-	0.77	0.28 – 2.03	0.61
Online games	1.87	0.86 – 4.09	0.11	-	-	-	1.80	0.79 – 4.15	0.16
4-6 social networks used ⁴	2.26	0.97 – 5.56	0.07	-	-	-	1.92	0.79 – 4.96	0.16
>6 social networks used	1.58	0.57 – 4.41	0.37	-	-	-	1.46	0.51 – 4.27	0.48
Posts daily	1.96	0.89 – 4.32	0.10	-	-	-	2.19	0.96 – 5.07	0.06
>500 photos	0.84	0.35 – 1.93	0.70	-	-	-	0.81	0.31 – 2.00	0.66
>500 contacts	1.50	0.73 – 3.11	0.26	-	-	-	1.18	0.54 – 2.58	0.67
Strangers as contacts	-	-	-	2.11	1.10 – 4.13	0.03	2.31	1.07 – 5.06	0.03
Displays social media details	-	-	-	0.60	0.23 – 1.42	0.27	0.35	0.12 – 0.93	0.04
No privacy settings	-	-	-	1.18	0.29 – 4.11	0.80	0.88	0.18 – 3.78	0.87

Note. Reference categories ¹ = 18-19 years; ² = men; ³ = European; ⁴ = 0-3 social networks used.

^a *n* = 181. AIC = 225.15. *pseudo-R*² = .15 (Nagelkerke); Model χ^2 (10) = 20.79, *p* = .02

^b *n* = 175. AIC = 218.56. *pseudo-R*² = .04 (Nagelkerke); Model χ^2 (3) = 5.72, *p* = .13

^c *n* = 173. AIC = 213.86. *pseudo-R*² = .21 (Nagelkerke); Model χ^2 (13) = 27.33, *p* = .01

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Table 3

Multivariate Logistic Regression Analyses using Target Visibility Variables (Model A), Target Accessibility Variables (Model B), and All Variables (Model C)

to Predict Cyberstalking

Variable	Model A ^a			Model B ^b			Model C ^c		
	OR	95% CI	p	OR	95% CI	p	OR	95% CI	p
Constant	0.08		.01	0.27		<.001	0.19		<.001
Porn sites	0.88	0.32 - 2.39	.80	-	-	-	0.63	0.22 - 1.66	.38
Pirate sites	1.71	0.57 - 5.07	.34	-	-	-	1.55	0.50 - 4.44	.42
Dating apps	1.99	0.58 - 6.80	.27	-	-	-	0.92	0.24 - 3.24	.90
Chatrooms	0.86	0.32 - 2.31	.77	-	-	-	0.62	0.21 - 1.68	.37
Online games	1.32	0.55 - 3.17	.54	-	-	-	1.18	0.50 - 2.76	.69
4-6 social networks used ⁴	1.37	0.51 - 3.67	.54	-	-	-	1.31	0.53 - 3.38	.55
>6 used	1.98	0.65 - 6.03	.23	-	-	-	1.50	0.53 - 4.29	.44
Posts daily	0.62	0.25 - 1.55	.30	-	-	-	0.50	0.18 - 1.24	.15
>500 photos	1.54	0.62 - 3.81	.35	-	-	-	1.67	0.67 - 4.08	.26
>500 contacts	1.76	0.80 - 3.87	.16	-	-	-	1.77	0.80 - 3.99	.16
Strangers as contacts	-	-	-	0.97	0.47 - 1.99	.93	0.86	0.38 - 1.88	.71
Displays social media details	-	-	-	5.57	2.42 - 13.31	<.001	5.32	2.10 - 14.12	<.001
No privacy settings	-	-	-	0.33	0.04 - 1.52	.21	0.38	0.04 - 2.06	.31

Note. Reference categories ⁴ = 0-3 social networks used.

^a *n* = 181. AIC = 224.61. *pseudo-R*² = .08 (Nagelkerke); Model χ^2 (18) = 14.68, *p* = .68

^b *n* = 175. AIC = 194.19. *pseudo-R*² = .14 (Nagelkerke); Model χ^2 (3) = 17.45, *p* = <.01

^c *n* = 173. AIC = 206.14. *pseudo-R*² = .19 (Nagelkerke); Model χ^2 (13) = 24.24, *p* = .03