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"Too much to handle": Impact of mobile social networking sites on information overload, depressive symptoms, and well-being

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ABSTRACT

Mobile social networking sites (SNS) are frequently theorized to lead to perceived information overload, which may affect the well-being of individuals in negative ways. However, the available body of research is mainly based on cross-sectional data. Based on the limited capacity model of motivated mediated message processing (Lang, 2002), we tested the over-time relationships between mobile SNS use, information overload, depressive symptoms, and well-being in a two-wave panel study. Using a quota sample of adults ($N_{T2} = 461$), we found that YouTube use increased perceived information overload for all individuals. WhatsApp and Snapchat use did only lead to perceived information overload for older adults. Facebook as well as Instagram use were unrelated to perceived information overload. Furthermore, perceptions of information overload were a significant predictor of depressive symptoms, which in turn, negatively influenced individuals' well-being over time. Implications of these findings are discussed.

1. Introduction

The rise of social networking sites (SNS) as well as the penetration of the smartphone into almost all areas of life have fundamentally changed the amount of information that individuals process on an average day. Literature suggests that individuals use their phone more than 2.5 h per day, oftentimes immediately after waking up, literally in any free available second (e.g., waiting for an elevator, during conversations, while driving a car), just before going to bed, or even during the night (Deng et al., 2018; Vorderer, Hefner, Reinecke, & Klimmt, 2018). Moreover, recent evidence from log data showed that users switch on average 101 times per day between apps, with mobile SNS being amongst the most popular apps (Deng et al., 2018). Mobile SNS are not only heavily used by young people, also adults increasingly use the smartphone to connect to friends, family, or colleagues (Pew Research Center, 2018; Vorderer, Hefner, Reinecke, & Klimmt, 2018). For adults, Facebook is still the most frequently used SNS, followed by the video-sharing site YouTube, and the photo-sharing platform Instagram (Pew Research Center, 2018).

In this context, Vorderer et al. (2018) have theorized that the permanent presence of the smartphone has formed a specific *Permanently Online and Permanently Connected* ("POPC") mindset in individuals. This mindset rests "on the assumption that attending to one's smartphone is possible and goal-serving virtually everywhere and anytime" (Klimmt, Hefner, Reinecke, Rieger, & Vorderer, 2018, p. 20). As Vorderer et al. (2018) argue, the individuals' online sphere is permanently present, which leads to a habitualized and active monitoring of the social network as well as a permanent communication among network members. On the one hand, mobile SNS use may empower individuals by opening up new avenues for cognitive performance, problem-solving or reducing feelings of loneliness (Klimmt et al., 2018; Rieger, Hefner, & Vorderer, 2017, pp. 161–177). On the other hand, the POPC mindset may also lead to feelings of being overwhelmed (Klimmt et al., 2018).

The overburdening stream of information, the permanent online interaction with other users, and the feeling that one's reactions are permanently observed as well as demanded may lead to what scholars have described as an "information overload" (IO) effect of mobile SNS use (Lee, Son, & Kim, 2016; Vorderer et al., 2018). In social science research, IO typically refers to a state in which a person perceives an

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imbalance between environmental demands and the available resources to respond to and cope with those demands (Eppler & Mengis, 2004). Other scholarly disciplines such as cognitive psychology focus more strongly on the acute phenomenon of IO, which can affect recall, judgment, and decision-making (e.g., Bargh & Thein, 1985). Following this definition, the limited capacity model of motivated mediated message processing (LC4MP) by Lang (2000) suggests that individuals have a limited amount of cognitive resources to process, store, and select mediated information. Grappling with the latest Facebook news, dealing with a backlog of tweets, or responding to numerous social demands by other network members can exceed the available capacities of users. Building upon this model, we assume that frequently experiencing a state of IO can manifest itself in a prolonged phenomenon of perceived IO reflecting a perceived imbalance between the environmental demands, that is, messages and information received on one's smartphone, and one's available resources to cope with those demands (Eppler & Mengis, 2004). This setting may lead to a feeling of a loss of control and stress, and ultimately, depressive symptoms and life dissatisfaction (e.g., Primack et al., 2017; Reinecke et al., 2016).

As predictors of IO, scholars have pointed to the role of information and system characteristics (Lee et al., 2016), social media efficacy (Schmitt, Debbelt, & Schneider, 2017), or push notifications (Schmitt et al., 2017). Other researchers looked at the consequences of IO, such as lowered self-esteem (Chen & Lee, 2013), depression (Baker & Algorta, 2016), or distress (Chen & Lee, 2013). Although these empirical findings have significantly contributed to our understanding of IO, some pressing research gaps remain.

First, none of the studies we are aware of have investigated the role of different types of mobile SNS on IO. Researchers have either exclusively focused on one SNS (e.g., Facebook; Chen & Lee, 2013, Twitter; Liang & Fu, 2017) or have measured overall SNS use while not differentiating between different platforms (e.g., Liu & Ma, 2018; Primack et al., 2017; Shensa et al., 2017). However, SNS differ in the amount of information, the habitual necessity of an immediate response to due read receipts, the underlying motivations, or the visibility of additional information due to automatic recommendations. Therefore, we need to distinguish the most prominent SNS (i.e., Facebook, Instagram, Snapchat, WhatsApp, YouTube; see Pew Research Center, 2018) and examine their roles for IO.

Second, the role of age in creating overload as a consequence of mobile SNS use has been neglected. The *Inhibitory Deficit Theory of Cognitive Aging* (Hasher & Zacks, 1988) suggests that age plays a key role in explaining how individuals react to technology-induced interruptions. That is, older users may exhibit more mobile SNS-induced IO than younger ones. However, the majority of studies have either employed student samples (e.g., Cao & Sun, 2018; Chen & Lee, 2013; Lee et al., 2016; Liu & Ma, 2018; Shensa et al., 2017; cf.; Chan, 2015) or studied young adults (Primack et al., 2017). Given that mobile SNS use is no longer limited to young people (Pew Research Center, 2018), we need studies on the entire adult population.

Third, most studies have investigated single outcomes of SNS use *or* IO, such as stress (Chen & Lee, 2013; Lee et al., 2016) or depression (Primack et al., 2017; Shensa et al., 2017). Thus far, none of the studies we are aware of has looked at the chain of relationships between SNS use, IO, and depressive symptoms or the consequences of these constructs for individuals' well-being. Moreover, almost all studies have relied on cross-sectional designs, which cannot establish a temporal or causal order of the relationships found. Therefore, we need to assess SNS use, IO, and depressive symptoms in a panel setting. To address those research gaps, the current study investigated the impact of various mobile SNS on IO, depressive symptoms, and well-being with a quota sample of diverse age groups in a two-wave panel study.

2. Mobile SNS and information overload: A limited capacity perspective

According to the LC4MP (Lang, 2000), people have a limited capacity to encode, store, and retrieve information. When being exposed to mediated messages, individuals tend to use only as much cognitive energy as necessary to reach the processing goal. In this process, people can deliberately direct resources to specific stimuli depending on their relevance. However, the more energy individuals use at one level, the less is available for the other levels. In the case of simultaneous or competing tasks, individuals may divide their resources or not allocate enough resources to process one task.

The limited capacity model suggests that activation of individual's motivational system can affect the cognitive processing of media messages (Lang, Sanders-Jackson, Wang, & Rubenking, 2012). The motivational system consists of the appetitive and the aversive system that are associated with benefits or threats experienced with certain stimuli (Cacioppo & Gardner, 1999; Lang, 2006; Lang et al., 2012). Lang et al. (2012) explain that the appetitive or the approach system automatically reacts to motivationally positive stimuli and results in attentive behavior. The aversive or avoid system automatically reacts to motivationally negative stimuli and protects an individual from potential threats (Lang, 2006; Lang et al., 2012). In our study, perceived IO represents the potential harm, which individuals detect with too much incoming information. Based on the motivational dual system, the aversive system takes place when smartphone users are exposed to an overwhelming stream of information.

Translated to mobile SNS use, the LC4MP helps to derive two theoretical explanations for why mobile SNS use may induce IO. First, the sheer amount of information that individuals are confronted with on mobile SNS use may induce overload. Empirical findings support this reasoning. For instance, research shows that the amount of information and communication is growing with the intensity of SNS use and the number of SNS contacts is a significant predictor of excessive communication demands (e.g., Lee et al., 2016; Schmitt et al., 2017). The time and resources individuals have to complete those demands may simply not be sufficient. Thus, individuals may feel overwhelmed by the incoming stream of messages and feel unable to process and respond to those messages given the available resources, creating a feeling of IO.

The second reason is the simultaneous nature of several SNS activities and their interruption of other activities. Media multitasking refers to simultaneous exposure to several types of media content (Garaus, Wagner, & Bäck, 2017). Previous literature suggested that one medium is a primary focus of the individual and every concurrent medium is a secondary focus or task (e.g., Segijn, Voorveld, Vandeberg, Pennekamp, & Smit, 2017). Research has shown that smartphone use is often regarded as a second screen, or secondary task when being exposed to political information on television (Schaap, Kleemans, & Van Cauwenberge, 2018). Findings indicated that one of the main motivations for second screen use is pursuing further information. Moreover, multitasking may also refer to other activities than just media. Previous studies showed that mobile phone multitasking during learning or driving results in distraction (see review by Chen & Yan, 2016).

Furthermore, media multitasking implies task-switching activities that can be done on a single device (e.g., Yeykelis, Cummings, & Reeves, 2014). The smartphone offers ample possibilities to engage in media multitasking by using various SNSs, sometimes even simultaneously. For example, a user can have one SNS opened on the smartphone while receiving messages on another SNS which is shown in the form of a notification on the smartphone screen. This specific situation refers to multitasking because the attention is divided between the primary and secondary task within one device.

Moreover, individuals may allocate their resources to a primary task, related or unrelated to a SNS. They then may, either as a habitual checking or prompted by a SNS notification, allocate their attention to a secondary task with only spare capacity left for the primary task. The capacity needed for the secondary task is taken away from a primary task. However, to complete the primary task, individuals need to allocate their resources back to this task, which may require additional resources because the information stored (i.e., when the task was abandoned) needs to be retrieved again. With mobile SNS use, switching between *several* tasks requires additional cognitive resources. Thus, SNS use may inhibit or slow down the completion of primary tasks, leading to a situation in which there appear to be too many tasks to complete simultaneously (Stephens & Rains, 2011). As a consequence, individuals may experience IO. It is important to note that IO refers to the subjective impression of being "burdened by large amounts of information received at a rate too high to be processed efficiently" (Misra & Stokols, 2012, p. 739). In the research literature, IO is thus conceptualized as a perception, rather than an objective state (Misra & Stokols, 2012).

The scarce body of literature lends some first support for this reasoning. Using a cross-sectional survey with a college student sample, Chen and Lee (2013) showed that Facebook use was positively correlated with communication overload, which in turn predicted psychological distress. Studies on news exposure, however, yielded conflicting results. On the one hand, Holton and Chyi (2012) investigated how different platforms influence IO among news consumers. Their findings revealed that only Facebook use positively predicted IO. On the other hand, using a convenience sample of news users, Schmitt et al. (2017) found that none of the platforms investigated (i.e., Twitter, social networks in general, or blogs) increased IO. Although these are seminal studies, their cross-sectional nature limits the substantial conclusions we can draw from this research. To investigate the role of mobile SNS use on IO, we therefore need panel studies. Moreover, we need to distinguish different mobile SNS to understand why several SNS may lead to overload, and why they may not. The majority of U.S. adults use Facebook and YouTube, whereas younger adults (18- to 24-year-olds) also have a strong preference for Instagram and Snapchat (Pew Research Center, 2018). In Germany, where the study has been conducted, WhatsApp represents the most popular messaging app among the population of 14 years and older (Bitkom, 2018). Typically, smartphone users are involved in multiple simultaneous interactions and they use a range of strategies to manage attention between them (Birnholtz, Davison, & Li, 2017).

On a more general level, we distinguish between instant messaging platforms (i.e., WhatsApp and Snapchat), newsfeed-based platforms (i.e., Facebook and Instagram), and a video-sharing platform (i.e., YouTube). We hypothesize that SNS platforms in general can increase IO over time, although they may differ with respect to their underlying motivations. In what follows, we present a theoretical and empirical rationale for each of the platforms investigated.

2.1. Instant messaging platforms

WhatsApp is a mobile phone-based messaging application. Notifications from instant messaging platforms might foster a "checking-habit", which has been defined as brief, repetitive inspection of content quickly available on the smartphone (Oulasvirta, Rattenbury, Ma, & Raita, 2012). Push notifications typically come with an (audio)visual cue and—depending on the app and the individual setting—might induce the feeling that an immediate reaction is necessary (Oulasvirta et al., 2012). Snapchat has been defined as a time-limited instant messaging service that allows ephemeral social interaction (Piwek & Joinson, 2016). British college students indicated that they use Snapchat primarily to communicate with a single person rather than with a group of people (Piwek & Joinson, 2016). In contrast to Facebook, Snapchat users tend to communicate with a smaller and rather close social network, mostly for sending and receiving selfies (Piwek & Joinson, 2016). Snapchat has no specific affordances for aggregated social feedback (i.e., "Like"-Buttons on Facebook and YouTube, "Love"-Button on Instagram). Similar to WhatsApp, the sender gets informed about who has seen the message. However, since the received messages are only available for a limited amount of time, individuals might feel the urge to check the message, before it disappears. In terms of a limited capacity perspective, WhatsApp and Snapchat may lead to perceived IO due to the sheer amount of messages, the interruption of a primary task by a message, and the perception that an immediate response is socially expected. We therefore hypothesize that:

H1a. Mobile WhatsApp use increases perceived IO over time.

H1b. Mobile Snapchat use increases perceived IO over time.

2.2. Newsfeed-based platforms

Facebook and Instagram can be regarded as newsfeed-based platforms. They are primarily used for the exchange of information on public walls, although both social networks also allow private communication or communication to a limited group of persons (Quan-Haase & Young, 2010). Users can receive push notifications on mobile phones. Usually, they watch and see information on individuals they follow, but users can also post and share information themselves. The Facebook newsfeed, for example, may include updates from friends, from liked pages, from shared groups, or information about important events or news selected by the algorithm. Instagram can be regarded as an image-based platform, that is, users post photos and videos to their profiles. Similarly to Facebook, people can follow other individuals, companies, or organizations. In addition, users can tag others on their images and label their posted content with hashtags. Recently, both Facebook and Instagram launched a new feature, which allows users to post ephemeral content (i.e., text, pictures, videos). IO can occur when users struggle to keep up with the seemingly endless stream of incoming information present in a newsfeed, especially when users are unable to follow the updates in realtime and need to catch up later on about what they have potentially missed. Furthermore, users may want to separate relevant from irrelevant information by scrolling and working through the newsfeed, which arguably requires considerable cognitive resources. We therefore hypothesize that mobile Facebook and Instagram use cause perceived IO:

H1c. Mobile Facebook use increases perceived IO over time.

H1d. Mobile Instagram use increases perceived IO over time.

2.3. Video-sharing platform

According to a recent study, there are three main gratification purposes of the video-sharing site YouTube: information, pleasure/entertainment, and individual learning (Klobas, McGill, Moghavvemi, & Paramanathan, 2018). Users can watch and upload videos, although most users watch and only a few produce content (Purcell, 2013). Popular video bloggers on YouTube (i.e., YouTube celebrities) have a large group of followers and create and post videos regularly. In response, users may experience the urge to be up-to-date and see their latest uploads. The content available on YouTube is seemingly endless because anybody can create and share a video on any given topic (Balakrishnan & Griffiths, 2017). Users may find it difficult to select the appropriate videos in the first place and then watch them entirely without jumping to the next one. Obviously, one can only watch one video at a time, but the fact that there is a multitude of others is immediately salient. Moreover, the auto-play feature by YouTube allows for continuous watching of videos, in which YouTube algorithms select which video will be played next. The constant and continuous stream of information on YouTube increases the time spent by users on the platform, which may not only foster addictive behavior but also result in perceived IO among users (Balakrishnan & Griffiths, 2017; Cao & Sun, 2018). Together, the specific affordances of YouTube may create the impression that the available time and resources are not sufficient to process the amount of information present on YouTube. We therefore hypothesize:

H1e. Mobile YouTube use increases perceived IO over time.

2.4. The role of age

Since information processing capabilities vary with age (Park, 2000), there are grounds to assume that age is a key moderator for the relationship between mobile SNS use and IO. According to the Inhibitory Deficit Theory of Cognitive Aging (Hasher & Zacks, 1988; also referred to as the Inhibitory Deficit Hypothesis; Weeks & Hasher, 2018), our ability to suppress the processing of distracting thoughts declines with age. Inhibitory processes enable individuals to regulate their thinking by suppressing the activation of irrelevant information (Weeks & Hasher, 2018). The theory posits that distractions gain more access to mental resources for older people compared to younger people. In other words, older individuals react differently to distractions than their younger counterparts. To provide an example, imagine the situation where we look at a menu in a restaurant. We typically try to memorize our choices before we are called to place an order (i.e., primary task). Once we made our choice, this information is stored in our working memory. Now a distraction (i.e., a secondary task), for instance, when we talk to someone while waiting for the waiter to come, may inhibit the retrieval of the original information from the working memory. In this sense, older individuals are more vulnerable to such distractions when performing their primary task compared to younger ones. This means, there is a greater interference of the distraction (i.e., the secondary task) on the primary task. As Weeks and Hasher (2018) put it, "if older adults automatically and involuntarily encode a broad range of relevant and irrelevant information at study, their explicit memory may be more vulnerable to the disruptive effects of interference than that of younger adults" (p. 9). This view has important implications for the effects of mobile SNS use on IO. Given that older individuals' performance of a primary task is affected by a secondary task to a greater extent compared to younger individuals, and mobile SNS provide numerous distractions, IO should occur more likely for older than for younger individuals.

This hypothesis also coincides with the general age-related decline in cognitive functioning (Park, 2000). Older adults have fewer mental resources to perform mental tasks than younger individuals. Ziefle and Bay (2005), for instance, show that older smartphone users have a lower navigation performance than younger users. The reason is that older users often need a considerable amount of mental resources to navigate the smartphone (e.g., identifying what button to push or finding the correct operating functions), and as a result, fewer resources are available for the primary task. Together, the theory suggests that older mobile SNS users should be more likely to experience a perceived imbalance between the environmental demands provided by SNS and their available resources to cope with those demands. That is, they should be more likely to demonstrate perceived IO compared to younger ones.

H2. The influence of mobile (a) WhatsApp, (b) Snapchat, (c) Instagram, (d) Facebook, and (e) YouTube use on perceived IO increases with rising age.

3. Information overload, depressive symptoms, and well-being

A large body of literature suggests that perceived IO leads to a chain of negative outcomes, such as psychological stress (e.g., Lee et al., 2016; Reinecke et al., 2016), exhaustion (Cao & Sun, 2018), anxiety (e.g., Bawden & Robinson, 2008), negative affect (LaRose, Connolly, Lee, Li, & Hales, 2014), or decreases in work performance (e.g., Karr-Wisniewski & Lu, 2010). Other researchers have shown that excessive SNS use (Liu & Ma, 2018) leads to social media fatigue, which is defined as a negative emotional reaction to SNS such as burnout, tiredness, and boredom. All of the suggested outcomes are aspects of negative affect and typically relate to symptoms of depressive states (Radloff, 1977). Therefore, the findings indicate that there might be a significant association between IO and depressive symptoms.

Other studies have directly looked at depressive symptoms as a consequence of SNS use (e.g., Baker & Algorta, 2016; Primack et al., 2017). It is important to stress that depressive symptoms—also referred to as minor depression—should not be equated with a major depressive disorder (Rapaport et al., 2002). They are milder in symptomatology or duration compared to a depressive disorder and can be defined as "nonpsychotic episodes of illness in which the most prominent disturbance is a relatively sustained mood of depression without the full depressive syndrome" (Spitzer, Endicott, & Robins, 1978, p. 773). Using a cross-sectional sample of 19- to 32-year-old adults, findings by Shensa et al. (2017) suggest that excessive use of SNS may lead to depression. Additionally, usage of more than seven social media platforms has been related to a higher probability of increased depressive symptoms, in comparison to using just a few social media channels (Primack et al., 2017).

However, the relationship between SNS and depressive symptoms may be due to several underlying processes (i.e., social comparison or cyberbullying), with IO only being one. IO signals the individuals that the information processing demands of the environment cannot be met. This feeling, in turn, creates stress which has been found to be one key predictor of depression (Reinecke et al., 2016). Yet, despite the consistent empirical evidence demonstrating a positive relationship between perceived IO, caused by SNS use, and depressive symptoms, the change of this relationship over time has not yet been examined longitudinally. Therefore, the temporal order of the two constructs has not yet been established. We thus propose the following hypothesis:

H3. Perceived IO positively predicts depressive symptoms over time.

Finally, depressive symptoms, such as a depressed mood or the absence of positive affect, can also have consequences for individuals' well-being more generally. Well-being is usually assessed by subjective well-being indicators, such as life satisfaction or quality of life (Diener, Oishi, & Tay, 2018). It encompasses individuals' feelings to consider their current life as close to their general ideals and to be generally satisfied with what they have achieved in life. Well--being—conceptualized as life satisfaction—arguably evolves more over the long-term compared to depressive symptoms. It depends on various factors such as relationship quality, wealth, or health of an individual (e.g., Edwards & Klemmack, 1973). Yet, there is strong evidence to assume that the occurrence of depressive symptoms in response to technology use will impact an individuals' general well-being (e.g., Bargeron & Hormes, 2017). Again, since both concepts can be theorized to be highly correlated, it is crucial to determine the temporal order of this relationship. We therefore hypothesize:

H4. Depressive symptoms will negatively predict individuals' well-being over time.

In sum, the current study aims to investigate the relationships between mobile SNS use, perceived IO, depressive symptoms, and well-being. Moreover, the moderating role of age will be studied. Fig. 1 displays the hypothesized model.

4. Method

4.1. Sample and procedure

We conducted a two-wave panel survey with a four-month-interval in March/April 2018 (= T1) and July/August 2018 (= T2). Participants were contacted via a private polling institute to participate in a study on smartphone use and SNS use. A quota sample was used, stratified by age, gender, and educational level in Germany. Possession of an internet-enabled mobile phone (i.e., a smartphone) and prior SNS use (i.e., at least once) were considered as eligibility criteria to participate in the study. A total of $N = 833$ participants (54.1% women, $M_{age} = 45.44$, $SD = 14.83$) completed the study in the first wave, and $N = 461$

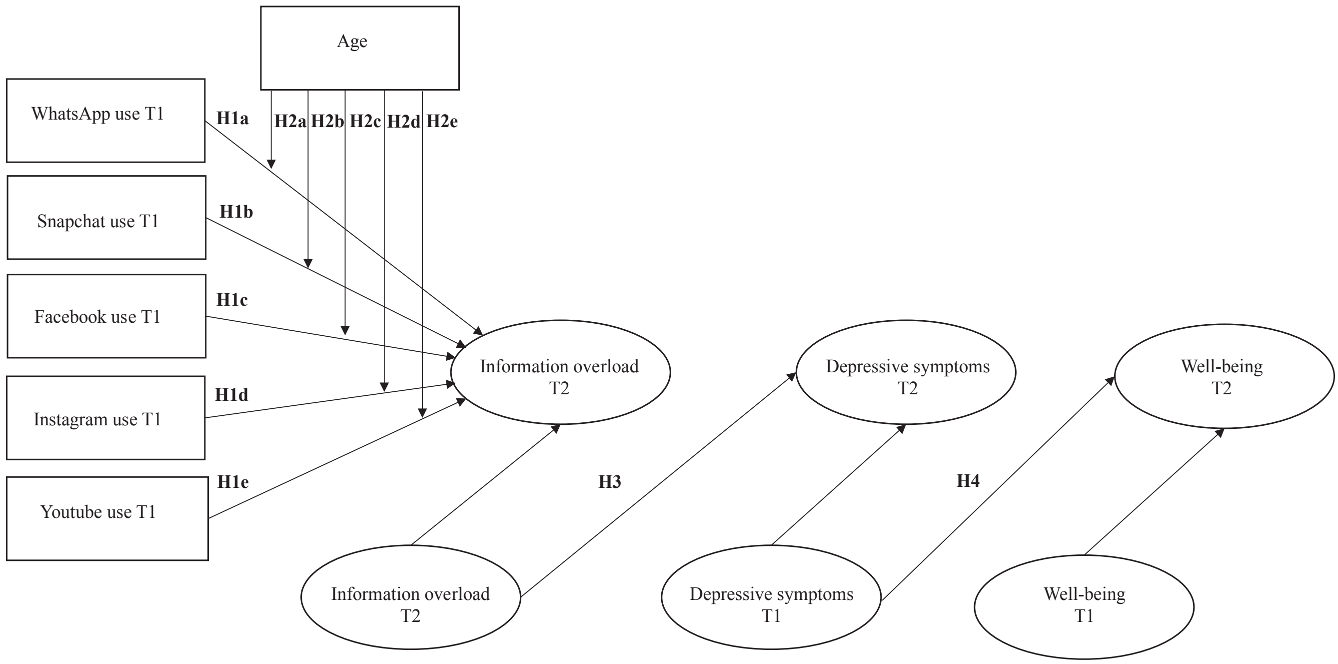

Fig. 1. Model examining the relationships between different types of mobile SNS use, age, information overload, depressive symptoms, and well-being.

participants (53% women, M_{age} = 48.65, SD = 13.02) in the second wave. The attrition rate was 45% for T2. Participants who dropped out at T2 used WhatsApp, $F(1,825) = 6.41$, $p = .012$, Facebook $F(1,824) = 7.76$, $p = .005$, Snapchat $F(1,802) = 23.31$, $p < .001$, YouTube, $F(1,819) = 21.01$, $p < .001$, and Instagram $F(1,809) = 26.61$, $p < .001$, more frequently, and indicated higher levels of IO, $F(1,831) = 10.74$, $p = .001$, and depressive symptoms at T1 $F(1,831) = 8.06$, $p = .005$. The respondents who dropped out at T2 did not show any difference with regards to well-being at T1 $F(1,831) = 0.62$, $p = .433$. The current paper uses data that is part of a larger study project that examines the links between smartphone use and well-being. More information about the study project can be obtained from the first author.

4.2. *Measures*

4.2.1. *Mobile SNS use*

The respondents indicated on a 6-point Likert scale how often they use particular SNS on their smartphones: "*never*", "*rarely*", "*about once a week*", "*several times a week*", "*daily*", "*several times during the day*". Specifically, we assessed the use of WhatsApp (T1: $M = 4.86$, $SD = 1.42$; T2: $M = 4.7$, $SD = 1.52$), Facebook (T1: $M = 3.44$, $SD = 1.98$; T2: $M = 3.21$, $SD = 1.99$), Instagram (T1: $M = 2.21$, $SD = 1.82$; T2: $M = 1.97$, $SD = 1.67$), Snapchat (T1: $M = 1.58$, $SD = 1.31$; T2, $M = 1.34$, $SD = 0.99$), and YouTube (T1: $M = 2.77$, $SD = 1.63$; T2: $M = 2.5$, $SD = 1.58$). We selected the mobile SNS based on their popularity (Bitkom, 2018; Pew Research Center, 2018).

4.2.2. *Information overload*

We measured perceived IO due to mobile phone use across situations. We asked the participants to indicate their agreement on three items on a 5-point Likert scale: "*strongly disagree*", "*disagree*", "*uncertain*", "*agree*", "*fully agree*". We adapted the original items by Karr-Wisniewski and Lu (2010) to fit them to the topic of our study: "I often have the feeling that I get too much information on my mobile phone to make a good decision."; "I find that I am overwhelmed by the amount of information I have to process on my mobile phone on a daily basis."; "I am often distracted by the excessive amount of information available to me due to my mobile phone." (T1: α = 0.87, $M = 2.43$, $SD = 1.03$; T2: α = 0.85, $M = 2.24$, $SD = 1.02$).

4.2.3. *Depressive symptoms*

We asked the participants to indicate how they felt during the past week using a 5-point-Likert scale ("*strongly disagree*" – "*fully agree*"). We used four items from the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977): "I was bothered by things that usually don't bother me."; "I had trouble keeping my mind on what I was doing."; "I felt depressed."; "I felt fearful." (T1: α = 0.84, $M = 2.49$, $SD = 1.00$; T2: α = 0.84, $M = 2.41$, $SD = 1.00$).

4.2.4. *Well-being*

We assessed well-being with all five items from the Satisfaction with Life Scale (SWLS; Diener, Emmons, Larsen, & Griffin, 1985). The respondents indicated their agreement on a 5-point Likert scale ("*strongly disagree*" – "*fully agree*") with the following statements: "In most ways my life is close to my ideal"; "The conditions of my life are excellent"; "I am satisfied with my life"; "So far I have gotten the important things I want in life"; and "If I could live my life over, I would change almost nothing"; (T1: α = 0.90, $M = 3.18$, $SD = 0.91$; T2: α = 0.89, $M = 3.27$, $SD = 0.90$).

4.2.5. *Socio-demographic variables*

We included the key socio-demographic measures of age (T1: $M = 45.44$ years, $SD = 14.83$; T2: $M = 48.65$ years, $SD = 13.02$), gender (54.1% women), and educational level (34.3% indicated possessing a high school degree) as control variables.

4.3. *Data analysis*

Using the *lavaan* (Rosseel, 2012) package in R, we conducted Structural Equation Modeling with full information maximum likelihood procedure to estimate the missing values. The comparative fit index (CFI), the Tucker-Lewis-Index (TLI), the chi-squared to degrees of freedom ratio (χ^2/df), and the root mean square error of approximation (RMSEA) were used to determine the goodness-of-fit of the model. We controlled for gender, age, and educational level (dummy-coded: below high school degree vs. high school degree or higher degree). We also controlled for autoregressive relationships (e.g., IO at T1 as a predictor of IO at T2).

Before testing the proposed hypotheses and answering the research question, we checked for *longitudinal measurement invariance* of all outcome variables (Vandenberg & Lance, 2000). Without evidence of measurement invariance (i.e., in path analysis), the observed relations may stem from changes in meaning over time. For each construct, we constrained all factor loadings and intercepts of the latent variables at T1 and T2 as equal to test for measurement invariance. The model fit of the constrained model revealed a good model fit: CFI = 0.98; TLI = 0.97; χ/df = 1.92, p < .001; RMSEA = 0.03, 90%-CI [0.03; 0.04]. When comparing the constrained model to the unconstrained model, we found no significant difference between IO at T1 and T2 (p = .929), depressive symptoms at T1 and T2 (p = .304), and well-being at T1 and T2 (p = .064). Thus, metric and scalar invariance over time were established for the constructs.

5. Results

Table 1 shows the zero-order-correlations, and Table 2 and Fig. 2 display all main results. The hypothesized model indicated a good model fit, CFI = 0.95; TLI = 0.94, χ^2/df = 2.12, p < .001; RMSEA = 0.04, 90%-CI [0.03; 0.04]. Answering H1a, the findings showed that frequent WhatsApp use at T1 predicted perceived IO at T2, b = 0.06, SE = 0.03, β = 0.10, p = .038. Furthermore, frequent use of YouTube (T1) also predicted perceived IO (T2), b = 0.06, SE = 0.03, β = 0.12, p = .044, which confirmed H1e. We found no other significant relationships between Snapchat use 09; T1, b = 0.08, SE = 0.05, β = 0.12, p = .092), Facebook use (H1c; T1, b = 0.01, SE = 0.02, β = 0.01, p = .667), or Instagram use (H1d; T1, b = −0.06, SE = 0.03, β = −0.13, p = .056) and perceived IO (T2). Thus, our findings do not support H1b, H1c, and H1d.

In our second hypothesis, we assumed that the influence of mobile SNS use on perceived IO increases with rising age. To test this hypothesis, we separately included the interaction terms of age and mobile SNS channels in our structural equation model (not shown in Table 2 and Fig. 2). All other predictors were the same as in Table 2. In line with H2a, we found a significant interaction between WhatsApp use and age on perceived IO (T2), b = 0.00, SE = 0.00, β = 0.45, p = .043. We probed the interaction by using the factor scores of the variable perceived IO (T2). A Johnson-Neyman analysis (Hayes & Matthes, 2009; Long, 2018) revealed that there was a significant interaction of WhatsApp use on perceived IO for those over 48.34 years (see Fig. 3). For the younger ones, the association between WhatsApp use and perceived IO (T2) was not significant. The direct association found for H1a can thus not be interpreted anymore.

A similar pattern occurred for the model testing H2b: There was a significant positive interaction of Snapchat use and age on perceived IO (T2), b = 0.01, SE = 0.00, β = 0.30, p = .013. Probing the interaction using the factor scores of the variable perceived IO (T2), revealed a significant association of Snapchat use on perceived IO for those over 40.55 years (see Fig. 4). For those younger than that age, we found no significant association of Snapchat use on perceived IO.

For the remaining mobile SNS, we found no significant interactions. We had to reject H2c, as we found no significant interaction for Facebook use and age on perceived IO (T2), b = 0.00, SE = 0.00, β = 0.19, p = .246. The same was true for Instagram use (H2d; T2, b = 0.00, SE = 0.00, β = 0.10, p = .453) and YouTube use (H2e; T2, b = 0.00, SE = 0.00, β = 0.16, p = .261).

Our third hypothesis postulated that perceived IO (T1) would positively predict individuals' depressive symptoms (T2). The results confirmed H3 by showing that perceived IO (T1) predicted higher levels of depressive symptoms (T2), b = 0.08, SE = 0.04, β = −0.11, p = .039. Additionally, we found a direct significant negative association of YouTube use (T1) on depressive symptoms (T2), b = 0.07, SE = 0.03, β = 0.15, p = .008.

We postulated in H4 a positive relationship between users' depressive symptoms and their overall well-being. We found that depressive symptoms (T1) positively predicted lower levels of well-being (T2), b = −0.03, SE = 0.06, β = −0.20, p < .001, thus confirming H4. Furthermore, we also found a direct negative influence of Instagram use (T1) on depressive symptoms (T2), b = −0.05, SE = 0.02, β = −0.10, p = .044. Looking at the covariates, we found no influence of gender, age, or educational level (low vs. high) on perceived IO, depressive symptoms, or well-being.

5.1. Additional analyses

Building upon previous research showing nonlinear effects between digital screen time and well-being (Przybylski & Weinstein, 2017), we conducted nonlinear analyses between the main independent variables (i.e., mobile SNSs use at Time 1) and the dependent variable (i.e., IO at Time 2). To account for a curvilinear relationship, we conducted several quadratic regressions (Hayes, 2005). For each of the five mobile SNSs we squared a predictor variable. We included the original, the squared variable, the autoregressive relationships, and the control variables in the quadratic regression models.

The quadratic regressions showed no statistical significance for the association between WhatsApp use (T1) and perceived IO (T2), b = −0.01, p = .28, between Facebook use (T1) and perceived IO (T2), b = 0.01, p = .29, between Instagram use (T1) and perceived IO (T2), b = 0.02, p = .20, between Snapchat use (T1) and perceived IO (T2), b = 0.01, p = .63, and between YouTube use (T1) and perceived IO (T2), b = 0.01, p = .42. Therefore, our additional analyses revealed that there are no nonlinear associations between the five mobile SNS platforms and perceived IO.

To rule out potential confounding variables, we also ran our model controlling for individuals' perceived smartphone literacy ("How competent do you feel about using your smartphone?"), as higher competence might be associated with less IO. However, when controlling for smartphone literacy, we still find significant relationships between YouTube use and WhatsApp use and IO. Additionally, the relationships between IO and depressive symptoms as well as between depressive symptoms and well-being remain significant. Also, the

Table 1
Zero-order-correlations of the key variables.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. WhatsApp use (T1)	1										
2. Snapchat use (T1)	.19**	1									
3. Facebook use (T1)	.29***	.21***	1								
4. Instagram use (T1)	.28***	.57***	.40***	1							
5. YouTube use (T1)	.25***	.43***	.40***	.50***	1						
6. Information overload (T1)	.15***	.22***	.26***	.25***	.27***	1					
7. Information overload (T2)	.19***	.22***	.22***	.17***	.29***	.51***	1				
8. Depressive symptoms (T1)	.19***	.22***	.22***	.17***	.29***	-.31***	.25***	1			
9. Depressive symptoms (T2)	.02	.08	.11*	13**	.20***	−26***	-.36***	.55***	1		
10. Well-being (T1)	.06	.02	-.03	-.04	-.09*	-.01	-.09	-.36***	-.44***	1	
11. Well-being (T2)	.04	.04	-.06	-.10*	-.07	-.07	-.07	-.46***	-.40***	.74***	1

Note. T1 = Time 1, T2 = Time 2. *p < .05, **p < .01, ***p < .01.

Table 2
Results of the hypothesized structural equation model based on the Full Information Maximum Likelihood procedure controlling for baseline assessments of the outcomes to assess residual changes.

Predictor	Information overload (T2)			Depressive symptoms (T2)			Well-being (T2)		
	b	SE	β	b	SE	β	b	SE	β
Gender	.02	.08	.01	-.09	.06	-.06	-.02	.06	-.01
Age	-.01	.00	-.10	-.01	.00	-.10	-.01	.00	-.09
Education (low vs. high)	-.03	.09	-.01	-.11	.07	-.07	-.06	.07	-.03
WhatsApp use (T1)	.06*	.03	.10	-.01	.02	-.02	-.00	.02	-.00
Snapchat use (T1)	.08	.05	.09	-.02	.04	-.04	.04	.03	.05
Facebook use (T1)	.01	.02	.01	-.01	.02	-.02	.01	.02	.02
Instagram use (T1)	-.06	.03	-.13	-.02	.03	-.05	-.05*	.02	-.10
YouTube use (T1)	.06*	.03	.12	.07**	.03	.15	.00	.02	.00
Information overload (T1)	.46***	.05	.52	.08*	.04	-.11	-.00	.04	-.00
Depressive symptoms (T1)	–	–	–	.58***	.07	.56	-.25***	.06	-.20
Well-being (T1)	–	–	–	–	–	–	.70***	.05	.69
Adj. R^2	.33			.40			.65		

Note. T1 = Time 1, T2 = Time 2. **p* < .05, ***p* < .01, ****p* < .001.

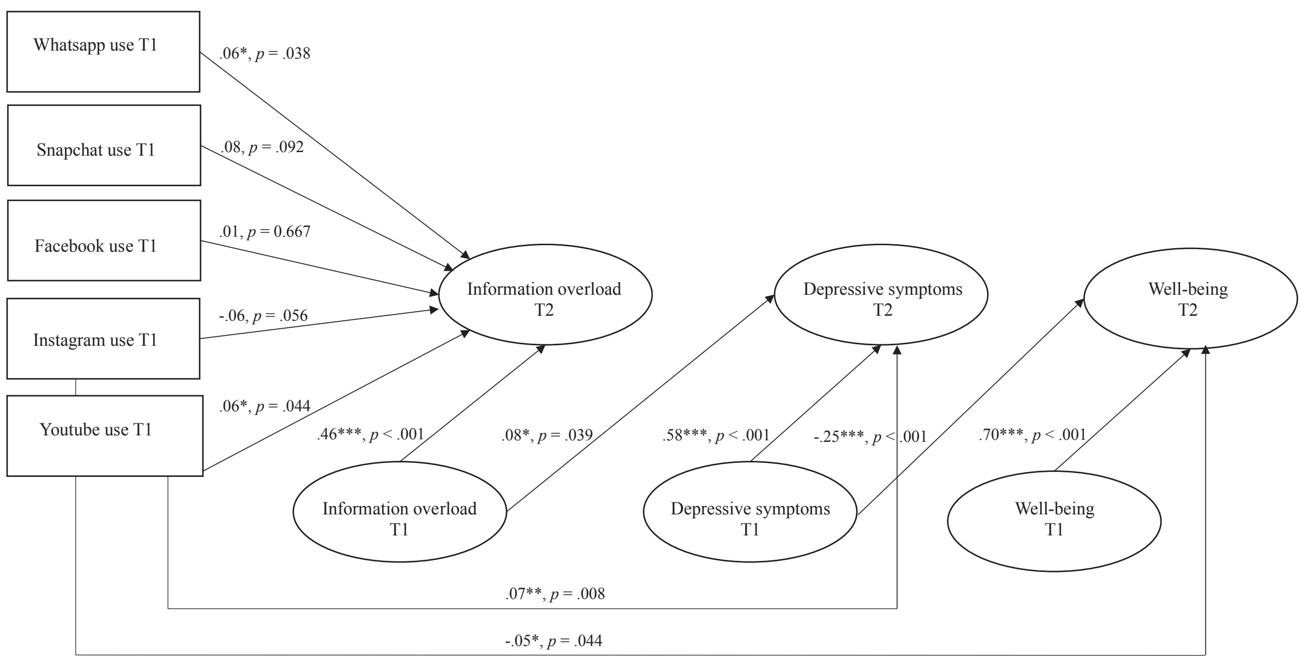

Fig. 2. Model examining the relationships between different types of mobile SNS use, information overload, depressive symptoms, and well-being. *Note*. Values reflect unstandardized coefficients. Rectangles reflect manifest variables, ovals reflect latent variables. For clarity, error terms, covariances, control variables, and measurement items are not shown. T1 = Time 1; T2 = Time 2. **p* < .05, ***p* < .01, ****p* < .001.

interaction effects with age remain significant. Furthermore, we aimed to rule out that the moderating relationship of age is due to a stronger integration of the smartphone in peoples' lives. Thus, we ran the model controlling for excessive smartphone use using three items ("Even if I am busy with something else, I often look at my mobile phone or check messages, I often think of my mobile phone when I'm doing something else, If I see the mobile phone lying somewhere or get a message, then I just have to look at it – there's no other way", Cronbach's α = .83). When controlling for excessive smartphone use, the main effects found in the original model and the interaction effects with age remain robust.

6. Discussion

Informed by a LC4MP perspective, we demonstrated, first of all, that YouTube use had a significant direct influence on IO. This finding may be explained by the sheer amount of available videos on any given topic. Either when users search for information, or when they receive automatic alerts from the channels they subscribed to, it becomes immediately salient that there are more videos than one can process. This impression is most likely caused by the automated recommendation window, which suggests additional videos based on prior selections. Additionally, a study by Pew Research (2018) found that the YouTube recommendation system suggests users progressively longer and more popular content in each round of recommendations (Smith, Toor, & van Kessel, 2018), which may lead to users' prolonged YouTube consumption, which has also been referred to as "YouTube stickiness" (Chiang & Hsiao, 2015, p. 91). Findings from previous research suggest that both content viewing and content creation on YouTube is associated with excessive and problematic usage patterns (Balakrishnan & Griffiths, 2017). Our findings corroborate these results by showing that the constant and continuous stream of information on YouTube does not only increase the potential for addictive behavior but also result in a sense of perceived IO due to being exposed to a list of recommended videos and not having sufficient time to process all the available information (Cao & Sun, 2018). Furthermore, YouTube mainly hosts audiovisual material which generally is more information-dense than visual-only or audio-only information (Bergen, Grimes, & Potter, 2005). It is important to note that the association of YouTube use on IO does not depend on age

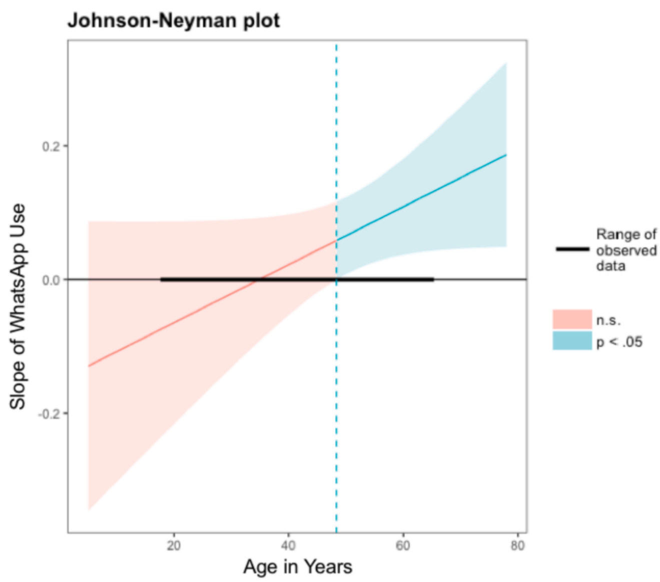

Fig. 3. Johnson-Neyman plot for the interaction of WhatsApp use and age on perceived information overload.

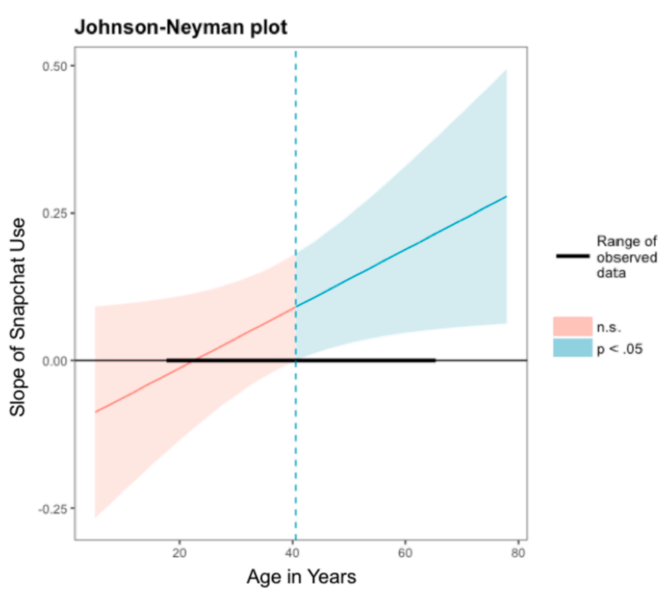

Fig. 4. Johnson-Neyman plot for the interaction of Snapchat use and age on perceived information overload.

suggesting that the endless stream of available videos signals older and younger users alike that they don't have the available resources to process the information they would like to process.

When it comes to instant messaging platforms, we found significant associations depending on the users' age. Older individuals experienced more IO when using WhatsApp and Snapchat compared to younger ones. As explained by the Inhibitory Deficit Theory of Cognitive Aging (Hasher & Zacks, 1988), older individuals' capabilities to complete primary tasks are more affected by distractions compared to their younger counterparts. When receiving a notification on WhatsApp, for instance, there may be a habitualized impulse to check and respond to the prompt (Oulasvirta et al., 2012). Typically, the sender of a message can see whether the message has been received and read, which might result in a social norm to respond immediately. Although we have no data on this social norm, it can be assumed that the impulse to read and respond is equally strong for younger and older adults. Checking a WhatsApp notification, however, may affect the original task more for older than for younger individuals. The reason is an inhibitory deficit in older adults, that is, they struggle to suppress the activation of irrelevant information (i.e., the WhatsApp notification) for the primary task. As a consequence, more resources are needed to complete the primary task making IO more likely. It is also important to note that these relationships were independent of individuals' smartphone literacy and excessive smartphone use.

In contrast to video-sharing and instant messaging platforms, we found no associations of IO for newsfeed-based platforms such as Facebook and Instagram. Although we have no data at hand on whether our respondents saw videos or images on Instagram, unlike on YouTube, Instagram users are not exclusively exposed to videos, but also to images because Instagram is "intended for mainly image sharing" (Thelwall & Vis, 2017, p. 703). Images are arguably easier to process compared to texts and videos. This may inhibit the impression of IO. Rephrased, one can easily scroll through 1000 images but not through 1000 texts or videos.

Furthermore, on Facebook, Instagram, or WhatsApp information is typically provided by friends or people who know each other personally. One may argue that individuals perceive the posted information as personally relevant and therefore such content prevents the impression of IO. The study by Beaudoin (2008), for instance, supports this reasoning. The findings suggest that the motivation to use the Internet for social purposes negatively predicts IO. Thus, we assume that the use of and exposure to personally relevant SNS content is less likely to induce IO among users. However, we did find that WhatsApp positively predicts IO for older adults presumably due to highly private communication, i.e., the content is not broadcasted to the public but only to selected contacts (e.g., Thelwall & Vis, 2017). Older individuals might feel obliged to respond to incoming messages because of the strong personal connections which results in IO. Future research is needed to confirm this explanation. Facebook and Instagram require no immediate reactions when compared to instant messaging services. This factor may additionally inhibit overload.

As additional findings, and in line with previous cross-sectional research, our data revealed a positive association of IO on depressive symptoms, which in turn, negatively predicted well-being over time. Previous research suggests that feeling overwhelmed by accessibility demands due to one's mobile phone increases the risks of stress, sleep disturbances, and symptoms of depression over time—all factors that are crucial for individuals' overall well-being (Thomée, Härenstam, & Hagberg, 2011). Additionally, our findings confirm the association between depressive symptoms and well-being that has been repeatedly shown in other domains of technology use such as using computer games (Bargeron & Hormes, 2017; Mentzoni et al., 2011). We also observed two direct associations which we did not hypothesize in our model: There was a significant positive direct association between YouTube use and depressive symptoms as well as a negative association between Instagram use and well-being. These findings suggest the presence of other mediators unrelated to IO, such as, for instance, social comparison.

6.1. Limitations and suggestions for future research

Some limitations must be noted. First, although we used an autoregressive panel study controlling the prior states of our dependent variables, we would like to highlight the fact that we cannot estimate mediated paths over time with two panel waves only. From the perspective of panel analysis, however, we can establish longitudinal associations between an independent and a dependent variable separately, while controlling for all other variables. In contrast to cross-sectional research, this analysis can be considered as more conservative and therefore superior. In future research, a study using a minimum of four panel waves should be employed to firmly establish whether the change over time between mobile SNS use, IO, depressive symptoms, and well-being is consistent. This design would also allow scholars to estimate the indirect association between mobile SNS use and well-being via perceived IO and depressive symptoms.

Second, we were unable to measure the specific activities that are performed while using each SNS. This is important because literature suggests that the relationship between SNS use and well-being depends on the specific type of use (e.g., Burke & Kraut, 2016). This also concerns the motivations of use. Related to that, our data do not allow assumptions about smartphone use as a primary or secondary task. Thus, we recommend including different types of SNS use, motivations of SNS use, and designs that incorporate primary and secondary smartphone use when investigating the postulated relationships.

Third, when it comes to older individuals, additional qualitative research is needed to understand *why* they experience overload in response to instant messaging platforms. This may also help us to understand how older individuals can be better equipped to deal with IO, preventing negative effects on well-being. Also, future research should extend the age range used in this study, because individuals above the age of 65 may show stronger or weaker associations. Finally, our study is limited to five different mobile SNS, which were the most frequently used SNS in Germany at the time of study. Other SNS such as Pinterest, Twitter, or LinkedIn should be taken into account in future research.

Fourth, from a methodological perspective, we relied on self-reports (Scharkow, 2019), as almost the entire body of research in this area. This type of measure is problematic because judging mobile SNS use is a demanding task due to the fragmented and scattered usage patterns across situations. However, self-reports are inevitable in the case of smartphone use. Due to data protection laws and privacy issues, it is difficult to obtain more specific smartphone use data by tracking smartphone use. Another important thing to consider is the possibility to provide a more specific frequency of use, i.e., screen time data. Not all of the smartphone users have the new updated software and applications which allow them to check their screen time. Some of the smartphone users might not even be aware of this function, e.g., older adults in our sample. Alternative measures such as log-data or mobile experience sampling should be applied in future research (Boase & Ling, 2013; Naab, Karnowski, & Schlütz, 2019). Also, the relationship between mobile SNS use and perceived IO should be studied in controlled experiments, to truly draw causal conclusions.

6.2. Theoretical and empirical implications

These limitations notwithstanding, we believe our findings bear several important implications. First, establishing an overtime relationship between mobile SNS use and negative outcomes such as IO is no doubt important. However, this view needs to be complemented by a more comprehensive perspective asking about the individual resources that help to tame the current information tide stemming from SNS. We need a better understanding of why some individuals react with IO and others do not. This, in turn, is the key to inform the public about how they can be equipped to deal with the endless stream of incoming information as well as with the POPC mindset. We believe such a view is largely missing in the area of mobile SNS use, yet it is highly overdue. This perspective encompasses a partial shift of our scholarly attention away from a *deficit perspective* of mobile SNS use to a *resources and coping perspective.* Therefore, existing theoretical models need to be advanced to understand the psychological processes and skills that may inhibit IO in adults.

More specifically, we need to improve our theoretical models as well as empirical designs when it comes to the role of age. Despite its relevance, the role of age has been ignored in extant research. We need to understand how the patterns and content of mobile SNS use differ between older and younger adults, and we need to study these questions in longitudinal designs tracking the developments of cohorts. Even if we find that older adults react with more IO in response to WhatsApp or Snapchat, this doesn't necessarily mean that they cannot overcome this effect. However, research is needed to improve our understanding of how older adults can be equipped with techniques, technical devices, and resources to prevent IO.

Third, although the relationship between SNS usage and IO is plausible and backed up with theory, we need to study the variety of practices that adults engage in when using mobile SNS leading to a focus on "content" instead of "use". Arguably, the content of SNS is more important than the specific platform under investigation. When it comes to Facebook, for example, overload may depend on the actual content that adults are exposed to. Some content may cause perceived IO, some may not. There may also be important differences in how visuals, videos, or texts affect overload. The same is true for affect-based or non-affective content. Thus, rather than asking if SNS cause negative outcomes, we should ask *when and why* such associations may occur by integrating the content of SNS in theoretical models and empirical studies.

7. Conclusion

Given that smartphone users tend to be permanently online and permanently connected, our study is the first to track how mobile SNS use can affect perceived IO and subsequent outcomes over time. We provided substantial evidence that the use of SNS can create perceptions of IO, especially for older adults. However, not all SNS lead to overload and not all respondents are affected equally. Overall, our findings underline the statement that the smartphone may not only empower individuals, it may also potentially overwhelm them and lead to negative outcomes. In particular, in a digital environment, the public needs to be made aware of the risks associated with IO due to SNS use on the one hand. On the other hand, SNS users may prevent falling victim to perceived IO by reflectively using SNSs, e.g., by regulating the time and frequency spent on SNSs with self-monitoring applications, which are nowadays readily available on many smartphones.

Author contributions

Jörg Matthes: Supervision, Conceptualization, Methodology, Writing - Reviewing and Editing, Kathrin Karsay: Conceptualization, Methodology, Writing - Original draft preparation, Writing- Reviewing and Editing, Desirée Schmuck: Conceptualization, Methodology, Formal analysis, Visualization, Writing - Reviewing and Editing., Anja Stevic: Formal analysis, Writing- Reviewing and Editing.

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