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Review

Social media use and well-being: What we know and what we need to know

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Abstract

Research into the impact of social media use (SMU) on well-being (e.g., happiness) and ill-being (e.g., depression) has exploded over the past few years. From 2019 to August 2021, 27 reviews have been published: nine meta-analyses, nine systematic reviews, and nine narrative reviews, which together included hundreds of empirical studies. The aim of this umbrella review is to synthesize the results of these meta-analyses and reviews. Even though the meta-analyses are supposed to rely on the same evidence base, they yielded disagreeing associations with well- and ill-being, especially for time spent on SM, active SMU, and passive SMU. This umbrella review explains why their results disagree, summarizes the gaps in the literature, and ends with recommendations for future research.

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Review, Meta-analysis, Facebook, Instagram, Social media, Mental health, Well-being, Depression, Idiographic approach, Social comparison, Problematic social media use.

Introduction

It is almost a truism: In the past decade, social media have become a massive and meaningful part of our daily existence. Individuals, adults and adolescents alike, use on average five social media platforms in a complementary way [1], to interact privately with family members and friends, and/or to interact publicly with broader audiences of friends, acquaintances, and colleagues [2]. In parallel with this surging social media use (SMU), research into its potential impact on well-being (e.g., life satisfaction) and ill-being (e.g., depression) has also accumulated dramatically [3]. As recent reviews demonstrate [4–6], the past years have witnessed at least 300 studies on the impact of SMU on well- and ill-being.

Together with the exponential increase in empirical studies, *reviews* of the impact of SMU on well- and ill-being have also surged in the past few years. Because this rapidly expanding research output makes it ever more difficult for researchers to keep track of it, an up-to-date umbrella review of this literature is necessary and important. An umbrella review, also called a meta-review, is a synthesis of existing reviews [7]. Three earlier umbrella reviews have focused on the associations of SMU with well- and ill-being [3,8,9]. One of these focused on adolescents, thereby excluding reviews on adults [9], and neither of the two others included the 22 reviews on the effects of SMU on well-/ill-being published in 2020 and 2021.

In this article, I first outline the search method of this umbrella review as well as the operational definitions of SMU, well-being, and ill-being. To assess “what we know,” I use the meta-analyses to discuss the associations of seven different types of SMU with well- and ill-being. The systematic and narrative reviews are used to complement the meta-analytical results, as well as to summarize the identified gaps in the literature and the suggestions for future research. To assess “what we need to know,” the article ends with some general conclusions and three additional recommendations for future research.

Method and operational definitions

Two coders used the same search strategy and terms as applied in the umbrella review of Valkenburg et al. [9], except for the search terms related to adolescents (as the current umbrella review excluded reviews focusing on adolescents). SMU was operationally defined as the active (e.g., posting), passive (e.g., browsing), private,

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and public uses of platforms such as Facebook, WeChat, and WhatsApp. As for the outcomes of SMU, the focus lied on three well-being components (happiness; life satisfaction; positive affect) and three ill-being components (depressive symptoms/depression; anxiety symptoms/anxiety; negative affect). Due to space restrictions, other components of well-being (e.g., eudaimonic well-being) and ill-being (e.g., stress), as well as risk and resilience factors of well- and ill-being, such as self-esteem, cyberbullying, and body image concerns, were not considered.

Results: what we know …

The search yielded 27 reviews: nine meta-analyses [4,6,10–16], nine systematic reviews [5,17–24], and nine narrative reviews [25–33] published from January 2019 to August 2021. Except for five meta-analyses, which included studies on both adolescents and adults, none of the remaining 22 reviews were included in the earlier umbrella review of Valkenburg et al. [9].

Seven social media activities

As Table 1 shows, some meta-analyses investigated (a) general time spent with SM, or (b) time spent with active and (c) passive SMU. Some (also) focused on specific behaviors and mechanisms afforded by SM, including (d) the size of one's SM network, (e) the intensity of SMU, (f) problematic SMU (i.e., an enduring preoccupation with SM, reflected in a persistent neglect of one's own health and important life areas), and (g) SM-induced social comparison (the tendency to observe others to assess how we are looking, thinking, or behaving in comparison with these others) [34].

Conceptualizations of well-being and ill-being

Two out of the nine meta-analyses [6,12] reversed different ill-being components (e.g., depression) and combined them with well-being components (e.g., life satisfaction) to create an "aggregated well-/ill-being" outcome. Furthermore, five meta-analyses [6,10,11,14,15] lumped together components like life satisfaction and self-esteem to create an "aggregated well-being" outcome. Likewise, they combined components like depression and loneliness to create an "aggregated ill-being" outcome. However, because mental health theories agree that a low well-being (e.g., low life satisfaction) does not necessary imply a high ill-being (e.g., suffering from depression) and vice versa [8,35,36], this umbrella review investigated whether the three aggregated outcomes, that is, (a) aggregated *well-/ill*-being, (b) aggregated *well*-being and (c) aggregated *ill*-being, led to different associations with SMU.

General SMU

The three types of aggregated well- and/or ill-being outcomes yielded inconsistent associations with general SMU (also called time spent using SM, general SNS use, or the frequency of SM checking). As for aggregated well-/ill-being, one meta-analysis yielded no association [6], and another a small positive association with general SMU [12]. As for aggregated well-being, one meta-analysis yielded a small negative [6], and another a small positive association with general SMU [15]. Remarkably though, his latter meta-analysis also reported a small positive association with aggregated ill-being [15]. Finally, general SMU was consistently associated with higher levels of depression/depressive symptoms [4,6,12,16] and anxiety [6,12], but, again surprisingly, also with higher happiness levels [12].

Active versus passive social media use

Three meta-analyses compared time spent on active and passive SMU, again with highly inconsistent results. Active SMU was not [12] or weakly positively associated [6] with aggregated well-/ill-being. Furthermore, it was not [15] or weakly positively associated [6] with aggregated well-being, but not with aggregated ill-being [15]. *Passive* SMU, in contrast, was not [6] or *negatively* [12] associated with aggregated well-/ill-being, but not with aggregated well-being [6,15] and not with aggregated ill-being [15]. Yet, both active and passive SMU were associated with higher levels of depression/depressive symptoms [6] and anxiety [6].

In all, the meta-analyses yielded scant support for both the "active SMU hypothesis" and "passive SMU hypothesis," which respectively argue that active SMU elicits likes and support, which results in higher well-being/lower ill-being. And that passive SMU induces social comparisons and envy, which leads to lower well-being/higher ill-being [37]. An elaborate explanation of this lack of support can be found in a review by Valkenburg et al. [24].

Social comparison

Even though the direct meta-analytic associations of active and passive SMU with well- and ill-being were inconsistent, two meta-analyses have addressed one part of the passive SMU hypothesis, which states that SM-induced social comparison results in lower well-being/higher ill-being [33]. Indeed, SM-induced social comparison was associated with lower aggregated well-being and life satisfaction [14] and higher depression [16]. It must be noted, though, that 78% of SM users report never feeling worse after comparing themselves to other users [38], that only a minority of SM users feel envious while using SM [39], that they more often feel enjoyment [40], and that they sometimes also get inspired from SM-induced social comparisons [41].

Network size

The results of the two meta-analyses focusing on network size were rather consistent: The size of one's SM network size was associated with higher aggregated well-being [11,15], happiness [11], and life satisfaction [11]. It was not [15] or weakly associated [11] with lower aggregated ill-being, and not with depression [11]. Network size was not related to anxiety [11], but negatively to higher *social* anxiety [11]. However, this latter association has mostly been investigated within the social compensation framework [42], in which social anxiety is conceptualized as a predictor rather than an outcome of SMU. Socially anxious people spend more time on SM [42], but particularly more time on *passive* SMU [22]. Obviously, expanding one's network does not occur via passive but via interactive SMU, which could explain why socially anxious users tend to have smaller SM networks than their less socially anxious counterparts.

SM intensity and problematic SMU

Intensity of SMU refers to a mixture of users' emotional attachment to SM and the extent to which SMU is integrated into their lives [4]. It is mostly measured with (adaptions of) the Facebook Intensity Scale (FIS) [43]. Even though the FIS was not designed as a measure of problematic SMU, it is highly correlated with problematic SMU (e.g., $\beta = .57$) [44], and in some studies, intensity of SMU is even included as an indicator of problematic SMU [19]. It is no surprise, therefore, that, most meta-analytic effect sizes for intensity of SMU and problematic SMU are not significantly different [4]. Intensity of SMU was consistently associated with lower aggregated well-being [6], higher depression/depressive symptoms [4,6] and higher anxiety [6].

Comparatively, problematic SMU was associated with lower aggregated well-being [6,10], lower happiness [10], and life satisfaction [10]. And it was associated with higher aggregated ill-being [10], depression/depressive symptoms [4,6,10,13], and anxiety [6,10]. A likely explanation for the consistent associations of problematic SMU with well- and ill-being outcomes may lie in "construct overlap" [4]. After all, it should be no surprise that well- and ill-being outcomes correlate with problematic SMU scales consisting of items like "How often during the last year ..." "did you use SM to escape negative feelings" [45] and "have you become restless or troubled if you were prohibited from using social media?" [46].

Identified gaps and directions for future research

Seventeen out of the 27 reviews agreed that the evidence on which their conclusions were based is primarily cross-sectional and called for longitudinal and/or experimental studies to determine the causal direction of the effects of SMU [3,5,12,28,29,47], or for research designed to investigate why and/or for whom SMU is associated with well- or ill-being [4,5,17,20,31,32]. Other reviews observed an over-reliance on measures of time spent on SM [4,6,22,28,29] and active and passive SMU [22,24] at the expense of more fine-grained measures, such as the purpose of SMU or the type of communication partners [12,29]. Finally, some reviews criticized the over-reliance on self-reports [3,5,25,28–30] and called for more objective measures of SMU, such as log-based data obtained though screen-time apps [28,29].

Discussion: what we need to know ...

The nine meta-analyses in this umbrella review disagreed in their conclusions about the associations of different types of SMU with well-being. This particularly applied to the time-based predictors and not or less to the other predictors. However, despite these inconsistencies, all meta-analyses yielded pooled associations that were mostly small (for the time-based predictors), occasionally moderate (for problematic SMU), but never large. The conclusions of the meta-analyses were largely supported by the narrative and systematic reviews, which observed comparable gaps in the literature and provided comparable suggestions for future research. I end this article with three additional recommendations for future research.

Recommendation 1: don't collapse across well- and ill-being outcomes

Meta-analyses of the effects of SMU can provide indispensable summaries of the evidence in this vastly expanding literature [3]. But they can also suffer from the same shortcomings as any other type of study. An important shortcoming involves their arbitrary choices to collapse across distinct well-being and ill-being components. In fact, the inconsistencies in effect sizes applied particularly to the six meta-analyses that created well-being, ill-being, and well-/ill-being composites. As Table 1 shows, these meta-analyses collapsed across a great variety of well- and ill-being components in addition to a range of risk and resilience factors of well- and ill-being, such as envy, stress, self-esteem, self-harm, and suicidal ideation.

This lumping together of different well- and ill-being components and their risk-resilience factors hampers the validity of the meta-analytic effect sizes for two reasons. First, ill-being is not simply the flip side of well-being [36], as demonstrated, for example, by the positive meta-analytic associations of time spent on SM with both the well-being component "happiness" and the ill-being component "depression" [12]. Second, components *within* well- or ill-being composites also led to different associations with SMU, as confirmed by the sheer opposite meta-analytic associations of SM network size with anxiety versus *social* anxiety [11]. Therefore, a first crucial step for future research is to avoid lumping together well- and ill-being components that deserve to be investigated in their own right [30].

Table 1

Associations of different types of social media use (SMU) with indicators of well-being and ill-being.

Study	# Articles	Operational definitions of outcomes	Main results	
Cunningham et al. (2021)	62	Depressive symptoms	r = .11*	Time spent on SNS with depressive symptoms
			r = .09ns	Intensity of SNS use with depressive symptoms
			r = .29*	Problematic SNS use with depressive symptoms
Hancock et al. (2019)	256	Well-/ill-being = aggregate of anxiety, depression, loneliness, & eudaimonic, hedonic, and relational well-being	r = −.00ns	General SMU with well-/Ill-being
			r = .13*	General SMU with depression
			r = .11*	General SMU with anxiety
			r = −.03*	General SMU with (hedonic) well-being
			r = .11*	Intensity of SMU with well-/ill-being
		Hedonic well-being = aggregate of happiness, positive affect, subjective well-being, and negative affect	r = .10*	Intensity of SMU with depression
			r = .13*	Intensity of SMU with anxiety
			r = −.16ns	Intensity of SMU with (hedonic) well-being
			r = .06*	Active SMU with well-/ill-being
			r = .08*	Active SMU with depression
			r = .06*	Active SMU with anxiety
			r = .06*	Active SMU with (hedonic) well-being
			r = −.03ns	Passive SMU with well-/ill-being
			r = .07*	Passive SMU with depression
			r = .21*	Passive SMU with anxiety
			r = .24ns	Passive SMU with (hedonic) well-being
			r = −.21*	Problematic SMU with well-/ill-being
			r = .34*	Problematic SMU with depression
			r = .32*	Problematic SMU with anxiety
			r = −.26*	Problematic SMU with hedonic well-being
Huang (2020)	123	Well-being = aggregate of life satisfaction, self-esteem, happiness, and positive affect	r = −.16*	Problematic SMU with well-being
			r = −.30*	Problematic SMU with happiness
			r = −.18*	Problematic SMU with positive affect
			r = −.11*	Problematic SMU with life satisfaction
		Ill-being (distress) = aggregate of depression, anxiety, loneliness, and negative affect	r = .27*	Problematic SMU with ill-being
			r = .31*	Problematic SMU with depression
			r = .30*	Problematic SMU with anxiety
Huang (2021)	90	Well-being = aggregate of life satisfaction, self-esteem, happiness	r = .08*	Network size with well-being
			r = .15*	Network size with happiness
			r = .10*	Network size with life satisfaction
		Ill-being (distress) = aggregate of depression, loneliness, social anxiety, and suicidal ideation	r = −.06*	Network size with ill-being
			r = .01ns	Network size with depression
			r = .08ns	Network size with anxiety
			r = −.19*	Network size with social anxiety
Liu et al. (2019)	93	Well-/ill-being = aggregate of life satisfaction, happiness, self-esteem, anxiety, depression, loneliness, and stress	r = −.06*	General SNS use with well-/ill-being
			r = .09ns	General SNS use with life satisfaction
			r = .14*	General SNS use with happiness
			r = .13*	General SNS use with depression
			r = .10*	General SNS use with anxiety
			r = .02ns	Active SNS use with well-/ill-being
			r = −.14*	Passive SNS use with well-/ill-being
Vahedi et al. (2021)	55	Depressive symptoms	r = .11*	General SNS use with depressive symptoms
			r = .27*	Problematic use with depressive symptoms
Yang et al. (2019)	13	Well-being = aggregate of life satisfaction, self-esteem, and psychological well-being	r = −.20*	Facebook social comparison with well-being
			r = −.21*	Facebook social comparison with life satisfaction
Yin et al. (2019)	63	Well-being = aggregate of life satisfaction, well-being, self-esteem, and positive affect	r = .05*	General SNS use with well-being
			r = .06*	General SNS use with ill-being
			r = .13*	Network size with well-being
			r = −.03ns	Network size with ill-being
		Ill-being = aggregate of depression, loneliness, anxiety, envy, and negative affect	r = .04ns	Active SNS use with well-being
			r = .04ns	Active SNS use with ill-being
			r = −.10ns	Passive SNS use with well-being
			r = .07ns	Passive SNS use with ill-being

Table 1 (*continued*)

Study	# Articles	Operational definitions of outcomes	Main results	
Yoon et al. (2019)	45	Depression	r = .11*	Time spent on SNS with depression
			r = .10*	Frequency of checking SNS with depression
			r = .23*	Non-directional social comparison with depression
			r = .33*	Upward social comparison with depression

Notes. *Significant at least at $p < .05$. Table excludes effects for components of well-being (e.g., eudaimonic well-being) and ill-being (e.g., stress) that do not fit within my operational definitions of well- and ill-being. SNS = Social network sites.

Recommendation 2: we need content-based SM predictors of well- and ill-being

The inconsistencies in the associations of the time-based SM predictors may be caused by discrepancies in their operationalizations. For example, in some meta-analyses "general SNS use" referred to time spent on SNS [12], in others to a combination of time spent on SNS and the frequency of checking SNS [6,15], and in yet others it was not defined [13].

Unfortunately though, the time-based predictors not only led to heterogeneity *across* the meta-analyses but also *within* the meta-analyses (e.g., I^2s ranging from 57% for active SMU [12] to 97% for time spent on SM [4]), which could not or only partly be explained by moderators like age and gender. However, in case of considerable and (partly) unexplained heterogeneity, meta-analytic effect sizes may not be adequate and reliable [48]. A plausible explanation for the heterogeneity *within* meta-analyses is that the time-based predictors were operationalized differently in the included empirical studies. This has been confirmed in a recent scoping review, which revealed that of the 40 included survey-based studies, 90% used a unique, self-created operationalization of active and/or passive SMU, which led to a range of inconsistent associations with well- and ill-being components [24].

Yet even though the synchronization of time-based predictors in meta-analyses and empirical research may be a first step, there are also conceptual concerns. Time-based predictors may simply be too coarse to lead to meaningful associations with well- and ill-being components [30]. Such predictors may be valuable for outcomes like distraction or procrastination, which may be a direct consequence of time spent using SM [49,50]. In addition, they may be valuable when investigating time-based hypotheses, such as the displacement hypothesis, which states that SMU takes away time that could otherwise be spent on activities that are more conducive to well-being than SMU. But since well- and ill-being may be more amenable to the valence of SM interactions (cf. humor vs hate, support vs neglect) than to their duration, a second important step for future research is to pay more attention to content-based SMU predictors [24].

Recommendation 3: we need a causal effect heterogeneity paradigm

Several reviews have pointed at the need for studies that allow for the investigation of within-person associations of SMU with well-being [24,27]. In recent years, a growing number of such more rigorous studies have appeared [51–56]. But—again—most of these studies found weak average associations with well- and ill-being that were close to zero. What is still too often overlooked in these studies is that such average associations are derived from heterogeneous populations of SM users who differ in how they select and respond to SM [57], a finding that has repeatedly been confirmed in qualitative studies [58]. To truly understand the effects of SMU, researchers need to take the next step, that is, adopting a "causal effect heterogeneity" approach [59,60], which enables them to better understand why and how individuals differ in their responses to SMU.

To my knowledge, two communication research teams have adopted a causal effect heterogeneity paradigm [50,61], which led to the discovery of striking person-specific effects of SMU on well-being. They found, for example, that about 20% of respondents experienced a negative effect of passive SMU on happiness, 20% a positive effect, and 60% no effect at all [51]. A causal effect heterogeneity paradigm may not only help researchers resolve inconsistencies in findings (and replication failures) across studies [60], but it may also help them to arrive at a better understanding of why individuals may or may not be affected by SMU.

A causal effect heterogeneity approach, sometimes called an idiographic or person-specific approach, can be applied in experimental designs [59,62], as well as in non-experimental intensive longitudinal designs (e.g., experience sampling studies) [61,63]. The idiographic approach has recently raised concerns among some communication scholars. One of these concerns is that an idiographic approach in non-experimental settings would hinder inferences from an individual to a targeted population. Another concern is that this approach hinders or even ignores the investigation of moderators to explain differences among subgroups in this targeted population [64,65].

While these are valid concerns, they are well addressed in recent idiographic modeling techniques, such as Dynamic Structural Equation Modeling (DSEM), which combine the strengths of "traditional" methods of analysis (i.e., structural equation modelling and multi-level analysis) with N = 1 time-series analysis [63]. These modeling techniques require the same sizeable samples to generalize to targeted populations as traditional (nomothetic) approaches do. Also, they can be flexibly used to investigate the role of moderators in the person-specific effects of SMU on certain outcomes, see for example [40,66,67]. In fact, an important strength of these modelling techniques is that they allow for the investigation of two types of moderators, (a) trait-like moderators, such as ethnicity and extraversion, and (b) contextual moderators that are assumed to fluctuate within participants, such as their motivations for using SM, as well as their experience of envy or enjoyment during SMU [40].

Idiographic approaches are thus complementing rather than replacing nomothetic approaches. They enable researchers to report aggregated between-person and within-person associations of SMU with well- and ill-being. And in addition to these aggregated statistics, they can demonstrate for how many participants an experimental treatment works or for how many participants certain hypotheses hold [40]. Moreover, as argued by Bryan et al. [60], a causal effect heterogeneity approach can improve interventions and "make them effective for the diverse gamut of populations and contexts policy must address" (p. 7).

Conclusion

In sum, in addition to the wealth of valuable suggestions for future research raised in the 27 reviews that have appeared in the past 2.5 years, this umbrella review showed why well-being and ill-being components deserve to be investigated as two separate continuums (see also [8]). In addition, it made a case that we no longer need additional meta-analyses reporting weak aggregate between-person effect sizes of time-based SMU predictors, thereby reiterating the "one-size-fits-all approach" that has long characterized media effects research. Indeed, "we have a bright future before us, and it begins where the average ends." [[68], p. 191].

Conflict of interest statement

Nothing declared.

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