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How It Feels to Be "Left on Read": Social Surveillance on Snapchat and Young Individuals' Mental Health

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Abstract

Research has shown that young individuals frequently turn to social networking sites (SNSs) to monitor others' behaviors. This is especially likely with Snapchat, as this platform offers extensive monitoring options in real time, for instance through the use of the "snap map". However, despite the growth of surveillance features, little is known about the use of these features and their possible association with individuals' mental health. Consequently, this cross-sectional survey among 16- to 25-year-olds (N = 360, M_{age} = 19.51) examines (1) whether individuals with a higher need for popularity are more likely to engage in Snapchat surveillance behaviors, (2) whether these behaviors, in turn, are associated with indicators of individuals' mental health, specifically feelings of loneliness and depressive symptoms, and (3) whether fear of missing out mediates the association between surveillance behaviors and these mental health indicators. The findings show that a higher need for popularity is associated with the monitoring of others through Snapchat, which, in turn, was associated with health indicators via fear of missing out. These associations were, however, not found for general Snapchat use, indicating that specific uses of this platform are more detrimental than others. Future research should, therefore, focus more thoroughly on the relationships between specific SNS behaviors and individuals' mental health.

Keywords: social media; mental health; surveillance; emerging adults; adolescents

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Introduction

In a report by IMEC conducted among Belgian inhabitants, 98% of individuals aged 16 to 25 years indicated using at least one social networking site (SNS) daily, some of which even indicated spending 80 minutes per day on certain apps (e.g., TikTok; Sevenhant et al., 2021). This extensive use has raised concern as to whether this is beneficial or detrimental to young individuals' mental health, with studies generally showing mixed results. While some studies found no associations between general SNS use and individuals' mental health, others report small negative associations with specific SNS behaviors (e.g., instant messaging and texting) and mental health indicators (e.g., depressive symptoms, loneliness; Meier & Reinecke, 2021). Scholars argue that these mixed findings can be attributed to variations in how SNS use and mental health are defined and operationalized in previous research (Meier & Reinecke, 2021; Valkenburg, 2022). Previous studies predominantly focused on general time spent on SNSs and/or overall mental health, thereby overlooking specific SNS behaviors that may be more or less detrimental to individuals' mental health than others.

One specific SNS behavior that has recently attracted scholarly attention is the practice of monitoring others, also known as social surveillance (Pertegal et al., 2019). SNS platforms offer various features that enable users to continuously monitor the activities of others (e.g., last seen online function, scrolling through others' profiles). This monitoring behavior has raised concerns among researchers due to the observed links between SNS surveillance and adverse mental health outcomes (e.g., depression; Niu et al., 2018; Scherr et al., 2019; Smith et al., 2017). However, these prior studies primarily focused on the surveillance of romantic partners and/or were conducted on older platforms (i.e., Facebook; e.g., Muise et al., 2014; Scherr et al., 2019; Tokunaga, 2011). As a result, there remains a gap in our understanding of social surveillance among peers and on newer platforms.

One platform that is particularly popular among young individuals and known for surveillance features, is Snapchat (Dunn & Langlais, 2020). Reports, for example, indicate that 91% of young individuals use Snapchat (Vanwynsberghe et al., 2022). While Snapchat shares similarities with other platforms (e.g., Instagram, Facebook) in terms of content sharing and viewing, it distinguishes itself through unique surveillance features, such as the Snap Map that allows the continuous and real time monitoring of friends' live locations (Sachs, 2018). Despite these emerging surveillance features on Snapchat, our understanding of these behaviors and their potential role in individuals' mental health remains limited.

This study contributes to the literature on social surveillance in three ways. First, we examine the factors that increase individuals' likelihood of engaging in social surveillance on Snapchat, specifically exploring individual characteristics such as the need for popularity. Second, we examine whether this Snapchat surveillance is associated with young individuals' mental health, while also taking into account the role of general Snapchat use. We focus on two commonly studied mental health outcomes: depressive symptoms, which encompass psychopathological feelings, and feelings of loneliness, which are recognized as a risk factor for such psychopathological feelings (Cacioppo et al., 2006). Finally, we look at the underlying mechanisms between Snapchat surveillance and mental health outcomes by examining fear of missing out as a possible mediator. An online survey among people aged 16–25 years (i.e., young individuals) was conducted to investigate these aims.

SNS Surveillance Behaviors

As mentioned, young individuals spent a lot of their time on SNSs (Sevenhant et al., 2021), which might be attributed to the multiple purposes they serve, such as self-presentation, social connection, and social surveillance (Pertegal et al., 2019). Social surveillance, in particular, appears to be a central motive for young individuals' use of SNSs. This is likely influenced by adolescents' and emerging adults' phase of identity development in which they seek to fit in with important peer groups and shape their identity based on group expectations (Arnett, 2000; Berk, 2017). To gain insight into the group norms, individuals follow the actions, interests, and beliefs of the group, which has significantly been facilitated by the rise of SNSs. These platforms allow individuals to continuously exchange and search for social cues that indicate group norms and assist with forming one's identity (Tokunaga, 2011). This active search for social cues can also be defined as social surveillance, aimed at maintaining relationships and increasing online social capital by tracking and collecting information about others (Park et al., 2015).

Initially, online social surveillance involved passively observing others' activities by looking at their posts and reactions (Lampe et al., 2006; Park et al., 2015). However, with the advent of new features and SNS practices, more invasive monitoring of others' whereabouts has become possible (Masur, 2018). These practices include real-time location tracking, checking others' online presence, and verifying if one's own content has been viewed (Knight & Carey, 2022; Gower, 2021).

Among the various SNS platforms, Snapchat is frequently used by young individuals and is particularly associated with surveillance practices (Bayer et al., 2016; Sevenhant et al., 2021). Specifically, Snapchat's unique surveillance features, such as the Snap Map, provide information about friends' whereabouts by showing their real-time location (Sachs, 2018). Moreover, the Snap Map includes "heat maps" indicating popular events and locations based on user activity or "Snapping" (Moreau, 2022). This feature thus enables young individuals to stay up to date about their contacts' day-to-day social gatherings which aligns with the motive of monitoring/social surveillance (Pertegal et al., 2019).

Individual Differences in SNS Surveillance Behaviors

Despite the increased possibilities for social surveillance, research shows that not everyone is equally inclined to utilize these features (Park et al., 2015). In a study by Park et al. (2015), users were classified based on their levels of surveillance behaviors (high vs low), highlighting the presence of individual differences among SNS users. These findings align with the predictions of the Differential Susceptibility to Media Effects Model (Valkenburg & Peter, 2013), which posits that media users exhibit variations in their preferences and responses to media, with these differences often attributed to personal and dynamic states.

An important factor that might explain the various levels of engagement in surveillance behaviors might be need for popularity—referred to as "doing certain things to be viewed as popular with friends" (Santor et al., 2000, p. 166). This need for popularity is particularly relevant among young individuals as they strive to attain social status within their peer groups (Arnett, 2000). Furthermore, the need for popularity has also been linked to increased engagement in social grooming activities online, which include leaving messages on friends' profiles or exploring their profiles with the intent of fostering social connections and improving one's status (Tufekci, 2008; Utz et al., 2012).

Since the emergence of surveillance features has increased the opportunities for social grooming activities online (Orlan, 2020), those who seek popularity may also be more inclined to use these features to stay connected and browse social information about friends and the broader peer group (Dahl et al., 2016; Tufekci, 2008). Given that it is important to unravel which variables predispose media use, i.e., social surveillance, the following hypothesis was explored:

H1: Young individuals who report the greatest need for popularity engage in more social surveillance on Snapchat.

Surveillance Behaviors and Young Individuals' Mental Health

In addition to examining which individuals are more likely to engage in social surveillance, it is also important to examine how this surveillance links to young individuals' mental health. Numerous studies have already explored the consequences of SNS use on mental health, with particular emphasis on feelings of loneliness and depressive symptoms (for review see Meier & Reinecke, 2021). However, these studies have yielded mixed results, possibly due to their focus on overall SNS use. According to Smith et al. (2021), it is however crucial to consider the specific nature of use in order to determine under which circumstances SNS use might either enhance or diminish feelings of loneliness. For example; as mentioned, people use SNSs for various purposes ranging from passively scrolling through content to kill time to actively monitoring others' SNS content (Pertegal et al., 2019). It is, in turn, important to differentiate between these specific behaviors as they might lead to different outcomes on individuals' mental health (Meier & Reinecke, 2021). This notion is further supported by empirical research that demonstrates a more consistent negative impact on mental health outcomes, such as loneliness and depression, when examining problematic SNS use (e.g., excessive engagement with SNSs; Hussain & Griffiths, 2018; Marttila et al., 2021).

This problematic SNS use, in turn, shares similarities with surveillance practices because researchers have identified these practices as unhealthy given their intrusive nature (Fox & Moreland, 2015; Pertegal et al., 2019). In a similar vein, reports indicate that increased monitoring, compulsive checking, and excessive engagement with SNSs can result in adverse psychological outcomes (Oberst et al., 2017). This is also showcased in the study of Lutz (2023), which revealed that repeatedly encountering a lack of responses to messages was negatively associated with users' needs (e.g., need to belong, self-esteem) and overall well-being.

These results can be understood through the lens of the temporal need-threat model (TNTM; Williams, 2009) which postulates that experiences of ostracism, i.e., being ignored or excluded by others, threatens individuals' fundamental needs, such as the need to belong. This, in turn, can exacerbate feelings of loneliness (Yue et al., 2022). Moreover, according to TNTM, the recurrent experience of ostracism can even lead to feelings of alienation, and ultimately depression, if individuals lack the necessary coping resources (Williams, 2009).

While initially developed to explain offline exclusion (Williams, 2009), the concept of ostracism has also been extended to the online environment (i.e., cyberostracism) with the rise of SNS features that visualize social exclusion by social others (Lutz, 2023). However, despite the interesting results of previous studies, research has largely overlooked Snapchat, a platform that might especially increase (the visibility of) social exclusion. To illustrate, by monitoring the Snapchat map and seeing friends gathering somewhere (Sachs, 2018), individuals might feel excluded or lonely. Participants in the research of Dunn and Langlais (2020), for example, reported feelings of exclusion and depressive symptoms when obsessively speculating about unanswered Snapchat messages or constantly checking the Snap Map to track their friends' whereabouts. However, existing research, including other studies on surveillance (Dunn & Langlais, 2020; Muise et al., 2014; Tokunaga, 2011), predominantly focused on romantic relationships and has not adequately explored surveillance within peer relationships.

Given the heightened importance of peer feedback and social status among young individuals (Somerville, 2013), coupled with the ease and availability of surveillance through SNSs, it seems imperative to link Snapchat surveillance of peers with mental health outcomes. Building on previous theoretical (TNTM; Williams, 2009) and empirical insights (Dunn & Langlais, 2020; Lutz, 2023; Meier & Reinecke, 2021), our research therefore examines whether surveillance behaviors on Snapchat are associated with both feelings of loneliness and depressive symptoms.

H2: Social surveillance on Snapchat is positively associated with feelings of loneliness.

H3: Social surveillance on Snapchat is positively associated with depressive symptoms.

Building on the Two-Continua Model of Mental Health (Meier & Reinecke, 2021), this research also explores the idea that perceived loneliness might be a risk factor for the development of depressive symptoms. In particular, the model makes a distinction between manifestations/indicators of psychopathology (e.g., depressive symptoms) and risk factors thereof (e.g., perceived loneliness). It recognizes that not all individuals are equally likely to experience psychopathological manifestations. Despite this distinction, most of the research in the field of SNS use and mental health has primarily focused on studying risk factors and psychopathology manifestations without necessarily considering their interrelatedness (Meier & Reinecke, 2021). Consequently, our research aimed to fill this gap by proposing the following hypothesis:

H4: Feelings of loneliness are positively associated with depressive symptoms.

FOMO as Underlying Mechanism

In addition to studying the associations between surveillance behaviors and young individuals' mental health, it is important to investigate the underlying mechanisms that might explain these associations (Boer et al., 2021). An interesting construct that has recurrently been linked to cyberostracism and a lack of belongingness is fear of missing out (FOMO; Abel et al., 2016; Buglass et al., 2017; Elhai et al., 2021; Gupta et al., 2016). FOMO has been characterized by Przybylski et al. (2013, p. 1841) as "a pervasive apprehension that others might be having rewarding experiences from which one is absent". This apprehension might, in turn, be exacerbated by observing online updates about events from which one was excluded (Buglass et al., 2017; Gupta et al., 2016).

However, despite the increased possibility of observing others' whereabouts, little is known about social surveillance practices and FOMO because research predominantly focused on general SNS use. According to Tandon et al. (2021), FOMO should however be studied from a more holistic digital perspective as it is evolving into a broader construct than originally conceptualized (e.g., previous focus on general SNS use). The authors, for example, illustrate that one could focus on specific digital applications, such as content monitoring, as the presence of notifications about important digital content (e.g., social events) could fuel individuals' fear of missing out (Tandon et al., 2021). This, however, remains speculative because—to the best of our knowledge—little research has linked social surveillance with FOMO. Our research, therefore, aims to address this gap by examining whether social surveillance on Snapchat is associated with FOMO and whether this, in turn, is associated with feelings of loneliness and depressive symptoms.

H5: FOMO mediates the association between social surveillance on Snapchat and feelings of loneliness.

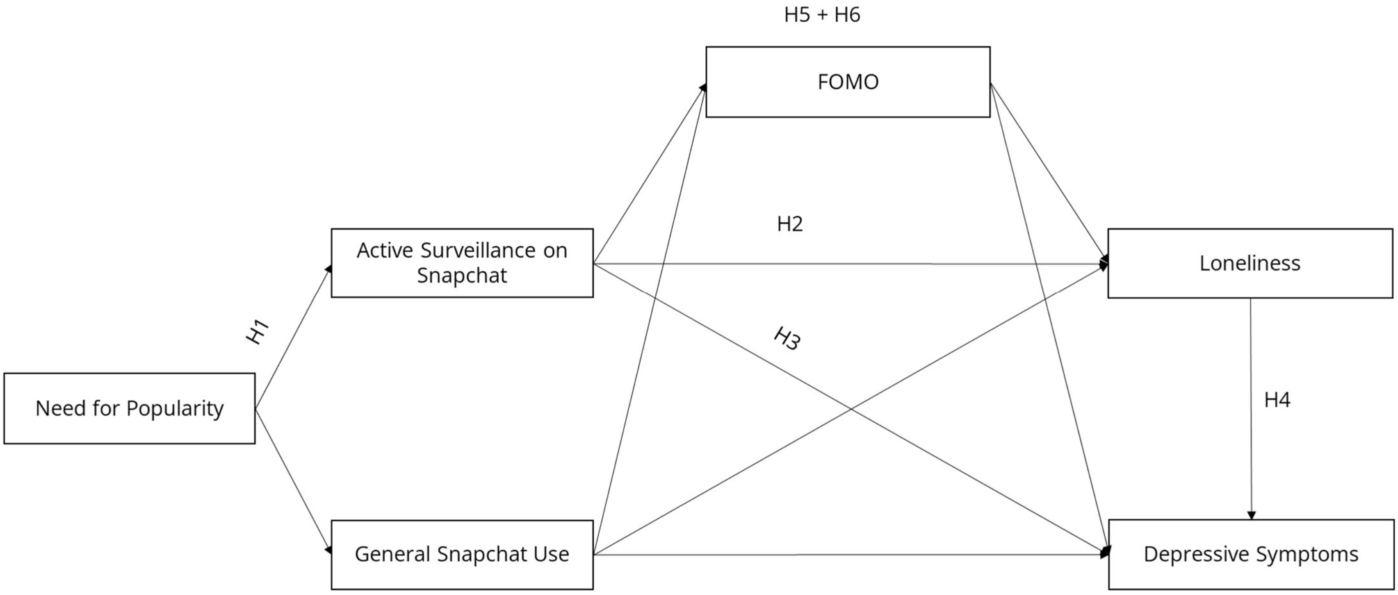
H6: FOMO mediates the association between social surveillance on Snapchat and depressive symptoms.

As can be seen in our hypotheses, FOMO serves as a mediator but it is important to acknowledge that this construct has taken on various roles in previous SNS literature. Whereas some studies have considered it an important predictor of SNS use (see meta-review by Fioravanti et al., 2021), others have looked at the moderating or mediating role of FOMO in the association between SNS use and mental health outcomes (Buglass et al., 2017; Leung et al., 2021). While there is no consensus on how to study FOMO, we built on Tsai et al. (2019) and interpreted FOMO as a feeling that can be fueled by experiencing a negative online social exchange, such as being excluded from a social event (Tandon et al., 2021), rather than an anticipatory fear of missing out (i.e., state) that predicts or moderates SNS experiences.

Hypothesized Model

Altogether, the hypotheses result in the following model to be tested (Figure 1). Of note is that our hypotheses are also subjected to a test with general time spent on Snapchat, which allows us to differentiate between the operationalization of specific behaviors (i.e., social surveillance) and general time-based SNS measures (Meier & Reinecke, 2021; Valkenburg et al., 2022). This approach enables us to clarify that if certain studies fail to find a direct link between Snapchat use and mental health outcomes, it doesn't necessarily imply that there are no associations but that it might depend on particular behaviors. Additionally, we need to control for general SNS use whilst studying social surveillance behaviors to ensure that the observed associations are genuinely attributed to the specific behaviors under investigation.

Figure 1. *Hypothesized Model.*



Note. The demographic variables age and gender (1 = *female*, 0 = *male*) were also included as controls for all endogenous variables because it is important to control for these when studying SNS use (Prinstein et al., 2020). Previous literature, for example, found differences in gender and age for both Snapchat use and engagement in social surveillance of romantic partners (Muise et al., 2014; Thelwall & Vis, 2017; Tokunaga, 2011; Vanwynsberghe et al., 2022). Therefore, we deemed it necessary to control for these variables in order to demonstrate that these do not cause any unforeseen bias whilst interpreting the associations. Furthermore, we tested for the covariation between social surveillance and general Snapchat use.

Methods

Sample

In this study, we sampled young individuals between the ages of 16 and 25 years, thereby including both the period of adolescence and emerging adulthood. This was based on the fact that identity exploration, specifically regarding relationship exploration and group belongingness, usually starts during adolescence but extends into emerging adulthood (Arnett, 2000). Moreover, both groups experience the onset of many psychiatric disorders (Paus et al., 2008) and are among the most prevalent users of Snapchat (Sevenhant et al., 2021), making them of interest for this study.

In total, 521 people participated in our cross-sectional survey. However, 161 individuals did not properly fill out the informed consent form or provided incomplete answers; these individuals were deleted from the dataset, resulting in a final sample of 360 participants. Of this sample, 74.4% indicated that they were female, 24.4% indicated that they were male, and 1.1% selected X (identify as another gender). Furthermore, participants were on average 19.72 (SD = 2.38) years of age. The majority of participants reported being enrolled in higher education (55.8%), while 30.6% reported being enrolled in secondary school, 8.6% identified as working individuals, and 5.0% indicated "Other."

Procedure

Respondents were recruited by two research assistants. To obtain a representative sample, a list of Belgian secondary schools was used to send out research invitations. However, due to COVID-19 and the corresponding missed time in classes, only three schools agreed to participate, making it necessary to expand our sampling approach. Therefore, research assistants also approached participants by contacting personal networks and youth movements (e.g., soccer teams). This was done either offline by directly approaching participants or online using SNS platforms, such as Instagram and Facebook. Building on a snowball sampling approach, interested participants were then asked to spread the information in their personal networks.

Before entering the study, respondents filled in an informed consent form provided through the mail, social media, or their school's online platform. This form discussed the topic of the study (i.e., social media use and mental health) and emphasized the confidentiality and anonymity of respondents' participation. Furthermore, contact details of the researchers and health practitioners were provided in case of feelings of discomfort after the study. In line with guidelines from the university's ethics committee, participants under 18 years of age were subject to passive parental consent: Parents were informed of the purpose of the study and only had to reply when they did not want their child to take part in the study. The study and its procedures were approved by the university's ethics committee (IRB clearance number G-2021-4629).

To collect the data, an online survey was administered via a Qualtrics link sent out by the participating school or a research assistant in March–April 2022. The survey contained 24 items that concerned demographic variables (e.g., age, school year, gender), SNS use, and mental health variables.

Measures

Social Snapchat Surveillance

The Passive and Active Facebook Use Measure (PAUM) scale developed by Gerson et al. (2017) was adapted and used to measure surveillance behaviors on Snapchat. More specifically, participants were asked how often they performed the following behaviors on Snapchat: *View a Snapchat friend's location without further action*, *See when others were last online*, *View location of a Snapchat friend and start chatting with this person*, *View a friend's Snapchat score to see if they're active*, and *See who has already opened your story or Snap*. Possible answers ranged from (1) *never* to (5) *very often*. The combination of all five items showed good reliability (α = .82; see Table E in Appendix).

General Snapchat Use

One item measured general Snapchat use by asking participants how often they use Snapchat, ranging from (1) *less than one hour a day* to (6) *more than six hours a day*. As this can be difficult for participants to estimate, they were instructed to take a look at their screen time to see how often they daily use Snapchat. They also had the chance to indicate that they did not use this platform but this answer was classified as "missing", thereby not being included in the analyses.

Depressive Symptoms

To measure depressive symptoms, the Short Mood and Feelings Questionnaire (SMFQ) by Angold et al. (1995) was used. Participants answered 13 items while keeping in mind how they felt during the previous two weeks. Example items were *I felt miserable or unhappy* and *I cried a lot*. The items could be answered on a 3-point scale consisting of (1) *not true*, (2) *sometimes*, and (3) *true*. Based on confirmatory factor analysis (CFA; see Tables B1–3 in Appendix), eight items were combined to measure depressive symptoms (α = .89).

Loneliness

Feelings of loneliness were measured using the UCLA Loneliness Scale by Russell et al. (1978). Participants were asked to indicate whether they agreed with 20 statements, such as *I feel completely alone* and *There is no one I can turn to*. These statements could be answered using the following options: (1) *never*, (2) *seldom*, (3) *sometimes*, and

(4) *often*. Again, 14 items were combined to measure loneliness (α = .93) based on CFA (see Tables A1–3 in Appendix).

Fear of Missing Out

FOMO was measured using the 5-point fear of missing out scale (FOMOs) created by Przybylski et al. (2013). Participants indicated the applicability of 10 statements on a scale from (1) *totally did not apply to them* to (5) *totally applied to them*. Examples of statements *were I get worried when I find out my friends are having fun without me* and *It bothers me when I miss an opportunity to meet up with friends*. To measure the final construct of FOMO (α = .80), three items were combined based on CFA (see Tables D1–2 in Appendix).

Need for Popularity

The popularity scale by Santor et al. (2000) was used to measure need for popularity. Participants rated 10 statements, such as *It's important that people think I'm popular* and *I've gone to parties, just to be part of the crowd* on a 5-point scale ranging from (1) *strongly disagree* to (5) *strongly agree*. The final need for popularity construct consisted of eight items and showed good reliability (α = .89; see Tables C1–2 in Appendix).

Control Variables

Age and gender were also included in the model as control variables. Gender was measured using four categories consisting of (1) *male*, (2) *female*, (3) X, and (4) *Rather not say*. However, options three and four were left out of the analyses because these were indicated only once (3) or never (4) by the respondents.

Analyses

Structural equation modeling (SEM) with an integrated CFA was conducted in R using the Lavaan Package (Rosseel, 2012) to test our hypothesized model. This model contained two control variables (age and gender), three predictor variables (need for popularity, social surveillance on Snapchat, and general Snapchat use), one mediator (FOMO), and two outcome variables (loneliness and depressive symptoms). By integrating two predictors and two outcome variables, it was possible to simultaneously examine multiple mechanisms and control for correlations between the variables (i.e., social surveillance Snapchat and general Snapchat use; see Figure 1 for an overview of the model). Before testing this final model, assumptions were checked to assess whether there were violations in the data (e.g., normal distribution, uncorrelatedness of the residuals). We also calculated the means, standard deviations, and bootstrapped correlations to gain more insight into the variables of the CFA (Table 1). The data, as well as the codes used to prepare, visualize, and analyze the data, are on the Open Science Framework (OSF; https://osf.io/rbked/).

The first SEM model showed a low model fit, χ^2 = 3,411.04, df = 1,749, p < .001, CFI = .78, RMSEA = .06, 90% CI [.06, .07], SRMR = .10. Based on insights from Awang (2012), all items with a factor loading lower than .60 (for established items) and .50 (for newly developed items) were omitted from the measurement model (Please see Appendix for insight into the specific omitted items). Furthermore, based on the modification indices, we allowed some error terms of the loneliness construct to correlate if they contained similarly worded test items (Brown, 2015; Kenny & Judd, 1984). For example, *I feel left out* was allowed to correlate with *I feel left out and excluded by others* (for all correlated error terms, please see Appendix Tables A1–3). In addition, we also omitted one additional item of depressive symptoms (*I felt lonely*) because the modification indices indicated that the model fit would improve by 31.90 if this item would be included in the loneliness construct, hence possibly pointing toward a cross-loading. By making these adjustments[1], the model fit was slightly better, χ^2 = 1,266.71, df = 717, p < .001, CFI = .90, RMSEA = .06, 90% CI [.05, .06], SRMR = .09. The results are presented in Table 2 and Figure 2. For more insight into the CFA's and modification indices process please be referred to the Appendix available on OSF (https://osf.io/rbked/).

Results

Descriptive Statistics

Means and standard deviations can be found in Table 1. On average, participants indicated rarely engaging in social surveillance on Snapchat. In addition, they mostly disagreed with the need for popularity statements but slightly agreed with the FOMO statements. Regarding their mental health, participants generally indicated they sometimes experienced depressive symptoms but seldomly experienced feelings of loneliness (Table 1).

Regarding correlations with control variables, the results showed gender to be associated with both feelings of loneliness and depressive symptoms (Table 1), with females reporting these feelings more often than males. In addition, age was negatively associated with social surveillance, Snapchat use, and depressive symptoms. Finally, social surveillance on Snapchat was strongly associated with general Snapchat use (Table 1). However, all correlations were lower than the severe cut-off point of multicollinearity (.80; Berry & Feldman, 1985).

Table 1. *Global Means, SDs, and Bootstrapped Correlations.*

	1.	2.	3.	4.	5.	6.	7.	8.	
1.Loneliness	1								M = 1.73, SD = 0.63
2.Depressive symptoms	.72**	1							M = 1.52, SD = 0.53
3.NfP	.29**	.31**	1						M = 1.92, SD = 0.74
4.FOMO	.28**	.36**	.33**	1					M = 2.35, SD = 0.92
5.Social Surveillance	.18*	.25**	.26**	.21**	1				M = 1.94, SD = 0.81
6.Snapchat use	.04	.14*	.07	.04	.45**	1			M = 1.98, SD = 1.50
7.Gender	.21**	.26**	−.05	.11	.11	.04	1		M = 1.75, SD = 0.43
8. Age	−.12	−.19**	.07	−.08	−.45**	−.39**	−.04	1	M = 19.72, SD = 2.38

Note. N = 360, $^{*}p < .05$, $^{**}p < .01$, NfP = Need for Popularity, FOMO = Fear of missing out.

Predictors of Social Surveillance on Snapchat

Regarding hypothesis one, the correlation analyses and SEM model showed that need for popularity was significantly associated with social surveillance on Snapchat (but not general Snapchat use; Table, 1, Table 2 and Figure 2). This indicates that individuals who felt the need to appear popular also engaged more frequently in surveillance behaviors on Snapchat, thereby confirming hypothesis one.

The Association Between Social Surveillance and Health Outcomes

In confirmation of hypotheses two and three, the correlation analysis showed that social surveillance was positively associated with both feelings of loneliness and depressive symptoms, whereas general Snapchat use was only associated with depressive symptoms (Table 1). In addition, in confirmation of hypothesis four, feelings of loneliness were also strongly associated with depressive symptoms (Table 1).

However, when looking at the SEM model (Table 2), no direct associations were found between social surveillance and mental health outcomes, which can possibly be explained by the mediating role of FOMO.

The Mediation of FOMO

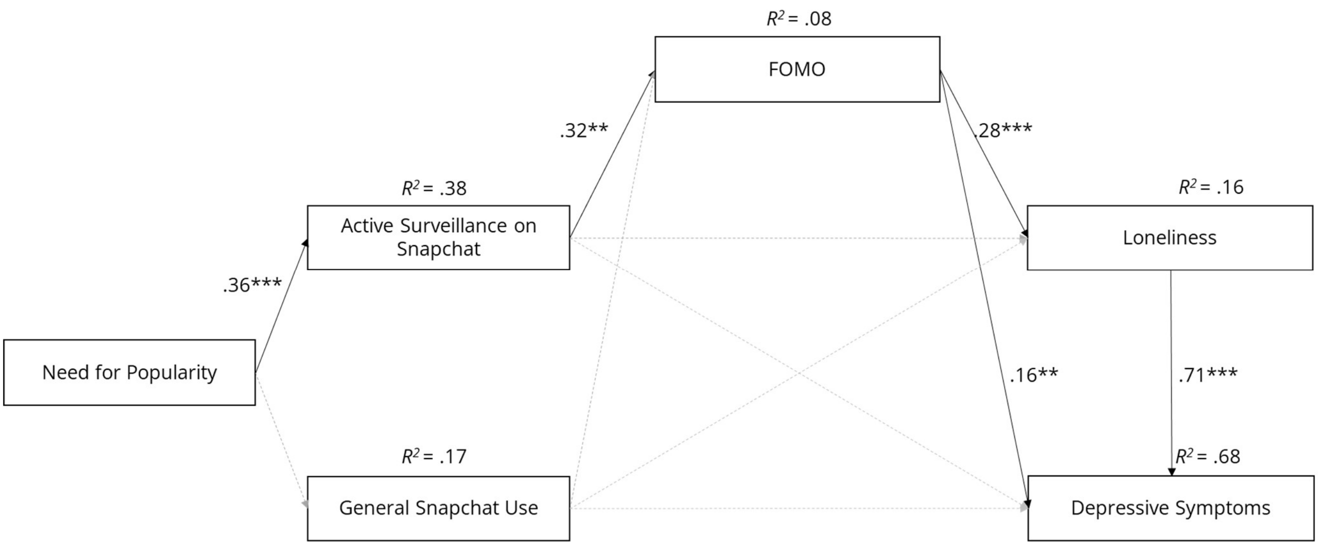
Regarding hypothesis five, we expected that FOMO would mediate the association between social surveillance and feelings of loneliness. When looking at the total, direct, and indirect effects[2] of the SEM model, we found a significant total effect between social surveillance on Snapchat and feelings of loneliness (β = .20, p = .023) but no direct effect (β = .11, p = .210). This can be explained by the underlying role of FOMO. More specifically, social surveillance on Snapchat was positively associated with feelings of FOMO, which, in turn, were associated with higher feelings of loneliness (Table 2 and Figure 2). Building on the significant indirect effect (β = .09, p = .010), the results therefore point towards a full mediation of FOMO between social surveillance behaviors on Snapchat and feelings of loneliness, thereby confirming hypothesis five.

Table 2. *Unstandardized and Standardized Coefficients of the SEM Model.*

	Estimate	Std. Err	*p*-value	Std. Est	R^2
Depressive symptoms					.68
FOMO	.09***	.03	.002	.16	
Loneliness	.54***	.07	< .001	.71	
Social surveillance	.01	.03	.835	.01	
Snapchat use	.02	.02	.122	.08	
Age	−.01	.01	.208	−.07	
Gender	.09*	.05	.068	.08	
Loneliness					.16
FOMO	.19***	.05	< .001	.28	
Social surveillance	.06	.05	.210	.11	
Snapchat use	−.02	.03	.403	−.06	
Age	−.02	.02	.276	−.08	
Gender	.25*	.09	.005	.18	
FOMO					.08
Social surveillance	.27**	.08	.001	.32	
Snapchat use	−.05	.05	.297	−.08	
Age	.02	.03	.540	.05	
Gender	.12	.14	.379	.06	
Social surveillance					.38
NfP	.57***	.11	< .001	.36	
Age	−.21***	.03	< .001	−.47	
Gender	.29*	.13	.029	.12	
Snapchat use					.17
NfP	.24	.14	.088	.11	
Age	−.25***	.04	< .001	−.40	
Gender	.08	.20	.688	.02	

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$; FOMO = Fear of missing out; NfP = Need for Popularity.

Figure 2. *Standardized Coefficients of the SEM Model.*



Note. Observed SEM based on data from N = 360 participants. Fit indices are χ^2 = 1,266.71, *df* = 717, $p < .001$, CFI = .90, RMSEA = .06, 90% CI [.05, .06], SRMR = .09. Scores in the figure represent standardized path coefficients and *p*-values. Age and gender (1 = *female*, 0 = *male*) were also included as controls for all endogenous variables but are not displayed here for clarity purposes. Furthermore, we tested for the covariation between social surveillance and general Snapchat use which was .32***. The grey dotted lines represent non-significant relationships. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

As for hypothesis six, we expected that FOMO would also mediate the association between social surveillance and depressive symptoms. In this case, the total and direct effects between social surveillance and depressive symptoms were not significant (total effect: $\beta = .06$, $p = .285$; direct effect: $\beta = .01$, $p = .835$), but the indirect effect via FOMO once again was significant ($\beta = .05$, $p = .021$), thereby potentially pointing towards an indirect-only mediation (Agler & De Boeck, 2017; Zhao et al., 2010). To be specific, we found that greater feelings of FOMO were also associated with greater depressive symptoms (Table 2 and Figure 2). Social surveillance on Snapchat might increase feelings of FOMO and, in turn, depressive symptoms. Mediation, or presumably indirect-only mediation, hence seems to take place given the lack of a significant total effect.

These mediations were also tested for general Snapchat use, but the results of the SEM model showed that general Snapchat use was not associated with FOMO ($\beta = -.08$, $p = .297$), feelings of loneliness ($\beta = -.06$, $p = .403$), or depressive symptoms ($\beta = .08$, $p = .122$). Furthermore, no indirect effects via FOMO were found.

Discussion

The current study adds to a growing body of literature by being one of the first to examine social surveillance of peers on Snapchat. In particular, our study showed that a higher need for popularity was associated with the monitoring of others through Snapchat. Moreover, this social surveillance on Snapchat was, in turn, associated with both feelings of loneliness and depressive symptoms via fear of missing out. We believe our study provides three important contributions to the literature.

First, in line with research from Park et al. (2015), the current study shows that need for popularity might be one factor determining individuals' likelihood of engaging in social surveillance on Snapchat. Specifically, popularity-striving individuals have been shown to use SNSs for social grooming behaviors (e.g., leaving messages on profiles; Utz et al., 2012) and might also employ Snapchat's surveillance features. They may, for instance, use Snapchat surveillance features to check responses to their own messages (i.e., monitoring popularity status). This might, in turn, lead to positive and affirmatory feelings when getting many views and responses but it is also plausible that this leads to negative and insecure feelings when attracting less attention than desired (Lee et al., 2020).

Second, in line with research by Dunn and Langlais (2020), this study also shows that social surveillance behaviors on Snapchat are associated with feelings of loneliness and depressive symptoms. These findings are alerting because research shows that individuals frequently turn to SNSs to monitor others' opinions and activities because this might help them to maintain relationships and increase online social capital (Park et al., 2015). However, instead of helping them, these behaviors might thus also result in negative outcomes. In the study of Fox and Moreland (2015), SNS users for example reported how the constant visibility and connectivity of SNS platforms can be taxing. Nevertheless, despite experiencing stress from constantly monitoring others' activities, participants still felt compelled to maintain an active online presence (Fox & Moreland, 2015), suggesting the possibility of a reciprocal and reinforcing cycle. This reciprocal relationship might, in turn, also be relevant when looking at the results of our study.

That is, in the current cross-sectional study, we initially assumed that social surveillance precedes feelings of loneliness and depressive symptoms but it is very likely that these associations are bidirectional and/or transactional. For example, Lutz (2023) found that although cyber-ostracism (e.g., not receiving an answer) led to feelings of exclusion, participants were still more inclined to use these services the following day, thereby hinting toward an approach coping tendency. Thus, individuals' mental health states may also precede social surveillance practices. This assumption is further supported by the longitudinal study of Scherr et al. (2019), where Facebook surveillance did not necessarily increase depression but depression did predict surveillance practices, both at the beginning of the study and one year later. Building on these insights and in line with the argumentation of Lutz (2023), surveillance features might play a dual role by acting as both sources of and tools to manage the mental health of young individuals. However, it should be noted that our study is based on cross-sectional data, making these assertions speculative. Therefore, future research is necessary to investigate the directionality of the associations in more detail.

Finally, this study also revealed some mechanisms that potentially underlie surveillance behaviors, with FOMO emerging as a significant factor in the association between Snapchat surveillance behaviors and individuals' mental health. This aligns with research from Lutz (2023) who found that being ostracized via messenger led to feelings of exclusion and, in turn, lower affect. In a similar vein, the qualitative study of Dunn and Langlais (2020) focusing on Snapchat illustrated that checking the Snap Map to gather information about future or ongoing social gatherings, led to feelings of exclusion and lower mental health outcomes. Building on these insights, it hence seems that not receiving direct answers and/or being exposed to content in which others are having fruitful social lives might intensify feelings of exclusion (Przybylski et al., 2013), which might negatively impact individuals' mental health (Buglass et al., 2017; Leung et al., 2021). However, apart from studying FOMO as a feeling resulting from online social exclusions (i.e., social media-induced feeling), it is important to acknowledge that FOMO can also take on other roles. In line with research focusing on SNS use in general (Buglass et al., 2017; Fioravanti et al., 2021), it is likely that FOMO predicts and/or moderates surveillance practices on Snapchat. Future research is necessary to achieve a clearer understanding of the role of FOMO in the association between SNS use and mental health. For instance, future studies could employ more rigorous research methods and distinguish between state and trait level FOMO by measuring "daily" FOMO, similar to the daily diary study of Hartanto et al. (2022). This method of capturing daily fluctuations in FOMO can yield more precise measures of the feelings resulting from daily exclusions, such as observing the online content of others.

Theoretical Implications

The results of our study offer both theoretical and practical implications for the current field of knowledge. From a theoretical point of view, this study adds to the debate on how to conceptualize SNS measures (Meier & Reinecke, 2021; Valkenburg et al., 2022). Rather than understanding SNSs as broad channels using time-based SNS measurements (e.g., how often do you use Snapchat?), one should tear them into smaller pieces and focus on the specific behaviors that are provoked by the features of these channels. To illustrate, this study found that only surveillance behaviors on Snapchat were associated with mental health outcomes whereas general time spent on Snapchat was not. This supports the idea that one should forgo studying time-based SNS measurements, as these might be insufficient to predict individuals' mental health (Meier & Reinecke, 2021; Valkenburg et al., 2022). By focusing on time spent on specific SNSs, there remains a crucial void in knowledge about what individuals are actually doing on these platforms (Meier & Reinecke, 2021). It is, however, important to grasp these actions as different behaviors might render different results. In the qualitative study by Vaterlaus et al. (2016), participants indicated that using Snapchat led to negative feelings, such as jealousy, when checking features such as the best friend list, as well as positive feelings, such as belonging, when using messaging features. These different feelings would not have been captured when measuring overall Snapchat use. This shows the necessity of focusing on specific SNS behaviors, as isolating particular behaviors could further nuance the media effects debate about how SNS use can be beneficial or detrimental to young individuals' mental health (Valkenburg et al., 2022).

Moreover, future research should extrapolate this line of reasoning across platforms. For example, this study focused on Snapchat as a case study for examining surveillance behaviors, whereas future research should also include other platforms, such as WhatsApp, Instagram, and Facebook Messenger, as these platforms also permit the monitoring of others. For instance, Facebook Messenger displays green dots next to someone's name when they are active, WhatsApp displays blue check marks next to messages when they have been read, and Instagram stories show the list of people who have seen your content. Still, despite similar opportunities for surveillance, these platforms differ from each other because of their culture of use (Boczkowski et al., 2018). Whereas Snapchat, WhatsApp, and Facebook Messenger are mostly used for interacting with (close) friends (Bayer et al., 2016; Sevenhant et al., 2021), Instagram is, despite its direct messaging function, still known for self-portrayal needs (Sheldon & Bryant, 2016). Consequently, surveillance behaviors across these platforms might be driven by different underlying motives. On the one hand, individuals might fulfill social connection needs by visiting messaging platforms and checking others' availability; on the other hand, they might fulfill impression management needs by visiting Instagram and checking views and likes on their curated self-presentations. Future research could examine (1) which platforms are mostly used for surveillance behaviors, (2) which underlying motives steer these behaviors, and (3) how these behaviors across platforms are related to young individuals' mental health.

Practical Implications

From a practical point of view, this study provides more insight into which individuals might engage in surveillance behaviors and how these, in turn, are associated with individuals' mental health, thereby providing two insights for intervention approaches. First, given that need for popularity has been associated with various SNS behaviors (Utz et al., 2012), including social surveillance behaviors, research should further explore what exactly drives popularity-striving individuals to SNSs. This is particularly important in light of research indicating that popularity-seeking behaviors, such as gaining followers on Instagram, increase the chances of developing a behavioral addiction to this platform, which in turn negatively impacts SNS users' well-being (Longobardi et al., 2020). Similarly, it is conceivable that individuals driven by the need for popularity, who recurrently utilize Snapchat's surveillance features to monitor their digital status, may also be at risk of developing behavioral addictions. Thus, it is imperative to identify and support these individuals in managing their media practices (Piotrowski & Valkenburg, 2015).

In addition, it would also be valuable to investigate other identifying factors, such as age. In line with the study of Tokunaga (2011), age appeared to be negatively associated with Snapchat surveillance in our study, hence possibly indicating that younger individuals might be more inclined to participate in social surveillance practices. This propensity may be attributed to the fact that younger individuals often have more unstable and fluctuating peer relationships (de Goede et al., 2021). Consequently, they may engage in surveillance behaviors in an attempt to seek social confirmation, or perhaps, to monitor the lack thereof (e.g., not receiving an answer while someone was online). However, this explanation remains speculative, and further research is necessary to identify potential precursors for social surveillance behaviors.

Second, given that surveillance behaviors were negatively associated with young individuals' mental health, intervention approaches could be developed to dampen the possible negative outcomes. Building on the Social Media Literacy model (Schreurs & Vandenbosch, 2020), media literacy interventions could be implemented to make individuals more aware of how social surveillance behaviors can play a role in their health. This may be done by reshaping their cognitive and affective thinking processes (by creating a critical mindset, for example) to prepare individuals for the possible adverse consequences of surveillance behaviors. For instance, interventions could be developed to educate individuals about the fact that SNSs may present a distorted reality, exaggerating some elements. Particularly, since pictures of socialization are often snapshots of one particular moment (Bayer et al., 2016)

Developing this critical mindset might, however, be easier said than done, as SNS behaviors often occur habitually and out of boredom (Griffioen et al., 2021). Surveillance behaviors often consist of small cues (e.g., blue check marks on WhatsApp messages) with which individuals might unconsciously engage. It might, therefore, also be beneficial to teach individuals about specific SNS settings, as some surveillance cues can be disabled (e.g., check marks on WhatsApp; https://faq.whatsapp.com/1138190983240010/?locale=en_US). A mix between internal critical awareness and external feature settings might, therefore, be promising for future interventions aiming to improve individuals' mental health when using SNSs.

Limitations

Despite the contributions of this study, several limitations are addressed. First, this study used a snowball sampling approach to recruit participants, and although this approach eases the sampling process, it remains impossible to determine sampling errors and generalize the results across a population. Specifically, since the sample was overrepresented by females. Given that this unequal representation might have impacted the results, future research should try to incorporate a more balanced sample.

Second, this study retrospectively measured surveillance behaviors, potentially resulting in recall bias. In particular, surveillance behaviors consist of minor cues that can be easily forgotten during the day. Future research could, therefore, benefit from using experience sampling methods (ESMs) as these make it possible to capture behaviors and thoughts immediately after they are experienced. Moreover, given that ESM consists of multiple assessments per day, it would be possible to specify the directions of the tested associations and prove causality (which was impossible in our cross-sectional design). Research could, for example, test the transactionality between social surveillance and mental health outcomes and further examine whether these associations appear in the short-term (it appears immediately after engaging in surveillance behaviors on a day) or long-term (it accumulates with surveillance behaviors over time).

Third, our cross-sectional non-experimental design could lead to biased mediation claims for two reasons (Bullock & Green, 2021; Rohrer et al., 2021). First, we did not manipulate our mediator, so confounding variables cannot be excluded and uncorrelatedness between our mediator and other unobserved mediators cannot be guaranteed. The results should therefore be interpreted under these specific assumptions: the estimate corresponds to the causal effect of social surveillance (X) and mental health outcomes (Y) under the assumption that, apart from A (surveillance --> FOMO), B (FOMO --> mental health outcomes), and C (surveillance --> mental health outcomes), there are no common causes between X and Y (Rohrer et al., 2021). Given that we cannot be entirely sure of this, we suggest that future research examines our model experimentally using the proper manipulations. Second, bias might have also occurred because the indirect effects of FOMO might not hold for every individual within the sample. Studies using ESM and multilevel modeling would again be helpful in this regard since subjects would be measured over time, thereby making it possible to measure the indirect effect for each subject (Bullock & Green, 2021).

Footnotes

[1] By adjusting the model based on the modification indices, we acknowledge that we have moved from model verification to exploration (Kline, 2011), and future research is hence needed to verify the respecified model.

[2] To discuss the results of the SEM model, we make use of the term "effect" as this is also how it is reported in the statistical output of SEM. However, we do acknowledge that our study, consisting of cross-sectional data, does not allow us to make causal effect claims. Consequently, these results should be interpreted as associations.

Conflict of Interest

The authors declare that there is no conflict of interest, given that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors' Contribution

Robyn Vanherle: conceptualization, methodology, software, formal analysis, writing—original draft, writing—review & editing, visualization. **Jolien Trekels**: writing—review & editing. **Sien Hermans**: conceptualization, data collection. **Pauline Vranken**: conceptualization, data collection. **Kathleen Beullens***:* conceptualization, methodology, resources, writing—review & editing, supervision, funding acquisition.

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All data and syntaxes related to this study can be found on OSF: https://osf.io/rbked/

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Appendices

Appendix A: Loneliness

Table A1. *Standardized and Unstandardized Coefficients of CFA Model 1 (Loneliness).*

Latent	Observed variable	β	*B*	*SE*	α
Loneliness	**I am unhappy doing so many things alone**	**.29**	1	/	.92
	I have nobody to talk to	.68	2.46	0.55	
	I cannot tolerate being so alone	**.19**	0.74	0.30	
	I lack companionship	.69	2.26	0.50	
	I feel as if nobody really understands me	.74	2.93	0.64	
	I find myself waiting for people to call or write	**.43**	1.67	0.42	
	There is no one I can turn to	.68	2.20	0.49	
	I am no longer close to anyone	.63	1.68	0.38	
	My interests and ideas are not shared by those around me	**.59**	2.10	0.48	
	I feel left out	.77	2.72	0.59	
	I feel completely alone	.84	3.04	0.66	
	I am unable to reach out and communicate with those around me	.65	2.28	0.51	
	My social relationships are superficial	.63	2.30	0.52	
	I feel starved for company	**.20**	0.75	0.29	
	No one really knows me well	.68	2.70	0.60	
	I feel isolated from others	.83	3.00	0.65	
	I am unhappy being so withdrawn	.73	2.51	0.55	
	It is difficult for me to make friends	**.53**	2.11	0.50	
	I feel left out and excluded by others	.74	2.50	0.55	
	People are around me but not with me	.76	2.67	0.58	

Note. CFA = confirmatory factor analysis of initial model with all items included (Model 1). / indicates that the standard error was not estimated. Model fit was: χ^2 = 3,411.04, *df* = 1,749, *p* < .001, CFI = .78, RMSEA = .06, 90% CI [.06, .07], SRMR = .10. The sentences and numbers in bold refer to items that had factor loadings lower than .60. Given that literature suggests that loadings of previously established items should be at least .60 to define components whatever the sample size used (Awang, 2012; Field, 2005; Guadagnoli & Velicer, 1988), we omitted these items of loneliness and ran a new model (Model 2; see Table A2 for results).

Table A2. *Standardized and Unstandardized Coefficients of CFA Model 2 (Loneliness).*

Latent construct	Observed variable	β	*B*	*SE*	α
Loneliness	I have nobody to talk to	.68	1		.93
	I lack companionship	.70	0.92	0.09	
	I feel as if nobody really understands me	.73	1.17	0.11	
	There is no one I can turn to	.68	0.89	0.09	
	I am no longer close to anyone	.64	0.69	0.07	
	I feel left out	.77	1.09	0.10	
	I feel completely alone	.85	1.24	0.10	
	I am unable to reach out and communicate with those around me	.64	0.91	0.10	
	My social relationships are superficial	.63	0.92	0.10	
	No one really knows me well	.68	1.08	0.11	
	I feel isolated from others	.84	1.22	0.10	
	I am unhappy being so withdrawn	.71	0.99	0.09	
	I feel left out and excluded by others	.73	0.99	0.09	
	People are around me but not with me	.75	1.07	0.10	

Note. CFA = confirmatory factor analysis. / indicates that the standard error was not estimated. Contrary to model 1, now all items of loneliness with factor loadings lower than .60 have been omitted. The model fit of model 2 was slightly better, χ^2 = 1,527.91, *df* = 759, *p* < .001, CFI = .87, RMSEA = .06, 90% CI [.06, .07], SRMR = .09, than Model 1. By looking at the modification indices of model 2, we decided to adjust the model a little bit more by allowing some error terms to correlate of the items measuring loneliness (Abbott et al., 2003; Brown, 2015; Kenny & Judd, 1984, Kline, 2011). Brown (2015), for example, argues that it is legitimate to correlate indicators' error terms if they contain similarly worded test items. Consequently, similar to the study of Maes et al. (2017), who measured loneliness in adolescence, we allowed certain error terms to correlate for items measuring loneliness containing the same wording in Dutch (see final model with correlated error terms in Table A3).

I feel left out~~ I feel left out and excluded by others

I feel completely alone ~~ I feel isolated from others

I have nobody to talk to ~~ I lack companionship

The first two items would for example read as “Ik voel me buitengesloten” and “Ik voel me buitengesloten door anderen”, hence showing the similarity in wording.

Table A3. *Standardized and Unstandardized Coefficients of CFA Model 3 (Loneliness).*

Latent construct	Observed variable	β	*B*	*SE*	α
Loneliness	I have nobody to talk to	.67	1		.93
	I lack companionship	.69	0.92	0.07	
	I feel as if nobody really understands me	.75	1.21	0.11	
	There is no one I can turn to	.68	0.90	0.09	
	I am no longer close to anyone	.65	0.71	0.08	
	I feel left out	.74	1.07	0.10	
	I feel completely alone	.82	1.21	0.10	
	I am unable to reach out and communicate with those around me	.66	0.95	0.10	
	My social relationships are superficial	.65	0.96	0.10	
	No one really knows me well	.70	1.13	0.11	
	I feel isolated from others	.81	1.19	0.10	
	I am unhappy being so withdrawn	.72	1.02	0.10	
	I feel left out and excluded by others	.72	0.99	0.10	
	People are around me but not with me	.76	1.09	0.10	

Note. CFA = confirmatory factor analysis. / indicates that the standard error was not estimated. Model 3 is similar to Model 2 (Table A2) but now some error terms of the loneliness items are correlated, resulting in an acceptable model fit, χ^2 = 1,266.71, *df* = 717, *p* < .001, CFI = .90, RMSEA = .06, 90% CI [.05, .06], SRMR = .09.

Appendix B: Depressive Symptoms

Table B1. *Standardized and Unstandardized Coefficients of CFA Model 1 (Depressive Symptoms).*

Latent construct	Observed variable	β	*B*	*SE*	α
Depressive Symptoms	I felt miserable or unhappy	.71	1	/	.90
	I didn't enjoy anything	**.54**	0.57	0.07	
	I felt so tired I just sat around and did nothing	**.40**	0.57	0.09	
	I was restless	**.52**	0.81	0.10	
	I felt I was no good anymore	.77	1.24	0.11	
	I cried a lot	**.57**	0.89	0.10	
	I found It hard to think properly and	**.44**	0.69	0.10	
	I hated myself	.78	1.08	0.09	
	I was a bad person	.64	0.72	0.07	
	I felt lonely	.76	1.08	0.09	
	I thought nobody really loved me	.79	1.08	0.09	
	I thought I could never be as good as others	.79	1.31	0.11	
	I did everything wrong	.77	0.98	0.08	

Note. CFA = confirmatory factor analysis of initial model with all items included (Model 1). / indicates that the standard error was not estimated. Model fit was χ^2 = 3,411.04, *df* = 1,749, *p* < .001, CFI = .78, RMSEA = .06, 90% CI [.06, .07], SRMR = .10. The sentences and numbers in bold refer to items that had factor loadings lower than .60. Given that literature suggests that loadings of previously established items should be at least .60 to define components whatever the sample size used (Awang, 2012; Field, 2005; Guadagnoli & Velicer, 1988), we omitted these items of depressive symptoms and ran a new model (model 2; see Table B2 for results).

Table B2. *Standardized and Unstandardized Coefficients of CFA Model 2 (Depressive Symptoms).*

Latent construct	Observed variable	β	*B*	*SE*	α
Depressive Symptoms	I felt miserable or unhappy	.67	1	/	.90
	I felt I was no good anymore	.76	1.29	0.12	
	I hated myself	.79	1.15	0.10	
	I was a bad person	.63	0.76	0.08	
	I felt lonely	**.77**	1.16	0.11	
	I thought nobody really loved me	.82	1.19	0.10	
	I thought I could never be as good as others	.82	1.43	0.13	
	I did everything wrong	.76	1.04	0.10	

Note. CFA = confirmatory factor analysis. / indicates that the standard error was not estimated. Contrary to Model 1, now all items of depressive symptoms with factor loadings lower than .60 have been omitted. The model fit of Model 2 was slightly better, χ^2 = 1,527.91, *df* = 759, *p* < .001, CFI = .87, RMSEA = .06, 90% CI [.06, .07], SRMR = .09, than Model 1. By looking at the modification indices of Model 2, we decided to adjust the model a little bit more by removing the item *I felt lonely*. The modification indices namely showed that the model fit would improve with 31.90 if a path was added between this depressive symptoms item and the loneliness construct, hence possibly pointing toward a cross-loading. In fact, to test the severity of this problem, we tested an exploratory CFA with this item included with the loneliness construct and found that the item had a loading of .77 on the loneliness factor. Based on the modification indices and the similarity of wording between this item and the loneliness items, we thus decided to remove it (hence resulting in Model 3, Table B3).

Table B3. *Standardized and Unstandardized Coefficients of CFA Model 3 (Depressive Symptoms).*

Latent construct	Observed variable	β	*B*	*SE*	α
Depressive Symptoms	I felt miserable or unhappy	.67	1	/	.89
	I felt I was no good anymore	.76	1.29	0.12	
	I hated myself	.81	1.18	0.10	
	I was a bad person	.66	0.79	0.08	
	I thought nobody really loved me	.80	1.16	0.10	
	I thought I could never be as good as others	.81	1.42	0.13	
	I did everything wrong	.79	1.07	0.10	

Note. CFA = confirmatory factor analysis. / indicates that the standard error was not estimated. Model 3 is similar to Model 2 (Table B2) but now the item of *I felt lonely* is deleted (on top of correlated error terms in the loneliness construct), resulting in an acceptable model fit, χ^2 = 1,266.71, *df* = 717, *p* < .001, CFI = .90, RMSEA = .06, 90% CI [.05, .06], SRMR = .09.

Appendix C: Need for Popularity

Table C1. *Standardized and Unstandardized Coefficients of CFA Model 1 (Need for Popularity).*

Latent construct	Observed variable	β	*B*	*SE*	α
NfP	I have done things to make me more popular, even when it meant doing something I would not usually do	.62	1	/	.89
	I've neglected some friends because of what other people might think	.60	0.90	0.11	
	At times, I've ignored some people in order to be more popular with others	.73	1.09	0.12	
	I'd do almost anything to avoid being seen as a "loser"	**.56**	0.87	0.11	
	It's important that people think I'm popular	.68	1.02	0.11	
	At times, I've gone out with people, just because they were popular	.76	0.97	0.10	
	I've been friends with some people, just because others liked them	.64	1.13	0.13	
	I've gone to parties, just to be part of the crowd	**.59**	1.01	0.13	
	I often do things just to be popular with people at school	.80	0.94	0.09	
	At times, I've hung out with some people, so others wouldn't think I was unpopular	.83	1.25	0.12	

Note. CFA = confirmatory factor analysis of initial model with all items included (Model 1). / indicates that the standard error was not estimated. Model fit was: χ^2 = 3,411.04, *df* = 1,749, *p* < .001, CFI = .78, RMSEA = .06, 90% CI [.06, .07], SRMR = .10. The sentences and numbers in bold refer to items that had factor loadings lower than .60. Given that literature suggests that loadings of previously established items should be at least .60 to define components whatever the sample size used (Awang, 2012; Field, 2005; Guadagnoli & Velicer, 1988), we omitted these items of need for popularity and ran a new model (Model 2; see Table C2 for results).

Table C2. *Standardized and Unstandardized Coefficients of CFA Model 2 (Need for Popularity).*

Latent construct	Observed variable	β	*B*	*SE*	α
NfP	I have done things to make me more popular, even when it meant doing something I would not usually do	.62	1	/	.89
	I've neglected some friends because of what other people might think	.61	0.92	0.11	
	At times, I've ignored some people in order to be more popular with others	.72	1.09	0.12	
	It's important that people think I'm popular	.67	1.01	0.12	
	At times, I've gone out with people, just because they were popular	.77	0.99	0.10	
	I've been friends with some people, just because others liked them	.63	1.13	0.14	
	I often do things just to be popular with people at school	.79	0.94	0.09	
	At times, I've hung out with some people, so others wouldn't think I was unpopular	.84	1.26	0.12	

Note. CFA = confirmatory factor analysis. / indicates that the standard error was not estimated. Contrary to Model 1, now all need for popularity items with factor loadings lower than .60 have been omitted. The model fit of Model 2 was slightly better, χ^2 = 1,527.91, *df* = 759, *p* < .001, CFI = .87, RMSEA = .06, 90% CI [.06, .07], SRMR = .09, than Model 1. The coefficients of the need for popularity items remained exactly the same in Model 3 so this table is not provided separately for Need for Popularity. For an entire table of Model 3 (final model with all constructs together), please see Table F.

Appendix D: Fear of Missing Out

Table D1. *Standardized and Unstandardized Coefficients of CFA Model 1 (Fear of Missing Out).*

Latent construct	Observed variable	β	*B*	*SE*	α
FOMO	I fear others have more rewarding experiences than me	.71	1	/	.80
	I fear my friends have more rewarding experiences than me	.75	1.09	0.11	
	I get worried when I find out my friends are having fun without me	.72	1.16	0.12	
	I get anxious when I don't know what my friends are up to	**.59**	0.68	0.08	
	It is important that I understand my friends "in jokes"	**.52**	0.74	0.10	
	Sometimes, I wonder if I spend too much time keeping up with what is going on	**.47**	0.76	0.11	
	It bothers me when I miss an opportunity to meet up with friends	**.54**	0.87	0.11	
	When I have a good time it is important for me to share the details online (e.g., updating status)	**.31**	0.35	0.08	
	When I miss out on a planned get-together it bothers me	**.41**	0.60	0.10	
	When I go on vacation, I continue to keep tabs on what my friends are doing	**.38**	0.56	0.10	

Note. CFA = confirmatory factor analysis of initial model with all items included (Model 1). / indicates that the standard error was not estimated. Model fit was: χ^2 = 3,411.04, *df* = 1,749, *p* < .001, CFI = .78, RMSEA = .06, 90% CI [.06, .07], SRMR = .10. The sentences and numbers in bold refer to items that had factor loadings lower than .60. Given that literature suggests that loadings of previously established items should be at least .60 to define components whatever the sample size used (Awang, 2012; Field, 2005; Guadagnoli & Velicer, 1988), we omitted these items of fear of missing out and ran a new model (Model 2; see Table D2 for results).

Table D2. *Standardized and Unstandardized Coefficients of CFA Model 2 (Fear of Missing Out).*

Latent construct	Observed variable	β	*B*	*SE*	α
FOMO	I fear others have more rewarding experiences than me	.85	1	/	.80
	I fear my friends have more rewarding experiences than me	.85	1.04	0.09	
	I get worried when I find out my friends are having fun without me	.59	0.80	0.09	

Note. CFA = confirmatory factor analysis. / indicates that the standard error was not estimated. Contrary to Model 1, now all fear of missing out items with factor loadings lower than .60 have been omitted. The model fit of Model 2 was slightly better, χ^2 = 1,527.91, *df* = 759, *p* < .001, CFI = .87, RMSEA = .06, 90% CI [.06, .07], SRMR = .09, than Model 1. The coefficients of the fear of missing out items remained exactly the same in Model 3 so this table is not provided separately for fear of missing out. For an entire table of Model 3 (final model with all constructs together), please see Table F.

Appendix E: Social Surveillance

Table E1. *Standardized and Unstandardized Coefficients of CFA Model 1 (Social Surveillance).*

Latent construct	Observed variable	β	*B*	*SE*	α
Social Surveillance	View location of a Snapchat friend without further action	.81	1	/	.82
	See when others were last online	.86	1.06	0.07	
	View location of a Snapchat friend and start chatting with them	.68	0.53	0.05	
	Viewing a friend's Snapchat score to see if they are active	.52	0.46	0.06	
	See who has already opened your story or Snap	.62	0.72	0.07	

Note. CFA = confirmatory factor analysis of initial model with all items included. / indicates that the standard error was not estimated. Model fit was χ^2 = 3,411.04, *df* = 1,749, *p* < .001, CFI = .78, RMSEA = .06, 90% CI [.06, .07], SRMR = .10. No items were deleted because we relied on a .50 threshold for factor loadings of newly developed constructs instead of a .60 threshold for established items (Awang, 2012). The coefficients of the social surveillance items remained exactly the same in Model 2 and 3 so these tables are not provided here. For an entire table of Model 3 (final model with all constructs together), please see Table F.

Appendix F: Final Model: All Scales Together

Table F1. *Standardized and Unstandardized Coefficients of Model 3.*

Latent construct	Observed variable	β	*B*	*SE*	α
Loneliness	I have nobody talk to	.67	1		.93
	I lack companionship	.69	0.92	0.07	
	I feel as if nobody really understands me	.75	1.21	0.11	
	There is no one I can turn to	.68	0.90	0.09	
	I am no longer close to anyone	.65	0.71	0.08	
	I feel left out	.74	1.07	0.10	
	I feel completely alone	.82	1.21	0.10	
	I am unable to reach out and communicate with those around me	.66	0.95	0.10	
	My social relationships are superficial	.65	0.96	0.10	
	No one really knows me well	.70	1.13	0.11	
	I feel isolated from others	.81	1.19	0.10	
	I am unhappy being so withdrawn	.72	1.02	0.10	
	I feel shut out and excluded by others	.72	0.99	0.10	
	People are around me but not with me	.76	1.09	0.10	
Depressive Symptoms	I felt miserable or unhappy	.67	1	/	.89
	I felt I was no good anymore	.76	1.29	0.12	
	I hated myself	.81	1.18	0.10	
	I was a bad person	.66	0.79	0.08	

	I thought nobody really loved me	.80	1.16	0.10	
	I thought I could never be as good as others	.81	1.42	0.13	
	I did everything wrong	.79	1.07	0.10	
NfP	I have done things to make me more popular, even when it meant doing something I would not usually do	.62	1	/	.89
	I've neglected some friends because of what other people might think	.61	0.92	0.11	
	At times, I've ignored some people in order to be more popular with others	.72	1.09	0.12	
	It's important that people think I'm popular	.67	1.01	0.12	
	At times, I've gone out with people, just because they were popular	.77	0.99	0.10	
	I've been friends with some people, just because others liked them	.63	1.13	0.14	
	I often do things just to be popular with people at school	.79	0.94	0.09	
	At times, I've hung out with some people, so others wouldn't think I was unpopular	.84	1.26	0.12	
FOMO	I fear others have more rewarding experiences than me	.85	1	/	.80
	I fear my friends have more rewarding experiences than me	.85	1.04	0.09	
	I get worried when I find out my friends are having fun without me	.59	0.80	0.09	
Social Surveillance	View location of a Snapchat friend without further action	.81	1	/	.82
	See when others were last online	.86	1.06	0.07	
	View location of a Snapchat friend and start chatting with them	.68	0.53	0.05	
	Viewing a friend's Snapchat score to see if they are active	.52	0.47	0.06	
	See who has already opened your story or Snap	.62	0.72	0.07	

Note. CFA = confirmatory factor analysis. / indicates that the standard error was not estimated. This table represents model 3, the final model, with all scales together. The model fit is: χ^2 = 1,266.71, *df* = 717, *p* < .001, CFI = .90, RMSEA = .06, 90% CI [.05, .06], SRMR = .09.

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