Computer-mediated communication, social media, and mental health: A conceptual and empirical meta-review

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Abstract

Computer-mediated communication (CMC), and specifically social media, may affect the mental health (MH) and well-being of its users, for better or worse. Research on this topic has accumulated rapidly, accompanied by controversial public debate and numerous systematic reviews and meta-analyses. Yet, a higher-level integration of the multiple disparate *conceptual* and *operational approaches* to CMC and MH and individual *review findings* is desperately needed. To this end, we first develop two organizing frameworks that systematize conceptual and operational approaches to CMC and MH. Based on these frameworks, we integrate the literature through a *meta-review* of 34 reviews and a content analysis of 594 publications. Meta-analytic evidence, overall, suggests a small negative association between social media use and MH. However, effects are complex and depend on the CMC and MH indicators investigated. Based on our conceptual review and the evidence synthesis, we devise an agenda for future research in this interdisciplinary field.

Keywords: computer-mediated communication, social media, mental health, well-being, psychopathology, meta-analysis

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Computer-mediated communication (CMC), the Internet, and now social and mobile media have repeatedly been characterized as a blessing or a curse for users' mental health (MH). Widely different claims about the impact of CMC on MH have been reiterated for decades and across disciplines (e.g., Burke & Kraut, 2016; Chan, 2015; Meier et al., 2020; Orben & Przybylski, 2019; Twenge et al., 2018). Research on this relationship has accumulated particularly rapidly in recent years, with a strong focus on social media (Meier et al., 2020). Yet, the fast-paced, interdisciplinary, and fragmented nature of the field requires researchers to keep track of a staggering, ever-growing, and seemingly incompatible evidence base (for initial meta-reviews, see Appel et al., 2020; Orben, 2020).

A key driver as well as consequence of this state of the field is the *conceptual diversity* of researchers' approaches to CMC and MH. Many studies and reviews seem to work from narrow, unsystematic approaches to CMC and MH, investigating widely different technology indicators (e.g., "screen time", self-presentation on SNS, intensity of Facebook use) and a disconnected smorgasbord of MH indicators (e.g., self-esteem, loneliness, depression, life satisfaction) (e.g., Huang, 2017; Twomey & O'Reilly, 2017). Recent specification curve analyses demonstrate that the relationship between CMC and MH can differ drastically, depending on how researchers operationalize them (e.g., Orben & Przybylski, 2019). Hence, without a higher-level conceptual and empirical integration, the bigger picture of associations between CMC and MH cannot be systematically evaluated. In addition, the choice of indicators and identification of research gaps remain largely idiosyncratic.

This study addresses the need for such higher-level integration twofold. We first develop two *organizing frameworks* that specify how CMC and MH are conceptualized and operationalized in the literature. These frameworks allow researchers to navigate the field more reliably and facilitate systematic identification of patterns, gaps, and conceptual

conflation. Moreover, they provide the background of our empirical analysis, a *meta-review* of systematic reviews and meta-analyses on CMC and MH. This empirical meta-review aims to (a) synthesize the main findings on the relationships between CMC and MH indicators from existing reviews. In addition, (b) we seek to apply the two organizing frameworks to the primary studies included in these reviews, to systematically identify the conceptual foci of prior research, potential conceptual conflation, and research gaps.

To this end, we first develop the theoretical frameworks of CMC and MH based on conceptual reviews and relevant empirical literature. Using these frameworks as organizing principles for the empirical meta-review, we then synthesize the findings from 34 systematically identified meta-analyses and systematic reviews as well as 594 publications included in these syntheses. By reflecting on the empirical meta-review findings through the lens of the new organizing frameworks, we conclude with an agenda for future research.

The Hierarchical CMC Taxonomy

We understand *computer-mediated communication* (CMC) as an inclusive umbrella term for multimodal human-to-human social interaction mediated by information and communication technologies (ICTs). Social interaction here includes all forms of interpersonal message exchange, encompassing everything from mere social attention (e.g., browsing through the Instagram feed) to deep communication (e.g., a conversation via WhatsApp voice call; Hall, 2018). This meta-review also limits ICTs to those whose *primary and original*—though not exclusive—function is the facilitation of CMC as social interaction (e.g., email, mobile texting, instant messenger, social network sites, but not, e.g., games). These ICTs have been at the center of recent public concern and research regarding MH effects (e.g., Twenge et al., 2018), thus representing a reasonable focus for this meta-review.

A first step of our synthesis is a systematization of the conceptual and operational approaches to CMC. A key question guided this conceptual review: How can we organize as many CMC indicators with as few *levels of analysis* as possible? Since no such framework

existed, we used concept mapping (Booth et al., 2012) on all CMC indicators included in literature reviews on CMC and MH (see Method for the sample of included reviews). That is, we iteratively mapped out existing CMC measures in a conceptual space to reveal their key conceptual and operational similarities, hierarchies, and differences. This was done until theoretical saturation was reached, meaning that no further levels were needed to encompass all available indicators. Additionally, we grounded the identified levels and approaches in literature that theorizes CMC (see next section). This approach was advantageous over adopting, for instance, an affordances approach (Evans et al., 2017), since none of the reviewed empirical studies on CMC and MH used measures that explicitly operationalized distinct affordances as commonly defined in the literature.

Instead, by breaking down CMC measures into their basic levels of analysis, we build a parsimonious taxonomy that applies not just to one single or a few ICTs (e.g., Facebook, smartphones), but remains useful even in the face of technological change (Ellison & boyd, 2013). This taxonomy should further be exhaustive enough to encompass a wide range of CMC variables and hence facilitate navigation through the entire research landscape. With both analytical parsimony and conceptual inclusivity as our guiding principles, we propose The Hierarchical CMC Taxonomy (see Fig. 1).

[Figure 1 about here]

Channel-Centered vs. Communication-Centered Conceptual Approaches to CMC

To explicate the taxonomy, we first distinguish two overarching *conceptual approaches* to CMC: the channel-centered and the communication-centered approach (e.g., Carr & Hayes, 2015; Ledbetter, 2014). The *channel-centered approach* aligns with classic (mass) media uses and effects research that studies the channel as a whole but treats the communication within the channel largely as a black box. Typical examples for the channel-centered approach are investigations of "screen time" spent on a device (e.g., the smartphone) in relation to MH (e.g., Twenge et al., 2018). The *communication-centered approach*, on the

contrary, opens up the channel black box and investigates communication as a complex social process of interaction via messages that enfolds within (Walther, 2010).

We propose that channels—and, hence, the channel-centered approach—can be further differentiated into four main *levels of analysis*: (1) device, (2) type of application, (3) branded application, and (4) feature. Likewise, the communication-centered approach can be differentiated into (5) an interaction and (6) a message level. These levels of analysis are crucial to reflect upon for at least two reasons. First, each level focusses on unique aspects of CMC. For instance, studies at the device level imply that the presence, absence, or usage of the device (e.g., the smartphone) *itself* has implications for MH, irrespective of the specific applications or features used, or the exact nature of the communication via the device (e.g., Gonzales & Wu, 2016). In contrast, studies at the message level may, for instance, assume that certain message content is the crucial driver of CMC effects on MH (e.g., Holland & Tiggemann, 2016). Studies differing in the levels at which they operationalize CMC are likely to differ drastically in how they can explain effects of CMC on MH. They will thus differ in their implications for users, ICT developers, and MH practitioners.

Second, depending on the level of CMC analysis, studies may differ in the effects they find. For instance, studies at the interaction level may find that CMC and face-to-face communication reinforce one another and, thus, CMC can be beneficial for MH. However, this does not preclude that studies at the device level come to the conclusion that CMC is negatively related to MH, for instance, because the device can distract from other activities. Researchers wishing to draw conclusions about the bigger picture of relationships between CMC and MH need to consider the *multiple* levels of analysis at which CMC can be studied. In the following, we therefore briefly illustrate how each level is conceptualized.

Six Levels of CMC Analysis

(1) *Devices* represent the physically palpable ICTs (e.g., laptops, smartphones, or tablets) that enable CMC. Research at the device level, for instance, investigates how the

number of devices used to connect to strong and weak ties (i.e., media multiplexity; Chan, 2015), smartphone use during face-to-face interactions ("phubbing"; Gonzales & Wu, 2016), or overall "screen time" (Twenge et al., 2018) relates to MH.

(2) Devices enable CMC because they allow access to *types of applications* built around mediated social interaction and user-generated content. As unique applications often share a specific set of core characteristics and features, they are studied under a common label (Ellison & boyd, 2013). For instance, classic types of CMC applications include email, chat rooms, or discussion boards, later joined by texting and instant messengers. More recently, applications allowing users to engage in interactions with both broad and narrow audiences have been defined under the labels of social media, with social network sites (SNS) often considered a sub-type (see Bayer et al., 2020, for a detailed discussion). Studying such types of applications is typically more precise than the device level, as it avoids conflating CMC and non-CMC device uses in a simplistic overall measure of "screen time".

(3) The *branded application* level refers to variables that focus only on one or several branded application(s), such as Facebook or Instagram. While these branded applications can be subsumed under the broader types outlined above (e.g., SNS), they are frequently studied individually as key exemplars (e.g., Meier & Schäfer, 2018). It is important to distinguish this level of analysis from the previous one, as unique applications may have properties and user cultures that diverge from related applications or their broader types. For instance, while both Facebook and Twitter are considered SNS, Facebook currently affords more diverse uses (e.g., closed groups formed around specific interests). Finally, whether research investigates types of applications, or just single brands, affects the generalizability of findings.

(4) CMC channels, at their most detailed level of analysis, are constituted by individual *features*, the building blocks of applications. We understand a feature as "a technical tool […] that enables activity on the part of the user" (Smock et al., 2011, p. 2323). Facebook users, for instance, may use the site for status updates, comments, private messages,

groups, the news feed, or any combination of these features, resulting in a unique user experience, with unique relations to MH (e.g., Burke & Kraut, 2016). Crucially, research investigating the feature level specifies in more detail the kind of interactions a specific channel enables. It thus allows researchers to test channel effects even while channels change in design (i.e., lose or gain certain features).

(5) Moving from the channel-centered to the communication-centered approach, we specify the *interaction* level. In contrast to previous levels, this level goes beyond the mere technological properties of channels and instead clarifies the process of how and with whom users communicate within a channel. Early on, CMC research conceptualized the configuration of interaction partners (e.g., one-to-one, one-to-many, many-to-one), clarifying the source and audience size of a communication episode, and distinguished between synchronous and asynchronous communication (e.g., Morris & Ogan, 1996). Beyond their configuration, the characteristics of communication partners (e.g., their tie strength) can be specified and studied in relation to MH (Burke & Kraut, 2016). If either the sender or receiver of a mediated communication is a group of individuals ("many"), the characteristics of the network structure of this group (e.g., network size, diversity) can also be considered at this level. Interactions may further differ in their interaction functions, such as self-disclosure or self-presentation (Walther, 2010). Another key concept clarifying the *how* of communication is the directionality of interaction. Rafaeli's (1988) definition of interactivity specifies interaction as a continuum of contingent responsiveness between communication partners, reaching from two-way truly interactive (e.g., a continuous message exchange), over two-way reactive (e.g., an Instagram like), to one-way non-interactive communication (e.g., browsing through the Instagram feed). Similarly, in research on CMC (specifically, SNS) and MH, usage is often grouped into "active" and "passive". While active usage, in its broadest sense, refers to "activities that facilitate direct exchanges with other(s)" (Verduyn et al., 2017, p. 281), passive usage refers to the mere consumption of messages from status updates,

comments, profiles, or stories without any direct response to the sender, akin to classic mass media usage (e.g., watching TV). Thus, passive usage is entirely non-interactive and instead can be thought of as one-way communication from the recipient's perspective, solely entailing non-directed messages (i.e., messages not sent in reaction to a previous message) (Burke & Kraut, 2016). Active usage, in contrast, may entail both non-interactive one-way communication from the sender's perspective (e.g., posting a status update without getting any response), as well as two-way reactive, and fully interactive communication (Rafaeli, 1988). In conclusion, the interaction level focusses on social interaction as the process of message exchange, including instances in which this "exchange" is one-sided (i.e., sending or receiving without any response).

(6) While interactions have specific properties, each individual *message* within an interaction can be considered as the final level of analysis (Ledbetter, 2014). A first distinction is made between different modes of messages (e.g., text, image, voice, video, or one-click reactions such as likes or emojis; Burke & Kraut, 2016; Walther, 2010). While originally a property of separate (types of) applications (e.g., email vs. video-conferencing), many modes of communication can now be readily switched within a single application or even a message exchange (e.g., receiving a text message in WhatsApp and replying with a short voice recording). The mode of a communication is thus best placed at the message level. Along with the mode varies bandwidth (i.e., the available cues) and social presence (Walther, 2010). Similarly, the persistence versus ephemerality of a message used to be a fixed channel characteristic but can now often be modified from message to message (e.g., on Snapchat). The same applies to the accessibility of a message, varying on a continuum from private to public (O'Sullivan & Carr, 2018). The content of a message is another key variable at this level, with multiple possible specifications (e.g., concerning topic or valence).

Note that the taxonomy organizes the six CMC levels in a hierarchy, emphasizing that each lower level (e.g., a single message) can be nested in a higher level (e.g., an interaction).

Thus, necessarily, properties of lower levels (e.g., whether an interaction is active or passive) can be incorporated at higher levels (e.g., active vs. passive use of Instagram). The six levels of analysis are conceptualized as rigorously distinguishable ideal types. However, empirical research may often (inadvertently) conflate hierarchical analytical levels, that is, combine properties of several levels in a single CMC indicator. For instance, "passive usage of the Facebook news feed" entails information on a unique branded application, a feature, and the directionality of an interaction process. Finding that such an indicator affects MH raises the question whether this is caused by Facebook (but not other applications), the news feed (but not other features), or passive usage (but not other forms of engaging with the Facebook news feed). We hope that by reflecting on the conceptualization of CMC more systematically through the taxonomy, researchers will be better able to identify at which level(s) of analysis their explanatory focus is located, hence avoiding conflation and increasing construct validity.

Technology-Centered vs. User-Centered Operational Approaches

Beyond the two conceptual approaches (channel- vs. communication-centered) and the six levels of analysis, we supplement our taxonomy with two *operational approaches* to separate measurement from level of analysis. Prior research on CMC and MH has used a staggering number of measures, ranging from time spent with a device, over types of self-presentation on Facebook, to the content of messages encountered on SNS (e.g., Holland & Tiggemann, 2016; Twenge et al., 2018; Twomey & O'Reilly, 2017). We contend that the operationalizations of CMC differ crucially in whether they are *technology-centered* or *user-centered*. Technology-centered operationalizations are descriptive measures that capture some aspect of technology usage, such as its volume (time spent, frequency) or message content, which can principally be observed (e.g., digitally tracked), though they are often measured via self-report. User-centered operationalizations, in contrast, have a psychological-perceptual component that qualifies how a person processes using a CMC technology or why he or she uses it, which is often most validly captured by self-reports (e.g., attitudes about technology,

motivations for usage, perceptions of message content). This distinction is critical, because the two approaches imply drastically different explanatory foci when relating a CMC variable to MH. Essentially, the technology-centered approach argues that the mere exposure to some aspect of a technology itself is related to MH, whereas the user-centered approach explains any relation between CMC and MH through the user's psychology in interaction with the technology. We note that, in principle, both operational approaches can be applied to all six levels of analysis.

The Extended Two-Continua Model of Mental Health

Mental health (MH), according to the World Health Organization, is more than the absence of mental disorders, but "a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community" (World Health Organization, 2005, p. 2). Although this comprehensive understanding of MH is now widely recognized and implemented in policy and practice (e.g., Saxena et al., 2013), research on MH is still mostly divided into two distinct perspectives, psychopathology and psychological well-being. *Psychopathology* (PTH) refers to "any pattern of behavior—broadly defined to include actions, emotions, motivations, and cognitive and regulatory processes—that causes personal distress or impairs significant life functions, such as social relationships, education, work, and health maintenance" (Lahey et al., 2017, p. 143). While *well-being*, in contrast, means "how well individuals are doing in life, including social, health, material, and subjective dimensions of well-being" (Diener et al., 2018, p. 3), *psychological well-being* (PWB), specifically, is understood as "optimal psychological functioning and experience" (Ryan & Deci, 2001, p. 142).

The present study builds on a *two-continua model of mental health* that integrates these two perspectives into a single coherent framework (Greenspoon & Saklofske, 2001; Keyes, 2007). Several arguments call for such a twofold perspective on MH. First, PTH and

PWB represent different psychological states. PTH indicates severe disturbance of a person's psychological functioning (i.e., dysfunction). PTH narrows an individual's attention towards the source(s) of disturbance and inhibits normal functioning until the disturbance has been mitigated or eliminated (Lahey et al., 2017). PWB, in turn, indicates how well a person is doing and how much (s)he thrives psychologically. Higher PWB is associated with a variety of positive outcomes such as longevity and prosocial behavior (Diener et al., 2018). Thus, PWB is not the absence of PTH, just as PTH is not the absence of PWB. Second, PTH and PWB are sensitive to different individual and environmental influences (e.g., genes, age, life events) and their indicators fluctuate in unique patterns and timeframes (Diener et al., 2018; Lahey et al., 2017). Third, PTH and PWB are sometimes empirically dissociated. That is, individuals can show high levels on some aspects of PWB while also reporting moderate to high levels on indicators of PTH, or vice versa (e.g., Greenspoon & Saklofske, 2001; Hides et al., 2020). In conclusion, researchers should understand and assess MH as two continua, PTH and PWB, and reflect upon which of these continua is relevant for their research.

Since researchers in the field of CMC and MH employ a variety of so far disconnected MH indicators (e.g., loneliness, self-esteem, life satisfaction, depression, or anxiety; see, e.g., Huang, 2017; Liu et al., 2019), we refine and explicate the classic two-continua model by integrating main *dimensions* and *manifestations* of both PTH and PWB, as well as *risk* and *resilience factors*, in an Extended Two-Continua Model of Mental Health (see Fig. A1 in Online Appendix I). In doing so, we enable researchers to locate and reflect upon MH indicators within the broader context of MH research, both clinical and non-clinical. This should not only facilitate integration of future research on CMC and MH but also lays the foundation for our empirical meta-review. In the following, we will outline how PTH and PWB are further differentiated into main dimensions and manifestations.

Dimensions and Manifestations of Psychopathology

PTH research and practice traditionally distinguishes categorically separable *disorders* from *symptoms* (e.g., Lahey et al., 2017). Clusters of symptoms represent the (more or less) manifest basis for the categorical diagnosis of disorders, which are described in diagnostic manuals such as the DSM-5 (American Psychiatric Association, 2013). A disorder comprises a set of *symptoms* relevant for a specific diagnosis (e.g., depressive symptoms for major depressive disorder). While clinical disorders are categorically diagnosed as either present or absent (American Psychiatric Association, 2013), symptoms are often measured via self- or other-report on a continuum (e.g., depressive symptomatology). This reflects that PTH is "continuously distributed in the population" (Conway et al., 2019, p. 428) and individuals healthy from a clinical point of view can show sub-clinical levels of PTH symptomatology.

Recently, MH research increasingly (re-)discovers that categorical distinctions between PTH disorders are largely artificial, as symptoms across disorders show high systematic covariation (i.e., comorbidity; Lahey et al., 2017). Specifically, researchers now believe PTH manifestations (symptoms and, hence, disorders) to be expressions of several underlying latent dimensions (see Conway et al., 2019, for a detailed mapping of disorders onto PTH dimensions). In the context of CMC research, we focus on the *internalizing* and *externalizing* dimensions of PTH, as these (a) are most widely recognized, especially in Clinical Psychology research on children and adolescents (e.g., Lahey et al., 2017), and (b) show the clearest connections to CMC (e.g., Sarmiento et al., 2018). While internalizing PTH refers to overcontrolled behavior, cognitions, and emotions (e.g., anxiety, social phobia, and depression), externalizing PTH refers to undercontrolled behavior, cognitions, and emotions (e.g., hyperactivity, aggression, delinquency, and substance abuse; Conway et al., 2019; Lahey et al., 2017). We thus extend the dual-factor model of MH by clustering PTH manifestations in the two dimensions of internalizing and externalizing PTH. Crucially, instead of investigating disconnected PTH indicators, this allows for the recognition of effect patterns between CMC and higher-level dimensions and manifestations of PTH (see Conway

et al., 2019, for additional arguments supporting a dimensional approach to PTH). However, as the research integration of major PTH dimensions is still ongoing (Conway et al., 2019), future revisions of the MH model may include additional PTH dimensions. Moreover, categorical diagnoses are expedient for clinical practice and thus remain relevant.

Dimensions and Manifestations of Psychological Well-Being

Research on PWB distinguishes two key dimensions, *hedonic well-being* and *eudaimonic well-being* (Huta & Waterman, 2014; Martela & Sheldon, 2019; Ryan & Deci, 2001). According to the hedonic view, happiness and well-being are defined purely by a subjective experience of pleasure and contentment. A prominent operationalization of this approach is Diener et al.'s subjective well-being (Diener et al., 2018; Huta & Waterman, 2014), consisting of the two interrelated components affective well-being (high positive and low negative affect) and cognitive well-being (satisfaction with life overall and specific life domains). In contrast, the eudaimonic view understands well-being as more than just pleasure and satisfaction. Instead, it propagates the realization of a "true self" (i.e., the daímōn), a concept often associated with striving for meaning and purpose, personal growth, authenticity, and excellence (Huta & Waterman, 2014). At its core, hedonic well-being is about "feeling well", whereas eudaimonic well-being is about "doing well" (Martela & Sheldon, 2019). While appearing somewhat "elitist" at first glance, eudaimonic well-being is present in the everyday lives of the general population (for recent reviews, see Huta, 2017; Huta & Waterman, 2014; Martela & Sheldon, 2019). Individuals may experience eudaimonic well-being by pursuing their personal or professional goals, engaging in meaningful social interactions, or living autonomously (Martela & Sheldon, 2019). Importantly, experiencing hedonic well-being does not have to be associated with increased eudaimonic well-being and vice versa (Huta, 2017). From this, it follows that investigations into the relationship between CMC and PWB should consider both sides of well-being, hedonic and eudaimonic.

The two dimensions of hedonic and eudaimonic well-being can be further distinguished by their manifestations in daily life. Huta (2017; Huta & Waterman, 2014) proposes that PWB concepts can be differentiated by their (1) category of analysis and (2) level of measurement (trait vs. state). The *category of analysis* specifies what exactly the well-being indicator measures: *orientations* (i.e., values, motives, and goals), *behaviors* (i.e., overt activities such as socializing or writing a diary), *experiences* (i.e., subjective cognitive and affective states), and *functioning* (i.e., how well a person is doing, e.g., concerning abilities, accomplishments, or healthy habits; see Huta, 2017, for a detailed description).

Finally, the *level of measurement* distinguishes between *traits* that are relatively stable over time, though not immutable, and *states* that capture the construct of interest with regard to a specific timeframe (e.g., in the moment, the last week, or the last month). As these distinctions crucially specify what exactly researchers are studying when they employ PWB measures, we incorporate Huta's distinctions into the MH model (see Fig. A1 in Online Appendix I). We refer readers interested in the multitude of potential PWB indicators and their place in this model to Huta (2017), as a detailed mapping of all indicators goes beyond the scope of this paper.

Risk and Resilience Factors

As a final extension of the original two-continua model of MH (Greenspoon & Saklofske, 2001; Keyes, 2007), we complement it with *risk and resilience factors*. Adding these factors appears necessary, as they comprise several variables that have been studied extensively in relation to CMC and are often interpreted as directly indicative of MH (e.g., Huang, 2017; Liu et al., 2019). However, they do not distinctively map onto underlying dimensions of PTH (internalizing, externalizing) or PWB (hedonic, eudaimonic) as defined in the MH literature (see the sections above). Instead, risk factors are here defined as sub-clinical aspects of psychosocial functioning that are (a) non-specific to PTH or PWB dimensions and (b) may increase an individual's vulnerability to develop PTH symptomatology or decrease

PWB (and vice versa for resilience factors). Risk factors may include perceived loneliness, actual social isolation, perceived stress, or poor sleep quality, among many others. Resilience factors include, for instance, social capital, social support, self-esteem, or high sleep quality.

The Present Study

With these two newly developed organizing frameworks as theoretical background, we turn our attention to the evidence on the relationship between CMC and MH. Currently, researchers, practitioners, and members of the general public (e.g., parents, teachers, policy makers, or entrepreneurs) are left with a disconnected and fast-growing review literature that lacks higher-level conceptual and empirical integration. We thus aim to move this field forward by conducting a meta-review—a review of reviews.

First, we aim to synthesize the main findings on the relationship between CMC and MH, considering all available evidence that matches the definitions of CMC and MH. Based on this evidence, we can arrive at (1) more reliable conclusions about the associations between CMC and MH and (2) the current state of the field as well as (3) discover higher-level patterns of results. These efforts are guided by the following research question:

RQ1: What are the *main findings* of research syntheses on the relationship between CMC and MH?

Beyond reviewing the findings of research syntheses, we also aim to apply the two newly developed organizing frameworks to the empirical studies conducted on CMC and MH so far. Specifically, we seek to explore which levels of CMC analysis and which dimensions of MH have been primarily investigated so far. In doing so, we will be able to systematically identify patterns of prior research focus, discuss their implications, and uncover where research attention may be particularly needed. This is guided by the following question:

RQ2: Which (a) *indicators of CMC* and (b) *indicators of MH* have been studied by prior research and (c) which *gaps* can be identified based on this assessment?

The literature proposes multiple theoretical links and boundary conditions for CMC and MH effects. These include displacement or disruption of activities beneficial for well-being, such as face-to-face communication or sleep (e.g., Sbarra et al., 2019); social comparison (Verduyn et al., 2017); or relational maintenance (Burke & Kraut, 2016), among many others. While these mechanisms currently lack higher-level integration, as well, this is outside the scope of the present study. Instead, we prioritize conceptual approaches to the key variables, CMC and MH, and their empirical association.

Method

Meta-Review as a Method of Research Synthesis

Meta-reviews, also called overviews or umbrella reviews, "compile information from multiple systematic reviews to provide a comprehensive synthesis of evidence" (Ballard & Montgomery, 2017, p. 92), focusing "on breadth rather than depth of coverage" (Thomson et al., 2010, p. 198). Therefore, they typically investigate broader constructs (here: CMC and MH) and include a range of operationalizations. They allow comparisons between research foci, results, and conclusions from multiple reviews. Thus, meta-reviews help identify inconsistencies and discord in the literature and point to future directions (Polanin et al., 2017).

While the methodology of meta-reviews is still developing (Ballard & Montgomery, 2017), researchers can generally apply the steps undertaken in systematic reviews of primary research to conduct a meta-review (Polanin et al., 2017). Accordingly, we (1) state pre-defined eligibility criteria, (2) use a systematic, multi-step literature search, and (3) systematically synthesize and present the characteristics and findings of included reviews (Booth et al., 2012). As a deviation from common meta-review methodology, we also synthesize information from the primary research included in all reviews to answer RQ2.

Eligibility Criteria

To be eligible, a review had to meet seven inclusion criteria concerning *scope* (i.e., meet our definitions of (1) CMC and (2) MH, (3) their conceptual independence, and (4) include investigations of non-clinical samples) and *methodology* (i.e., synthesis articles had to be (5) systematic (Booth et al., 2012), (6) synthesize empirical evidence, and be (7) written in English and published). A more detailed description as well as exclusions resulting from these criteria can be found in Online Appendix II. Note that we purposefully *excluded research on problematic or addictive ICT usage*, as this research, by default, defines and measures CMC as a pathological behavior that impairs MH. Similarly, we excluded clinical samples since we were interested in CMC and MH in the general population. In case a review included evidence on excluded constructs (e.g., pathological usage) or populations (e.g., clinical participants) next to evidence matching our inclusion criteria, we included it and synthesized only eligible evidence (e.g., on non-pathological usage or non-clinical participants).

Systematic Literature Search and Selection

Following recommendations from research synthesis literature (e.g., Polanin et al., 2017), we combined several methods to maximize recall of eligible reviews. As part of a larger effort to review literature on CMC and MH, we conducted standardized academic database searches, citation searches, and reference searches. This was complemented by a Google Scholar title search, targeted specifically at finding systematic reviews and meta-analyses. A detailed description of all steps undertaken in the literature search and selection, including reliability analysis, can be found in Online Appendix III. The search was first completed in December 2017 and then updated during peer review in September 2019. The final sample consisted of 34 reviews, described in detail in Online Appendix IV.

A common issue in meta-reviews is *overlap*, meaning that more weight is given to publications included in more than one review (Pieper et al., 2014). Our sample of reviews included 1313 unique publications. Based on the formula provided by Pieper et al. (2014),

overlap can be characterized as “slight”, with a corrected covered area (CCA) of 1.3%. Bias due to overlap is thus very unlikely.

Methods of Synthesis

Synthesis was conducted in two stages. In stage one, we descriptively synthesized the information (i.e., narrative conclusions, investigated constructs, effect sizes) from the 34 reviews to answer RQ1. In stage two, we synthesized the CMC and MH indicators investigated in all relevant primary research publications included in the 34 reviews to answer RQ2. For this stage, a coding protocol was developed. We first determined whether a publication was eligible for our meta-review (see eligibility criteria 1-4 and 7) and then coded all relevant CMC and MH indicators. A description of the coding protocol and results of inter-coder reliability tests can be found in Online Appendix III.

Results

Main Findings of Reviews and Meta-Analyses

To answer RQ1, we first summarize the *narrative conclusions* about the relationship between CMC and MH from all 34 reviews. Since the reviews included 14 meta-analyses and these provide more informative and conclusive evidence synthesis than narrative reviews, we then summarize the *meta-analytic effects*, *effect heterogeneity*, and *moderator analyses*.

Narrative Conclusions

First results on RQ1 (see Online Appendix IV for details) show that 14 out of 34 reviews concluded the relationship was *mixed*, finding evidence for positive, negative, and non-significant associations between CMC and MH. Notably, these were mostly narrative reviews rather than meta-analyses. While an additional 11 reviews concluded that *negative* relationships prevailed, 6 found predominantly *positive* relationships between CMC and MH. However, these six reviews exclusively synthesized evidence on social resources (capital or support) and/or older adults. Notably, 24 of 34 reviews qualified the investigated effects as

conditional, emphasizing that their strength or direction depended on moderators or mediators. Finally, 7 reviews qualified the evidence as *insufficient* for a definitive conclusion.

Meta-Analytic Effects

We collected all meta-analytic effect sizes on relationships between CMC and MH indicators that matched our conceptual definitions. Almost all meta-analyses focused on indicators of *global SNS use* (i.e., time spent, frequency, and/or intensity). We refer to these simply as *SNS use* below and summarize all effects of SNS use in Fig. 2. As meta-analyses mostly assessed the type of or branded application levels, we organize this section along the MH dimensions. Wherever available, we highlight findings on CMC indicators other than SNS use, if they rely on $k > 2$ effect sizes. If multiple effects for the same relationship are available, we only report the one relying on the largest number of *k* effect sizes within the text. For details on all effect sizes, meta-analyses, and references, see Online Appendix V.

[Figure 2 about here]

Resilience factors. Consistent with narrative conclusions, all meta-analyses on *social resources* (capital and support) showed small to moderate positive associations with SNS use. While general Internet use, blogs, chat, and email were not significantly associated with perceived social resources, SNS (r = .30, 95% CI [.14; .46]) and forum use (r = .14, 95% CI [.09; .20]) were. Notably, user-centered attitudinal measures of "intensity" (e.g., the Facebook intensity scale) consistently generated larger effect sizes than technology-centered ones (time spent or frequency). Almost all SNS features and interaction properties of SNS use were positively associated with increased social resources, albeit at varying strength (see Online Appendix V for details and references). Only few meta-analyses specifically investigated *self-esteem*, and none reported findings on other resilience factors. General time spent online was unrelated to self-esteem, but SNS use was slightly negatively related to self-esteem in three meta-analyses finding similar effect sizes (e.g., r = -.05, 95% CI [-.09; -.01]).

Psychological well-being. The only meta-analyzed indicator tapping into hedonic well-being was *life satisfaction*. No meta-analytic results on eudaimonic well-being were found (see also RQ2 below). General time spent online showed a small negative association with life satisfaction (r = -.05, 95% CI [-.12; -.01]). SNS use, however, showed no significant association with life satisfaction in two meta-analyses. One meta-analysis reported an overall effect size of SNS use (i.e., global use, number of friends, active and passive use) on "positive indicators of MH", comprising life satisfaction, well-being, self-esteem, and positive affect (r = .05, 95% CI [.01; .08]). However, when separated by SNS indicators, only the number of SNS friends showed a small positive association with "positive MH" (r = .13, 95% CI [.05; .21]). Three other meta-analyses reported effects on "well-being" that included reverse coded negative indicators (e.g., depressive symptoms or loneliness) alongside resilience factors (e.g., self-esteem) and life satisfaction. Time spent online was found to be slightly negatively associated with such "overall well-being" (r = -.04, 95% CI [-.07; -.01]), though this relationship was nonsignificant for social Internet use. SNS use, however, was slightly negatively associated with overall well-being in two meta-analyses (e.g., r = -.06, 95% CI [-.09; -.03]). Differentiating between SNS uses revealed that "self-presentational" use (status updates, photos) was unrelated to overall well-being, "content consumption" (browsing, searching, monitoring) was negatively (r = -.14, 95% CI [-.20; -.08]), and "interactions" (replying, commenting, liking) were positively related (r = .14, 95% CI [.08; .20]). While phone calls showed a small positive association with overall well-being (r = .10, 95% CI [.06; .15]), texting and instant messenger use were not related to overall well-being.

Risk factors. Findings on risk factors are limited to loneliness and stress. While two smaller meta-analyses (both k = 23) found a small positive association between SNS use and *loneliness*, a considerably larger one (k = 196) found no association (r = .01, 95% CI [-.02; .05]). Phone calls, texting, and instant messaging showed small negative associations with

loneliness, though based on only a few studies each (see Online Appendix V for details). SNS use showed a small positive association with *stress* (r = .13, 95% CI [.05; .21]).

Psychopathology. The most commonly meta-analyzed indicator of internalizing PTH was *depressive symptoms*. No meta-analyses of externalizing PTH were found (see also RQ2 below). Five meta-analytic effect sizes for the relationship between SNS use and depressive symptoms existed, all showing a small positive association (e.g., r = .11, 95% CI [.08; .14]). In addition, one meta-analysis reported a small positive association between general social comparison on SNS and depressive symptoms (r = .23, 95% CI [.12; .34]), and a somewhat higher one for upward comparison (r = .33, 95% CI [.20; .47]). General time spent online was slightly negatively associated with reverse-coded depressive symptoms (r = -.05, 95% CI [-.07; -.02]), while instant messaging was not associated. SNS use further showed a small positive relation to *social anxiety* (r = .10, 95% CI, [.05; .15]) and to *anxiety symptoms* in general (r = .10, 95% CI [.03; .18]). Time spent online, instant messaging, texting, or email use were not related to (social) anxiety. However, social comfort experienced online (r = .34, 95% CI [.25; .41]) and comfort specifically due to reduced non-verbal cues online (r = .27, 95% CI [.23; .31]) showed moderate positive associations with social anxiety.

One meta-analysis focused on SNS and *body image disturbance*, which can be considered an indicator of internalizing PTH. Combining all measures of SNS use (general use and appearance-focused use), there was a small positive association with disturbed body image (r = .17, 95% CI [.13; .21]). When analyzed separately, similar effects were found for using multiple SNS or Facebook, but not for Instagram or other SNS (though based on $k \leq 5$). Notably, technology-centered measures of SNS use showed about a third of the effect (r = .11, 95% CI [.08; .15]) of appearance-focused use (r = .31, 95% CI [.22; .39]), which included upward comparison and appearance-related interactions on SNS. Finally, one meta-analysis reported an overall effect of SNS use (i.e., global use, number of friends, active and passive use) on “negative indicators of MH”, comprising depression, anxiety, and loneliness (r = .06,

95% CI [.03; .09]). However, when separated by indicators, only global SNS use (time spent, frequency) showed a small association with negative MH (r = .11, 95% CI [.06; .15]).

Effect Heterogeneity, Moderator Analyses, and Publication Bias

All meta-analyses tested for effect size heterogeneity based on the Q statistic, and nearly all concluded that there was "significant heterogeneity", with I^2 often exceeding 75%. We thus synthesized findings from moderator analyses on three key sample characteristics (i.e., age, gender, and culture/country) as well as on publication bias.

Age. Of the 14 meta-analyses, 11 reported moderation effects of sample age. Two found that with increasing age the effects of SNS use on MH became less negative (concerning body image disturbance) or more positive (concerning social support), respectively. Two others found that the relationship between several CMC measures and social anxiety was stronger in older samples. Seven meta-analyses found no effect of age. Overall, there is little evidence for age effects, but age had a range restricted to young users in most analyses.

Gender. Ten meta-analyses reported moderation effects of the proportion of females in study samples. Three meta-analyses found some evidence for a moderation by gender, albeit with no consistent overall trend for who benefited more or less from SNS use. Seven meta-analyses found no gender effects. Overall, there is little meta-analytic evidence for gender effects.

Culture/country. Seven meta-analyses reported moderation effects of culture or country. Only one found no moderation effect. However, the evidence from the remaining six is incoherent, with two finding more positive effects in Western/individualistic countries, two in Eastern/collectivistic countries, and two finding mixed results. Overall, culture seems to be an important moderator, but yields complex effect patterns.

Publication bias. Seven meta-analyses concluded that there was "no bias" at all. Three meta-analyses concluded there was "little bias" and two found "some bias" for specific CMC indicators. Accordingly, meta-analysts overall found little evidence of publication bias.

CMC and MH Indicators

One key source of the high heterogeneity of effects in previous meta-analyses may be the diversity with which CMC and MH are operationalized in studies. To systematize this diversity and answer RQ2, we turn to the primary research included in all 34 reviews. Of the 1313 publications coded, 594 (45%) met our eligibility criteria 1-4 and 7. The remaining 719 publications were excluded due to lack of a relevant MH (30%) or CMC variable (15%), the manuscript being unpublished (16%) or its full text unavailable (10%), or because the publication exclusively investigated addictive or problematic usage (17%). Moreover, 7% contained only qualitative research, which was unsuitable for this stage of synthesis.

Regarding CMC, most publications included either one (23%) or two (24%) indicators, followed by three (19%), four (16%), or more (18%) ($M = 3$, $SD = 2.1$). Of the 1829 CMC indicators in total, 51% addressed more than just one of the six CMC levels of analysis. This demonstrates considerable conflation of analytical levels within many CMC measures. Turning to the four levels of the channel-centered approach, 16% of all indicators addressed the *device* level (of which 68% mobile/smartphone, 19% computer, 8% various[1], 5% other), 27% the *types of application* level (43% SNS, 15% various, 13% texting, 12% social media, 6% email, 4% instant messenger, 7% other), 54% the *branded application* level (78% Facebook, 4% Instagram, 9% various, 9% other), and 15% the *feature* level (37% various, 24% status update, 15% profile, 8% comment, 16% other). With regard to the two levels of the communication-centered approach, 39% of all indicators addressed the *interaction* level (27% network characteristics, 18% sending messages one-to-one or one-to-

[1] "Various" refers to measures that address *several* manifestations of the same level (e.g., several devices, apps, interaction characteristics) in a single indicator.

many, 9% self-disclosure, 8% passive usage, 38% other) and 9% the *message* level (51% content, 24% content of images, 9% accessibility, 6% various, 10% other).

Overall, most indicators (55%) were exclusively channel-centered, in contrast to only 5% being exclusively communication-centered. A high number of indicators (35%), however, addressed aspects of both channel and communication, suggesting that lower levels (interaction or message) were often studied in the context of a specific channel (e.g., a branded application). Six percent of indicators assessed generalized "Internet use", neither specifying channel nor communication aspects. Concerning operationalization approaches, most indicators followed the technology-centered (69%) rather than the user-centered approach (28%). Three percent of indicators included aspects of both.

Concerning MH, most publications included only one MH indicator (43%), followed by two (28%), three (16%) or more (13%) (M = 2, SD = 1.5). Of the 1258 MH indicators in total, 28% addressed *internalizing PTH* (of which 39% depressive symptoms, 22% social anxiety/social phobia, 14% anxiety symptoms, 11% eating disorder symptoms, 14% other), 3% *externalizing PTH* (e.g., substance abuse, aggression, AD/HD), 18% *hedonic PWB* (36% life satisfaction, 25% domain-specific satisfaction, 21% affect, 10% discrete emotions, 8% other), 2% *eudaimonic PWB* (e.g., meaning, authenticity, mastery), 17% *risk factors* (53% loneliness, 20% poor sleep, 19% stress, 8% other) and 31% *resilience factors* (38% self-esteem, 24% social support, 22% social capital, 8% good sleep, 8% other). Thus, the most studied indicators overall were risk and resilience factors (47%), followed by PTH (31%) and PWB (20%). A majority of PTH (57%) and PWB (79%) indicators as well as risk (84%) and resilience factors (91%) were measured at the trait level, without specifying a timeframe.

Discussion

Extending prior work (Appel et al., 2020; Orben, 2020), this study synthesized the fast-growing—yet conceptually and empirically fragmented—literature on CMC, social media, and MH through a meta-review. Our contribution to the literature is twofold. First, we

contribute to theory building by presenting two parsimonious frameworks that offer increased organizing power, harmonize conceptual overlaps, and allow comparisons between conceptual approaches to CMC and MH. Second, we contribute to evidence synthesis by connecting and comparing review findings (RQ1) as well as units of analysis (RQ2).

Evidence on the Association Between CMC and MH

In a first step, we synthesized main findings of prior reviews (RQ1). This offers several key insights. (1) Meta-analyses condensing various CMC and MH measures into one overall effect size find a (very) small negative association ($r \approx$ -.05 to -.15). Yet, when associations are investigated by CMC and MH indicators separately, effect patterns become more complex. (2) There is consistent evidence that those who use SNS more intensely perceive moderately ($r \approx$ .20 to .40) increased social resources (social capital and support). However, there is little evidence for other positive associations between CMC and MH. (3) The remaining evidence consistently suggests those who use SNS more intensely experience slightly ($r \approx$ .05 to .20) more internalizing PTH (e.g., depressive symptoms), stress, and lower self-esteem. (3) Meta-analyses show no evidence for an association between SNS use and life satisfaction, the only meta-analyzed PWB indicator. Thus, SNS use is not associated with the cognitive side of hedonic well-being. The largest available meta-analysis also revealed no association between SNS use and loneliness. (4) There was little indication of publication bias across meta-analyses. Nonetheless, effect sizes should be interpreted in light of evidence that meta-analyses produce almost three-times larger effects than preregistered replication studies (Kvarven et al., 2020).

(5) For applications other than SNS, the evidence base is small and, overall, shows little to no association with MH. There is narrative review evidence for a negative association between the device level and MH, specifically for mobile CMC. However, this requires further meta-analytic synthesis. (6) The meta-analytic evidence for the feature or interaction level (e.g., active vs. passive use) is scarce and inconsistent (cf. Online Appendix V).

However, it currently suggests that effects are more nuanced than for higher levels of the CMC taxonomy (i.e., types of or branded applications). The clearest pattern for the message level is a positive association between appearance-focused content and body image disturbance. Overall, findings suggest the need for more systematic research relating the feature, interaction, and message levels to MH. (7) Across several meta-analyses, there was consistent evidence that user-centered measures (e.g., attitudes toward Facebook, social comparison on SNS) resulted in two- to three times larger effect sizes than technology-centered ones (e.g., time spent, frequency). Whether this suggests that user-centered measures reveal stronger, potentially more relevant effects or produce artifacts due to, for instance, common method variance of self-report scales remains an important question.

(8) Among all 34 reviews, the most common narrative conclusion was that effects depended on moderators and/or mediators. However, meta-analyses revealed little evidence for moderating effects of age and gender—despite popular concerns about more negative effects particularly among younger and female users (e.g., Twenge et al., 2018). It should be noted, however, that the age range was quite restricted (participants were mostly adolescents or young adults) and that narrative reviews on CMC among older adults highlighted mostly positive effects, specifically on social resources. Thus, future research needs to sample across the life span (e.g., Chan, 2015). The culture or country a study was conducted in did emerge as a relevant moderator in meta-analyses, yet showed no consistent trend. Future research should thus compare cultures more systematically. Overall, research needs to test additional moderators (e.g., personality) to explain the large heterogeneity found in meta-analyses.

Conceptual and Operational Approaches to CMC and MH

Given the range of average effects across meta-analyses (i.e., $r \approx .00$ to $|.40|$), how researchers measure CMC and MH seems to matter considerably for the conclusions drawn in this field (see also Orben & Przybylski, 2019). In a second step, we thus synthesized

conceptual and operational approaches (RQ2). Based on the detailed analysis of 1829 CMC and 1258 MH indicators from 594 publications, we arrive at several implications.

Measuring CMC and Social Media Use

(1) Research has largely relied on the channel-centered (e.g., devices, applications) rather than the communication-centered (e.g., interactions, messages) approach. Notably, the default approach of the field has been to study individual branded applications, specifically Facebook. This limits the evidence base severely, as findings on single applications may demonstrate little generalizability over time (e.g., due to changes in design or popularity). Instead, identifying key features used for CMC in numerous applications (e.g., status updates, profiles, private messages) should be a more future-proof way to study channels (Bayer et al., 2020).

(2) The measures of CMC in this field show considerable conflation of analytical levels, thus potentially resulting in misattribution of effects to the wrong causes (e.g., to "screen time" on a device rather than to a certain type of interaction). Research on the communication-centered approach (i.e., the interaction and message level), specifically, has conflated most measures with individual channels (e.g., "passive Facebook use"). Given that users now communicate via a multitude of channels simultaneously (i.e., media multiplexity; Chan, 2015) and the dynamic design changes of these channels, the low generalizability of the channel-centered approach also applies to most of the available evidence at the interaction and message level. Research should thus strive to develop measures that capture interaction and message characteristics *independently* of users' devices or applications. In addition to (a) the low generalizability of the current channel-centered approach (Bayer et al., 2020), studying characteristics of interactions or messages (b) avoids technological determinism (i.e., social media as overall "good" or "bad"); (c) helps clarify whether one assumes effects to result from mass communication, interpersonal communication, or masspersonal communication (O'Sullivan & Carr, 2018) rather than unspecific "screen time"; and (d) allows for more

nuanced conclusions about the causes of any effects, hence facilitating the development of effective interventions, if necessary.

(3) Beyond illuminating conceptual approaches, our analysis shows that researchers have largely relied on technology-centered (e.g., time spent, frequency) rather than user-centered operational approaches (i.e., how technology use was processed). However, both approaches have their pitfalls. Technology-centered measures of exposure, especially self-reports, are notoriously unreliable (Orben, 2020) and risk conflation of distinct phenomena such as interpersonal and mass communication (O'Sullivan & Carr, 2018). User-centered measures, in contrast, may artificially inflate the association between outcome (i.e., perceptions of MH) and predictor (i.e., perceptions of CMC). Moreover, they may result in misattributing outcomes of psychological processing to technology. For instance, a study finding upward comparison on Instagram negatively affects well-being cannot inform upon whether this is an effect of upward comparison, characteristics of Instagram, or both (e.g., Meier & Schäfer, 2018). Our recommendation for future research is therefore a combination of the technology- and user-centered approaches. Studies should strive to measure technology use descriptively, ideally via digital tracking (e.g., Bayer et al., 2018) and at multiple levels of the taxonomy, to allow level comparisons. Additionally, studies should assess key motivations and psychological processes that occur across channels (e.g., social comparison or social support seeking), and test how these processes are modulated by channel features and their affordances (Evans et al., 2017).

(4) Finally, we observe a discrepancy between the CMC measures meta-analyzed so far and the measures identified in our conceptual synthesis. Meta-analytic evidence is mostly limited to "global SNS use", that is, time spent on, frequency of, or intensity of using a SNS, while many more CMC measures exist. More research on the other levels (i.e., devices, features, interactions, messages), and meta-analyses comparing these levels, are needed to ground conclusions about the role of CMC for MH in a more comprehensive evidence base.

Measuring Mental Health

(1) Existing research focusses largely on internalizing PTH, the cognitive side of hedonic PWB (i.e., life satisfaction and domain-specific satisfaction), and risk and resilience factors. Research has paid less attention to eudaimonic and affective PWB as well as externalizing PTH. Yet, these dimensions capture relevant and unique aspects of MH. Ignoring them in empirical research on CMC may thus overlook crucial effect patterns. Recent research, for instance, suggests that conclusions about the effects of social comparison on SNS partly depend on whether one investigates internalizing PTH (e.g., depression) or outcomes such as inspiration (eudaimonic PWB) and positive affect (hedonic PWB) (Meier & Schäfer, 2018). Externalizing PTH (e.g., aggression) could, in turn, be affected by online incivility and may be a more relevant PTH indicator among men (e.g., Kramer et al., 2008). The field should thus broaden its empirical approach in order to cover the two continua of MH more completely.

(2) A second finding is a strong reliance on risk (e.g., loneliness) and resilience factors (e.g., self-esteem). These factors tap into important aspects of psychosocial functioning, relevant to MH in multiple ways. They are crucial predictors or boundary conditions for MH (e.g., social support as a buffer that increases PWB; Burke & Kraut, 2016) or link CMC indirectly to more central MH indicators (e.g., stress as a risk factor for depressive symptoms; Aalbers et al., 2019). However, our review of MH literature reveals that none of the prominent risk and resilience factors (e.g., self-esteem, loneliness, social capital) is integrated into current conceptual models of PTH or PWB. This remains an important task for MH research at large. For researchers interested in effects of CMC on MH, this suggests, however, that to truly measure MH studies should include indicators more central to our current understanding of PWB and PTH, next to risk and resilience factors.

(3) We identified a great diversity of MH indicators across the empirical literature on CMC, which hinders research synthesis. The field should thus agree on a *core outcome set* of

MH indicators (Brunton et al., 2020). If studies were to measure a set of the same indicators, tapping into core aspects of MH, this would greatly enhance evidence accumulation and research integration (e.g., meta-analyses). Our tentative proposal for such an outcome set would be a selection of cross-culturally validated scales covering the most central internalizing and externalizing PTH symptoms (Conway et al., 2019); cognitive and affective well-being (Diener et al., 2018); meaning as the most useful "proxy for eudaimonic experience" (Huta, 2017, p. 22); and competence, autonomy, and relatedness need satisfaction as a self-determination theory approach to eudaimonia (Martela & Sheldon, 2019). This set may, of course, be complemented by key risk and resilience factors (e.g., self-esteem, loneliness, social resources, or perceived stress) or limited to only a sub-set.

(4) Finally, findings show that most evidence on CMC and MH relies on trait level assessments of MH, that is, measures that do not specify a timeframe. This is problematic for several reasons. First, individual MH constructs (e.g., affective well-being) fluctuate in specific timeframes (e.g., Diener et al., 2018), which the measurement should reflect. Second, MH constructs may be temporally connected to each other—and to CMC—in unique ways. For instance, from a network perspective on PTH, phenomena such as depression are "a complex, dynamic network of symptoms that cause each other" (Aalbers et al., 2019, p. 1454). Thus, risk factors such as stress, and depressive symptoms such as sad mood, may cause other, increasingly more severe symptoms (e.g., suicidal ideation; Aalbers et al., 2019). Identifying at which points of this temporal symptom network CMC is particularly relevant is thus a crucial direction for future research. More generally, MH research should theorize and test the dynamic interplay between PTH and PWB indicators over time. For instance, individuals suffering from internalizing PTH may lack the energy necessary to pursue eudaimonic PWB. Finally, a temporal perspective on MH and CMC would also sensitize for prospective or reciprocal effects of MH on CMC (e.g., Aalbers et al., 2019).

Limitations

Several limitations need to be considered. First, evidence on the relationship between CMC and MH is largely based on small-scale, cross-sectional studies. The findings on the association, let alone causal order, of CMC and MH should be treated as preliminary (for an extended discussion, see Orben, 2020). In addition, our review, while relying on comprehensive conceptual approaches to CMC and MH and an extensive evidence base, is limited. First, we excluded some research areas, particularly on "addictive" usage of CMC and cyberbullying. These may come to different conclusions about the relationship between CMC and MH. Second, we excluded evidence from clinical samples, as research on these populations differs markedly from the evidence reviewed here. Third, we did not review theoretical mechanisms on the relationship between CMC and MH. Several reviews provide crucial syntheses of such mechanisms (e.g., Bayer et al., 2020; Liu et al., 2019; Sbarra et al., 2019). However, a comprehensive theoretical review of *all* relevant mechanisms and boundary conditions is outside the scope of our work. Fourth, our conceptual framework of MH by no means reflects and integrates *all* approaches to, and dimensions of, MH. For instance, there may be several additional dimensions of PTH beyond the internalizing and externalizing spectra (see Conway et al., 2019). Rather, our proposed MH model presents a working model covering the most relevant aspects of PTH and PWB that current theorizing from Clinical and Positive Psychology can agree on. We call on future researchers to revise the MH model based on new developments in MH research. Fifth, a necessary limitation of any literature review is a time lag between the available evidence and the evidence included in the review. Thus, there may be conceptual and empirical approaches to CMC and MH this meta-review does not include. However, given the scope of our evidence base, spanning nearly 20 years of research, we are confident that this meta-review is reasonably representative of the field's conceptualization of and findings on CMC and MH.

Conclusion

Public concern and research attention on the impact of CMC, specifically social media, on the mental health and well-being of (young) users has dramatically increased in recent years. This study offers a conceptual and empirical review of reviews. Findings suggest an overall (very) small negative association between using SNS, the most researched CMC application, and mental health. Findings further show, however, that associations partly depend on the choice of MH indicators. On both conceptual and empirical grounds, research thus needs to develop and measure a more comprehensive set of MH outcomes, so as not to overlook effects. Moreover, associations become more complex when research addresses not just the channels used for CMC (i.e., "screen time" spent on devices or applications), but the types of interactions and messages transmitted via those channels. Instead of investigating "screen time" monolithically, the new decade of research on CMC, social media, and MH should operationalize channels through their core features, tease apart the types of interactions users engage in across channels, and consider the characteristics of messages they send and receive. Ideally, research tests how these interactions and messages are modulated by the core features and affordances of social media. By reflecting on the CMC taxonomy proposed here, specifically by avoiding conflation of its levels in measures, future research can more rigorously test which uses of social media contribute to, impair, or are irrelevant for mental health.

References

Aalbers, G., McNally, R. J., Heeren, A., Wit, S. de, & Fried, E. I. (2019). Social media and depression symptoms: A network perspective. *Journal of Experimental Psychology: General*, *148*(8), 1454–1462. https://doi.org/10.1037/xge0000528

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders: Dsm-5* (5th ed.). American Psychiatric Publishing.

Appel, M., Marker, C., & Gnambs, T. (2020). Are social media ruining our lives? A review of meta-analytic evidence. *Review of General Psychology*, *24*(1), 60–74. https://doi.org/10.1177/1089268019880891

Ballard, M., & Montgomery, P. (2017). Risk of bias in overviews of reviews: A scoping review of methodological guidance and four-item checklist. *Research Synthesis Methods*, *8*(1), 92–108. https://doi.org/10.1002/jrsm.1229

Bayer, J. B., Ellison, N., Schoenebeck, S., Brady, E., & Falk, E. B. (2018). Facebook in context(s): Measuring emotional responses across time and space. *New Media & Society*, *20*(3), 1047-1067. https://doi.org/10.1177/1461444816681522

Bayer, J. B., Triệu, P., & Ellison, N. B. (2020). Social media elements, ecologies and effects. *Annual Review of Psychology*, *71*, 10.1–10.27. https://doi.org/10.1146/annurev-psych-010419-050944

Booth, A., Papaioannou, D., & Sutton, A. (2012). *Systematic approaches to a successful literature review*. Sage.

Brunton, G., Webbe, J., Oliver, S., & Gale, C. (2020). Adding value to core outcome set development using multimethod systematic reviews. *Research Synthesis Methods*, *11*(2), 248–259. https://doi.org/10.1002/jrsm.1391

Burke, M., & Kraut, R. E. (2016). The relationship between Facebook use and well-being depends on communication type and tie strength. *Journal of Computer-Mediated Communication*, *21*(4), 265–281. https://doi.org/10.1111/jcc4.12162

Carr, C. T., & Hayes, R. A. (2015). Social media: Defining, developing, and divining. *Atlantic Journal of Communication*, *23*(1), 46–65. https://doi.org/10.1080/15456870.2015.972282

Chan, M. (2015). Multimodal connectedness and quality of life: Examining the influences of technology adoption and interpersonal communication on well-being across the life span. *Journal of Computer-Mediated Communication*, *20*(1), 3–18. https://doi.org/10.1111/jcc4.12089

Conway, C. C., Forbes, M. K., Forbush, K. T., Fried, E. I., Hallquist, M. N., Kotov, R., Mullins-Sweatt, S. N., Shackman, A. J., Skodol, A. E., South, S. C., Sunderland, M., Waszczuk, M. A., Zald, D. H., Afzali, M. H., Bornovalova, M. A., Carragher, N., Docherty, A. R., Jonas, K. G., Krueger, R. F., . . . Eaton, N. R. (2019). A hierarchical taxonomy of psychopathology can transform mental health research. *Perspectives on Psychological Science*, *14*(3), 419–436. https://doi.org/10.1177/1745691618810696

Diener, E., Lucas, R. E., & Oishi, S. (2018). Advances and open questions in the science of subjective well-being. *Collabra: Psychology*, *4*(1), 1–49. https://doi.org/10.1525/collabra.115

Ellison, N. B., & boyd, d. m. (2013). Sociality through social network sites. In W. H. Dutton (Ed.), *The Oxford handbook of Internet studies* (pp. 151–172). Oxford University Press.

Evans, S. K., Pearce, K. E., Vitak, J., & Treem, J. W. (2017). Explicating affordances: A conceptual framework for understanding affordances in communication research. *Journal of Computer-Mediated Communication*, *22*(1), 35–52. https://doi.org/10.1111/jcc4.12180

Gonzales, A. L., & Wu, Y. (2016). Public cellphone use does not activate negative responses in others… unless they hate cellphones. *Journal of Computer-Mediated Communication*, *21*(5), 384–398. https://doi.org/10.1111/jcc4.12174

Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an integration of subjective well-being and psychopathology. *Social Indicators Research*, *54*(1), 81–108. https://doi.org/10.1023/A:1007219227883

Hall, J. A. (2018). When is social media use social interaction? Defining mediated social interaction. *New Media & Society*, *20*(1), 162–179. https://doi.org/10.1177/1461444816660782

Hides, L., Quinn, C., Stoyanov, S., Cockshaw, W., Kavanagh, D. J., Shochet, I., Deane, F., Kelly, P., & Keyes, C. L. M. (2020). Testing the interrelationship between mental well-being and mental distress in young people. *The Journal of Positive Psychology*, *15*(3), 314–324. https://doi.org/10.1080/17439760.2019.1610478

Holland, G., & Tiggemann, M. (2016). A systematic review of the impact of the use of social networking sites on body image and disordered eating outcomes. *Body Image*, *17*, 100–110. https://doi.org/10.1016/j.bodyim.2016.02.008

Huang, C. (2017). Time spent on social network sites and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *20*(6), 346–354. https://doi.org/10.1089/cyber.2016.0758

Huta, V. (2017). An overview of hedonic and eudaimonic well-being concepts. In L. Reinecke & M. B. Oliver (Eds.), *The Routledge handbook of media use and well-being: International perspectives on theory and research on positive media effects* (pp. 14–33). Routledge.

Huta, V., & Waterman, A. S. (2014). Eudaimonia and its distinction from hedonia: Developing a classification and terminology for understanding conceptual and operational

definitions. *Journal of Happiness Studies*, *15*(6), 1425–1456. https://doi.org/10.1007/s10902-013-9485-0

Keyes, C. L. M. (2007). Promoting and protecting mental health as flourishing: A complementary strategy for improving national mental health. *American Psychologist*, *62*(2), 95–108. https://doi.org/10.1037/0003-066X.62.2.95

Kramer, M. D., Krueger, R. F., & Hicks, B. M. (2008). The role of internalizing and externalizing liability factors in accounting for gender differences in the prevalence of common psychopathological syndromes. *Psychological Medicine*, *38*(1), 51–61. https://doi.org/10.1017/S0033291707001572

Kvarven, A., Strømland, E., & Johannesson, M. (2020). Comparing meta-analyses and preregistered multiple-laboratory replication projects. *Nature Human Behaviour*, *4*, 423–434. https://doi.org/10.1038/s41562-019-0787-z

Lahey, B. B., Krueger, R. F., Rathouz, P. J., Waldman, I. D., & Zald, D. H. (2017). A hierarchical causal taxonomy of psychopathology across the life span. *Psychological Bulletin*, *143*(2), 142–186. https://doi.org/10.1037/bul0000069

Ledbetter, A. M. (2014). The past and future of technology in interpersonal communication theory and research. *Communication Studies*, *65*(4), 456–459. https://doi.org/10.1080/10510974.2014.927298

Liu, D., Baumeister, R. F., Yang, C.-C., & Hu, B. (2019). Digital communication media use and psychological well-being: A meta-analysis. *Journal of Computer-Mediated Communication*, *24*(5), 259–274. https://doi.org/10.1093/ccc/zmz013

Martela, F., & Sheldon, K. M. (2019). Clarifying the concept of well-being: Psychological need satisfaction as the common core connecting eudaimonic and subjective well-being. *Review of General Psychology*, *23*(4), 458–474. https://doi.org/10.1177/1089268019880886

Meier, A., Domahidi, E., & Günther, E. (2020). Computer-mediated communication and mental health: A computational scoping review of an interdisciplinary field. In S. Yates & R. E. Rice (Eds.), *The Oxford handbook of digital technology and society* (pp. 79–110). Oxford Univ. Press.

Meier, A., & Schäfer, S. (2018). The positive side of social comparison on social network sites: How envy can drive inspiration on Instagram. *Cyberpsychology, Behavior, and Social Networking*, *21*(7), 411–417. https://doi.org/10.1089/cyber.2017.0708

Morris, M., & Ogan, C. (1996). The Internet as mass medium. *Journal of Computer-Mediated Communication*, *1*(4), 39–50. https://doi.org/10.1111/j.1083-6101.1996.tb00174.x

O'Sullivan, P. B., & Carr, C. T. (2018). Masspersonal communication: A model bridging the mass-interpersonal divide. *New Media & Society*, *20*(3), 1161-1180. https://doi.org/10.1177/1461444816686104

Orben, A. (2020). Teenagers, screens and social media: A narrative review of reviews and key studies. *Social Psychiatry and Psychiatric Epidemiology*, *55*, 407–414. https://doi.org/10.1007/s00127-019-01825-4

Orben, A., & Przybylski, A. K. (2019). The association between adolescent well-being and digital technology use. *Nature Human Behaviour*, *3*(2), 173–182. https://doi.org/10.1038/s41562-018-0506-1

Pieper, D., Antoine, S.-L., Mathes, T., Neugebauer, E. A. M., & Eikermann, M. (2014). Systematic review finds overlapping reviews were not mentioned in every other overview. *Journal of Clinical Epidemiology*, *67*(4), 368–375. https://doi.org/10.1016/j.jclinepi.2013.11.007

Polanin, J. R., Maynard, B. R., & Dell, N. A. (2017). Overviews in education research: A systematic review and analysis. *Review of Educational Research*, *87*(1), 172–203. https://doi.org/10.3102/0034654316631117

Rafaeli, S. (1988). Interactivity: From new media to communication. *Sage Annual Review of Communication Research: Advancing Communication Science*, *16*, 110–134.

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, *52*(1), 141–166. https://doi.org/10.1146/annurev.psych.52.1.141

Sarmiento, I. G., Olson, C., Yeo, G., Chen, Y. A., Toma, C. L., Brown, B. B., Bellmore, A., & Mares, M.-L. (2018). How does social media use relate to adolescents' internalizing symptoms? Conclusions from a systematic narrative review. *Adolescent Research Review*, *36*(5), 517. https://doi.org/10.1007/s40894-018-0095-2

Saxena, S., Funk, M., & Chisholm, D. (2013). World health assembly adopts comprehensive mental health action plan 2013–2020. *The Lancet*, *381*, 1970–1971. https://doi.org/10.1016/S0140-6736(13)61139-3

Sbarra, D. A., Briskin, J. L., & Slatcher, R. B. (2019). Smartphones and close relationships: The case for an evolutionary mismatch. *Perspectives on Psychological Science*, *14*(4), 596–618. https://doi.org/10.1177/1745691619826535

Smock, A. D., Ellison, N. B., Lampe, C., & Wohn, D. Y. (2011). Facebook as a toolkit: A uses and gratification approach to unbundling feature use. *Computers in Human Behavior*, *27*(6), 2322–2329. https://doi.org/10.1016/j.chb.2011.07.011

Thomson, D., Russell, K., Becker, L., Klassen, T., & Hartling, L. (2010). The evolution of a new publication type: Steps and challenges of producing overviews of reviews. *Research Synthesis Methods*, *1*(3-4), 198–211. https://doi.org/10.1002/jrsm.30

Twenge, J. M., Martin, G. N., & Campbell, W. K. (2018). Decreases in psychological well-being among American adolescents after 2012 and links to screen time during the rise of smartphone technology. *Emotion*, *18*(6), 765–780. https://doi.org/10.1037/emo0000403

Twomey, C., & O'Reilly, G. (2017). Associations of self-presentation on Facebook with mental health and personality variables: A systematic review. *Cyberpsychology, Behavior, and Social Networking*, *20*(10), 587–595. https://doi.org/10.1089/cyber.2017.0247

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review*, *11*(1), 274–302. https://doi.org/10.1111/sipr.12033

Walther, J. B. (2010). Computer-mediated communication. In C. R. Berger, M. E. Roloff, & D. R. Roskos-Ewoldsen (Eds.), *The handbook of communication science* (2nd ed., pp. 489–505). Sage.

World Health Organization. (2005). *Promoting mental health: Concepts, emerging evidence, practice*. http://www.who.int/mental_health/evidence/MH_Promotion_Book.pdf

Figures

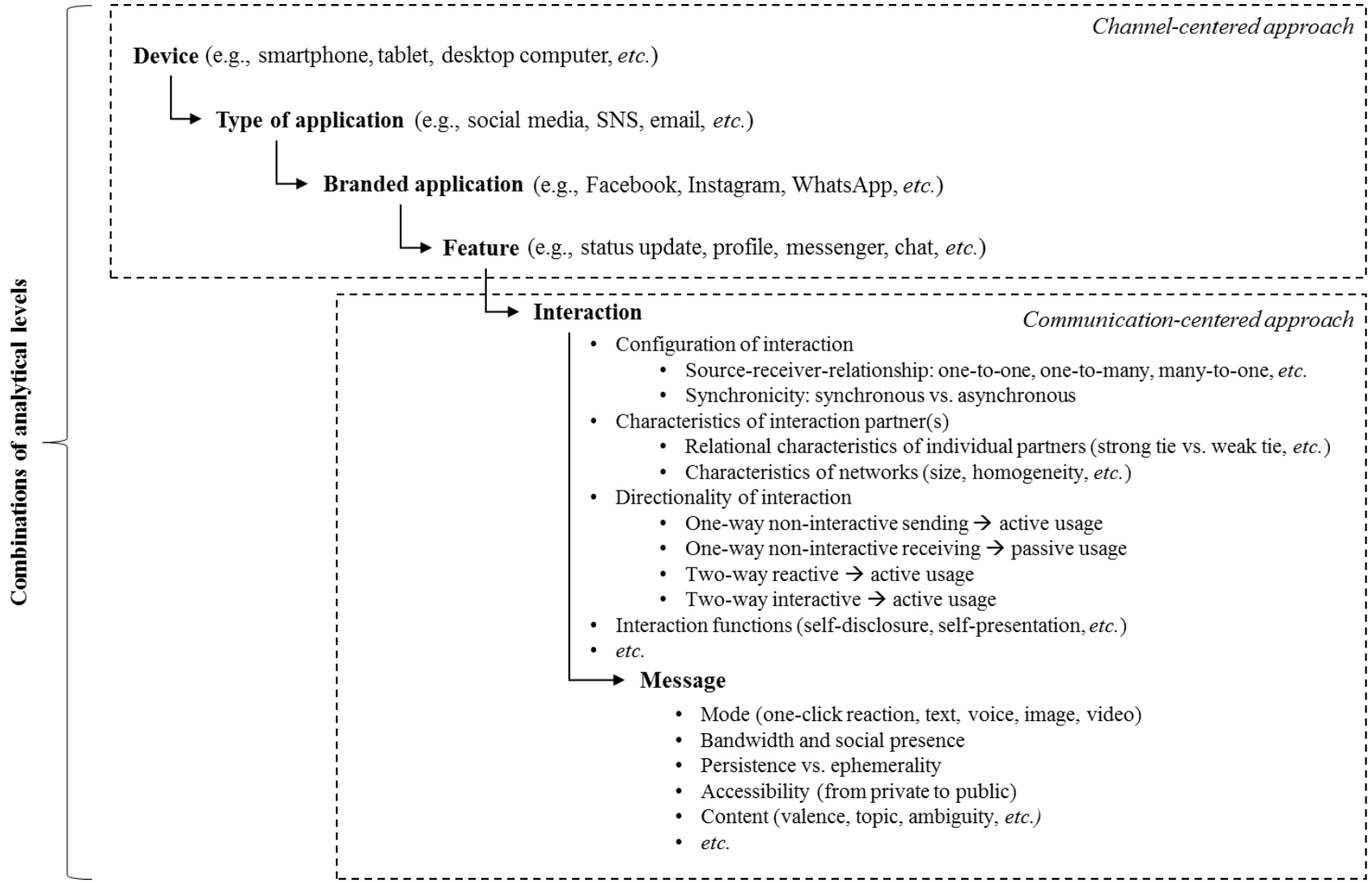
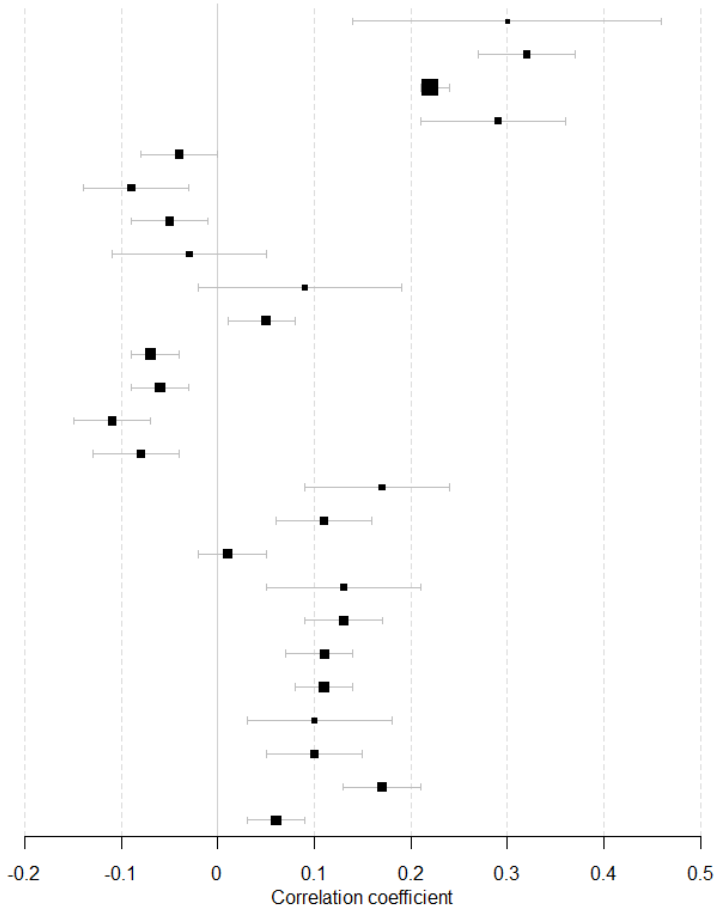


Figure 1. The hierarchical CMC taxonomy

Publication	Mental health indicator	*k* effect sizes	*N*
Domahidi, 2018	social capital/support	99	27779
Liu, Ainsworth et al., 2016	bridging social capital	50	22290
Liu, Ainsworth et al., 2016	bonding social capital	43	19439
Liu, Wright, et al., 2018	social support	21	7214
Huang, 2017	self-esteem	30	
Liu & Baumeister, 2016*	self-esteem	33	10627
Liu, Baumeister, et al., 2019	self-esteem	34	
Huang, 2017	life satisfaction	8	
Liu, Baumeister, et al., 2019	life satisfaction	16	
Yin et al., 2018	positive MH indicators	62	23442
Huang, 2017	well-being (total)	67	19652
Liu, Baumeister, et al., 2019	well-being (total)	94	34475
Huang, 2017	depressive symptoms (reversed)	24	
Huang, 2017	loneliness (reversed)	20	
Liu & Baumeister, 2016*	loneliness	23	7397
Liu, Baumeister, et al., 2019	loneliness	23	
Cheng et al., 2019	loneliness	196	
Liu, Baumeister, et al., 2019	stress	5	
Liu, Baumeister, et al., 2019	depressive symptoms	25	
Vahedi & Zannella, 2019	depressive symptoms	34	44027
Yoon et al., 2019	depressive symptoms	37	15881
Liu, Baumeister, et al., 2019	anxiety symptoms	14	
Cheng et al., 2019	social anxiety	194	
Saiphoo & Vahedi, 2019	body image disturbance	63	36552
Yin et al., 2018	negative MH indicators	82	27240



Note. Effects within as well as between individual publications are not independent, due to overlap of primary studies. Empty cells are due to missing information. Larger effect size squares correspond to narrower confidence intervals. Effect sizes are sorted by resilience factors, positive MH indicators, risk factors, negative MH indicators. *Liu and Baumeister reported 95% credible intervals instead of confidence intervals.

Figure 2. Forest plot of effect sizes for global SNS use (i.e., time spent, frequency, and/or intensity) and mental health

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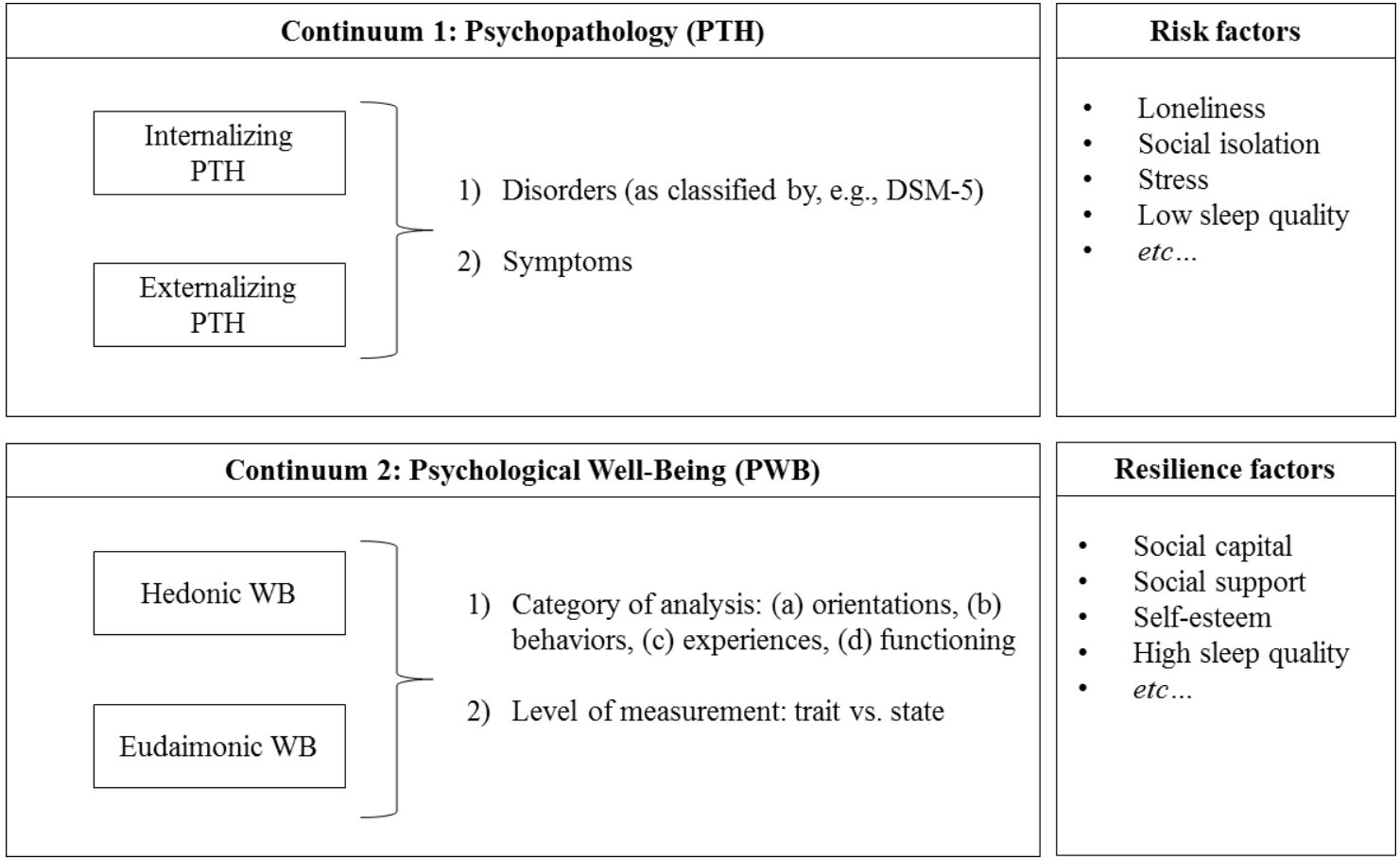
Appendix I: The Extended Two-Continua Model of Mental Health

Figure A1

The extended two-continua model of mental health



Note. The two-continua model of mental health is based on Greenspoon and Saklofske (2001) and Keyes (2005). The distinction between internalizing and externalizing PTH dimensions is based on various sources (e.g., Conway et al., 2019; Krueger et al., 2001; Lahey et al., 2017). The explication of PTH manifestations as disorders and symptoms is based on the DSM-5 (American Psychiatric Association, 2013). The distinction between the hedonic and eudaimonic well-being dimensions is based on various sources (e.g., Diener et al., 2018; Huta & Waterman, 2014; Martela & Sheldon, 2019; Ryan & Deci, 2001). Manifestations of PWB (i.e., category of analysis and level of measurement) are explicated in Huta (2017) and Huta and Waterman (2014). The distinction of risk and resilience factors is made by the authors, based on extensive literature on these concepts and their lacking integration into existing models of PTH and PWB.

Appendix II: Detailed Eligibility Criteria and Review Exclusions

Below, we note all seven eligibility criteria of the meta-review in detail and explain synthesis exclusions resulting from the respective criterion, if applicable.

1. The synthesis had to investigate *CMC as non-pathological usage of ICTs whose primary and original function is the facilitation of human social interaction.*
    a. In line with our CMC definition and previous work in this field (Huang, 2017; Wu et al., 2016), we excluded reviews that exclusively investigated problematic Internet use, generalized Internet addiction, or specific Internet addictions such as SNS addictions (cf., e.g., Çikrıkci, 2016; Elhai et al., 2017; Ryan et al., 2014; Tokunaga & Rains, 2010). Research on problematic or addictive usage does not provide evidence about the relationship between *non-pathological*, *everyday* usage of CMC and MH, which is the focus of this meta-review.
    b. For this reason, we also excluded research on *extreme* forms of mediated social interaction (e.g., cyberbullying or sexting). While certainly prevalent and relevant for MH, these forms of CMC are highly specific concerning message style, interaction context, and user characteristics. Moreover, they have been extensively reviewed elsewhere and thus lie outside the scope of this review (Chen et al., 2017; Kosenko et al., 2017; Kowalski et al., 2014; Kwan et al., 2020; Tokunaga, 2010).
    c. Furthermore, and in line with our focus on CMC, we excluded reviews on Internet-based mass communication and MH. Specifically, this refers to mass communication or interactive entertainment media that are nowadays predominantly accessed online such as pornography, video streaming, and games. The effects of online pornography and online games on MH (e.g., on sexual satisfaction and aggression, respectively) are researched in highly

specialized fields and comparatively well-reviewed (e.g., Anderson et al., 2010; Ferguson et al., 2011; Greitemeyer & Mügge, 2014; Li et al., 2016; Wright et al., 2017). Moreover, these lines of research do not predominantly investigate mediated social interaction, which is the focus of this meta-review.

d. Finally, reviews that only investigated the *physical proximity* of information and communication technology devices (e.g., mobile phones) and its physiological and psychological effects (e.g., of electromagnetic fields) were also excluded (e.g., Klaps et al., 2016), as these do not inform research on CMC as a form of social interaction.

2. The synthesis had to investigate MH with at least one construct that is an *established marker of either psychopathology or psychological well-being, or a risk or resilience factor commonly associated with PTH or PWB*.

    a. Whether a variable is an established marker of PTH or PWB or a risk or resilience factor was determined via the extended dual-factor model of MH (see Appendix II) and the literature this model is based on (e.g., Conway et al., 2019; Huta & Waterman, 2014). Thus, if a review assessed *only* outcomes not considered indicators of MH as defined in our model (e.g., attitudes, academic or cognitive performance, friendship closeness), it was excluded (e.g., Liu et al., 2017; Liu & Yang, 2016; Yang & Shen, 2018). If a review confounded relevant indicators (e.g., loneliness) with irrelevant ones (e.g., extraversion) in all analyses, it was also excluded (Song et al., 2014).

    b. Reviews assessing CMC only in relation to personality traits such as narcissism or the “big five” were excluded (e.g., Gnambs & Appel, 2018; Liu & Campbell, 2017). Personality is reflective of genetic dispositions (Lahey et al., 2017) and is predictive of certain sets of adaptive or dysfunctional behavior (DeYoung, 2015), hence systematically affecting MH. However, personality is

not indicative of MH *per se*, particularly due to its relatively high temporal stability. However, syntheses of variables that are often interpreted as resilience factors or even markers of MH, albeit originally being conceptualized as personality constructs (specifically, self-esteem; Chung et al., 2014), were included in this review (e.g., Liu & Baumeister, 2016).

3. The synthesis had to be based on research that assessed *CMC and MH as distinct and conceptually independent variables*, in order to be able to make claims about their association.

    a. If a review mostly included studies that did not empirically distinguish between CMC and a MH variable, it was excluded. For instance, reviews predominantly focusing on identity expression (Wängqvist & Frisén, 2016), self-disclosure (Ruppel et al., 2017), or emotion expression in CMC (Derks et al., 2008) were excluded for this reason (see also Gilmour et al., 2020). While these reviews provide insights into processes crucial to CMC research, they do not explicitly inform research on the empirical *association* between CMC and MH. For instance, the review by Derks et al. (2008) synthesized evidence on how emotions are differently communicated in CMC vs. face-to-face contexts. While emotions are certainly key to MH (e.g., affective well-being or anxiety), studies that investigate emotion *expression* in CMC contexts inherently confound the usage of CMC channels with a potential MH indicator. Thus, from this research, it is impossible to assess a media effect, that is, whether CMC has led to "changes in cognitions (including beliefs), emotions, attitudes, and behavior" as a *result* from technology usage (Valkenburg et al., 2016, p. 316)—or whether changes in cognitions, emotions, attitudes, and behavior have led to changes in CMC usage. On a more practical level, meta-analyses

on topics such as self-disclosure in CMC do not provide effect sizes that indicate changes in MH (Ruppel et al., 2017).

   b. For the same reason, reviews assessing how CMC content (e.g., Facebook status updates) can be analyzed for indications of MH issues were excluded (Wongkoblap et al., 2017).

4. Fourth, the synthesis had to include studies with *healthy, non-clinical participants from the general population*.

   a. Reviews investigating CMC (e.g., SNS or online support groups) as a means of treatment or intervention to improve well-being in clinical populations were excluded for this reason (e.g., Grajales et al., 2014, Laranjo et al., 2015; Rains & Young, 2009)

   b. Research on the effects of CMC among people with special needs (e.g., disabilities; Cheatham, 2012) was also excluded based on this criterion.

5. Fifth, concerning *review methodology*, the synthesis had to contain a systematic and, in principle, replicable literature search (i.e., use databases and search terms), clearly specified eligibility criteria, and should not fully overlap with a more recent review.

   a. We therefore excluded all non-systematic, selective reviews from our analysis, even if they reviewed relevant research literature and provided insights into their respective subject matter (e.g., Bargh & McKenna, 2004; Verduyn et al., 2017). Non-systematic narrative reviews are a common form of literature synthesis that is widespread in many fields. However, due to their unstandardized approach and because they do not necessarily use keywords such as “review” or “meta-analysis” in the title, they are particularly difficult to identify in a systematic literature search. More importantly, this form of synthesis is an inherently selective assessment of the literature. Including selective reviews would thus introduce bias. Solely relying on systematic

reviews and meta-analyses, in contrast, is a means of bias control without engaging in the controversial technique of quality coding (Card, 2012).

   b. We excluded Mingoia et al. (2017) since a more recent meta-analysis including all studies from Mingoia et al. (2017) was available (i.e., Saiphoo & Vahedi, 2019).

6. Sixth, the synthesis article had to contain *empirical studies (quantitative and/or qualitative)* as the reviewed literature.
   a. We are unaware of any articles that would have to be excluded for this reason, but nonetheless specified this criterion to emphasize our reliance on empirical evidence.
7. Seventh, we only included articles *written in English* and those that were *published* or *accepted for publication* in a *peer-reviewed* outlet.
   a. We are unaware of any articles that would have to be excluded for this reason, but nonetheless specified this criterion to emphasize our reliance on internationally accessible (i.e., written in English) and peer-reviewed evidence.

Appendix III: Details of the Systematic Literature Search and Coding

1. Systematic search and selection of synthesis articles

As recommended in method literature (Card, 2012), we combined several methods of searching the literature, which are outlined in detail below.

(1) First, as part of an ongoing effort to identify relevant literature on CMC and MH, we searched seven academic databases (*EBSCO: Business Source Premier, Communication Abstracts, EconLit, LISTA, PSYNDEX; ScienceDirect; and Web of Science*) using pretested search terms. The search string used Boolean operators to combine synonyms of CMC with synonyms of MH. The generic string for all databases was:

(Internet OR cyber* OR web OR online OR chat* OR “e-mail” OR “computer-mediated” OR “CMC” OR mobile OR smartphone OR “instant mess*” OR “IM” OR “mobile messaging applications” OR “MMA” OR text* OR “social media” OR “social network” OR “SNS” OR "ICT" OR "information and communication technology" OR Facebook) AND (“Well-being” OR wellness OR happiness OR functioning OR flourishing OR “the good life” OR “quality of life” OR “the full life” OR “life satisfaction” OR “satisfaction with life” OR “SWL” OR “positive affect” OR “negative affect” OR “PANAS” OR “subjective well-being” OR “SWB”).

A number of search terms (e.g., social support, social capital, psychopathology, mental health, depression) were considered during string development, but excluded from the final string. We decided to exclude these terms due to very high rates of false-positive hits (sometimes in the tens of thousands), which would have decreased search precision and thus impeded feasibility. This first search was restricted to the timespan from January 1995 to April 2016.

We retrieved 9.427 abstracts from the database searches, which were then pre-screened for relevant articles (both primary research studies and reviews) by three trained

student coders (two undergraduates, one graduate) based on a coding protocol. Inclusion and exclusion criteria for the screening were the same as the ones outlined in Appendix III, with two exceptions. For this first step of the search, we also included research on problematic or addictive forms of CMC as studies in this field often assess regular CMC as well (i.e., not just scales of problematic or pathological usage, but also of regular usage) and often rely on non-clinical samples (see, e.g., Tokunaga & Rains, 2010). Moreover, at this point, we still included all *non*-systematic review articles on CMC and MH.

Inclusion versus exclusion decisions had *inter-coder* reliabilities of pairwise agreement = 96% and Krippdendorf's alpha = .73. *Intra-coder* reliabilities with a one month difference between T1 and T2 were Coder 1: Pairwise agreement = 96%, Krippendorf's alpha = .68; Coder 2: Pairwise agreement = 96%, Krippendorf's alpha = .68; Coder 3: Pairwise agreement = 93%, Krippendorf's alpha = .62. It should be noted that the comparatively low alpha coefficients are strongly influenced by the highly skewed distribution of coding decisions (i.e., zero-inflation, indicating that most of the coding decisions in abstract screening were exclusions, as is typical for systematic reviews) (Lacy et al., 2015). The pairwise agreements show that reliabilities were overall acceptable.

The pre-screening of studies resulted in a reduced sample of 409 records that were then "forward searched" (Card, 2012) via Google Scholar's "cited by" function by the same student coders. For each article, coders screened the first 50 citations, thereby retrieving an additional 381 articles. All articles were entered into a literature database, which was subsequently searched for the terms "review" and "meta-analysis" to identify eligible research synthesis articles. This resulted in the identification of seven review articles.

(2) Second, to accommodate for any limitations of our previous database search attempts, we then "forward searched" all citations and "backward searched " all references of the identified seven review articles and repeated this procedure for any new review articles found in the process. This procedure is highly common for meta-reviews as synthesis articles

typically cite related syntheses in order to clarify their unique contribution in contrast to already published syntheses articles (Polanin et al., 2017). These searches resulted in nine additional review articles.

(3) Finally, we conducted a complementary Google Scholar title search targeted specifically at finding systematic reviews and meta-analyses on CMC and MH. In doing so, we were able to compare the results of our previous broader systematic literature search with a more targeted search, testing whether our previous search attempts were exhaustive. This final search used the search string from the systematic database search and several additional terms omitted from the first string (e.g., "social support" or "social capital"). The resulting string was then combined with the terms "systematic review", "narrative review", "review", and "meta-analysis". This complementary search resulted in only five additional review articles in December 2017, underlining the exhaustiveness and validity of our previous search efforts. This last step of the search was then updated during peer review in September 2019, resulting in an additional 15 reviews published in 2018 and 2019. The final sample of eligible reviews consisted of 34 publications.

2. Coding of primary research publications

An inter-coder reliability analysis was conducted with 20 randomly selected *primary research publications* from the review articles and including 58 MH and 74 CMC indicators overall. Based on recommendations by Lacy et al. (2015), we report simple agreement alongside Krippendorf's α, as several categories showed skewed distributions. For ratio-scaled data, we only report α. For most categories, reliability was sufficient: number of MH variables in a publication (α = .83), number of CMC variables in a publication (α = .96), MH dimension (97%, α = .95), MH manifestation (91%, α = .88), MH trait vs. state measurement (95%, α = .89), CMC device (100%, α = 1.00), type of application (96%, α = .87), branded application (97%, α = .94), interaction (93%, α = .86), and message level (92%, α = .66), and

the conceptual approach to CMC (91%, $\alpha = .84$). For the operational approach (80%, $\alpha = .55$) and the feature level (88%, $\alpha = .46$), α values were low. These disagreements were discussed until consensus was reached and the full dataset was recoded accordingly.

Appendix IV: Descriptive Overview of Included Meta-Analyses and Systematic Reviews

Table A1

Descriptive overview of included meta-analyses and systematic reviews

Author(s)	Year	Review type	Population investigated	Publications included	Type of studies	CMC concept(s) synthesized	MH concept(s) synthesized	Narrative conclusion about overall relationship
Baker & Algorta	2016	SR	General	30	QN	SNS use (various)	Depression	Mixed; Conditional
Best et al.	2014	SR	Adolescents	43	QN & QL	SM use (various)	Various (e.g., self-esteem, social support, social capital, social isolation, depression)	(Mixed; Conditional)
Cheng et al.	2019	MA	General	161	QN	SNS use (various)	Social capital, social anxiety, loneliness	Mixed: Conditional
Dobrean & Pasarelu	2016	SR	General	20	QN	SNS use (various)	Social anxiety	(Mixed)
Domahidi	2018	MA	General	63	QN	Internet, SM & SNS use (various)	Social support, social capital	Positive; Conditional
Erfani & Abedin	2018	SR	General	22	QN & QL	SNS use (various)	Various (e.g., life satisfaction, self-esteem, affect)	Mixed: Conditional
Forsman & Nordmyr	2015	SR	Older Adults	32	QN & QL	Internet use (various)	Various (e.g., quality of life, depression, loneliness)	Positive
Frost & Rickwood	2017	SR	General	65	QN	FB use (various)	Various (e.g., anxiety, depression, disordered eating, alcohol abuse)	Mixed; Conditional

Holland & Tiggemann	2016	SR	General	20	QN	SNS use (various)	Eating disorder symptoms	(Negative; Conditional)
Huang	2010	MA	General	40	QN	Internet use (various)	Various (depression, loneliness, self-esteem, life satisfaction)	Negative
Huang	2017	MA	General	61	QN	SNS use (time spent)	Various (depression, loneliness, self-esteem, life satisfaction)	Negative; Conditional
Keles et al.	2019	SR	Adolescents	13	QN	SM use (various)	Depression, anxiety, distress	Negative; Conditional
Khosravi et al.	2016	SR	Older Adults	34	QN	ICT & SNS use (various)	Social isolation, loneliness	Positive
Krause et al.	2019	SR	General	49	QN	SNS use (various)	Self-esteem	Mixed; Conditional
Liu, Ainsworth et al.	2016	MA	General	58	QN	SNS use (various)	Social capital	Positive; Conditional
Liu & Baumeister	2016	MA	General	80	QN	SNS use (various)	Self-esteem, loneliness	Negative; Conditional
Liu, Baumeister, et al.	2019	MA	General	124	QN	ICT & SNS use (various)	Various (e.g., anxiety, depression, happiness, loneliness, self-esteem)	Mixed; Conditional
Liu, Wright, et al.	2018	MA	Students	31	QN	SNS use (various)	Social support	Positive; Conditional
McCrae et al.	2017	MA	Children & Adolescents	11	QN	SM use (various)	Depression	(Negative; Conditional)
Meng et al.	2017	SR	General	88	QN	SNS use (various)	Social support	Unclear

Prizant-Passal et al.	2016	MA	General	23	QN	Internet use (various)	Social anxiety	Mixed; Conditional
Rodgers & Melioli	2016	SR	General	67	QN & QL	Internet & SNS use (various)	Eating disorder symptoms	Negative
Rus & Tiemensma	2017	SR	General	26	QN	SNS use (various)	Relationship satisfaction, jealousy	(Mixed; Conditional)
Saiphoo & Vahedi	2019	MA	General	56	QN	SNS use (various)	Various (e.g., body satisfaction, body esteem, eating disorder symptoms)	Negative; Conditional
Sarmiento et al.	2018	SR	Adolescents	68	QN	SM use (various)	Anxiety, depression, loneliness	(Negative; Conditional)
Seabrook et al.	2016	SR	General	70	QN & QL	SNS use (various)	Depression, anxiety	Mixed; Conditional
Shapiro & Margolin	2014	SR	Adolescents	27	QN	SNS use (various)	Various (e.g., connectedness, self-esteem)	Mixed; Conditional
Thomée	2018	SR	General	290	QN	Mobile phone use (various)	Various (e.g., depression, sleep problems, stress, anxiety)	(Negative)
Twomey & O'Reilly	2017	SR	General	21	QN	Self-presentation on FB	Various (e.g., self-esteem, social support, social anxiety, depression)	Mixed; Conditional
Vahedi & Zannella	2019	MA	General	55	QN	SNS use (various)	Depression	Negative; Conditional
Williams	2019	SR	General	54	QN & QL	SNS use (various)	Social capital	Positive
Wu et al.	2016	SR	Adolescents	12	QN	Internet & SM use (various)	Various (e.g., connectedness, loneliness, social isolation, depression, anxiety)	Mixed

Yin et al.	2019	MA	General	63	QN	SNS use (various)	Various (e.g., depression, loneliness, anxiety, envy, affect, life satisfaction, self-esteem)	Mixed; Conditional
Yoon et al.	2019	MA	General	45	QN	SNS use (various)	Depression	Negative; Conditional

Note. *Review type*: *SR*: systematic narrative review, *MA*: meta-analysis. *Type of studies*: *QN*: quantitative, *QL*: qualitative. *SNS:* social network sites. *SM:* social media. *FB:* Facebook. *ICT:* information and communication technology. *PTH:* psychopathology. *PWB:* psychological well-being. *Conclusion*: The conclusion refers to the relationship between CMC and MH as operationalized in the respective review, with higher levels of MH meaning higher levels of PWB and lower levels of PTH. *Negative*: negative relationships between CMC and MH prevail. *Positive*: positive relationships prevail. *Mixed*: positive, negative, and/or non-significant relationships were found. *Unclear*: no explicit conclusion about the relationship was articulated. *Conditional:* the strength and/or direction of the relationships depend on moderators (e.g., age, gender, culture, concepts or measures investigated) and/or mediators. *Brackets* indicate that author(s) found the evidence insufficient for a definitive conclusion.

Appendix V: Detailed Findings of Meta-Analyses on CMC and Mental Health

Table A2

Effect sizes of the relationship between CMC and MH indicators from fourteen meta-analyses

Publication	CMC indicator	MH indicator	*k* effect sizes	*N* participants	Effect size *r* 95% CI [LL; UL]
Cheng et al., 2019[b]	Global SNS use	Loneliness	196	—	.01 [-.02; .05]
		Social anxiety	194	—	**.10 [.05; .15]**
Domahidi, 2018[a,b,d]	Internet use	Social resources (capital/support)	108	78,958	.06 [-.01; .12]
	SNS use		99	27,779	**.30 [.14; .46]**
	Forum use		41	8,171	**.14 [.09; .20]**
	Blog use		21	8,501	.20 [-.01; .42]
	Chat use		18	5,432	.06 [-.18; .31]
	Email use		11	3,970	-.01 [-.24; .22]
Huang, 2010	Time spent online	Well-being (total)	39	—	**-.04 [-.07; -.01]**
		-- Loneliness[(r)]	37	—	-.02 [-.05; .02]
		-- Depression[(r)]	33	—	**-.05 [-.07; -.02]**
		-- Life satisfaction	7	—	**-.05 [-.12; -.01]**
		-- Self-esteem	5	—	-.01 [-.06; .05]
	Social Internet use	Well-being (total)	22	—	-.02 [-.08; .02]
Huang, 2017	Time spent on SNS	Well-being (total)	67	19,652	**-.07 [-.09; -.04]**
		-- Self-esteem	30	—	**-.04 [-.08; -.00]**
		-- Depression[(r)]	24	—	**-.11 [-.15; -.07]**
		-- Loneliness[(r)]	20	—	**-.08 [-.13; -.04]**
		-- Life satisfaction	8	—	-.03 [-.11; .05]
Liu, Ainsworth et al., 2016[a]	Global SNS use (total)	Bridging social capital	50	22,290	**.32 [.27; .37]**
	-- intensity		32	14,711	**.35 [.34; .36]**
	-- time		13	5,726	**.15 [.12; .17]**
	-- frequency		5	1,853	**.19 [.14; .23]**
	Information seeking (direct questions, following status updates)		13	4,532	**.25 [.18; .32]**
	Replying and maintaining		11	5,221	**.36 [.27; .44]**
	Self-disclosure (status updates, photos, sharing information)		9	3,792	**.19 [.11; .26]**
	Including offline friends		6	1,937	**.23 [.19; .27]**
	Initiating online friendships		2	1,055	**.09 [.03; .15]**
	Global SNS use (total)	Bonding social capital	43	19,439	**.22 [.21; .24]**

	-- intensity		27	12,551	**.27 [.25; .28]**
	-- time		10	4,547	**.14 [.11; .17]**
	-- frequency		6	2,341	**.14 [.10; .18]**
	Information seeking (direct questions, following status updates)		9	2,765	**.18 [.14; .21]**
	Replying and maintaining		9	4,418	**.24 [.21; .27]**
	Self-disclosure (status updates, photos, sharing information)		7	2,768	**.20 [.16; .24]**
	Including offline friends		5	1,817	**.25 [.21; .30]**
	Initiating online friendships		2	1,055	.03 [-.03; .09]
Liu & Baumeister, 2016[a,c]	Global SNS use	Loneliness	23	7,397	**.17 [.09; .24]**
	Global SNS use	Self-esteem	33	10,627	**-.09 [-.14; -.03]**
	No. of friends		11	3,035	**.07 [.01; .14]**
	No. of photos		8	1,964	-.01 [-.13; .10]
	Status updates		4	685	-.02 [-.10; .07]
	Interactions		3	969	**-.09 [-.14; -.03]**
Liu, Baumeister, et al., 2019	Global SNS use	Well-being (total)	94	34,475	**-.06 [-.09; -.03]**
		-- Self-esteem	34	—	**-.05 [-.09; -.01]**
		-- Depression	25	—	**.13 [.09; .17]**
		-- Loneliness	23	—	**.11 [.06; .16]**
		-- Satisfaction	16	—	.09 [-.02; .19]
		-- Anxiety	14	—	**.10 [.03; .18]**
		-- Stress	5	—	**.13 [.05; .21]**
		-- Happiness	1	—	**.14 [.06; .22]**
	Self-presentation (status updates, photos)	Well-being (total)	13	3,012	.02 [-.04; .08]
	Content consumption (browsing, searching, monitoring)		9	3,384	**-.14 [-.20; -.08]**
	Interactions (replying, commenting, liking)		5	1,366	**.14 [.08; .20]**
	Phone calls	Well-being (total)	9	3,257	**.10 [.06; .15]**
		-- Loneliness	5	—	**-.11 [-.20; -.03]**
		-- Self-esteem	2	—	.03 [-.05; .11]
		-- Satisfaction	1	—	**.13 [.04; .21]**
		-- Happiness	1	—	**.13 [.06; .20]**
	Texting	Well-being (total)	9	2,063	.10 [.02; .17]
		-- Loneliness	8	—	**-.16 [-.22; -.11]**
		-- Anxiety	4	—	-.14 [-.34; .06]
		-- Satisfaction	2	—	-.01 [-.10; .07]
		-- Self-esteem	2	—	.07 [-.01; .15]
	Instant messaging	Well-being (total)	8	3,981	.06 [-.06; .16]
		-- Loneliness	4	—	**-.06 [- .11; -.02]**
		-- Depression	3	—	.00 [-.22; .22]
		-- Anxiety	2	—	**-.21 [-.27; -.15]**
		-- Satisfaction	1	—	-.03 [-.09; .03]

		-- Self-esteem	1	—	**-.28 [-.40; -.15]**
Liu, Wright et al., 2018[a]	Global SNS use	Social support (total)	21	7,214	**.29 [.21; .36]**
		-- Offline	17	5,842	**.18 [.11; .24]**
		-- Online	10	3,504	**.39 [.25; .51]**
	No. of friends		8	2,039	**.13 [.09; .17]**
	Self-presentation (status updates, photos)		6	2,689	**.28 [.20; .36]**
	Interactions		5	938	.13 [-.14; .38]
	Content consumption		2	1,114	.29 [-.01; .54]
	SNS use (total)	Emotional support	5	1,734	**.38 [.32; .43]**
		Informational support	5	1,744	**.23 [.04; .42]**
		Tangible support	2	329	.23 [-.11; .52]
		Esteem support	2	295	.11 [-.17; .37]
McCrae et al., 2017	Social media use (various)	Depression symptoms	11	12,646	**.13 [.05; .20]**
Prizant-Passal et al., 2016[b]	Social comfort online	Social anxiety	10	—	**.34 [.25; .41]**
	Time spent online		7	—	.07 [-.05; .18]
	Time spent on instant messaging		7	—	.12 [-.10; .32]
	Time spent on email		3	—	-.03 [-.09; .04]
	Comfort due to reduced non-verbal cues		4	—	**.27 [.23; .31]**
Saiphoo & Vahedi, 2019	SNS use (total)	Body image disturbance (total)	63	36,552	**.17 [.13; .21]**
		-- general/ evaluative	39	—	**.13 [.08; .19]**
		-- behavioral	12	—	**.21 [.14; .28]**
		-- cognitive	9	—	**.23 [.17; .29]**
	-- Multiple SNS	Body image disturbance (total)	31	—	**.16 [.12; .20]**
	-- Facebook		23	—	**.21 [.14; .29]**
	-- Instagram		5	—	.10 [-.18; .36]
	-- Other SNS		4	—	.10 [-.06; .25]
	-- General use		44	—	**.11 [.08; .15]**
	-- Appearance-focused use		16	—	**.31 [.22; .39]**
Vahedi & Zannella, 2019	Global SNS use	Depression symptoms	34	44,027	**.11 [.07; .14]**

Yin et al., 2018	SNS use (total)	Positive MH indicators (e.g., life satisfaction, positive affect, self-esteem)	62	23,442	**.05 [.01; .08]**
	-- Global SNS use		27	13,007	.04 [-.02; .10]
	-- No. of friends		18	3,543	**.13 [.05; .21]**
	-- Active use		9	2,674	.04 [-.07; .14]
	-- Passive use		8	4,218	-.10 [-.20; .01]
	SNS use (total)	Negative MH indicators (e.g., depression, loneliness, anxiety)	82	27,240	**.06 [.03; .09]**
	-- Global SNS use		36	10,392	**.11 [.06; .15]**
	-- No. of friends		17	3,946	-.03 [-.10; .04]
	-- Active use		17	6,698	.04 [-.02; 10]
	-- Passive use		12	6,204	.07 [-.01; .14]
Yoon et al., 2019	Time spent on SNS	Depression symptoms	37	15,881	**.11 [.08; .14]**
	Frequency of checking SNS		14	8,041	**.10 [.03; .16]**
	General social comparison on SNS		8	1,715	**.23 [.12; .34]**
	Upward social comparison on SNS		6	2,298	**.33 [.20; .47]**

Note. Effect sizes within as well as between individual meta-analyses should not be treated as independent. Effect sizes statistically significant at $p < .05$ or lower are highlighted in bold. Empty cells in the *N* participants column are due to missing information (i.e., (sub-)sample sizes were not reported in the respective publications). If publications reported information on indicators that did not match our definitions of CMC (e.g., gaming, entertainment) or MH (e.g., narcissism), this information was omitted. Effect sizes collapsing indicators that matched and did not match our definitions were also omitted (e.g., an effect size including both general and problematic usage). As far as possible, we used the CMC and MH indicator labels as used by the original author(s) to facilitate reproducibility. However, the labeling was also slightly extended and harmonized across publications to facilitate interpretability of findings. "Global SNS use" refers to time spent on the SNS, frequency of, and/or intensity of use.

[a]Author(s) conducted a Hunter & Schmidt correction of effect sizes based on internal consistency (e.g., Cronbach's alpha) of the measures.

[b]Author(s) conducted a three-level (random effects or mixed effects) meta-analysis. All other findings are based on random effects models.

[c]Author(s) report credible intervals instead of confidence intervals.

[d]Author(s) used robust standard errors and confidence intervals.

[(r)]Measure was reversed by the author(s).

References in the Online Appendix

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders: Dsm-5* (5th ed.). American Psychiatric Publishing.

Anderson, C. A., Shibuya, A., Ihori, N., Swing, E. L., Bushman, B. J., Sakamoto, A., Rothstein, H. R., & Saleem, M. (2010). Violent video game effects on aggression, empathy, and prosocial behavior in eastern and western countries: A meta-analytic review. *Psychological Bulletin*, *136*(2), 151–173. https://doi.org/10.1037/a0018251

Baker, D. A., & Algorta, G. P. (2016). The relationship between online social networking and depression: A systematic review of quantitative studies. *Cyberpsychology, Behavior, and Social Networking*, *19*(11), 638–648. https://doi.org/10.1089/cyber.2016.0206

Bargh, J. A., & McKenna, K. Y. A. (2004). The internet and social life. *Annual Review of Psychology*, *55*, 573–590. https://doi.org/10.1146/annurev.psych.55.090902.141922

Best, P., Manktelow, R., & Taylor, B. (2014). Online communication, social media and adolescent wellbeing: A systematic narrative review. *Children and Youth Services Review*, *41*, 27–36. https://doi.org/10.1016/j.childyouth.2014.03.001

Card, N. A. (2012). *Applied meta-analysis for social science research*. Guilford Press.

Cheatham, L. P. (2012). Effects of Internet use on well-being among adults with physical disabilities: A review. *Disability and Rehabilitation: Assistive Technology*, *7*(3), 181–188. https://doi.org/10.3109/17483107.2011.625071

Chen, L., Ho, S. S., & Lwin, M. O. (2017). A meta-analysis of factors predicting cyberbullying perpetration and victimization: From the social cognitive and media effects approach. *New Media & Society*, *19*(8), 1194–1213. https://doi.org/10.1177/1461444816634037

Cheng, C., Wang, H.-Y., Sigerson, L., & Chau, C.-L. (2019). Do the socially rich get richer? A nuanced perspective on social network site use and online social capital accrual. *Psychological Bulletin*, *145*(7), 734–764. https://doi.org/10.1037/bul0000198

Chung, J. M., Robins, R. W., Trzesniewski, K. H., Noftle, E. E., Roberts, B. W., & Widaman, K. F. (2014). Continuity and change in self-esteem during emerging adulthood. *Journal of Personality and Social Psychology*, *106*(3), 469–483. https://doi.org/10.1037/a0035135.

Çikrıkci, Ö. (2016). The effect of internet use on well-being: Meta-analysis. *Computers in Human Behavior*, *65*, 560–566. https://doi.org/10.1016/j.chb.2016.09.021

Conway, C. C., Forbes, M. K., Forbush, K. T., Fried, E. I., Hallquist, M. N., Kotov, R., Mullins-Sweatt, S. N., Shackman, A. J., Skodol, A. E., South, S. C., Sunderland, M., Waszczuk, M. A., Zald, D. H., Afzali, M. H., Bornovalova, M. A., Carragher, N., Docherty, A. R., Jonas, K. G., Krueger, R. F., . . . Eaton, N. R. (2019). A hierarchical taxonomy of psychopathology can transform mental health research. *Perspectives on Psychological Science*, *14*(3), 419–436. https://doi.org/10.1177/1745691618810696

Derks, D., Fischer, A. H., & Bos, A. E.R. (2008). The role of emotion in computer-mediated communication: A review. *Computers in Human Behavior*, *24*(3), 766–785. https://doi.org/10.1016/j.chb.2007.04.004

DeYoung, C. G. (2015). Cybernetic big five theory. *Journal of Research in Personality*, *56*, 33–58. https://doi.org/10.1016/j.jrp.2014.07.004

Diener, E., Lucas, R. E., & Oishi, S. (2018). Advances and open questions in the science of subjective well-being. *Collabra: Psychology*, *4*(1), 1–49. https://doi.org/10.1525/collabra.115

Dobrean, A., & Pasarelu, C.-R. (2016). Impact of social media on social anxiety: A systematic review. In F. Durbano & B. Marchesi (Eds.), *New Developments in Anxiety Disorders.* InTechOpen. https://doi.org/10.5772/65188

Domahidi, E. (2018). The associations between online media use and users' perceived social resources: A meta-analysis. *Journal of Computer-Mediated Communication*, *23*, 181-200. https://doi.org/10.1093/jcmc/zmy007

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders*, *207*, 251–259. https://doi.org/10.1016/j.jad.2016.08.030

Erfani, S. S., & Abedin, B. (2018). Impacts of the use of social network sites on users' psychological well-being: A systematic review. *Journal of the Association for Information Science and Technology*, *69*(7), 900–912. https://doi.org/10.1002/asi.24015

Ferguson, C. J., Coulson, M., & Barnett, J. (2011). A meta-analysis of pathological gaming prevalence and comorbidity with mental health, academic and social problems. *Journal of Psychiatric Research*, *45*(12), 1573–1578. https://doi.org/10.1016/j.jpsychires.2011.09.005

Forsman, A. K., & Nordmyr, J. (2015). Psychosocial links between Internet use and mental health in later life: A systematic review of quantitative and qualitative evidence. *Journal of Applied Gerontology*, *36*(12), 1471-1518. https://doi.org/10.1177/0733464815595509

Frost, R. L., & Rickwood, D. J. (2017). A systematic review of the mental health outcomes associated with Facebook use. *Computers in Human Behavior*, *76*, 576–600. https://doi.org/10.1016/j.chb.2017.08.001

Gilmour, J., Machin, T., Brownlow, C., & Jeffries, C. (2020). Facebook-based social support and health: A systematic review. *Psychology of Popular Media Culture*, *9*(3), 328–346. https://doi.org/10.1037/ppm0000246

Gnambs, T., & Appel, M. (2018). Narcissism and social networking behavior: A meta-analysis. *Journal of Personality*, *86*(2), 200–212. https://doi.org/10.1111/jopy.12305

Grajales, F. J., Sheps, S., Ho, K., Novak-Lauscher, H., & Eysenbach, G. (2014). Social media: A review and tutorial of applications in medicine and health care. *Journal of Medical Internet Research*, *16*(2). https://doi.org/10.2196/jmir.2912

Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an integration of subjective well-being and psychopathology. *Social Indicators Research*, *54*(1), 81–108. https://doi.org/10.1023/A:1007219227883

Greitemeyer, T., & Mügge, D. O. (2014). Video games do affect social outcomes: A meta-analytic review of the effects of violent and prosocial video game play. *Personality and Social Psychology Bulletin*, *40*(5), 578–589. https://doi.org/10.1177/0146167213520459

Holland, G., & Tiggemann, M. (2016). A systematic review of the impact of the use of social networking sites on body image and disordered eating outcomes. *Body Image*, *17*, 100–110. https://doi.org/10.1016/j.bodyim.2016.02.008

Huang, C. (2010). Internet use and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *13*(3), 241–249. https://doi.org/10.1089/cyber.2009.0217

Huang, C. (2017). Time spent on social network sites and psychological well-being: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *20*(6), 346–354. https://doi.org/10.1089/cyber.2016.0758

Huta, V. (2017). An overview of hedonic and eudaimonic well-being concepts. In L. Reinecke & M. B. Oliver (Eds.), *The Routledge handbook of media use and well-being: International perspectives on theory and research on positive media effects* (pp. 14–33). Routledge.

Huta, V., & Waterman, A. S. (2014). Eudaimonia and its distinction from hedonia: Developing a classification and terminology for understanding conceptual and operational definitions. *Journal of Happiness Studies*, *15*(6), 1425–1456. https://doi.org/10.1007/s10902-013-9485-0

Keles, B., McCrae, N., & Grealish, A. (2019). A systematic review: The influence of social media on depression, anxiety and psychological distress in adolescents. *International Journal of Adolescence and Youth*, *3*(4), 1–15. https://doi.org/10.1080/02673843.2019.1590851

Keyes, C. L. M. (2005). Mental illness and/or mental health? Investigating axioms of the complete state model of health. *Journal of Consulting and Clinical Psychology*, *73*(3), 539–548. https://doi.org/10.1037/0022-006X.73.3.539

Khosravi, P., Rezvani, A., & Wiewiora, A. (2016). The impact of technology on older adults' social isolation. *Computers in Human Behavior*, *63*, 594–603. https://doi.org/10.1016/j.chb.2016.05.092

Klaps, A., Ponocny, I., Winker, R., Kundi, M., Auersperg, F., & Barth, A. (2016). Mobile phone base stations and well-being - A meta-analysis. *The Science of the Total Environment*, *544*, 24–30. https://doi.org/10.1016/j.scitotenv.2015.11.009

Kosenko, K., Luurs, G., & Binder, A. R. (2017). Sexting and sexual behavior, 2011-2015: A critical review and meta-analysis of a growing literature. *Journal of Computer-Mediated Communication*, *22*(3), 141–160. https://doi.org/10.1111/jcc4.12187

Kowalski, R. M., Giumetti, G. W., Schroeder, A. N., & Lattanner, M. R. (2014). Bullying in the digital age: A critical review and meta-analysis of cyberbullying research among youth. *Psychological Bulletin*, *140*(4), 1073–1137. https://doi.org/10.1037/a0035618

Krause, H.-V., Baum, K., Baumann, A., & Krasnova, H. (2019). Unifying the detrimental and beneficial effects of social network site use on self-esteem: a systematic literature review. *Media Psychology*, *37*(1), 1–38. https://doi.org/10.1080/15213269.2019.1656646

Krueger, R. F., McGue, M., & Iacono, W. G. (2001). The higher-order structure of common DSM mental disorders: Internalization, externalization, and their connections to personality. *Personality and Individual Differences*, *30*(7), 1245–1259. https://doi.org/10.1016/S0191-8869(00)00106-9

Kwan, I., Dickson, K., Richardson, M., MacDowall, W., Burchett, H., Stansfield, C., Brunton, G., Sutcliffe, K., & Thomas, J. (2020). Cyberbullying and children and young people's mental health: A systematic map of systematic reviews. *Cyberpsychology, Behavior, and Social Networking*, *23*(2), 72–82. https://doi.org/10.1089/cyber.2019.0370

Lacy, S., Watson, B. R., Riffe, D., & Lovejoy, J. (2015). Issues and best practices in content analysis. *Journalism & Mass Communication Quarterly*, *92*(4), 791–811. https://doi.org/10.1177/1077699015607338

Lahey, B. B., Krueger, R. F., Rathouz, P. J., Waldman, I. D., & Zald, D. H. (2017). A hierarchical causal taxonomy of psychopathology across the life span. *Psychological Bulletin*, *143*(2), 142–186. https://doi.org/10.1037/bul0000069

Laranjo, L., Arguel, A., Neves, A. L., Gallagher, A. M., Kaplan, R., Mortimer, N., Mendes, G. A., & Lau, A. Y. S. (2015). The influence of social networking sites on health behavior change: A systematic review and meta-analysis. *Journal of the American Medical Informatics Association*, *22*(1), 243–256. https://doi.org/10.1136/amiajnl-2014-002841

Li, J., Theng, Y.-L., & Foo, S. (2016). Effect of exergames on depression: A systematic review and meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *19*(1), 34–42. https://doi.org/10.1089/cyber.2015.0366

Liu, D., Ainsworth, S. E., & Baumeister, R. F. (2016). A meta-analysis of social networking online and social capital. *Review of General Psychology*, *20*(4), 369–391. https://doi.org/10.1037/gpr0000091

Liu, D., & Baumeister, R. F. (2016). Social networking online and personality of self-worth: A meta-analysis. *Journal of Research in Personality*, *64*, 79–89. https://doi.org/10.1016/j.jrp.2016.06.024

Liu, D., Baumeister, R. F., Yang, C.-C., & Hu, B. (2019). Digital communication media use and psychological well-being: A meta-analysis. *Journal of Computer-Mediated Communication*, *24*(5), 259–274. https://doi.org/10.1093/ccc/zmz013

Liu, D., & Campbell, W. K. (2017). The big five personality traits, big two metatraits and social media: A meta-analysis. *Journal of Research in Personality*, *70*, 229–240. https://doi.org/10.1016/j.jrp.2017.08.004

Liu, D., Kirschner, P. A., & Karpinski, A. C. (2017). A meta-analysis of the relationship of academic performance and social network site use among adolescents and young adults. *Computers in Human Behavior*, *77*, 148–157. https://doi.org/10.1016/j.chb.2017.08.039

Liu, D., Wright, K. B., & Hu, B. (2018). A meta-analysis of social network site use and social support. *Computers & Education*, *127*, 201–213. https://doi.org/10.1016/j.compedu.2018.08.024

Liu, D., & Yang, C.-C. (2016). Media niche of electronic communication channels in friendship: A meta-analysis. *Journal of Computer-Mediated Communication*, *21*(6), 451–466. https://doi.org/10.1111/jcc4.12175

Martela, F., & Sheldon, K. M. (2019). Clarifying the concept of well-being: Psychological need satisfaction as the common core connecting eudaimonic and subjective well-being. *Review of General Psychology*, *23*(4), 458–474. https://doi.org/10.1177/1089268019880886

McCrae, N., Gettings, S., & Purssell, E. (2017). Social media and depressive symptoms in childhood and adolescence: A systematic review. *Adolescent Research Review*, *2*(4), 315–330. https://doi.org/10.1007/s40894-017-0053-4

Meng, J., Martinez, L., Holmstrom, A., Chung, M., & Cox, J. (2017). Research on social networking sites and social support from 2004 to 2015: A narrative review and directions for future research. *Cyberpsychology, Behavior, and Social Networking*, *20*(1), 44–51. https://doi.org/10.1089/cyber.2016.0325

Mingoia, J., Hutchinson, A. D., Wilson, C., & Gleaves, D. H. (2017). The relationship between social networking site use and the internalization of a thin ideal in females: A meta-analytic review. *Frontiers in Psychology*, *8*, 1–10. https://doi.org/10.3389/fpsyg.2017.01351

Polanin, J. R., Maynard, B. R., & Dell, N. A. (2017). Overviews in education research: A systematic review and analysis. *Review of Educational Research*, *87*(1), 172–203. https://doi.org/10.3102/0034654316631117

Prizant-Passal, S., Shechner, T., & Aderka, I. M. (2016). Social anxiety and internet use – A meta-analysis: What do we know? What are we missing? *Computers in Human Behavior*, *62*, 221–229. https://doi.org/10.1016/j.chb.2016.04.003

Rains, S. A., & Young, V. (2009). A meta-analysis of research on formal computer-mediated support groups: Examining group characteristics and health outcomes. *Human Communication Research*, *35*(3), 309–336. https://doi.org/10.1111/j.1468-2958.2009.01353.x

Rodgers, R. F., & Melioli, T. (2016). The relationship between body image concerns, eating disorders and Internet use, part I: A review of empirical support. *Adolescent Research Review*, *1*(2), 95–119. https://doi.org/10.1007/s40894-015-0016-6

Ruppel, E. K., Gross, C., Stoll, A., Peck, B. S., Allen, M., & Kim, S.-Y. (2017). Reflecting on connecting: Meta-analysis of differences between computer-mediated and face-to-face self-disclosure. *Journal of Computer-Mediated Communication*, *22*(1), 18–34. https://doi.org/10.1111/jcc4.12179

Rus, H. M., & Tiemensma, J. (2017). "It's complicated." A systematic review of associations between social network site use and romantic relationships. *Computers in Human Behavior*, *75*, 684–703. https://doi.org/10.1016/j.chb.2017.06.004

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, *52*(1), 141–166. https://doi.org/10.1146/annurev.psych.52.1.141

Ryan, T., Chester, A., Reece, J., & Xenos, S. (2014). The uses and abuses of Facebook: A review of Facebook addiction. *Journal of Behavioral Addictions*, *3*(3), 133–148. https://doi.org/10.1556/JBA.3.2014.016

Saiphoo, A. N., & Vahedi, Z. (2019). A meta-analytic review of the relationship between social media use and body image disturbance. *Computers in Human Behavior*, *101*, 259–275. https://doi.org/10.1016/j.chb.2019.07.028

Sarmiento, I. G., Olson, C., Yeo, G., Chen, Y. A., Toma, C. L., Brown, B. B., Bellmore, A., & Mares, M.-L. (2018). How does social media use relate to adolescents' internalizing symptoms? Conclusions from a systematic narrative review. *Adolescent Research Review*, *36*(5), 517. https://doi.org/10.1007/s40894-018-0095-2

Seabrook, E. M., Kern, M. L., & Rickard, N. S. (2016). Social networking sites, depression, and anxiety: A systematic review. *JMIR Mental Health*, *3*(4), 1-19. https://doi.org/10.2196/mental.5842

Shapiro, L. A. S., & Margolin, G. (2014). Growing up wired: Social networking sites and adolescent psychosocial development. *Clinical Child and Family Psychology Review*, *17*(1), 1–18. https://doi.org/10.1007/s10567-013-0135-1

Song, H., Zmyslinski-Seelig, A., Kim, J., Drent, A., Victor, A., Omori, K., & Allen, M. (2014). Does Facebook make you lonely? A meta analysis. *Computers in Human Behavior*, *36*, 446–452. https://doi.org/10.1016/j.chb.2014.04.011

Thomée, S. (2018). Mobile phone use and mental health. A review of the research that takes a psychological perspective on exposure. *International Journal of Environmental Research and Public Health*, *15*(12), 1–25. https://doi.org/10.3390/ijerph15122692

Tokunaga, R. S. (2010). Following you home from school: A critical review and synthesis of research on cyberbullying victimization. *Computers in Human Behavior*, *26*(3), 277–287. https://doi.org/10.1016/j.chb.2009.11.014

Tokunaga, R. S., & Rains, S. A. (2010). An evaluation of two characterizations of the relationships between problematic Internet use, time spent using the Internet, and psychosocial problems. *Human Communication Research*, *36*(4), 512–545. https://doi.org/10.1111/j.1468-2958.2010.01386.x

Vahedi, Z., & Zannella, L. (2019). The association between self-reported depressive symptoms and the use of social networking sites (SNS): A meta-analysis. *Current Psychology*, *30*(2), 252. https://doi.org/10.1007/s12144-019-0150-6

Valkenburg, P. M., Peter, J., & Walther, J. B. (2016). Media effects: Theory and research. *Annual Review of Psychology*, *67*, 315–338. https://doi.org/10.1146/annurev-psych-122414-033608

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review*, *11*(1), 274–302. https://doi.org/10.1111/sipr.12033

Wängqvist, M., & Frisén, A. (2016). Who am I online? Understanding the meaning of online contexts for identity development. *Adolescent Research Review*, *1*(2), 139–151. https://doi.org/10.1007/s40894-016-0025-0

Williams, J. R. (2019). The use of online social networking sites to nurture and cultivate bonding social capital: A systematic review of the literature from 1997 to 2018. *New Media & Society*, *21*(11-12), 2710–2729. https://doi.org/10.1177/1461444819858749

Wongkoblap, A., Vadillo, M. A., & Curcin, V. (2017). Researching mental health disorders in the era of social media: Systematic review. *Journal of Medical Internet Research*, *19*(6), 1-17. https://doi.org/10.2196/jmir.7215

Wu, Y.-J., Outley, C., Matarrita-Cascante, D., & Murphrey, T. P. (2016). A systematic review of recent research on adolescent social connectedness and mental health with Internet technology use. *Adolescent Research Review*, *1*(2), 153–162. https://doi.org/10.1007/s40894-015-0013-9

Yang, F., & Shen, F. (2018). Effects of web interactivity: A meta-analysis. *Communication Research*, *45*(5), 635-658. https://doi.org/10.1177/0093650217700748

Yin, X.-Q., de Vries, D. A., Gentile, D. A., & Wang, J.-L. (2019). Cultural background and measurement of usage moderate the association between social networking sites (SNSs) usage and mental health: A meta-analysis. *Social Science Computer Review*, *37*(5), 631–648. https://doi.org/10.1177/0894439318784908

Yoon, S., Kleinman, M., Mertz, J., & Brannick, M. (2019). Is social network site usage related to depression? A meta-analysis of Facebook-depression relations. *Journal of Affective Disorders*, *248*, 65–72. https://doi.org/10.1016/j.jad.2019.01.026