Social media usage, wellbeing and mental health during the COVID-19 pandemic.

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Abstract

During the unusual circumstances of the COVID-19 pandemic and the ongoing social distancing measures it is likely that different types of social media usage will have a unique connection to wellbeing and mental health. It has therefore been hypothesized that active social network service (SNS) usage positively predicts wellbeing and negatively depression and stress, while passive SNS usage is hypothesized to negatively predict wellbeing and positively depression and stress. A cross sectional study, analyzing the online self-report measures of a community sample (N = 173), was designed to answer this question. Zero-order correlations between the variables were assessed and six hierarchical regression analyses were conducted. Little support for the predicted hypotheses could be found. The only significant prediction found (β = .167) indicates that active SNS usage positively predicts depression. A near significant positive prediction of stress by active usage has additionally be discovered. Notably, no prediction and only a neglectable correlation between both types of SNS usage and satisfaction with life (SWL) could be found, indicating no connection. While this finding falls in line with previous research, it is rather surprising that active SNS usage predicts depression, as active SNS usage has been previously established to be no predictor or even a protective factor. It can therefore be concluded that during the COVID-19 crisis the connection between active social media usage and depression might have changed to the worse. Further studies will be needed to confirm the direction of this prediction and potential causality.

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During the currently ongoing coronavirus pandemic (COVID-19 pandemic – "Coronavirus Crisis") public health authorities have advised, or even legally obliged citizens to engage in social distancing (Wilder-Smith and Freedman 2020; e.g. RIVM 2020). Social distancing is a significant interruption of daily life, and it is therefore likely that it will also significantly influence the mental health and wellbeing of citizens that are affected by these measures (Venkatesh and Edirappuli 2020). This makes it also likely that in this changed environment, psychological relationships between different constructs that have been researched before, will have also changed.

Social Media Usage and Wellbeing during the COVID-19 pandemic.

One of these psychological relationships that might have changed is the relationship between SNS usage and wellbeing. Social networking sites (SNS) like Facebook, Twitter, Instagram, and LinkedIn have become increasingly popular (Ahmed 2011) and are a frequently researched topic. There are multiple proposed mechanisms how SNS usage affects wellbeing.

For example, one of these mechanisms that have been previously proposed suggests that smartphone and SNS usage undermine the emotional benefits one reaps from casual social interactions (Sandstrom and Dunn 2014; Leung and Lee 2005; Baumeister and Leary 1995) by acting as a source of distraction (Bell et al. 2015; Dwyer et al. 2018). However, it is likely that this effect which has been found in a "normal" environment, will have changed during times of social distancing.

This change can be suggested as social distancing makes it difficult for individuals to reap the positive emotional benefits of casual social interaction. As there are very little casual social interactions that could be disrupted by smartphone usage, it is likely that the above mentioned subtle but significance negative effect of smartphone usage on wellbeing via distraction (Kushlev et al. 2019) shrinks below significance during the pandemic. It shall also be highlighted here that there is a clear connection between smartphone usage and SNS usage, as smartphone users report that they do spend 71% of their time on their smartphones on activities that can be either classified as active or passive social media consumption (Experian Marketing Services 2013). It can therefore be followed that not just the relationship between smartphone usage and wellbeing will have changed during social distancing, but also the relationship between SNS usage in total and wellbeing.

Additionally, the Coronavirus crisis has been described as highly stressful (Wang et al. 2020a; Duan and Zhu 2020), just like the social isolation that comes with it (Wang et al. 2020b). Interestingly, it has previously been shown that another benefit of smartphone usage could be that it reduces cortisol levels during stressful situations (Hunter et al. 2018), making them presumably less stressful. It could therefore be speculated that smartphone usage might even act as a protective factor against the acute stress during the crisis.

As another example of this “changed mechanisms due to changed circumstances“, it is also possible that active social media usage could even be used to satisfy our need to belong (Baumeister and Leary 1995; Gangadharbatla 2008; Kim et al. 2016) in times where it is discouraged to engage in day-to-day social interaction.

There is little research about the relation between social network services (SNS) usage and wellbeing during the coronavirus crisis yet as it is a newly emerging phenomena. However, previous research into another natural disaster with devastating consequences, the Japanese Earthquake of 2011, has found that social media usage during and after disaster might be useful in creating *Social Capital* by facilitating new ways of sharing the users thoughts and emotions that were just not possible before (Kaigo 2012). *Social Capital* has been defined as the strength of the interpersonal network someone has (Perkins et al. 2002), and has frequently found to be positively connected to wellbeing (e.g. Portela et al. 2013). This therefore suggests a novel way in which social media usage might influence wellbeing during this extraordinary time of crisis.

Due to this number of “changed mechanisms due to changed circumstances“ it can therefore be speculated that in this extraordinary time SNS usage might have a more positive effect on our wellbeing and mental health than during a normal time period. However, it shall first be examined how social media usage related to wellbeing during “normal“ circumstances.

Previous Research into the overarching correlation between SNS usage and Wellbeing.

Plenty of research has been conducted about the relationship between wellbeing and SNS usage previously. Subjective wellbeing has been described as a highly important concept, as it is a fundamental facet of life quality (Keyes 2012) and there is also evidence that wellbeing has a protective role for physical health (Steptoe et al. 2015). While the popular media, some outspoken scientists and common believes might suggest that social media consumption is by default harmful for individuals (for review: Bell et al. 2015), the negative effects of social media and smartphone usage on our wellbeing appear to be relatively subtle (Orben and Przybylski 2019; Verduyn et al. 2017; Huang 2017; Halfmann and Rieger 2019). However, these effects are still significant, even though their effect size is according to Orben and Przybylski (2019) comparable to reductions in wellbeing that can be experienced from relatively minor issues such having to wear glasses (145% as impactful) or consuming potatoes (86% as impactful), and is greatly surpassed by the effect sizes of e.g. smoking (1847% as impactful). This divergence between popular opinion and actual scientific findings can be explained partly by the fact that there are multiple processes how social media consumption influences our wellbeing in both negative and positive ways (Verduyn et al. 2017). This indicates that social consumption is neither all bad nor all good for an individual’s wellbeing, and the effect on wellbeing by different types of usage should be explored for a clearer picture.

Different Types of Social media Usage.

Two of these differing types of usage shall be highlighted here: Active social media usage and passive social media usage (Verduyn et al. 2017; Twenge et al. 2018; Deters and Mehl 2013). Interestingly, it has been shown that these types of usage have differing effects on wellbeing (Verduyn et al. 2017) . Active social media usage (“Active usage”) has been defined as active sharing or communicating with others, while passive social media usage (“Passive usage”) has been defined as simply consuming social media by monitoring other people’s lives without engaging with them (Burke and Marlow 2010). It is noteworthy that it has been suggested by e.g. Verduyn et al. (2017) that active SNS usage might actually be beneficial for individuals wellbeing as it helps to fulfill our need to belong (Baumeister and Leary 1995). Opposing to that it has further been shown that passive social media usage has negative effects on our wellbeing as it promotes upward social comparison (Appel et al. 2016). It is also noteworthy that original research, such as the surveys that Orben and Przybylski (2019) analyzed, did not specify between these two types of usage, but rather only asked for social media usage in general. This could possibly explain the very slight overall negative effect of active and passive social media usage on wellbeing when assessed together as one construct (i.e. total social media usage), while looking at these type of usage individually might lead to a differentiating perspective. It is therefore important to assess both types separately when researching the connection between SNS usage and wellbeing.

SNS’s potentially unique relationship with wellbeing during the Coronavirus Crisis.

Dealing with or dampening the negative psychological response due to social isolation during the coronavirus crisis has rarely been studies previously. This is due to the fact that this is a completely new field of research as the COVID-19 pandemic is a new, ongoing and unique disaster of unprecedented scale in modern history (World Health Organization 2020a) . As mentioned above, SNS relationship with wellbeing might have changed during the coronavirus crisis. This can be suggested as smartphone and SNS usage can no longer undermine the positive effects one reaps from social interaction (Dwyer et al. 2018; Sandstrom and Dunn 2014), smartphones and SNS usage might potentially act as a buffer against COVID-19 pandemic induced stress (Wang et al. 2020b; Hunter et al. 2018) and SNS usage might even help to fulfill our need to belong during this time of isolation (Baumeister and Leary 1995; Gangadharbatla 2008). This would additionally be in line with previous research that has shown that SNS usage facilitates social capital during times of crisis (Kaigo 2012) which in itself has been shown to improve wellbeing (Portela et al. 2013).

As demonstrated above, it is likely that the relationship between SNS usage and mental health have changed in a unique way during the COVID-19 Pandemic. It is therefore of great interest to research this relationship. However, there should still be attention paid to the differing effects of active and passive social media usage, as it has been shown that they do have differential relationships with wellbeing and mental health. It is therefore of great interest to study the potentially unique relationship between different types of SNS usage and wellbeing in the context of the coronavirus crisis.

It shall therefore be hypothesized:

1. Active social media usage will significantly positively predict wellbeing in the context of the coronavirus crisis, while significantly negatively predicting depression and stress.
2. Passive social media usage will significantly negatively predict wellbeing in the context of the coronavirus crisis, while significantly positively predicting depression and stress.

Methods

To answer these research questions, an online questionnaire was distributed to a community sample. This questionnaire was made up of pre-validated scales for each variable that were taken from the literature.

Design:

The study used a cross-sectional design. The independent variables in this study were active and passive social media usage, with the dependent variable being life satisfaction (as a proxy for wellbeing), perceived stress and depression. Demographics, such as age, gender were controlled for as possible confounds.

Participants:

Participants were gathered using convenience sampling, by distributing the questionnaire to family and friends. In total 274 Participants filled out the questionnaire, with 175 finishing it and replying to all questions. Note that one participant was removed who indicated his gender as *diverse* for convenience. Out of the remaining participants, 63.8% were female and coded as 0 = *male,* 1 = *female*. The total average age was 29.5 (SD = 12.1, also see Table 1).

Measures:

Active/Passive usage. To assess active and passive Facebook usage as independent variables, a modified version of the Multidimensional Scale of Facebook Use (MSFU) by Frison and Eggermont (2015) was used. It was originally designed to assess active and passive Facebook use, but was in this case re-designed to especially reference social media as a whole instead of Facebook, and items were added to assess passive and active usage in context of the coronavirus pandemic. The scale consisted of two subscales. The first being active usage, indicated by items such as “How often do you send someone a personal message on Social Media (Facebook)?“ and “How often do you post something on your own Social Media (Facebook) profile or timeline”. The second sub scale was passive usage (e.g. “How often do you visit Social Media (Facebook) profile of a friend or online follower”). Items were also added to fit the research question of the study better, by asking the participant about their social media usage in the context of the coronavirus crisis (e.g. for active usage “How often do you send someone a personal message about your thoughts on the current crisis on social media “, e.g. for passive usage “How often do you read posts of news organizations on social media about the current crisis “). Both active and passive usage subscales had 7 items each. All 14 items had 5 response options, ranging from *never* to *several times a day*. Overall, the scale had good reliability at Cohen’s $\alpha = .843$. The individual subscales also had good reliability, with $\alpha = .710$ for the active usage scale and $\alpha = .832$ for the passive usage scale.

Stress. To measure stress as a dependent variable, the Perceived Stress Scale (PSS) (Cohen et al. 1983) with 10 individual items was selected and modified to fit the current situation. The original scale asked about how the participant felt “ In the last month “. To fit the research question better, the introductory text of the scale was changed to reference how the participant felt since “ the beginning of the coronavirus outbreak in your area and the start of the social distancing measures “. The modified scale was named PSS_C. Exemplary items include “How often have you felt nervous and stressed out? “ or reverse coded items such as “How often have you been able to control irritations in your life? “. A four point scale was used, ranging from 1 = *Rarely or none of the time* to 7 = *Most or all of the time*. For analysis, the reverse items were recoded and the mean of all individual items and reverse coded items was calculated per subject. The scale had good reliability at $\alpha = .848$.

Depression. To measure depression as a dependent variable, the Center for Epidemiologic Studies Depression Scale (Radloff 1977) was selected. The short form with 10 items (CES-D-10) was used to reduce the overall length of the questionnaire. A modified version was used to fit to the research question better (CES-D-10_C). This was done by changing the time frame referenced in the items by replacing the phrase “During the last week “ with “Since the beginning of the coronavirus outbreak in your area and the start of the social distancing measures “. Its 10 Items included questions such as “You felt like you could not get going” or reverse coded questions such as “You were happy“ with a four point scale, ranging like the PSS from 1 = *Rarely or none of the time* to 7 = *Most or all of the time*. For analysis, the reverse items were recoded and the mean of all individual items and reverse coded items was calculated per subject. The scale had good reliability at α = .832.

Wellbeing. The construct of wellbeing can generally be measured in two parts: The cognitive component (“Satisfaction with life”) and its affective component (“how good or bad people feel”) (Diener 2009; Verduyn et al. 2017). It was chosen to assess to only assess satisfaction with life as it is a good proxy to determine global life satisfaction and does not tap related constructs such as positive affect or loneliness when measured correctly (Diener et al. 1985). The Satisfaction with Life Scale (SWLS) (Pavot and Diener 2008; Diener et al. 1985) was therefore selected to assess SWL as a proxy for wellbeing as a dependent variable as it meets all above mentioned required criteria by not tapping into related constructs. The SWLS is a widely used instrument has been called a good way to measure life satisfaction as a whole. This is due to the fact that it involves 5 questions about satisfaction with life-as-a-whole, that differ in phrasing but not in content (Veenhoven 1996). Therefore, the sum-score or mean can be confidently interpreted as a measurement of general life satisfaction. The SWLS includes 5 items with 7-point Likert scales, ranging from 1 = s*trongly agree* to 7 = *strongly disagree*. Exemplary items included “I am satisfied with my life.” or “If I could live my life over, I would change almost nothing “. The entire scale was reverse coded for ease of understanding so that a higher score would indicate higher agreement. For the analysis, the mean of all individual reverse coded items was taken. The scale also had good reliability at $\alpha = .841$.

Risk. Additionally, it was of concern to control for the objective risk the SARS-CoV-2 and the cooccurring social and financial crisis exerts on the participant, as this could possibly act as a confound by influencing both social media usage (Tandoc Jr and Takahashi 2017) and the dependent variables (World Health Organization 2020b). Therefore, the participant was asked: “Objectively speaking, how much is your health and wellbeing at risk from the coronavirus? “. The participant could rate this item on a scale from 1 to 7, ranging from 1 = *Not at all* to 7 = *At very high risk* (M = 2.87, SD = 1.641).

Demographics. Demographics were assessed to later control for them in the analysis. Age was assessed using a slider from 0 to 100. Gender was assessed in three categories (1 = male, 2 = female, 3 = diverse), but were recoded to (0 = male, 1 = female) while dropping the single participant who indicated “diverse“ as gender from the analysis. This was done for convenience reasons.

Descriptive and correlations for these scales can be found in Table 1.

Procedure

Qualtrics digital survey environment was used to assess the answers of the participants (Qualtrics 2020). The participants were introduced to the study and were informed about the benefits and risk of the study. They we were further notified that the data of the participants will be anonymized and stored for at least 10 years. If the participants intend to withdraw from the study, they were informed that they could do so at any time by simply closing the window of the questionnaire. Multiple questionnaires from multiple projects were presented to the participants in random order. At the end of the study the participants were asked to indicate their demographics. Data collection was opened on the 25^{th} of April and closed on the April 27^{th} 2020.

Table 1: Zero Order Correlations and Descriptives

	Age	Gender [a]	SWLS	CES_D_10_C	PSS_C	MSFU_A	MSFU_P
Age	-						
Gender [a]	-0.097	-					
SWLS	.155*	-.101	-				
CES_D_10_C	-.272**	.232**	-.387**	-			
PSS_C	-.292**	.235**	-.504**	.757**	-		
MSFU_A	-.238**	.297**	-.054	.313**	.289**	-	
MSFU _P	-.353**	.246**	-.065	.183*	.226**	.507**	-
N	174	174	195	196	184	178	178
M	29.50	.64	2.11	2.11	2.18	2.38	2.83
SD	12.14	.48	.56	.57	.56	.64	.94

*= $p \leq .05$, **= $p \leq .01$. [a] = was coded as 0 = male, 1 = female.

Statistical Analysis

It was tested whether and how active (Hypothesis 1) or passive usage (Hypothesis 2) predicted wellbeing, perceived stress and depression, after controlling for age, gender, and objective risk from the Coronavirus crisis. For this analysis SPSS 26.0 was used (IBM 2019). First, the zero order correlations between the different scales were assessed (also see Table 1). Next, it was checked if all relevant assumptions of the hierarchical regression analysis were met. Applying the sample size for hierarchical multiple regression calculator by Soper (2020), it was determined that a sample size of 173 was sufficient for this analysis. The assumption of singularity was also met as none of the independent variables was a combination of other independent variables (Abrams 2007; Tabachnick and Fidell 1989). Scatter and residual plots were generated for all variables. These indicated that the assumption of normality, linearity and homoscedasticity were all satisfied. For all variables, tests to see if the data met the assumption of collinearity indicated that multicollinearity was not a concern (Hair 1998): While the highest correlations between two predictors was only slightly below $r = .80$ (indicating a strong correlation) at r = .757 (for the PSS_C and CES_D_10_C), all relevant VIF's ranged from 1.022 to 1.215 and were therefore well within limits. Tolerances ranged from .832 to .978. (Johnson n.d.; Tabachnick and Fidell 1989). Note that active and passive usage were significantly correlated at $r = .507$ ($p = .000$).

Six hierarchical regression analyses were conducted. Three hierarchical regression analysis each of the three dependent variables were conducted for each hypothesis. The first step for all analyses was including either active or passive social media usage into the model. It was then assessed if this model predicted active or passive social media usage significantly. If a significant prediction was found, the relevant β was listed. Then, a second model was added that also included age, gender, and objective risk as potential confounds. This was done to find out if a possible prediction would remain significant if accounting for these variables. It was then compared if this model predicted the DV better than the first model. If this was the case, it was then checked if the IV predicted the DV significantly in that model. If a significant prediction was found, the β was listed. Overviews of the results for H1 can be found in table 2, while an overview of the results for H2 can be found in table 3.

Results

Hypothesis 1: Active SNS Usage

Satisfaction with life. The zero-order correlation between the SWLS and active SNS usage was minor and not significant (r = -.054). Next, a hierarchical regression analysis was conducted. For model 1, active usage was added. It did not significantly predict SWL (F(1) = .373, p = .589, R^2 = .002). In the second step, age, gender, and objective risk were added to the model. This second model did not predict SWL better than the first model (F(4) = 1.764, p = .142, R^2 = .040).

Perceived Stress. The zero-order correlation between the PSS_C and active SNS usage was small but significant (r = .289, $p \leq .01$). Next, a hierarchical regression analysis was conducted. For model 1, active usage was added. It did significantly positively predict perceived stress (F(1) = 12.780, p = .000, R^2 = .070) (β = .264, t = 3.575, $p \leq .001$). In the second step, age, gender, and objective risk were added to the model. This second model did predict perceived stress better than the first model (F(4) = 9.109, $p \leq .001$, R^2 = .178). In the second model active Usage did not significantly predict perceived stress (β = .137, t = 1.812, p = $.072$) at α = .05. However, the model would have been significant at significance level α= .10.

Depression. The zero-order correlation between the CES_D_10_C and active SNS usage was small but significant (r =-.313, $p \leq .01$). Next, a hierarchical regression analysis was conducted. For model 1, active usage was added. It did significantly positively predict depression (F(1) = 15.493, p = .000, R^2 = .083) (β = .288, t = 3.936, $p \leq .001$). In the second step, age, gender, and objective risk were added to the model. This second model did predict wellbeing better than the first model (F(4) = 9.432, $p \leq .001$, R^2 = .183). In the second model active usage did positively significantly predict depression (β = .167, t = 2.212, p = .028).

Also see Table 2 for a summary of all relevant results for the three hierarchical regression analyses involving active SNS usage.

Table 2: Hierarchical Regression analyses for IV active SNS usage (Hypothesis 1)

	β	t	R^2	ΔR^2
DV: Wellbeing				
Model 1			.002	
Active Usage	-.074	-.542		
Model 2			.040	.038
Active Usage	.034	.414		
Gender [a]	-.085	-1.075		
Age	.156	2.003*		
Risk	-.091	-1.187		
DV: Stress				
Model 1			.070***	
Active Usage	.264	3.575***		
Model 2			.159***	.95
Active Usage	.137	1.812[1]		
Gender [a]	.146	1.985*		
Age	-.247	-3.420***		
Risk	.176	2.484*		
DV: Depression				
Model 1			.083***	
Active Usage	.288	3.936***		
Model 2			.183***	.1
Active Usage	.167	2.212*		
Gender [a]	.145	1.975*		
Age	-.222	-3.087**		
Risk	.184	2.600**		

[1] = $p \leq .1$; *= $p \leq .05$, **= $p \leq .01$,***= $p \leq .001$. [a] = coded as 0 = male, 1 = female. N = 173.

Hypothesis 2: Passive Usage

Satisfaction with life. The zero-order correlation between the SWLS and passive SNS usage was minor and not significant (r = -.065). Next, a hierarchical regression analysis was conducted. For model 1, passive usage was added. It did not significantly predict SWL ($F(1) = .549$, $p = .460$, $R^2 = .003$). In the second step, age, gender, and objective risk were added to the model. This second model did not predict SWL better than the first model ($F(4) = 1.734$, $p = .145$, $R^2 = .040$).

Perceived Stress. The zero-order correlation between the PSS_10_C and passive SNS usage was small but significant ($r = .226$, $p \leq .01$). Next, a hierarchical regression analysis was conducted. For model 1, passive usage was added. It did significantly positively predict perceived stress ($F(1) = 7.384$, $p = .007$, $R^2 = .034$) ($\beta = .203$, $t = 2.717$, $p \leq .001$). In the second step, Age, Gender, and objective risk were added to the model. This second model did predict perceived stress better than the first model ($F(4) = 8.255$, , $p \leq .001$, $R^2 = .144$). In the second model passive usage did not significantly predict perceived stress ($\beta = .050$, $t = .649$, $p = .517$).

Depression. The zero-order correlation between the CES_D_10_C and passive SNS usage was small but significant ($r = .183$, $p \leq .05$). Next, a hierarchical regression analysis was conducted. For model 1, passive usage was added. It did significantly positively predict depression ($F(1) = 4.575$, $p = .034$, $R^2 = .026$) ($\beta = .161$, $t = 2.139$, $p = .034$). In the second step, age, gender, and objective risk were added to the model. This second model did predict depression better than the first model ($F(4) = 7.978$, $p \leq .001$, $R^2 = .160$). In the second model passive usage did not significantly predict depression ($\beta = .004$, $t = .050$, $p = .960$).

Also see Table 3 for a summary of all relevant results for the three hierarchical regression analyses involving active SNS usage.

Table 3: Hierarchical Regression analyses for IV passive SNS usage (Hypothesis 2)

	β	t	R^2	ΔR^2
DV: Wellbeing				
Model 1			.003	
Passive Usage	-.057	-.741		
Model 2			.040	.037
Passive Usage	.029	.347		
Gender	-.082	-1.052		
Age	.159	1.959		
Risk	-.090	-1.172		
DV: Stress				
Model 1			.041**	
Passive Usage	.203	2.717**		
Model 2			.164***	.123
Passive Usage	.050	.649		
Gender	.172	2.351*		
Age	-.259	-3.432***		
Risk	.187	2.484**		
DV: Depression				
Model 1			.026*	
Active Usage	.161	2.139*		
Model 2			.160***	.134
Passive Usage	.004	.050		
Gender	.188	2.565*		
Age	-.256	-3.686**		
Risk	.202	2.829**		

[1] = $p \leq .1$; *= $p \leq .05$, **= $p \leq .01$,***= $p \leq .001$. [a] = coded as 0 = male, 1 = female. N = 173.

Discussion

Little is known about the relationship between smartphone usage and wellbeing during the coronavirus Crisis 2020. After reviewing the literature, it was hypothesized in this study that active SNS usage would positively predict wellbeing in the context of this crisis, while negatively predicting depression and stress. As a contrast to active usage, it was additionally hypothesized that passive SNS usage would negatively predict wellbeing, while positively predicting depression and stress.

Findings in context of the Hypotheses

Only very limited support for the predicted hypotheses could be found.

Hypothesis 1. For the first hypothesis, when controlling for demographics and physical risk active usage was found not to significantly predict satisfaction with life. It is also highly noteworthy that only a zero order correlation at r = -.054 could be found, indicating that these two variables are not related at all. Active usage was also shown not to significantly negatively predict stress as assumed. Actually, the β was positive for stress at .137 while also being near significant . Also, a significant zero order correlation between active SNS usage and stress at r =.294 could be found. This is highly surprising, as it indicated that active usage during the Coronavirus crisis might have a positive connection to stress. Most importantly however, active usage s been found to be a significant positive predictor of depression (β = .167). Also, a noteworthy significant zero order correlation could be found between these variables at r = .318. The found prediction and correlation are in strong contrast to the hypotheses, as it was expected that active usage would negatively predict depression. It can therefore be concluded that hypothesis 1 can largely be rejected.

Hypothesis 2. For the second hypothesis, also little support could be found. Passive usage did not significantly predict satisfaction with life and only had a very weak insignificant zero order correlation to SWL at r = -.065. Passive usage also did not predict stress, with a β = .050 and p = .517. Notably, passive usage and stress had a positive significant zero-order correlation of r = .226. This is roughly in line with the hypothesis, but also noteworthy as this correlation is very comparable to the correlation found for active use. For depression, passive usage was also shown to be a non-significant predictor. However, a significant positive zero order correlation could be found at r = .183. For depression therefore the same applies as for stress here: The found correlations are roughly in line with what was expected in Hypothesis 2, but it is surprising that the zero order correlations between active and passive usage and depression are so similar.

Importance

Active usage predicting depression. The most noteworthy finding of this study is probably that even when controlling for factors such as physical risk and demographics, active smartphone usage significantly positively predicts depression. This is especially noteworthy as passive usage does not significantly predict depression. This is a strong contrast against previous research, as it has previously been shown (e.g. Escobar-Viera et al. 2018) that active usage is associated with a decrease in depressive symptoms while passive usage is associated with an increase in symptoms. It is also interesting that passive usage and active usage have very similar zero-order correlations to depression.

It is risky to read this finding as “Active social media usage is promoting depression “ as this study did not check for potential mediators, direction or causality. It is a possibility that the ongoing Coronavirus crisis might have led to this extraordinary finding. It could for example be speculated that by actively engaging in digital discussion and sharing during coronavirus crisis, that this information is somehow made more salient to the user and which leads to depressive symptoms. A further study inspecting the possible mediation of how salient the coronavirus crisis is would be needed. It is indeed also possible that individuals who experience depressive symptoms due to the coronavirus crisis do – unlike those who are rating themselves as rather depressed in “normal times“ – use social media actively to share their negative experiences. It is also possible that individuals who are experiencing symptoms of depression during the crisis are using social media as a coping mechanism. Both of these explanations could explain the significant correlation and regression, as this study did use a cross-sectional design and therefore did not test for the direction of the effect.

No significant prediction of satisfaction with life. Another noteworthy finding is actually the lack of a significant finding: Neither active nor passive usage do significantly predict satisfaction with life (as a proxy for wellbeing). Even the zero order correlations between both types of SNS usage are very small at r = -.054 and r = -.065 This indicates that social media usage in the context of the coronavirus crisis is not related at all to satisfaction with life.

Compared to previous research, this finding would not be surprising when looking at social media use in total but not if looking at passive and active social media usage in detail. For example, Huang (2017) found a small and comparable correlation of r = -.07 between social media usage(in total) and wellbeing in his meta-analysis and mentions that he also found a correlation near 0 between social media usage and life satisfaction. Orben and Przybylski (2019) also found that social media usage only explains about 0.4% of the variance in wellbeing in adolescents (compared to 0.002% for active and 0.003% for passive usage in this study).

However, it is interesting that when looking at active and passive social media usage in isolation, still no significant correlation or prediction can be found. It has been noted in a frequently cited paper by Verduyn et al. (2017) that passive usage of social network sites have been previously been linked with reduced levels of subjective well-being. However, this relation is rather small. While Verduyn et al do not mention any numbers in the 2017 paper, it has been found for example by Verduyn et al. (2015) that passive usage negatively predicted wellbeing at only B =-0.5. Another cross-sectional study mentioned by Verduyn et al. (2017) , Krasnova et al. (2015) found even only a very small insignificant direct effect of social media consumption on cognitive wellbeing at 0.054. As these studies have had much larger samples than this thesis it is possible that if this study also utilized a larger sample, a significant finding could have been found. It can therefore be concluded that the lack of a relationship found between passive social media usage and wellbeing in this study is noteworthy, but not extraordinary.

It is however noteworthy that it has been frequently found that active social media usage is good for wellbeing (for review: Verduyn et al. 2017), with noteworthy margins. For example, Kim and Lee (2011) found that positively presenting yourself online showed a significant positive association with subjective wellbeing ($\beta = 0.12$). Even though the difference in scale of these numbers found in previous research compared to the found predictions in this study is rather small, it is still of interest why this study was not able to replicate this positive regression, as it found no association between active usage and wellbeing. It can be speculated that this is due to the nature of the questionnaires used: While the participant was explicitly asked about his social media consumption during the coronavirus crisis, the SWLS asked more about the participants life in general. It has also been previously shown that SWL ratings are not necessarily influenced by day-to-day affect (Lucas 2013). As the crisis was still at the beginning of its outbreak when the data was assessed, it is possible that there was simply no relation yet between these two constructs Nevertheless, this is an interesting finding that should be researched further.

Near significant positive prediction of Stress by active usage. One more noteworthy finding is the near-significant prediction of stress by active usage. Active usage would have been significant predictors at significance level $\alpha = .1$ with $\beta = .137$. This is surprising, as it has been. found by previous research that being active and sharing ones thoughts on social media can decrease perceived stress and be beneficial (e.g. Niederhoffer and Pennebaker 2002; Nabi et al.

2013; Wang et al. 2020b). While the finding in this study is only near-significant, and could therefore be simply explained by chance, it is still noteworthy as it sticks out from the literature. It is also surprising that both active and passive use have a very similar significant zero order correlation to perceived stress (with r = .289 for active usage and r = .226 for passive usage). This could however be explained by the context of the coronavirus crisis. As a large part of all online discussion during the coronavirus crisis was defined by the crisis (e.g. Aguilar-Gallegos et al. 2020), both active and passive usage could have been mainly revolving around the coronavirus crisis. It has also been shown that dealing with any kind of coronavirus-related content in the media can be stressful (Lades et al. 2020). This might be able to explain why both significant zero order correlations were so similar.

Limitations & Alternative Explanations

The main weakness of this study was its cross-sectional correlational design. This only allows to draw conclusions about the correlation between the variables, and possible prediction, but not about the direction of an effect or causality. Additionally, it has been previously shown that self-report measures frequently lack validity as they are subject to response error (e.g. Bakker et al. 2016). It can therefore also be considered a weakness of the study as no observational or physiological measures could have been made.

Next, the question “Objectively speaking, how much is your health and wellbeing at risk from the Coronavirus?” in the questionnaire might not measure what it is intended to measure. It is very well possible that this question only allowed a look into the anxiety the subject has about the coronavirus crisis, and not the actual, objective risk the SARS-2 virus itself or the associated crisis exerts on the subject. An exploratory analysis showed that this question is correlated to perceived stress significantly (at p = .005) with r = .210. It is not clear from this analysis though if actual objective risk leads to more stress, or if more stress and anxiety could lead the participant to overestimate the objective risk the crisis has on his health and wellbeing (Alvord 2019). Additionally, the item was not particularly well formulated as it was intended to both control for the risk of the actual virus (i.e. SARS-CoV-2) exerts on the participant, just as the risk that comes for the participant from the ongoing social distancing measures and the 2020 economic crisis and stock market crash. However, the question was only formulated in a way so this was not completely clear and it might have appeared that the item was only about the risk that virus exerts directly on the participant.

Additionally as wellbeing has been described as a multi-faceted construct (Dodge et al. 2012) it can be considered a weakness that only the cognitive component of wellbeing was assessed (Life Satisfaction), but the cognitive component (How good or bad one feels) was not measured directly (Diener et al. 1985). This could have provided further insight and clarity.

Last, it could be considered a limitation that the questionnaire (MSFU_C) that was (re-)designed to capture active and passive smartphone usage did not differentiate between these two constructs enough. The active and passive subscales were also significantly correlated ($p \leq .001$, $r = .507$). This could possibly explain why both variables had very comparable zero order correlations to satisfaction with life, stress and depression. However, as causality and direction could not be determined it might also be possible that a frequent SNS user might engage in both kind of usage equally. It is also possible that this might have also been due to the design of the questionnaire. Very similar wording for all items was used and all items were brought up in the same question matrix. This could have led participants to read the items in less detail.

Suggestions for future research

Drawing from the limitations of this study, directions for further research can be proposed. It would be of great interest to study the relationship between active social media usage and depression in the context of the coronavirus crisis in more detail. It might be of interest to conduct some qualitative exploratory interviews with subjects to assess any potential mediators or confounds first. After this, quantitative studies could be conducted. These could either be designed as a cross-sectional design that assesses active social media usage and depression in more detail. To find a causal effect, an experimental study might be designed in which the participant is either advised or disadviced to actively share his thoughts and feelings on social media about the Coronavirus crisis, and is then assessed via the CES_D_10(_C) after a certain time period. This kind of study would also have a higher practical relevance for health authorities and therapists, which could then accordingly advice the participant to either engage or disengage in active usage during this crisis. Additionally, any future study about this topic should attempt to assess objective risk by the coronavirus crisis in more detail so that it provides a more accurate assessment of the objective risk as a possible confound. This is possible by asking more detailed questions about risk factors that are known to increase the risk of death from the virus itself, such as e.g. hypertension (Wu et al. 2020; Zhou et al. 2020). It should also be assessed how much the participant is at financial risk from the economic crisis that came with the pandemic, as this might also lead to changes in wellbeing and social media usage. Additionally, further research looking into the relationship between perceived stress and social media usage should be designed. As regression analysis has found multiple near significant results, it is not unlikely that if this study is repeated with a larger sample, significant results will be found.

Conclusion: The bigger picture and practical relevance

While none of the above findings is extraordinary and all found predictions and correlations are relatively subtle and roughly in line with previous research on social media usage, they should still be a fuel for future thought and research. It is especially surprising that active social usage predicted both depression and did not (positively) predict satisfaction with life. While this is, as mentioned, not completely surprising for research on active *social media usage*, it should still be surprising as it has been frequently shown that having strong relationships and sharing your thoughts with other people *in real life* is a predictor of not just higher wellbeing (Uchino et al. 1996a; Kawachi and Berkman 2001; Baumeister and Leary 1995) but also is a negative predictor of mental illness such as depression (Kawachi and Berkman 2001; Barnett and Gotlib 1988b). While there is currently little support for the “replacement hypothesis“ (i.e. that potentially health-positive social interactions are being increasingly replaced by individuals with health-neutral or health-negative online interactions, leading to negative effects of SNS use) (Hill 2014; Huang 2017), it should still be noted that this study shows once more that *social media* interaction can not and should not replace *real life* social interaction as it simply does not come with the same benefits for mental and physical health as real life interaction does. As the positive prediction of depression by active usage demonstrated, this also goes for social interaction during the COVID-19 pandemic. Interestingly, also social media giants like Facebook (Jin 2020) publicly claim to have recognized that they are no replacement to real life interaction with friends and family. For example, Facebook claims to have created a new “Quiet Mode“, that allows their users to toggle notifications and basically blocks the app during times when they intend to rest or spend time with their friends and family. In the same blog post, Facebook also claims to give the user now more freedom about what kind of notifications they want to receive. However, any of these kind of posts should be seen with great skepticism: It has been previously argued that a publicly traded company has no social responsibility to the public or society, but is simply only responsible to maximize profits for its shareholders (Friedman 1970). While there is plenty of discussion and controversy about this so called *Friedmann doctrine*, Facebook is indeed a publicly traded company that aims to maximize profits for its shareholders by maximizing the amount of ads a Facebook user sees (Burt 2019). Facebook also has been called on attempting to accomplished this goal by copying “gambling mechanisms“ to maximize the time their users spent on their site (and therefore maximizing the amount of ads a user sees) (Busby 2018). For example, Facebook is designed to draw its user into so called "*ludic loops* or repeated cycles of uncertainty, anticipation and feedback, with rewards that are just enough to keep you going" (Busby 2018). Facebook and other ad-revenue based SNS therefore should not be trusted to self-regulate and to have only genuine and user-oriented intentions in mind when claiming to put the health and wellbeing of their users first, or even when claiming about developing a tool for young people to develop healthy habits using technology (Jin 2020). This is due to the fact, as above mentioned, that these companies do have a strong financial conflict of interest with these genuine and user friendly goals.

Individuum's should therefore be empowered with knowledge by scientists and not by companies to improve their mental health and their wellbeing. Individuums should additionally be encouraged to engage in behaviors that have been found by research to be good for their health.

This study further confirms most previous scientific findings: Social media usage is probably neither good nor bad for your wellbeing, but it has been shown here to predict depression in the context of the coronavirus crisis. As this is just one of many studies about this topic that adds to the bulk of mixed findings in the literature, individuals can hardly be advised to minimize their time spent on social media, as this cannot be directly concluded based on the current evidence. However, there appears to be a clear scientific consensus that spending time with others and even casual interactions are good for human wellbeing and mental health (Epley and Schroeder 2014; Zelenski et al. 2012; Uchino et al. 1996b; Baumeister and Leary 1995; Barnett and Gotlib 1988a). Individuum's can therefore certainly be advised to maximize their time spent with others in real life. While this is of cause difficult during the time of the COVID-19 pandemic, it should still be advised for individuals to seek as much interpersonal and social connection as the social distancing measures allow them to keep up and improve their mental health and wellbeing. This could for example be a walk with friends while keeping safe distance or having an old fashioned call with extended family members. While this is definitely not an easy time for anyone, scientists can help by empowering individuals to receive this kind of information, which will help individuals to make these kind of informed health-positive choices about how they spend their time. This will allow individuals to get through this difficult time with as little mental disturbance as possible.

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