Permanently Online, Permanently Connected and the Fear of Missing Out - A Cross-Sectional Study about their Relations to Loneliness and Mental Well-being

Department of Behaviour Management and Social Science

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Lilli Baune

First supervisor: Dr. Alejandro Domínguez Rodríguez

Second supervisor: MSc. Maria Luisa Rispa Hoyos

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Abstract

Background. Social and digital media have an increasing importance in people's everyday lives. With the increase in usage, negative consequences may arise, especially regarding individuals' mental health and loneliness. Young adults and adolescents are especially at risk due to their general familiarity with digital and social media. The phenomenon of being permanently online and permanently connected (POPC) refers to the perceived pressure or necessity to be constantly connected via digital and social media applications. One of its causes is the Fear of Missing Out (FoMO), which describes the perceived need to not miss out on the activities of others, resulting in being constantly connected. Both POPC and FoMO have been found to negatively influence mental health and show relations to loneliness. Therefore, this study aimed to gain further knowledge regarding their impact towards loneliness and mental health.

Methods. 167 participants took part in this cross-sectional study by filling in an online questionnaire, which included the Online Vigilance Scale, the FoMO scale, the UCLA Loneliness scale, and the Mental Health Continuum Short form.

Results. The findings suggested a significant negative relationship between individuals' loneliness and mental health. Further, a moderated linear regression regarding the effects of FoMO and POPC showed no significant effects. However, significant negative effects were found for the impact of POPC and FoMO on mental well-being. Lastly, the sample was investigated regarding age differences among 18-to-30-year-olds (n= 117) and 31- to 65-year-olds (n= 50). A significant difference was found between individuals' POPC, FoMO and mental health scores. However, participants did not differ significantly in their loneliness.

Conclusion. The study findings showed that higher scores in both POPC and FoMO indicate lower mental well-being scores while further supporting prior findings that younger adults seem to be more at risk for negative consequences of both POPC and FoMO tendencies.

Keywords: Fear of Missing Out, Permanently Online Permanently Connected, Mental Health, Loneliness, Age differences

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1. Introduction

Over the last decade, a rapid increase in the availability of social media applications occurred that can be utilised for many different purposes. Many applications have a communication purpose, used for inter-individual and in-group communication, as well as an information resource or entertainment purpose (Best et al., 2014; Vorderer et al., 2016). In 2021, over 6 billion people worldwide had a smartphone, with this number hypothesised to increase over the next decade (Ericsson Mobility Visualizer - Mobility Report, 2023). One of the most frequent online activities is visiting social networking sites to stay connected to others (National Telecommunications and Information Administration (NTIA), 2022). Smart devices, like smartphones, allow individuals to connect and interact with other individuals, even when interaction partners are not directly physically available. Due to this development, individuals' habits of use for electronic media changed. A study conducted by Vorderer et al. (2016) found that most participants use their smart devices at least once every hour. Worldwide in 2022, the average time spent online daily was 146 minutes among a sample of 16- to 64-year-olds (We Are Social, DataReportal, & Hootsuite, 2022). Especially involved in media use are young adults and adolescents, due to multiple reasons, such as the general familiarity with electronic devices or the need to use electronic media in everyday life (Best et al., 2014; Cauberghe et al., 2021). For example, online platforms like Zoom or Skype are required for school or study purposes. During the COVID-19 pandemic, a common coping mechanism for many adolescents was additionally spending more time online, for example, to stay connected (Marciano et al., 2022). The consequences, both negative and positive, and related phenomena have increasingly been questioned every day.

1.1 Permanently Online, Permanently Connected

A related concept regarding social and digital media use is the phenomenon of *being permanently online and permanently connected* (POPC). This describes the felt need or felt pressure to be constantly connected via social media (Vorderer et al., 2016). Moreover, attention is shifting from a single communication partner to a rapid change between multiple individuals who do not need to be present in a situation, e.g., who are available via phone. Being POPC can be related along two dimensions, namely: "1) as an overt behaviour in the form of protracted use of electronic media and 2) as a psychological state of permanent communicative Vigilance" (Vorderer et al., 2016, p.2). Especially relevant is the subjective feeling of being permanently available or connected, as being experienced by both feelings of pull and push towards social media. For example, individuals who experience a high level of POPC tend to actively attend to their online interactions more and, in consequence, react more to online information (Vorderer et al., 2016; Quinn & Oldmeadow, 2013). POPC thereby not only occurs in situations when people are not engaged in another way but in most social situations (Lee, 2022, Quinn & Oldmeadow, 2013). The process of being both online and physically involved with content is named *permanently connected* (PC). In many studies, PC and being *permanently online* (PO) are used interchangeably. However, PC refers to social interactions, while PO can be more broadly related to the seeking of information or general media content use (Vorderer et al., 2016; Lee, 2022).

Besides PC and PO, further related concepts can be identified. Both concepts can be related to the concept of *Online Vigilance*. Online Vigilance describes individual's differences among three aspects: (1) their cognitive direction to constant, ubiquitous online connectivity; (2) their enduring attention to and constant integration of online-related aspects and stimuli into their thinking and feeling; and (3) their intrinsic motivation to favour online communication options over other (offline) behaviour (Reinecke et al., 2018). Those three aspects are expressed along three sub-dimensions. Salience of the online world indicated high thoughts about online content, if not being online, when Online Vigilance is high. Strong Online Vigilance also involves being prepared to respond rapidly towards information received through online communication, even if that action requires interrupting other activities (Reactibility). Lastly, monitoring is the desire to actively watch one's online communication environment simultaneously with other activities (Reinecke et al., 2018).

Research focused on the possible causes of being permanently online and connected. For example, social support through both online and offline relationships, maintenance of social relationships or a compromise in attention span may cause POPC (Vorderer et al., 2016; Quinn & Oldmeadow, 2012). And even though the reasons for both can be different, the research conducted is still insufficient. The actual perception of POPC varies from individual to individual. However, a study by Vorderer et al. (2016) found that many participants mentioned feelings of loneliness, disconnectedness, or emptiness, that something is missing. Others experienced relaxation, reduced stress, and a general relaxed feeling when being without an electronic device (Vorderer et al., 2016). For some participants, this feeling changed over time, starting with a feeling of emptiness at first, but after some time, changing to a more relieved feeling. Contradicting, a study by Reinecke et al. (2017) found that the feeling of being permanently available can also increase feelings of stress if the communication load, with a higher number of messages than personal resources, cannot be attended to properly.

1.2 Influencing Factors on Permanently Online Permanently Connected

Related to the concept of POPC, more related factors can be identified. A study by Vorderer et al. (2016) found that participants with a romantic partner generally experience a lower need to be permanently online or connected. Additionally, living conditions with a partner can further decrease feelings of loneliness (Pyle & Evans, 2018). Furthermore, it was found that being permanently online also influences the time spent with a partner, as more time is spent online, which might be related to the length of the relationship. As loneliness is experienced differently, not the number of social connections is relevant, but rather the quality of those relationships (Fumagalli et al., 2021). As studies showed, individuals with high feelings of loneliness still have a high desire to be connected (Achterbergh et al., 2020). Furthermore, loneliness can be related to problematic internet usage, as those individuals spend less time physically interacting and engaging with individuals, which might increase feelings of loneliness (Kim et al., 2009).

1.3 Fear of Missing Out

An additional related concept in this context is the *fear of missing out* (FoMO). It can be described as a perceived need to stay connected with the activities of others, often due to the feeling of missing out if one is absent from an activity (Przybylski et al., 2013). More specifically, the fear of being excluded from social interactions, events, and information that one experiences to be important to oneself (Vorderer et al., 2016). Additionally, it may lessen the costs of taking part in these events and be socially involved (Przybylski et al., 2013). Different researchers tried to analyse the underlying factors leading to the experience of FoMO. Przybylski et al. (2013) analysed FoMO through the lens of self-determination theory and mentioned the possibility of a low level of basic need satisfaction, which may cause increased feelings of FoMO. Hereby, FoMO is described as a negative emotional state.

Studies regarding the effects of FoMO towards social media use found that those individuals with perceived FoMO often use social media platforms to stay connected and informed (Hattingh et al., 2022). FoMO has been found as a predictor for increased social media engagement (Schneider & Hitzfeld, 2019), as it increases the desire and need, as well as the possibility to stay up-to-date with others (Able et al., 2016). Additionally, FoMO is often classified as a problematic attachment to social media, with negative consequences and feelings, like sleep problems, anxiety, deficiency in emotional control, or a general reduction in life competence (Altuwairiqi et al., 2019). Furthermore, studies found a relationship between FoMO and distractibility, as well as reduced productivity and a decrease in mental well-being (Gupta & Sharma, 2021). Moreover, it was hypothesised that through the view of social compensation theory, people who lack offline social support increasingly turn to online resources for online support. This may result in increased social media use, given the opportunity for self-presentation and reciprocal interactions, which is indicated through increased FoMO (Liu & Ma, 2020; Zell & Moeller, 2018). And while social and digital media platforms provide changes for social interaction and self-expression, their negative consequences, like FoMO, have a negative impact towards individuals' mental health.

1.4 Loneliness and Mental Health

Managing aspects of life is crucial for people's well-being. With the increased usage of social and digital media and individuals' constant need for connectedness, social relationships shifted (Fumagalli et al., 2021). Stressors like loneliness or increased media consumption are found to negatively affect one's mental well-being (Howarth, 2023). Reasons for accessing social media apps often include curiosity, need for information, loneliness, and work or health purposes (Howarth, 2023), as well as experiencing FoMO (Przybylski et al., 2013). Loneliness can typically be defined as "a complex set of feelings due to the absence of intimate and social needs" (Ernst & Cacioppo, 1999, p. 1) and is a subjective feeling (Fumagalli et al., 2021). Social psychology sees this emotional distress as developed through unmet needs for intimacy and companionship, while cognitive psychology explains it as a discrepancy between the actual social relationship and the individual desired relationships (APA Dictionary of Psychology, n.d.). During the beginning of the pandemic, levels of loneliness, especially among young adults, increased, with an important influence being the disruption of social support (Lee et al., 2020), as physical, social connections were limited (Fumagalli et al., 2021). This research found that, particularly for younger people, those circumstances lead to an increase in loneliness (Fumagalli et al., 2021).

A common stereotypical belief is that older adults report feelings of loneliness more frequently. It was found that younger adults, as well as adolescents, are most at risk for negative consequences of loneliness, like anxiety or depression symptoms. Additionally, studies found that younger adults more often reported loneliness in comparison to older adults (Pyle & Evans, 2018). A peak in loneliness can be found in adults older than 70 years and young adults, with a significant decrease among middle-aged adults (Hawkley et al., 2022). Furthermore, it has been found that younger adults increasingly use social media applications compared to older adults (Best et al., 2014), although, until now, most research regarding this focuses on students and adolescents.

However, there are contradictory findings regarding the effects of social media use on people, especially concerning the communication aspect. Banskota et al. (2020) found that for an older aged sample (age above 65), social communication media facilitated social contact, thereby resulting in a decrease in feelings of loneliness, as well as supplying information to improve physical and mental health. As the sample did not include a young population, the study suggested that the effects might be more intense for younger people, as those are the main users of most communication apps. On the other hand, other researchers found that the increased use of social media facilitates feelings of loneliness within young people, often also leading to increased symptoms of anxiety, depression, or low self-esteem, as well as a decrease in task performance and happiness (Brooks, 2015).

1.5 The Current Study

There is only limited research done regarding a comparison between middle-aged individuals and younger adults, as most studies regarding POPC, for now, focus on young adults and adolescents. Nowadays, many people spend a lot of time online instead of taking part in physical situations, and research regarding loneliness can still be further expanded. The goal of this study is, therefore, to conduct further research into the relationship between loneliness and being constantly online and feeling the need to be connected. Previous studies were contradictory regarding the positive or negative effects and relations between social media use and loneliness (e.g. Banskota et al., 2020; Brooks, 2015), which will be further analysed. The goal is to investigate the relationship between participants' social media use, their perceived FoMO and their need to be permanently connected concerning their mental well-being and their feelings of loneliness. Hence, within this paper, first, the methods will be further explained, followed by an analysis and discussion of the findings. The research question that is aimed to be answered is*: To what extent is the relationship between loneliness and mental well-being influenced by individuals' feelings of POPC and FoMO in adults (aged 18 to 65) in the Netherlands and Germany?*

Based on the reviewed literature aforementioned, it is therefore expected that higher levels of loneliness relate to worse scores in mental well-being (H1). Secondly, it is expected that POPC, as well as FoMO, act as moderators of the relationship between loneliness and mental well-being (H2). Consequently, it is expected that high scores in Online Vigilance and FoMO are associated with a worse mental health status (H3). Additionally, a difference is expected between young adults (aged 18 to 30) and middle-aged adults (aged 31 to 65) among the scores of Online Vigilance, FoMO, mental well-being as well as loneliness.

Precisely, it is expected that younger adults score higher on both loneliness, as well as mental health (H4).

2. Methods

2.1 Study Design

In this study, a cross-sectional online survey was used to investigate the aforementioned research question. It aimed at measuring the effects of the independent variable loneliness on mental health (dependent variable). POPC, measured through Online Vigilance, and FoMO were analysed as possible moderators.

2.2 Participants

The study consisted of a non-probability sample, including 167 participants, who filled out the entire questionnaire and met the requirements. Participants were eligible to participate in this study if they lived in either Germany or the Netherlands, were between 18 and 65 years old and were able to understand English. An additional inclusion criterion was the use of digital media, like Online News, WhatsApp, Instagram or similar, at least once a week, as self-indicated by participants. Exclusion criteria for this study were being outside the age range of 18 to 65, as well as being diagnosed with any psychological disorders.

A total of 297 responses were recorded, with 130 participants excluded from the study. As a result, the sample consisted of 167 participants, ranging in age from 18 to 64, with an average age of 29.9 (SD = 13.1). Therefore, a total of 117 participants (70%) belonged to the age group of 18 to 30, and 50 participants (30%) belonged to the age group of 31 to 65.

74 % of the participants were female (124 participants), 25 % were male (42 participants), and 1% of participants identified themselves as non-binary or third gender (1 participant). Furthermore, 67% of the participants were German (112 participants), 28% were Dutch (47 participants), 6% were other European (6 participants), and 1% were Non-European (2 participants). They were also asked about their education level and relationship status. 46% of participants received their highest degree from a secondary or high school (n = 76), 9% finished a secondary vocational or technical school (n = 15), 13% of participants had the highest degree of a University of Applied science (n = 18), and 20% of a University (n = 33). Furthermore, 1% of participants finished with a graduate degree from a University (n = 2), and 1% with a PhD or other doctoral degree (n= 2). Lastly, 42% of participants indicated not being in a relationship (n= 70). The remaining 58% of participants were in a relationship (n =97). 10% for less than a year (n =16), 10% were in a relationship for a duration between 1

and 2 years (n = 16), 16% of participants between 2 and 5 years (n =27), and 23% of participants for more than 5 years (n =38).

Participants had two different ways to be invited to take part in this study. Students at the University of Twente were able to register for this study through the online platform SONA System, which offers participation in different studies conducted at the University of Twente to gain credits. The sampling method for those participants was volunteer sampling. These students received 0.25 SONA credits as a token for their participation. A second way to take part in this study was through snowball sampling by receiving the link, for example, through digital media, like WhatsApp, or through advertisement via social media. The advertisement, including a link, was thereby openly shared via those social media platforms, accessible to many people. Participants were further motivated to share the link and advertisement with people who meet the inclusion and exclusion criteria.

2.3 Measures and Materials

The questionnaire was provided via the Qualtrics website, with the link being shared through Social media platforms, as well as through the Test Subject SONA system from the University of Twente. Participants answered the questionnaire using their own media devices. Within the questionnaire, four relevant scales were implemented, which will be further explained in the following. Participants further answered questions regarding the scales of the Pittsburgh Sleep Quality Index (PSQI; 24 items), Perceived Stress Scale (PSS; ten items), the Big Five Inventory (BFI-10; ten items) and the Generalised Anxiety Disorder Assessment (GAD-7; seven items), which are not relevant to this paper.

2.3.1 Online Vigilance Scale

Online Vigilance was measured using the Online Vigilance Scale (OVS), which was developed, as well as validated by Reinecke et al. (2018). The scale includes 12 items, four items for each dimension, namely salience, monitoring and reactivity. Reinecke et al. (2018) found high internal consistency of the scale (α = 0.89). Within this study, the OVS showed excellent internal consistency (α = .91; see George & Mallery, 2003). Participants answered along a five-point Likert scale, with answers ranging from 1 “Does Not Apply at All” to 5 “Fully Applies”. Statements included are, for example “My thoughts often drift to online content.”. Total scores range between 12 and 60, with higher scores indicating higher Online Vigilance.

2.3.2 FoMO Scale

Individuals’ perceived FoMO was measured using the Fear of Missing Out Scale (FoMOS), which includes ten items. The scale was developed by Przybylski et al. (2013), and participants were asked to answer along a five-point Likert scale, measuring the degree of how they perceived FoMO, e.g., for social events or similar. The answers varied from 1 “Not at all true”, to 5 “Extremely true”. An example statement implemented is “When I miss out on a planned get-together it bothers me.” (Bowman & Clark-Gordon, 2019). The scale has been found to have high internal consistency, with a Cronbach’s alpha of .82 (Przybylski et al., 2013). When analysing, the scores were summed together. Total scores vary between ten and 50, with a higher score indicating a higher level of FoMO (Przybylski et al., 2013). In this study, the FoMO Scale showed similar good internal consistency, with a Cronbach’s alpha of .89 (see George & Mallery, 2003).

2.3.3 Mental Health Continuum Short Form

To investigate participants’ mental health, the Mental Health Continuum Short Form (MHC-SF) was implemented. The MHC-SF scale includes 14 items, three items for emotional (hedonic) well-being, six for psychological well-being, and five for social well-being. Participants answered along a six-point Likert scale, varying from 0 “Never”, to 5 “Everyday”. An example statement included is “During the past month, how often do you feel satisfied with life?” (Lamers et al., 2011).

The MHC-SF is evaluated by summing the scores, resulting in scores between zero and 70. Higher scores indicate a higher level of mental well-being (Lamers et al., 2011). Studies found good internal consistency (α = .91), as well as sufficient convergent and divergent validity (Luijten et al., 2019). Cronbach’s alpha score calculated in this study further indicated excellent internal consistency (α = .91), according to George & Mallery (2003).

2.3.4 UCLA Loneliness Scale

Participants’ feelings of loneliness were assessed using the Revised UCLA Loneliness scale. The scale consists of 20 items and is constructed to measure subjective feelings of loneliness and social isolation. Participants were asked to answer the statements using a four-point Likert scale, varying from 1 “Never”, to 4 “Often” (Russell et al., 1980). The UCLA loneliness scale has been found to have high internal consistency of α = .96 (Russell et al., 1978). In the current study, a Cronbach’s alpha score of α = .88 was found, indicating good internal consistency, as identified by George & Mallery (2003). For scoring, the combined values of each statement are combined, whereby items one, five, six, nine, ten, 15, 16, 19, and 20 were reserve scored. When analysing the scores, scores between zero and 20 are seen as average, 21 to 30 as mild and scores above 31 to 60 indicated severe loneliness (Russel et al., 1978).

2.4 Procedure

During this cross-sectional study, participants were asked to fill out an online survey with an estimated duration of 20 to 25 minutes. Data collection took place between the 9th and the 27th of April, 2023. The study was approved by the BMS Ethics Committee from the University of Twente (Request Number 230333). Beforehand, participants taking part in this study received a link through multiple media types, like the SONA system, WhatsApp, Instagram or similar. Additionally, advertisement graphics were used, which included basic information regarding the study, like the inclusion criteria and the link or a QR code (see Appendix A). Students at the University of Twente were able to sign up via the SONA system website.

The survey was created with the Qualtrics Website. At the beginning of the questionnaire, participants were informed about the content of the study, the involved scales, as well as the general procedure (Appendix B). No information was held back, therefore, participants were informed about the variables analysed and the scales used. Afterwards, participants consented, by answering “Yes”, regarding the use of their data, the understanding of the purpose of the study, as well as that they match the inclusion and exclusion criteria. Participants were also informed about the possibility to withdraw at any given time without a reason. Additionally, contact details for all researchers were mentioned in case of further questions or remarks.

Firstly, demographic questions regarding the participants were asked, specifically their gender, age, relationship status, level of education, as well as their nationality. Questions regarding the participant’s digital and social media habits were asked (e.g. their average digital media time, their average social media usage). Then, participants were presented with the OVS, the FoMOS, the MHC-SF, as well as the UCLA Loneliness scale. The full questionnaire, including all scales, can be found in Appendix C.

After answering the questions, participants reached the debriefing of the questionnaire, during which they were presented with three possibilities to contact help if needed, for example, when feeling distressed (Appendix D), namely the Dutch Website and Telephone Service, De Luisterlijn, the German “TelefonSeelsorge”. For students of the University of Twente, a contact for the student psychologist was included. Participants were again asked for consent regarding the usage of their anonymised data, before lastly having the possibility to leave their email addresses if they wanted to receive a summary of the results found during the study. Lastly, they were thanked for their participation and presented with the four researchers’ contact details, as well as the contact details of the responsible supervisor for this study. Additionally, participants could leave their email addresses, if they are interested in a summary of the results of the study.

2.5 Data Analysis

For the analysis, the program R studio, version 2023.03.0+386, was used. The R packages, as well as the used codes, can be found in Appendix E. To investigate the aforementioned research question and hypotheses, the dependent variable is mental well-being, the independent variable is loneliness, and FoMO and POPC, measured through Online Vigilance will be investigated as moderators.

Firstly, the dataset was prepared by removing participants who either did not answer all required questions or did not meet the inclusion criteria. For these analyses, a separate dataset was created, excluding all data related to the scales of PSQI, PSS, BFI-10, and GAD-7. Then, the dataset was prepared for analysis by transferring all necessary variables into numerical values. Secondly, descriptive statistics were assessed, and the dataset was further explored. The main characteristics of the dataset, like mean, standard deviation, minimum, maximum or similar of each variable, were explored. For example, participants' mean age was assessed.

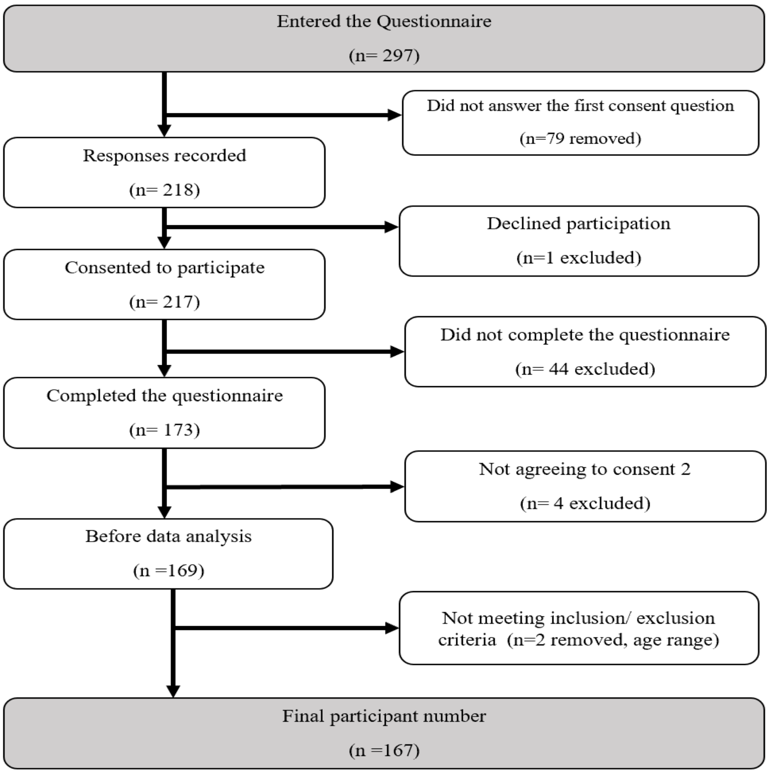
Afterwards, items belonging to a specific scale were merged and scored together as intended by it. For example, all items belonging to the MHC-SF were scored together for each participant. For all scales and subscales, participants' average scores were calculated. Before conducting further analyses, two linear models were created, one for POPC as a moderator, and one for FoMO. In the following, both models were analysed using the same steps. The models were checked for the assumptions of normality of distribution, linearity, homoscedasticity as well as multilinearity. Before testing for a moderating effect, it was tested whether the independent variable, loneliness, has an influence on the dependent variable, mental well-being, therefore also testing H1. A multi-linear regression analysis was conducted using an ANOVA (H2 & H3) if the assumptions were met. If not, non-parametric alternatives were conducted. Furthermore, the interaction effects were plotted. Lastly, to check H4, the participants were separated into two age groups (one below 30, and one above 30). Using a t-test, it was then analysed whether there is a difference in mean scores for online Vigilance, FoMO, mental health and loneliness.

3. Results

The final dataset included 167 participants a total of 130 responses were removed (see Figure 1). In total, 297 responses were recorded, with a total of 218 responses answering the first consent question (79 responses removed). First, participants who did not agree to the first consent question and were forwarded to the end of the survey were removed (*n* =1). Secondly, other participants who did not answer the complete questionnaire were removed (*n* = 44). Participants who did not agree to the second consent question asked were removed in the third step *(n* = 4). Lastly, participants who did not match the inclusion or exclusion criteria were removed (*n* = 2).

Figure 1

Flowchart Participants Removal



Note. n = participant number

3.1 Descriptive Statistics

3.1.1 Social and Digital Media Habits

Before testing the hypothesis, descriptive statistics of the dataset were assessed. Participants were asked about their daily average digital and social media time (Tables 1 and 2). Hereby, it is noticeable that overall, 36% of participants spend three to six hours a day using digital media. For the age group of 18 to 30-year-olds, both three to six hours and six to nine hours had the most participants (both 36%; *n* = 42). However, for those aged 31 to 65, most participants spend three to six hours using digital media (*n*= 18; 36%). Interestingly, the largest amount of time spent with digital media, more than 15 hours, was reported by the older age group (*n* = 1).

Table 1

Overview Participants Digital Media Hours

Hours	Between 18 & 30 (*n = 117*)	Above 30 (*n* = 50)
0-3 Hours	13 (11%)	20 (40 %)
3-6 Hours	42 (36 %)	18 (36 %)
6-9 Hours	42 (36%)	8 (16 %)
9-12 Hours	17 (15%)	3 (6 %)
12-15 Hours	3 (3%)	/
More than 15 Hours	/	1 (2%)

Note. n = Participant number; Group 1, Between 18- 30, includes participants aged between 18 and 30, while Group 2, Above 30 included participants aged 31 to 65. Participants were asked to self-identify the hours per day they spend using their digital media (e.g., smartphone, laptop/PC, TV, tablet, etc.)

Participants' average social media time was also investigated and presented in Table 2. When investigating the different age groups further, it can be noticed that the higher time frames are not distributed among the older aged group. However, for the younger group, most participants spend an average of one to three hours using social media (n = 72; 62%), while for the older group, most participants spend only less than an hour (n =26; 52%).

Table 2

Overview of Participants' Social Media Hours

Hours	Between 18-30 (*n = 117*)	Above 30 (*n* = 50)
0-1 Hour	8 (7%)	26 (52 %)
1-3 Hours	72 (62%)	20 (40 %)
3-5 Hours	24 (21 %)	4 (8%)
5-7 Hours	11 (9%)	/
More than 7 Hours	2 (2%)	/

Note. n = participant number per group. Group 1, Between 18-30, includes participants aged between 18 and 30, while Group 2, Above 30 included participants aged 31 to 65. Participants were asked to self-identify the hours per day they spend on any social media platform (e.g. Facebook, Instagram, TikTok, WhatsApp, Snapchat, YouTube, etc.)

Lastly, participants were asked about their preferred or most used media platforms. Participants were thereby able to select multiple options. The most frequently used media platform was WhatsApp, with 89.2% of participants using it (*n* = 149). The second most prominent was Instagram (*n* = 102; 61 %), and the third was YouTube (*n* = 92; 55 %). The media platforms did not differ too much between the age groups, as the same three platforms were most frequent (Table 3).

Table 3

Overview Participants Frequently Used Media Platforms

Media Platforms	Below 30 (*n = 117*)	Above 30 (*n* = 50)
Instagram	67 (57.3 %)	35 (70 %)
WhatsApp	103 (88 %)	46 (92 %)
TikTok	24 (20.5 %)	10 (20 %)
Facebook	13 (11.1%)	10 (20 %)
Snapchat	17 (14.5 %)	14 (28 %)
YouTube	64 (54.7 %)	28 (56 %)
Reddit	5 (4.2 %)	4 (8 %)
Twitter	6 (5.1 %)	3 (6 %)
Others	10 (8.5 %)	4 (8 %)

Note. n = Participant number; Below 30, includes participants aged between 18 and 30, Above 30 included participants aged 31 to 65. Participants were asked about their most frequently used media platform and were able to select multiple options; the percentages are rounded to one decimal.

3.1.2 Overview Scales

Before further investigating the hypotheses, total scores for each participant were calculated. A table summarising the total scores for the scales and their subscales can be found in Appendix F. Hereby, it can be noticed that for the MHC-SF questionnaire and its subdimensions, the older aged group had a higher average total score, indicating higher mental well-being. For all other questionnaires, however, the average scores were higher for the younger-aged group. For most scales, the scores would be seen as moderate. Contrastingly, participants' scores on the loneliness scale are above 31, indicating severe loneliness (Russell et al., 1978).

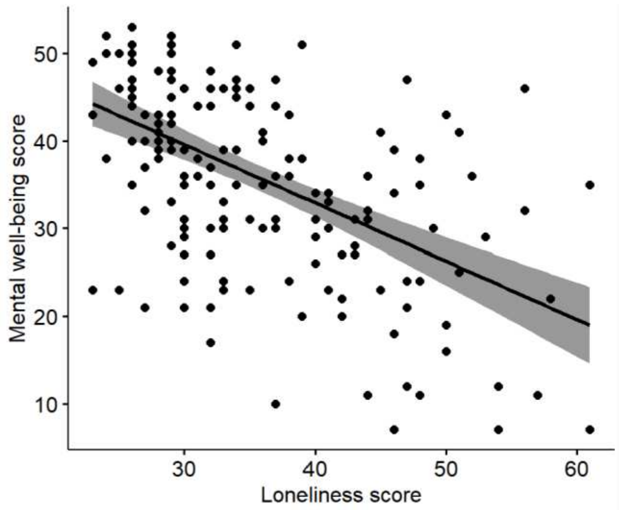
3.2 Statistical Analysis

3.2.1 Loneliness and Mental Health (H1)

After assessing the descriptive statistics, the first hypothesis was tested. It was assumed that higher levels of loneliness are related to lower scores in mental well-being (H1), therefore assuming a negative correlation. In order to test this hypothesis, a linear model was created, using loneliness, tested through the Revised UCLA Loneliness scale as the independent variable and mental well-being, tested through the MHC-SF as the dependent variable. Before conducting the analysis, the model was checked regarding the four assumptions of linear regression. However, the assumption of normal distribution of residuals was violated. The other assumptions, namely the assumption of a linear relationship and the assumption of equal variance were met. The assumption of Multicollinearity was not tested for this model, as it only included one independent and one dependent variable. However, as the assumption of normality was not met, a non-parametric test was conducted. The Spearman's rank correlation rho was assessed, and its results indicated a moderate negative correlation between loneliness and mental well-being (r (167) = -.51; p <. 001). Based on the results of the parametric and non-parametric tests, the linear regression analysis was carried out. The results of the linear regression analysis showed a significant effect of loneliness on mental well-being (b = -0.665, t(165) = -7.98, p < .001, R^2 = .279) and support the findings of the Spearman test. Therefore, these findings support the first hypothesis that loneliness significantly affects participants' mental well-being, and the hypothesis can be accepted (Figure 2).

Figure 2

Scatterplot of the Total Scores of Mental Well-being and Loneliness



3.2.2 Moderating Effect of FoMO and POPC (H2)

Afterwards, the second hypothesis was investigated. It was analysed whether POPC and FoMO act as moderators of the relationship between loneliness and mental well-being (H2). Therefore, two linear regression models were created, one for POPC and one for FoMO as possible moderating variables. Before conducting the analysis, the models were investigated in terms of their fit with the assumptions. All models met the assumption of linearity, as well as the assumption of no multicollinearity. However, both the Shapiro test, to assess the normal distribution of residuals, and the assumption of equal variance indicated a violation.

Therefore, the non-parametric Kendall test was conducted to investigate the correlation between the different variables. For both, POPC and FoMO, no significant effect was found. The correlation between POPC towards the relationship between loneliness and mental health, measured using the Online Vigilance scale and MHC-SF, was not significant (p = .06) and therefore suggests that it does not moderate the relationship between loneliness and mental well-being. Notably, however, the Kendall rank correlation coefficient test indicated a significant negative relation between OVS and mental well-being (τ= -0.16, z = -2.95, p = .003). Based on those, the linear regression analysis was conducted, which supports the results of the Kendall's test, that there is no significant effect (see Table 4).

Similarly, the influence of FoMO was not significant, indicated with a p-value higher than .05 (p = .23). Furthermore, a significant negative correlation was found between FoMO and MHC-SF scores using the Kendall rank test (τ = -0.227, z =-4.35, p < .001). However, both Kendall's tests again showed a significant relationship between loneliness and mental well-being, as also proven during the first hypothesis test (τ = -0.37, z = -6.93, p < .001), as well as in both linear models (POPC: t(164) = -2.38, p = 0.019). Furthermore, the findings of the linear analysis did not indicate a significant effect (b = .009, SE = 0.01, t(164) = .860, p = .391).

Based on those findings, it can be summarised that neither FoMO nor POPC act as moderators of the relationship between mental well-being and loneliness. The hypothesis can therefore be rejected.

Table 4

Results of Regression Analysis for POPC and FoMO as Moderators

	Estimate	Std. Error	t-value	p-value	CI
Intercept (Model POPC)	82.11	10.14	8.09	<.001*	[62.1 - 102]
Loneliness total (Model POPC)	-1.18	0.282	-4.17	<.001*	[-1.74-0.621]
OVS total	-0.825	0.347	-2.38	.019*	[-1.51-0.14]
Loneliness: OVS	0.0188	0.010	1.97	.051	[-0.0006–0.037]
Intercept (Model FoMO)	72.9	9.38	7.78	<.001*	[54.4–91.5]
Loneliness total (Model FoMO)	-0.812	0.262	-3.09	<.001*	[-133- (-0.294)]
FoMOS total	-0.678	0.386	-1.75	.08	[-1.44 -0.085]
Loneliness: FoMOS	0.009	0.011	0.86	.39	[-0.01 – 0.0298]

Note. * = p <.05, Std. Error = Standard Error, CI = Confidence Interval

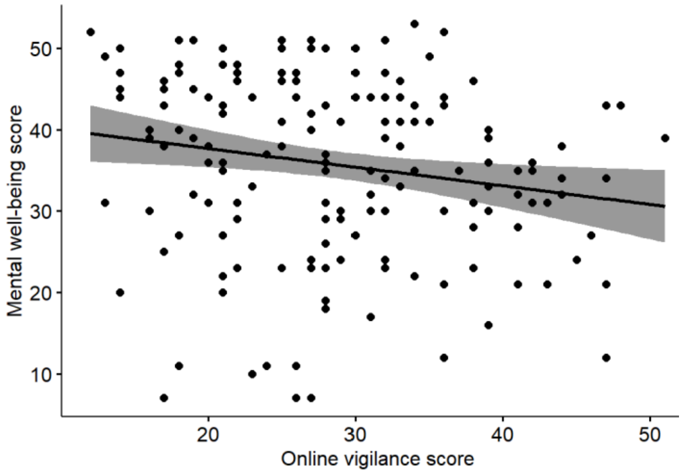
3.2.3 Online Vigilance, FoMO and Mental Well-being (H3)

Regarding the third hypothesis, it was expected that high scores in Online Vigilance and FoMO are associated with a worse mental health status (H3). To investigate this hypothesis, two linear models were created.

The model investigating the relationship between Online Vigilance and mental well-being met the assumption of multicollinearity, linearity, and equal variance. However, the assumption of normality of residuals was violated. Therefore, the non-parametric Spearman's rho test was conducted. The results indicate a significant negative relation between MHC-SF scores and Online Vigilance scores (r = -0.23, p = .0023). Therefore, higher scores in Online Vigilance indeed indicate lower scores in mental well-being (see Figure 3). However, the linear regression analysis indicated a relatively low R-squared (R^2= 0.036), which indicates a limited predicting power of Online Vigilance.

Figure 3

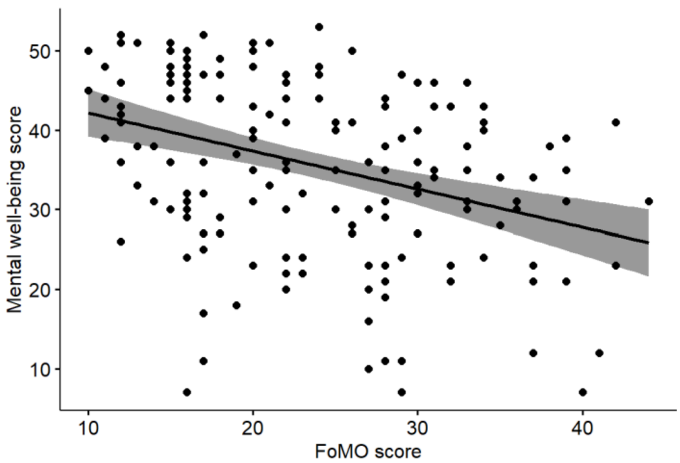
Relationship Online Vigilance Scores and Mental Health Scores



The second model to investigate the relationship between FoMO and mental health also did not meet all necessary assumptions. The assumption of normality of residuals was violated, while it met the other assumptions. Therefore, Spearman's rho test was conducted. A significant negative correlation was found, indicated by a p-value of below .001 (r = -0.38). Again, the model showed a relatively low R-squared value (R^2= 0.132). The relationship is further displayed in Figure 4. Therefore, as two significant effects ($p < .05$) were found, the third hypothesis can be accepted.

Figure 4

Relationship between FoMO Scores and Mental Health Scores



3.2.4 Age differences (H4)

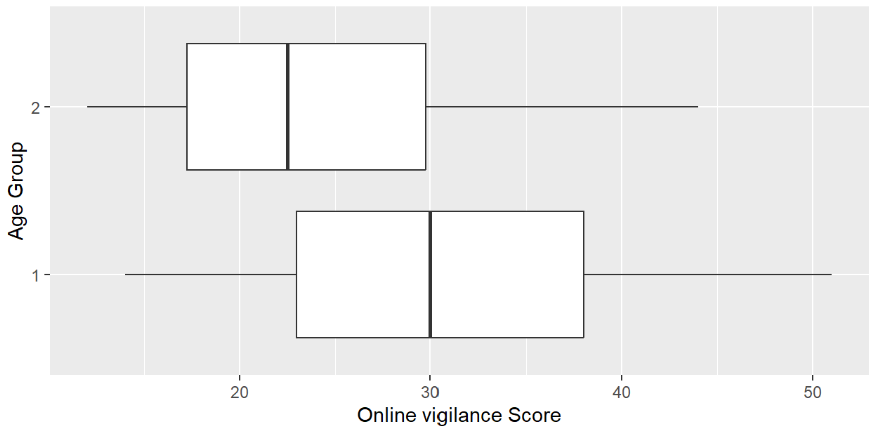
The last hypothesis was that a difference is expected between participants aged 18 to 30, and participants aged 31 to 65, regarding loneliness, Online Vigilance, FoMO and mental well-being (H4). In order to evaluate possible differences, four one-way between-groups ANOVA models were constructed. Age was utilised as a between-subject variable.

All models were checked regarding the assumptions. For all items, the assumption of no outliers was met. For the models of POPC, loneliness and mental well-being, the assumption of Normality was not met, as indicated by the Shapiro test ($p < .05$). For the FoMO model, the p-value was above .05 ($p = .056$), and the model was therefore assumed normal. However, all four models did not meet the assumption of homogeneity of variance, and therefore the non-parametric Wilcoxon rank sum test was conducted in order to compare the two age groups.

When conducting the non-parametric test, a significant difference was found for age towards Online Vigilance ($W = 42575$, $p < .001$). The findings from the ANOVA analysis further strengthened the evidence for the significant difference ($F(1, 165) = 24.29$, $p < .001$). The results therefore showed that the older age groups ($M = 30.80$, $SD = 8.70$) had significantly lower Online Vigilance scores than the younger age group ($M = 23.7$, $SD = 8.06$). Figure 5 further displays those differences.

Figure 5

Boxplot of the Total Scores on the Online Vigilance Scale, Grouped by Age

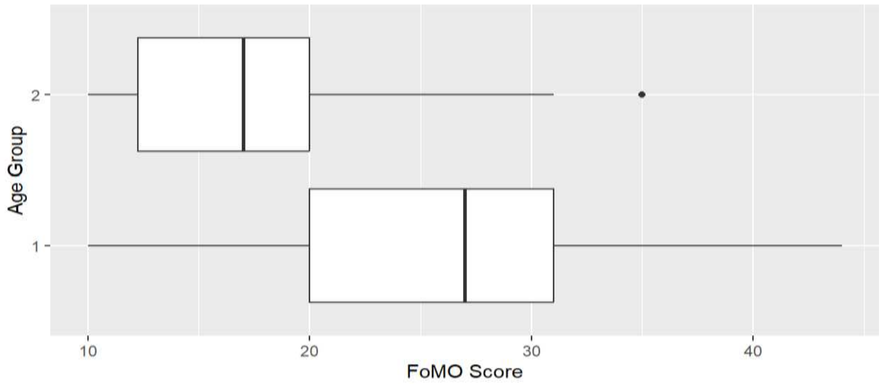


Note. Age group 1 = Participants aged 18 to 30, Age group 2 = Aged 31 to 65, y-axis= Age group, X-axis = Online Vigilance score

Regarding the effect of age on feelings of FoMO, another significant difference was found ($W = 4588$, $p < .001$), which indicated that the younger participants had a significantly higher total FoMO score ($M = 25.9$, $SD = 8.04$), compared to the older individuals ($M = 17.7$, $SD = 6.01$). The statistical difference was further proven within the ANOVA results $F(1, 165) = 41.82$, $p < .001$). Those differences are further displayed in Figure 6.

Figure 6

Boxplot displaying the Age Differences among FoMO Scores

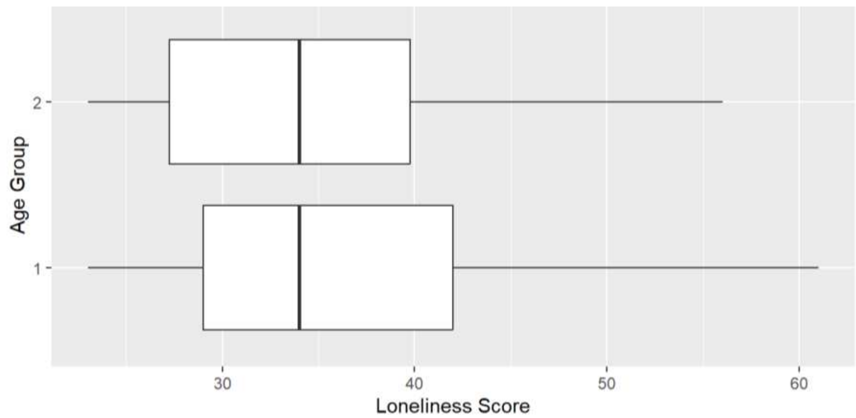


Note. y-axis=Age, x-axis =FoMO score; Age group 1 = Participants aged 18 to 30, Age group 2 = Aged 31 to 65

Furthermore, a difference among loneliness scores was investigated (Figure 7). No significant effect was found (*W* = 3177, *p* = 0.37), and therefore no significant difference among loneliness scores can be seen (Group 1: *M* = 36.2, *SD* = 8.83; Group 2: *M* = 35.0, *SD* = 8.69, $t(165) = -1.193$, $p = .423$). The results of the ANOVA analysis further support the findings ($F(1, 165) = 0.646$, $p = .423$).

Figure 7

Boxplot displaying the Differences in Total Score in Loneliness per Age group

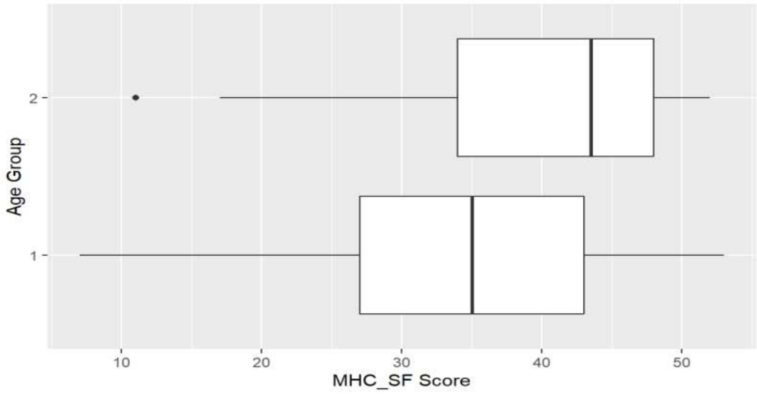


Note. Age group 1 = Participants aged 18 to 30, Age group 2 = Aged 31 to 65; y-axis= Age group, x-axis = Loneliness Score

The last scores that were investigated for age differences were those of the MHC-SF. The Wilcoxon rank sum test indicated a significant difference between the two age groups (W= 1853, $p < .001$). Therefore, the older aged participant had a significantly higher score in mental well-being (*M* = 40.2, *SD* = 10.2), compared to younger aged adults (*M* = 33.8; *SD*= 10.9). Figure 8 visualises the differences among scores.

Figure 8

Mental Well-being Scores (MHC-SF) as compared by Age Group



Note. Age group 1 = Participants ages 18 to 30, Age group 2 = Ages 31 to 65, y-axis= Age group, x-axis = Mental Well-being score

Based on these findings, hypothesis four needs to be rejected. While the dataset found significant differences among Online Vigilance scores, FoMO scores and MHC-SF scores, no significant differences in loneliness can be reported. Furthermore, a higher score of loneliness and mental health among younger adults was expected. The findings showed that older aged individuals, on average, score higher than younger aged individuals regarding their mental health, which does not match the expectations.

To summarise the findings, the first hypothesis, which assumed a negative relation between loneliness and mental well-being, was accepted, as a significant effect was found. The second hypothesis was rejected, as no significant effect of FoMO or POPC was found towards the relationship of loneliness on mental well-being. The third hypothesis of a correlation between POPC and FoMO towards mental well-being scores found two significant effects and can therefore be accepted. Lastly, the hypothesis that age differences can be found among the scores of Online Vigilance, FoMO, loneliness and MHC-SF, can be rejected, as no significant difference was found for an age difference in loneliness scores.

4. Discussion

The aim of this study was to analyse the relationship between loneliness and mental well-being and investigate which impact POPC and FoMO have towards this relation. Therefore, a cross-sectional online study was conducted, during which participants answered questions regarding their media habits, POPC, FoMO, loneliness and mental health. Additionally, the study investigated the differences between younger and older adults. Additionally, it aimed at investigating the contradicting findings regarding POPC´s influence towards mental health and loneliness. For example, a study by Banskota et al. (2020) found that social communication media improved social contact, which resulted in a decrease in loneliness and an increase in mental well-being. However, Brooks (2015) found that loneliness increases with higher social media use, which consequently leads to a decrease in mental well-being. Therefore, the study findings add value to the existing literature, by further investigating the relationship between FoMO, POPC and loneliness. With the increased usage and dependency of individuals towards digital and social media applications, understanding and investigating relevant connections is important. Based on the aforementioned literature, it was therefore expected that POPC and FoMO moderate the relationship between loneliness and mental well-being.

4.1 Digital and Social Media Habits

Compared to the findings of the report by We Are Social, DataReportal, & Hootsuite (2022), most participants spend between three to six hours using more digital media on average daily (n = 60), which is higher than the average 2.5 hours. Similarly to the results found by Best et al. (2014), it was identified in this study that the younger group spent on average more time using both digital and social media, as most participants of the older aged group used social media between zero and three hours (n = 20) and between zero and one hour (n= 26; see Table 1 and 2). A possible explanation for this increased use is the ever-growing importance, as well as the growing dependency on digital media. The COVID-19 pandemic increased the usage of digital media in people's everyday life, as people used it more and more to stay in touch, during work or similar(Marciano et al., 2022). Further, as found by Marcino et al. (2022), many younger people generally use their online environment as a coping mechanism. This might explain the higher average usage, as this behaviour might now become an everyday habit. However, no research has been conducted yet on how the end of the COVID-19 measurements changed these behaviours.

Also, the most popular social media sites differed. In a report by We Are Social, & DataReportal, & Meltwater (2023), Facebook had the most users worldwide, while it was only mentioned by 23 participants in this study. Within this study, WhatsApp was found to be most prominent, with Instagram scoring in second place, which was only third and fourth place in the report by We Are Social, & DataReportal, & Meltwater (see Table 3). Further, a study by Auxier & Anderson (2021) found that in a US sample, particularly younger adults more often use platforms like Instagram, Snapchat and TikTok, which might explain the found results, as the sample was predominantly younger adults.

4.2 Study findings

To investigate the aforementioned research question, four hypotheses were investigated. The first hypothesis investigated the relationship between loneliness and mental well-being, and it was expected that higher levels of loneliness relate to lower mental well-being scores. The results showed a negative relationship between loneliness and mental well-being, meaning that lower loneliness scores result in higher mental well-being scores for the participants. The study findings are consistent with previous literature and met expectations. For example, a study by Richardson et al. (2017) found that in the student sample, higher levels of loneliness indicated higher anxiety, stress and depression levels, as well as generally lower mental well-being.

A second investigation was conducted regarding the effects of FoMO and POPC towards loneliness and mental well-being. According to Banskota et al.'s (2020) research, social media applications helped older adults (over 65) make more social connections, which reduced their feelings of loneliness and provided them with information about how to enhance their physical and mental health. However, Brooks (2015) found that loneliness increases with higher social media use. Therefore, this study investigated these effects more in-depth. A study by Zell & Moeller (2018) found that individuals who lack social support increasingly turn to online media, as indicated by high FoMO scores, to receive reciprocal interaction and use opportunities for self-presentation. Some researchers linked the increased use of social media to a rise in symptoms of anxiety, sadness, or low self-esteem in young people, as well as a decline in task performance and happiness (Brooks, 2015). Therefore, it was assumed that both FoMO and POPC act as moderators. However, no significant effect was found, and therefore, neither the findings of Brooks (2015) nor Banskota et al. (2020) can be supported.

A third investigation was conducted regarding the effects of POPC and FoMO towards mental health. It was suspected that there is a negative relationship between both POPC, FoMO and mental health. The study found a significant negative relation between POPC and mental health, which indicates that higher scores on Online Vigilance led to lower mental well-being scores. Within the previous research, contradicting findings existed regarding the possible effects of POPC towards individuals' feelings. As aforementioned, Vorderer et al. (2016) found that after not using digital media over time, the feeling changed from feelings of emptiness to being more relaxed. However, Reinecke et al. (2017) found that feelings of being permanently online might increase feelings of stress. It was expected that higher levels of POPC would indicate lower mental well-being scores. The findings of this study support the results found by Reinecke et al. (2017). It was found that the need to be permanently online increases stress if the personal abilities to attend to messages and the number of messages do not match, which might explain the findings.

Similarly to POPC, the relationship between FoMO and mental well-being was investigated. A significant effect, and therefore a negative correlation between mental well-being and FoMO, was found. Altunwairqi et al. (2019) found that the experience of FoMO might lead to negative consequences, like sleep problems, anxiety, deficiency in emotional control or similar, and a decrease in mental well-being. These results can be supported by the study findings, as a significant effect was found. It indicated that higher scores among FoMO indicate lower scores in mental well-being and, therefore, worse mental health due to the negative consequences of FoMO.

Lastly, the scores of loneliness, POPC, FoMO and mental health were investigated for age differences. As expected, Online Vigilance, FoMO and mental health had significant differences for younger and older adults. As found by Vorderer et al. (2016), high levels of POPC indicate high monitoring of their online activities, which would also indicate higher average times for younger adults. As younger adults used social media applications more on average, the findings of Pryzbylski et al. (2013) that people who experience more fear of missing out use more social media were found here as well. However, there was no significant difference among the scores of loneliness. Further, compared to other scores, loneliness levels can be perceived as severe (Russell et al, 1978). It was expected that loneliness would be higher for younger adults than older adults (e.g., Fumagalli et al. 2021; Hawkley et al. 2022). A possible explanation for similar loneliness levels can be the occurrence of confounding variables that were not accounted for within the study, occurring within both age groups (e.g. stress). Further, a study by Pittman and Reich (2016) investigated the effects of Instagram and overall pictures and their relation to loneliness. Its findings suggest that image-based social media, like Instagram and Snapchat use may decrease loneliness among young adults, possibly due to the feeling of connectedness, after seeing images of friends or family online (Pittman & Reich, 2026). Another possible explanation could be related to the COVID-19 pandemic. While conducting the study, no regulations were in place for either Germany or the Netherlands. During the pandemic, loneliness increased overall (see Stolz et al., 2021). However, there is no research yet, investigating loneliness levels after the pandemic measurements ended.

As loneliness can be an indicator of problematic internet usage (Kim et al., 2009), comparing the findings to related studies can be of value. A systematic review conducted by Lozano-Blasco et al. (2022) investigated associated variables related to addictive use of the

Internet. They found an association between perceived stress, resilience problems or similar. Within this review, they found that FoMO, as well as other predictors like gender, age, geographical aspects and measurement instruments, act as moderators for Internet addiction. This can be interesting to be related to the higher FoMO scores among younger adults, as studies found that the intensity of problematic internet use is associated with greater FoMO and intrusive thoughts (Lozano-Blasco et al., 2022). Kim et al. (2009) further found that, due to their addictive behaviour, those individuals tend to spend less time interacting with friends, which increases their loneliness. As FoMO scores were higher for younger adults, they seem to be more at-risk for the aforementioned negative consequences of POPC, which is also indicated by the negative relationship between FoMO and mental health within this study.

Therefore, to answer the aforementioned research question, it can be noted that the existence of an influence of POPC and FoMO towards mental health, while not finding a significant effect for a moderating relationship, suggests that these factors contribute to decreased mental well-being, regardless of being a moderator. People who score high on either POPC or FoMO might be more vulnerable to mental health challenges. Understanding the associations of these variables might be valuable when constructing interventions or strategies to address future mental health concerns. Further, the age differences regarding POPC and FoMO showed that younger adults indicate higher levels of both, which is in line with previous research. As both are also negatively correlated to mental health it is important to further analyse their effects, consequences and causes.

4.3 Strengths and Limitations

Additionally, to the study findings, both strengths and limitations can be reported. A strength of the study is the topic involved. Both POPC and FoMO are still investigated to analyse their effects and how intervention can sufficiently deal with consequences that arise. Studies regarding the combined effects of FoMO and POPC do focus on their influence on mental health (e.g., Fumagalli et al., 2021; Vorderer et al., 2016), but not yet regarding the involvement of loneliness. This study aimed to further explore their effects and relations, to gain more insights, by adding to the consisting literature.

Another strength of the study is the use of relevant and reliable measurements. All included scales showed either high or good internal consistency, with Cronbach’s Alpha values ranging between .82 and .91 (i.e. Reinecke et al. 2018; Przybylski et al, 2013). This indicated that all items of each scale measure concepts closely related to each other, which strengthens the validity of the study and may reduce biases.

Moreover, the study involved a sample including the age group of older aged adults (aged 31 to 65). Prior literature regarding the effects of digital and social media, as well as POPC, oftentimes focuses on students, for example as done in the study of Vorderer et al. (2016). With this study, gaining more in-depth information regarding age differences is of value to gain deeper insights into both POPC and FoMO.

Lastly, the cross-sectional nature of the study can be noted as a strength. This technique can be of importance for collecting exploratory data. Gaining more in-depth information concerning both POPC and FoMO, which was the aim of this study, is of value when conducting future research studies and design interventions (Kesmodel, 2018). Additionally, its conductance is inexpensive and offers the possibility to reach a larger population, as it was distributed online (Wang & Chen, 2020). The cross-sectional design further, allowed for no harm for participants, as all information and content were openly mentioned within the consent form.

Regardless of its strengths, limitations of the study can also be identified. First, the conducted G-Power analysis before starting with the data collection yield a suggested sample size of 185, which was not met. Therefore, the results cannot be generalised, due to the sample size being too small, as well as the sampling technique of convenience sampling, as it lacks external validity. To improve further representativeness of the study, conducting a questionnaire with a larger sample size is suggested. For example, in the cross-sectional studies conducted by Freytag et al. (2021), samples included more than three thousand internet users. Similarly, in a study conducted by Zhou (2019), which investigated the effects of FoMO, PO and feelings of acceleration, the sample included 687 university students. However, a larger sample size was out of the scope of this paper.

Another limitation of this study is the language used within the questionnaire. Even though the inclusion criteria limited the participants to living in either the Netherlands or Germany, the questionnaire was only available in English. Not answering the questionnaire in the participant's mother tongue could lead to false results. For example, a study by Tyson et al. (1988) found that individuals respond differently to the same item in different languages. Participants who met the other requirements but were not able to understand English were excluded from the study, which might result in more broader findings. This was done, as not all included scales are yet available and validated in other languages like Dutch and German. Future research should therefore involve validated questionnaires in more languages, to reach a broader population.

Further, as the study was designed as a self-report questionnaire, the possibility of reporting bias might occur. The study accounted for it by using validated measurements, as well as being anonymous, which should reduce bias. Nonetheless, as personal details were asked, for example regarding participants' average digital and social media time, participants might answer falsely.

Lastly, the overall length of the questionnaire could be seen as a weakness. Even though this paper focuses only on four of the involved measurements, the overall questionnaire further included questionnaires regarding sleep, stress, personality and generalised anxiety disorder. This might also explain the high number of participants that needed to be removed (*n* = 130), who did not complete the questionnaire. A study by Rolstad et al. (2011) found that indeed the length of a questionnaire had a negative influence on the response rate, as it increases participants' response burden. However, as this association between length, content and questionnaire cannot be separated, it is suggested that instead of just investigating the length, the involved questionnaires and their reliability are of more importance, which was done beforehand.

4.4 Further Research

The presented cross-sectional study focused only on participants living in Germany and the Netherlands. For further studies, increasing the countries, and thereby increasing the variety and number of participants could be of use. For this sample, no cultural differences were analysed. If the sample would include a broader range of countries and cultural backgrounds, assessing cultural upbringing as a possible influencing variable can be interesting, as research until now rarely focuses on those differences among the relationship of loneliness, FoMO, POPC and mental well-being. A review by Blachnio et al., (2017), found great differences among internet addictive behaviours, not only due to cultural influences on measurement instruments but also due to society and culturally specific rules. It would be interesting to investigate the specific influences of FoMO and POPC. Further, a systematic review by Kim et al. (2009), found that European countries have lower prevalence rates of internet addiction than Asian countries. Gaining similar insights into the differences regarding POPC and FoMO can be valuable to identify risk groups and adapt interventions tailored to the relevant groups in the future.

Expanding the sample would offer the possibility to analyse more similar age groups. In the conducted study, 167 participants took part in total. However, more people belonged to the younger age group (*n* =117) compared to the older aged group (*n* = 50), indicating a predominantly younger sample. To make generalised statements about age differences, having equal groups would be valuable. Furthermore, the sample was predominantly female (n = 124, compared to male n= 42), even though the reasons for that are unknown, and do not match the generalised population of people living in Germany or the Netherlands. Therefore, aiming for more equal distribution regarding both age and gender is suggested for future studies, for example by introducing not only a token for university students (in this case SONA credits) but for all participants. Another solution would be to use a random sampling technique, instead of convenience or snowball sampling. For example utilising a stratified random sampling method, would ensure representativeness of the population investigated (Acharya et al., 2013).

Another interesting factor would be to analyse smaller age groups. Including ages 18 to 30 and 31 to 65, does yield an identification regarding the differences, however, the ranges include a large variety of participants' ages. Designing the study with smaller age ranges, to investigate the possibility of either generational or age differences would be interesting. Similarly, further investigating educational differences could yield information about which groups might be most at risk regarding the effects. Another factor of interest can be gender. A study by Chern & Huang (2018) investigated the differences in gender among Internet addiction and found that sex influences the average usage of mobile phones. They found that males diagnosed with internet addiction have a greater health-related quality of life. In turn, they are lacking within the social area, which they point back towards biological differences, like lifestyles. In the future, these results might be helpful to design interventions to decrease the effects of FoMO or POPC.

Further, it can be suggested to conduct longitudinal studies, to investigate whether the influence of POPC and FoMO changes over time. Thereby, it would be of value to investigate how it changes with the nowadays increased development and importance of both digital and social media. For example, a study by Booker et al. (2018) analysed gender differences in social media use and well-being, for five years. Their findings suggest an increase in social media interactions, while happiness decreased. However, until now, no longitudinal studies regarding the effects of POPC or FoMO have been conducted.

4.5 Conclusion

In summary, this cross-sectional study showed that for a non-probability sample of people aged 18 to 65, POPC and FoMO did not function as moderators of the relationship between loneliness and mental health. However, the presented study provided evidence for a relationship between loneliness and mental health, as well as the negative effects of POPC and FoMO towards mental health which suggests that these factors contribute to a decrease in mental health. Evidence for age differences among levels of POPC, FoMO and mental health among younger and older adults were found. Understanding the associations of these variables might be valuable when constructing interventions or strategies to address future mental health concerns.

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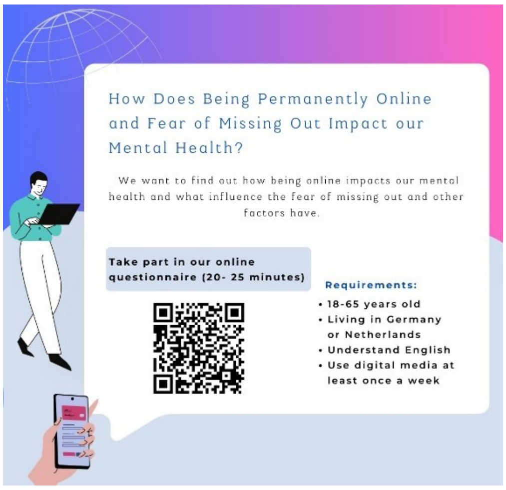
Appendix A

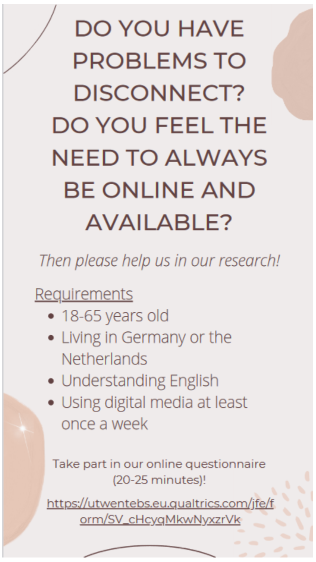
Graphics / Advertisements used to recruit participants

1:

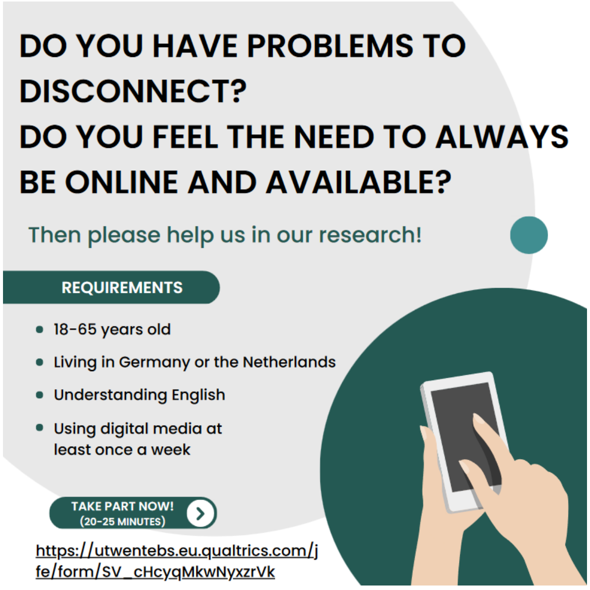


2:

3:



4:


DO YOU HAVE PROBLEMS TO DISCONNECT?
DO YOU FEEL THE NEED TO ALWAYS BE ONLINE AND AVAILABLE?
Then please help us in our research!
REQUIREMENTS
18-65 years old
Living in Germany or the Netherlands
Understanding English
Using digital media at least once a week
TAKE PART NOW!
(20-25 MINUTES)
https://utwentebs.eu.qualtrics.com/jfe/form/SV_cHcyqMkwNyxzrVk

5:


DO YOU HAVE PROBLEMS TO DISCONNECT?
DO YOU FEEL THE NEED TO ALWAYS BE ONLINE AND AVAILABLE?
Then please help us in our research!
Requirements
18-65 years old
Living in Germany or the Netherlands
Understanding English
Using digital media at least once a week
Take Part Now!
(20-25 minutes)
https://utwentebs.eu.qualtrics.com/jfe/form/SV_cHcyqMkwNyxzrVk

Appendix B

Informed consent and initial participant Information

UNIVERSITY OF TWENTE.

Welcome!

Thank you for participating in our study about the topic "Permanently Online - Permanently Connected and the Fear of Missing Out and its Impact on Mental Health".

>>

UNIVERSITY OF TWENTE.

Nowadays, many people are constantly online and available for digital media use. Social media apps are an important part of many people's everyday life. But what are the effects of constantly being online and why do we feel the psychological need to be connected?

This phenomenon of being permanently online and permanently connected (POPC) has different underlying reasons, the most common one being the fear of missing out. In this study, we request your support to answer the following questionnaires, for example regarding online vigilance, which is a term for psychological connectedness that people feel towards digital media use. The main purpose of this study is to investigate the effects of online vigilance (OVS) on overall mental well-being (MHC-SF), sleep quality (PSQI), loneliness (UCLA Loneliness scale), stress (PSS), personality (BFI10) and generalised anxiety disorder (GAD-7). This will be done with this online questionnaire. During this questionnaire general questions will be asked regarding different related topics, like your social media habits, your frequency of use or similar.

The study should take you around 20-25 minutes to complete. In order to take part in this study, you should be between 18 and 65 years old and live either in Germany or the Netherlands. Additionally, being able to answer this questionnaire in English is required and you should use online media apps (e.g., WhatsApp, Facebook, Instagram, online news, etc.) at least once a week.

Your participation in this research is voluntary and you have the right to withdraw at any point during the survey. If you choose to withdraw, by not answering the complete questionnaire, your data will be removed. All information you provide will be anonymized and therefore cannot be traced back to you. At the end of the questionnaire, you will once again be asked if you consent to your data being used or get the possibility to withdraw from the questionnaire, which will result in all your data being deleted.

This study has been reviewed and approved by the BMS Ethics Committee from the University of Twente (Approval Number 230333).

In case of any remarks or questions please contact:

Celi tudent.utwente.nl)
Lilli E nt.utwente.nl)
Ninja n@student.utwente.nl)
Michele Pe i@student.utwente.nl)

Supervisor: Alejandro Dominguez Rodriguez (z@utwente.nl)

<< >>

Informed consent

By clicking "Yes" below, I agree to the following:

- I have read the introduction of the study fully and I am aware of the purpose of this study.
- I understand that information I provide will be used for study purposes only and will be anonymized.
- I consent that my participation in this study is voluntary and I can withdraw from it at any time, without giving reasons.
- I understand that in order to take part in this study, I am between 18 and 65 years old and I live either in Germany or the Netherlands. Additionally, I use online media applications or communication applications (like Instagram, WhatsApp, Tik Tok, online news, etc.) in my daily life at least once a week.

● Yes, I agree to participate in the study.

○ No, I do not agree (you will be directed to the end of the study).

<< >>

Appendix C
Questionnaire and Items included

Descprptive questions

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Non-binary / third gender

How old are you?

What is your nationality?

- ◯ Dutch
- ◯ German
- ◯ Other European country
- ◯ Non-European country

Are you in a relationship at the moment?

- ◯ Yes
- ◯ No

If yes, for how long?

- ◯ Less than a year
- ◯ Between 1 and 2 years
- ◯ Between 2 and 5 years
- ◯ More than 5 years

Please indicate your highest attained degree of education.

- ◯ Secondary school / high school / Weiterführende Schule
- ◯ MBO / Secondary vocational or technical school or college / Ausbildung
- ◯ HBO / University of Applied Sciences / Fachhochschule (e.g., Bachelor of Science/ Arts or equivalent)
- ◯ College / University / Universität - Undergraduate degree (e.g. Bachelor of Science/Arts or equivalent)
- ◯ College / University / Universität - Graduate degree (e.g. Master of Science/Arts or equivalent)
- ◯ Doctoral degree / PhD
- ◯ Other:

Social and Digital Media Habits Questions

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We will start with a few questions regarding your media habits. Please try to answer as accurately as possible. All answers will remain anonymous.

How many hours a day do you spend using *digital media* on average (e.g. your smartphone, laptop/PC, TV, tablet, etc.)?

- ○ 0-3 hours
- ○ 3-6 hours
- ○ 6-9 hours
- ○ 9-12 hours
- ○ 12-15 hours
- ○ More than 15 hours

How many hours a day do you spend on any *social media platform* on average (e.g. Facebook, Instagram, TikTok, WhatsApp, Snapchat, YouTube, etc.)?

- ○ 0-1 hour
- ○ 1-3 hours
- ○ 3-5 hours
- ○ 5-7 hours
- ○ More than 7 hours

Which social media platform(s) do you use <u>most frequently</u>?

- ☐ Instagram
- ☐ WhatsApp
- ☐ TikTok
- ☐ Facebook
- ☐ Snapchat
- ☐ YouTube
- ☐ Reddit
- ☐ Twitter
- ☐ Other, please indicate: ______

Online Vigilance scale

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The following questions are about how you personally handle online content. Here you will find statements that describe various forms of dealing with the Internet. When we say “online” or “the Internet”, we don’t refer to the Internet as a whole, but the content that you make use of on a regular basis (e.g., your WhatsApp or Snapchat contacts, your favorite websites, online communities, or social media). Please indicate how the following statements apply to you personally.

	1. Does not apply at all	2.	3.	4.	5. Fully applies
My thoughts often drift to online content.	○	○	○	○	○
I have a hard time disengaging mentally from online content.	○	○	○	○	○
Even when I am in a conversation with other people, I often think about what is happening online.	○	○	○	○	○
Often online content occupies my thoughts, even as I am dealing with other things.	○	○	○	○	○
I constantly monitor what is happening online.	○	○	○	○	○
I often feel the urge to make sure I know what is happening online.	○	○	○	○	○
I often start certain online applications so I don´t miss out on any news.	○	○	○	○	○
I always keep an eye on what is happening online at the moment.	○	○	○	○	○

The following questions pertain to your personal reactions when you receive online messages (e.g., on your smartphone, laptop, or PC). When we say "online message" we refer to messages you receive on WhatsApp, Snapchat, Facebook, Twitter, or via E-Mails, as well as to push messages you receive from different applications (e.g., news apps, fitness apps, games, and learning apps). Please indicate how the following statements apply to you personally.

When I receive an online message...

	1. Does not apply at all	2.	3.	4.	5. Fully applies
My thoughts drift there immediately.	○	○	○	○	○
It triggers an impulse in me to check it right away.	○	○	○	○	○
I immediately attend to it, even if I am engaged in other things at that moment.	○	○	○	○	○
I immediately give it my full attention.	○	○	○	○	○

<< >>

FoMO Scale

In the following, a collection of statements about your everyday experiences is presented. Using the scale provided, please indicate how true each statement is of your general experiences.

Please answer according to what really reflects your experiences, rather than what you think your experiences should be. Please treat each item separately from every other item.

	Not at all true	Slightly true	Moderately true	Very true of me	Extremely true
I fear others have more rewarding experiences than me.	○	○	○	○	○
I fear my friends have more rewarding experiences than me.	○	○	○	○	○
I get worried when I find out my friends are having fun without me.	○	○	○	○	○
I get anxious when I don´t know what my friends are up to.	○	○	○	○	○
It is important that I understand my friends "in jokes".	○	○	○	○	○
Sometimes, I wonder if I spend too much time keeping up with what is going on.	○	○	○	○	○
It bothers me when I miss an opportunity to meet up with friends.	○	○	○	○	○
When I have a good time, it is important for me to share the details online (e.g., updating status).	○	○	○	○	○
When I miss out on a planned get-together it bothers me.	○	○	○	○	○
When I go on vacation, I continue to keep tabs on what my friends are doing.	○	○	○	○	○

Mental Health continuum short form

During the past month, how often did you feel...

	Never	Once or twice	About once a week	About 2 or 3 times a week	Almost every day	Everyday
Happy	○	○	○	○	○	○
Interested in life	○	○	○	○	○	○
Satisfied with life	○	○	○	○	○	○
That you had something important to contribute to society	○	○	○	○	○	○
That you belonged to a community (like a social group, or your neighborhood)	○	○	○	○	○	○
That our society is a good place, for all people	○	○	○	○	○	○
That people are basically good	○	○	○	○	○	○
That the way our society works makes sense to you	○	○	○	○	○	○
That you like most parts of your personality	○	○	○	○	○	○
Good at managing the responsibility of your daily life	○	○	○	○	○	○
That you had warm and trusting relationship with others	○	○	○	○	○	○
That you had experiences that challenge you to grow and become a better person	○	○	○	○	○	○
Confident to think or express your own ideas and opinions	○	○	○	○	○	○
That your life has a sense of direction or meaning to it	○	○	○	○	○	○

Revised Loneliness scale

Please indicate, how often those statements are descriptive of you.

	Never	Rarely	Sometimes	Often
I feel in tune with the people around me.	○	○	○	○
I lack companionship.	○	○	○	○
There is no one I can turn to.	○	○	○	○
I do not feel alone.	○	○	○	○
I feel part of a group of friends.	○	○	○	○
I have a lot in common with the people around me.	○	○	○	○
I am no longer close to anyone.	○	○	○	○
My interest and ideas are not shared by those around me.	○	○	○	○
I am an outgoing person.	○	○	○	○
There are people I feel close to.	○	○	○	○
I feel left out.	○	○	○	○
My social relationships are superficial.	○	○	○	○
No one really knows me well.	○	○	○	○
I feel isolated from others.	○	○	○	○
I can find companionship when I want it.	○	○	○	○
There are people who really understand me.	○	○	○	○
I am unhappy being so withdrawn.	○	○	○	○
People are around me, but not with me.	○	○	○	○
There are people I can talk to.	○	○	○	○
There are people I can turn to.	○	○	○	○

<< >>

Appendix D
Participant Debriefing

You have reached the end of the survey, thank you for your participation!

If you felt any discomfort as a result of taking part in this survey after reviewing your social media habits, or one of the discussed factors, you can contact De Luisterlijn (+31(0)88 0767 000), which offers a free telephone counselling service, as well as an online chat function, in both English and Dutch (https://www.deluisterlijn.nl/).
For German speaking participants it is also possible to contact the "TelefonSeelsorge", both online (https://online.telefonseelsorge.de/), or via phone (+49 0800/111 0 111)

Students of the University of Twente can also contact the student psychologist at the University of Twente (+31(0)53 489 2035).

In case of questions or remarks please contact:

Celi
Lilli
Ninj
Mic

Supervisor: Alejandro Dominguez Rodriguez (:@utwente.nl)

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UNIVERSITY OF TWENTE.

All information leading back to you will be anonymized. All data entered will only be available for members of the research team and will be stored for two years. After you finish this questionnaire, your data will be analyzed and it is not possible to withdraw from the study.

By clicking yes, you consent again and allow us to analyze your anonymized data.

- Yes
- No

Research outcomes will be reported in an academic thesis, and also may be used for journal articles and/or scientific congress presentations. However, all data and information will remain anonymous!

Are you interested in a summary of the results? Feel free to leave your email address!

(Contact details will be stored separately for anonymization.)

<< >>

Appendix E

R-script POPC, FoMO, Mental health and Loneliness

```
#R-script POPC, FoMO, Loneliness and Mental health - Lilli

#load and start required packages:
install.packages("tidyverse", dependencies = TRUE)
install.packages("foreign")
install.packages("broom")
install.packages("psych")
install.packages("haven")
install.packages("janitor")
install.packages("CTT")
install.packages("readxl")
install.packages("ggplot2")
install.packages("readxl")
install.packages("lifecycle")
install.packages("vtree")
install.packages("ggpubr")
install.packages("jtools")
install.packages("jmtools")

library(ggpubr)
library(vtree)
library(lifecycle)
library(tidyverse)
library(foreign)
library(readxl)
library(broom)
library(psych)
library(haven)
library(janitor)
library(CTT)
library(ggplot2)
```

```
library(dplyr)
library(car)
library (modelr)
library(ltm)
library(Hmisc)
library(reshape)
library(GGally)
library(jtools)
library(jmtools)

#set Working directory
setwd("C:/Users/liba9/OneDrive/Dokumente/University PSY/UT Year 3/Module 12
Bachelor Thesis")

#Orginal datenset --> not cleaned of other variables
data1 <- read_excel("POPC_Data_orginal.xlsx")
view(data1)
summary(data1)
#Dataset 2 --> with variables of the others
data2 <- read_excel("POPC_Data.xlsx")
view(data2)

##################################################################################
#open dataset --> only loneliness

data <- read_excel("POPC_Data_Loneliness.xlsx")

summary(data)

#check wath type of data
typeof(data)

#Remove participants outside of Age range
data <- data[data$Age >= 18 & data$Age <= 65, ]
```

```
#change from list to numeric
data <- data %>%
  mutate_if(!names(.) %in% c("contact details", "Education level_Others", "Media
platforms", "Media platforms_Others"), as.numeric)

#create dummy variable regarding the age group

data$age_dummy <- ifelse(data$Age >= 18 & data$Age <= 30, 1, 2)

#delete "unimportant" columns for analysis
data$`contact details` <- NULL
data$Progress <- NULL
data$`Duration (in seconds)`<- NULL
data$Finished <- NULL
data$`informed consent`<- NULL
data$`Consent 2` <- NULL

#Removing Media platforms --> so that dataset can all be in numeric
data$`Media platforms_Others`<- NULL
data$`Media platforms` <- NULL

#for relationship lenght --> change NA’s to 0
data$Length_relationship <- ifelse(is.na(data$Length_relationship), 0,
data$Length_relationship)

#for Education_others change NA to 0
data$`Education level_Others` <- ifelse(is.na(data$`Education level_Others`), 0,
data$`Education level_Others`)

# remove education level others
data$`Education level_Others`<- NULL

# OR change NA`s to O
data[is.na(data)] <- 0
```

```
#change Age to numeric:
data$age_dummy <- as.numeric(data$age_dummy)
summary(data)

cor(data)
ggpairs(data)
################################################################################
#Demographic data
#overview about the dataset
data %>% str()
#Age
data %>% summarise (mean = mean(Age), sd =sd (Age), var = var(Age), minimum =
min(Age), maximum = max(Age))
vtree(data, "age_dummy")

#count gender
vtree(data, "Gender")

#count Nationality
vtree(data, "Nationality")

#count Education
vtree(data, "Education_level")

#count relationship status
vtree(data, "Relationship_status")
#relationship length
vtree(data, "Length_relationship")

################################################################################
#Internet/ digital media usage participants

vtree(data, "hours_digital_media")
```

```
vtree(data, "hours_social_media")

table(data$`Media platforms`)
#hours digital and social media per group
vtree(data, c("age_dummy", "hours_digital_media"),
      fillcolor = c( group = "#e7d4e8", Age = "#99d8c9"),horiz = FALSE)

vtree(data, c("age_dummy", "hours_social_media"),
      fillcolor = c( group = "#e7d4e8", Age = "#99d8c9"),horiz = FALSE)

############SCALES########################################################
#total scores Online Vigilance scale

#Sub-Dimension Salience
data$OVS_S <- rowSums(data[,c("Online Vigilance 1_1", "Online Vigilance 1_2", "Online
Vigilance 1_3", "Online Vigilance 1_4")])
#Sub-Dimension Monitoring
data$OVS_M <- rowSums(data[,c("Online Vigilance 1_5", "Online Vigilance 1_6", "Online
Vigilance 1_7", "Online Vigilance 1_8")])
#Sub-dimension Reactibility
data$OVS_R <- rowSums(data[,c("Online Vigilance 2_1", "Online Vigilance 2_2", "Online
Vigilance 2_3", "Online Vigilance 2_4")])

#overall total scores
data$OVS_total <- rowSums(data[,c("Online Vigilance 1_1", "Online Vigilance 1_2",
"Online Vigilance 1_3", "Online Vigilance 1_4", "Online Vigilance 1_5", "Online Vigilance
1_6", "Online Vigilance 1_7", "Online Vigilance 1_8", "Online Vigilance 2_1", "Online
Vigilance 2_2", "Online Vigilance 2_3", "Online Vigilance 2_4")])

data %>% summarise (mean = mean(OVS_M), sd =sd (OVS_M), var = var(OVS_M),
minimum = min(OVS_M), maximum = max(OVS_M))
data %>% summarise (mean = mean(OVS_S), sd =sd (OVS_S), var = var(OVS_S),
minimum = min(OVS_S), maximum = max(OVS_S))
```

```
data %>% summarise (mean = mean(OVS_R), sd =sd (OVS_R), var = var(OVS_R),
minimum = min(OVS_R), maximum = max(OVS_R))
data %>% summarise (mean = mean(OVS_total), sd =sd (OVS_total), var = var(OVS_total),
minimum = min(OVS_total), maximum = max(OVS_total))

#FoMO scale

data$FoMOS_total <- rowSums(data[,c("FoMO Scale_1","FoMO Scale_2", "FoMO
Scale_3", "FoMO Scale_4", "FoMO Scale_5", "FoMO Scale_6", "FoMO Scale_7", "FoMO
Scale_8", "FoMO Scale_9", "FoMO Scale_10")])

data %>% summarise (mean = mean(FoMOS_total), sd =sd (FoMOS_total), var =
var(FoMOS_total), minimum = min(FoMOS_total), maximum = max(FoMOS_total))

#Plots FOMO and online Vigilance scale
library(ggplot2)

# Plot for Online Vigilance Scale
ggplot(data, aes(x = OVS_total)) +
  geom_histogram(binwidth = 1) +
  labs(x = "Online Vigilance Scale Total Score", y = "Count")

# Plot for FoMO scale
ggplot(data, aes(x = FoMOS_total)) +
  geom_histogram(binwidth = 1) +
  labs(x = "FoMO Scale Total Score", y = "Count")

# Plot for FoMO Scale by age group
ggplot(data, aes(x = FoMOS_total, fill = factor(age_dummy), group = age_dummy)) +
  geom_histogram(alpha = 0.7, position = "identity") +
  labs(x = "FoMO Scale Total Score", y = "Count", fill = "Age group") +
  scale_fill_manual(values = c("blue", "red"),
                    labels = c("Age Group <30", "Age Group >30")) +
  theme_classic()
```

```
# Plot for Online Vigilance Scale by age group
ggplot(data, aes(x = OVS_total, fill = factor(age_dummy), group = age_dummy)) +
  geom_histogram(alpha = 0.7, position = "identity") +
  labs(x = "Online Vigilance Scale Total Score", y = "Count", fill = "Age Group") +
  scale_fill_manual(values = c("blue", "red"),
                    labels = c("Age Group <30", "Age Group >30")) +
  theme_classic()


#MHC_SF

#Sub-Dimension Emotional well-being
data$MHC_SF_EM<- rowSums(data[,c("MHC-SF_1", "MHC-SF_2" , "MHC-SF_3")])
#Sub-Dimension Social Well-being
data$MHC_SF_SO <- rowSums(data[,c("MHC-SF_4", "MHC-SF_5" , "MHC-SF_6",
"MHC-SF_7", "MHC-SF_8")])
#Sub-dimension Psychological well-being
data$MHC_SF_PS<- rowSums(data[,c("MHC-SF_9", "MHC-SF_10" , "MHC-SF_11",
"MHC-SF_12", "MHC-SF_13", "MHC-SF_14")])
#overall total scores
data$MHC_SF_total <- rowSums(data[,c("MHC-SF_1", "MHC-SF_2" , "MHC-SF_3",
"MHC-SF_4", "MHC-SF_5" , "MHC-SF_6", "MHC-SF_7", "MHC-SF_8", "MHC-SF_9",
"MHC-SF_10" , "MHC-SF_11", "MHC-SF_12", "MHC-SF_13", "MHC-SF_14")])

#Plot MHC-SF
ggplot(data, aes(x = MHC_SF_total)) +
  geom_histogram(binwidth = 1) +
  labs(x = "MHC-SF Total Score", y = "Count")
#by age group
ggplot(data, aes(x = MHC_SF_total, fill = factor(age_dummy), group = age_dummy)) +
  geom_histogram(alpha = 0.7, position = "identity") +
  labs(x = "MHC-SF Total Scores", y = "Count", fill = "Age Group") +
  scale_fill_manual(values = c("blue", "red"),
```

```
         labels = c("Age Group <30", "Age Group >30")) +
  theme_classic()


#UCLA Loneliness scale

# Reverse score item 1
data$item1_reverse <- ifelse(data$`Loneliness scale_1` > 2.5, 5 - data$`Loneliness scale_1`,
data$`Loneliness scale_1`)

# Reverse score item 5
data$item5_reverse <- ifelse(data$`Loneliness scale_5` > 2.5, 5 - data$`Loneliness scale_5`,
data$`Loneliness scale_5`)

# Reverse score item 6
data$item6_reverse <- ifelse(data$`Loneliness scale_6` > 2.5, 5 - data$`Loneliness scale_6`,
data$`Loneliness scale_6`)

data$item9_reverse <- ifelse(data$`Loneliness scale_9` > 2.5, 5 - data$`Loneliness scale_6`,
data$`Loneliness scale_6`)
data$item10_reverse <- ifelse(data$`Loneliness scale_10` > 2.5, 5 - data$`Loneliness
scale_10`, data$`Loneliness scale_10`)
data$item15_reverse <- ifelse(data$`Loneliness scale_15` > 2.5, 5 - data$`Loneliness
scale_15`, data$`Loneliness scale_15`)
data$item16_reverse <- ifelse(data$`Loneliness scale_16` > 2.5, 5 - data$`Loneliness
scale_16`, data$`Loneliness scale_16`)
data$item19_reverse <- ifelse(data$`Loneliness scale_19` > 2.5, 5 - data$`Loneliness
scale_19`, data$`Loneliness scale_19`)
data$item20_reverse <- ifelse(data$`Loneliness scale_20` > 2.5, 5 - data$`Loneliness
scale_20`, data$`Loneliness scale_20`)

#somehow did not work for item 5 and 15 --> new code:
data$item5_reverseNEW <- 5 - data$`Loneliness scale_5`
data$item15_reverseNEW <- 5- data$`Loneliness scale_15`
```

```
# Compute total scale score using RowSum function
data$Loneliness_total <- rowSums(data[, c("item1_reverse", "Loneliness scale_2",
"Loneliness scale_3", "Loneliness scale_4", "item5_reverseNEW", "item6_reverse",
"Loneliness scale_7", "Loneliness scale_8", "item9_reverse", "item10_reverse", "Loneliness
scale_11", "Loneliness scale_12", "Loneliness scale_13", "Loneliness scale_14",
"item15_reverseNEW", "item16_reverse", "Loneliness scale_17", "Loneliness scale_18",
"item19_reverse", "item20_reverse")])

ggplot(data, aes(x = Loneliness_total)) +
  geom_histogram(binwidth = 1) +
  labs(x = "UCLA Loneliness Total scores", y = "Count")

ggplot(data, aes(x = Loneliness_total, fill = factor(age_dummy), group = age_dummy)) +
  geom_histogram(alpha = 0.7, position = "identity") +
  labs(x = "UCLA Loneliness Total scores", y = "Count", fill = "Age Group") +
  scale_fill_manual(values = c("blue", "red"),
                    labels = c("Age Group <30", "Age Group >30")) +
  theme_classic()


###Evaluate all scales
#mean, sd, min and max
data %>% filter (age_dummy == 1) %>% summarise (mean = mean (Loneliness_total),
                                          sd = sd (Loneliness_total),
                                          min = min (Loneliness_total),
                                          max = max(Loneliness_total))
data %>% filter (age_dummy == 2) %>% summarise (mean = mean (Loneliness_total),
                                          sd = sd (Loneliness_total),
                                          min = min (Loneliness_total),
                                          max = max(Loneliness_total))

data %>% summarise (mean = mean (Loneliness_total),
```

```
                              sd = sd (Loneliness_total),
                              min = min (Loneliness_total),
                              max = max(Loneliness_total))


data %>% filter (age_dummy == 1) %>% summarise (mean = mean (OVS_total),
                              sd = sd (OVS_total),
                              min = min (OVS_total),
                              max = max(OVS_total))
data %>% filter (age_dummy == 2) %>% summarise (mean = mean (OVS_total),
                              sd = sd (OVS_total),
                              min = min (OVS_total),
                              max = max(OVS_total))

data %>% summarise (mean = mean (OVS_total),
                              sd = sd (OVS_total),
                              min = min (OVS_total),
                              max = max(OVS_total))

data %>% filter (age_dummy == 1) %>% summarise (mean = mean (FoMOS_total),
                              sd = sd (FoMOS_total),
                              min = min (FoMOS_total),
                              max = max(FoMOS_total))

data %>% filter (age_dummy == 2) %>% summarise (mean = mean (FoMOS_total),
                              sd = sd (FoMOS_total),
                              min = min (FoMOS_total),
                              max = max(FoMOS_total))
data %>%  summarise (mean = mean (FoMOS_total),
                              sd = sd (FoMOS_total),
                              min = min (FoMOS_total),
                              max = max(FoMOS_total))

data %>% filter (age_dummy == 1) %>% summarise (mean = mean (MHC_SF_total),
```

```
                                        sd = sd (MHC_SF_total),
                                        min = min (MHC_SF_total),
                                        max = max(MHC_SF_total))
data %>% filter (age_dummy == 2) %>% summarise (mean = mean (MHC_SF_total),
                                        sd = sd (MHC_SF_total),
                                        min = min (MHC_SF_total),
                                        max = max(MHC_SF_total))
data  %>% summarise (mean = mean (MHC_SF_total),
                                        sd = sd (MHC_SF_total),
                                        min = min (MHC_SF_total),
                                        max = max(MHC_SF_total))



data %>% filter (age_dummy == 1) %>% summarise (mean = mean (OVS_S),
                                        sd = sd (OVS_S),
                                        min = min (OVS_S),
                                        max = max(OVS_S))

data %>% filter (age_dummy == 2) %>% summarise (mean = mean (OVS_S),
                                        sd = sd (OVS_S),
                                        min = min (OVS_S),
                                        max = max(OVS_S))

data %>% filter (age_dummy == 1) %>% summarise (mean = mean (OVS_M),
                                        sd = sd (OVS_M),
                                        min = min (OVS_M),
                                        max = max(OVS_M))

data %>% filter (age_dummy == 2) %>% summarise (mean = mean (OVS_M),
                                        sd = sd (OVS_M),
                                        min = min (OVS_M),
                                        max = max(OVS_M))
```

```
data %>% filter (age_dummy == 1) %>% summarise (mean = mean (OVS_R),
                                               sd = sd (OVS_R),
                                               min = min (OVS_R),
                                               max = max(OVS_R))

data %>% filter (age_dummy == 2) %>% summarise (mean = mean (OVS_R),
                                               sd = sd (OVS_R),
                                               min = min (OVS_R),
                                               max = max(OVS_R))

data %>% filter (age_dummy == 1) %>% summarise (mean = mean (MHC_SF_EM),
                                               sd = sd (MHC_SF_EM),
                                               min = min (MHC_SF_EM),
                                               max = max(MHC_SF_EM))
data %>% filter (age_dummy == 2) %>% summarise (mean = mean (MHC_SF_EM),
                                              sd = sd (MHC_SF_EM),
                                              min = min (MHC_SF_EM),
                                              max = max(MHC_SF_EM))

data %>% filter (age_dummy == 1) %>% summarise (mean = mean (MHC_SF_SO),
                                               sd = sd (MHC_SF_SO),
                                               min = min (MHC_SF_SO),
                                               max = max(MHC_SF_SO))
data %>% filter (age_dummy == 2) %>% summarise (mean = mean (MHC_SF_SO),
                                               sd = sd (MHC_SF_SO),
                                               min = min (MHC_SF_SO),
                                               max = max(MHC_SF_SO))

data %>% filter (age_dummy == 1) %>% summarise (mean = mean (MHC_SF_PS),
                                               sd = sd (MHC_SF_PS),
                                               min = min (MHC_SF_PS),
                                               max = max(MHC_SF_PS))
data %>% filter (age_dummy == 2) %>% summarise (mean = mean (MHC_SF_PS),
```

```
sd = sd (MHC_SF_PS),
min = min (MHC_SF_PS),
max = max(MHC_SF_PS))


################################################################################
#chronbach's alpha scales

#Online Vigilance
OVS <- subset(data, select = c("Online Vigilance 1_1", "Online Vigilance 1_2", "Online Vigilance 1_3", "Online Vigilance 1_4", "Online Vigilance 1_5", "Online Vigilance 1_6", "Online Vigilance 1_7", "Online Vigilance 1_8", "Online Vigilance 2_1", "Online Vigilance 2_2", "Online Vigilance 2_3", "Online Vigilance 2_4"))
alpha(OVS)

#FoMO scale
FoMOS <- subset(data, select = c("FoMO Scale_1","FoMO Scale_2", "FoMO Scale_3", "FoMO Scale_4", "FoMO Scale_5", "FoMO Scale_6", "FoMO Scale_7", "FoMO Scale_8", "FoMO Scale_9", "FoMO Scale_10"))
alpha(FoMOS)
#MHC_SF
MHC_SF <- subset(data, select = c("MHC-SF_1", "MHC-SF_2" , "MHC-SF_3", "MHC-SF_4", "MHC-SF_5" , "MHC-SF_6", "MHC-SF_7", "MHC-SF_8", "MHC-SF_9", "MHC-SF_10" , "MHC-SF_11", "MHC-SF_12", "MHC-SF_13", "MHC-SF_14"))
alpha(MHC_SF)
#Loneliness
UCLALoneliness <- subset( data, select = c("item1_reverse", "Loneliness scale_2", "Loneliness scale_3", "Loneliness scale_4", "item5_reverseNEW", "item6_reverse", "Loneliness scale_7", "Loneliness scale_8", "item9_reverse", "item10_reverse", "Loneliness scale_11", "Loneliness scale_12", "Loneliness scale_13", "Loneliness scale_14", "item15_reverseNEW", "item16_reverse", "Loneliness scale_17", "Loneliness scale_18", "item19_reverse", "item20_reverse"))
alpha(UCLALoneliness, check.keys = TRUE)
```

```
##############################################################################
#Test Hypothesis 1

#H1: It is therefore expected that higher levels of loneliness relate to worse scores in mental well-being
#Relationship between loneliness and mental well-being
# Well-being ~ Loneliness
# X --> Independent variable Loneliness
# Y --> Dependent variable Mental Well-being/ MHC_SF

library(ggplot2)

Loneliness <- data$Loneliness_total
Well_being <- data$MHC_SF_total

# Check distribution
ggplot(data, aes(x = Loneliness)) +
  geom_histogram() +
  labs(x = "Loneliness score", y = "Count")

ggplot(data, aes(x = Well_being)) +
  geom_histogram() +
  labs(x = "Mental well-being score", y = "Count")

# Check scatterplot
ggplot(data, aes(x = Loneliness, y = Well_being)) +
  geom_point() +
  labs(x = "Loneliness score", y = "Mental well-being score")+
  geom_smooth(method = "loess", span = 0.3, se = FALSE)

#Correlation coefficient
Correlation <- cor(Loneliness, Well_being)
print(Correlation)
```

```
#check significance of the relation
cor_test <- cor.test(Loneliness, Well_being)
print(cor_test)

#Visualize the relationship
library(ggpubr)
ggscatter(data, x = "Loneliness_total", y = "MHC_SF_total",
        add = "reg.line", conf.int = TRUE,
        cor.coef = TRUE, cor.method = "pearson",
        xlab = "Loneliness score", ylab = "Mental well-being score")
ggscatter(data, x = "Loneliness_total", y = "MHC_SF_total",
        add = "reg.line", conf.int = TRUE,
        cor.method = "pearson",
        xlab = "Loneliness score", ylab = "Mental well-being score")



# Run linear regression model
#lm (DV ~ IV * moderators)

model1 <- lm(MHC_SF_total ~ Loneliness_total, data = data)
summary(model1)
model1 %>%
  tidy(conf.int = TRUE)



#model 2 should give same results as model 1--> check!
model2 <- lm(Well_being ~ Loneliness)
summary(model2)

model2 %>%
  tidy(conf.int = TRUE)
###### Assumptions check Model1 + Model2#########

#preparation for assumption
```

```
data <- data %>%
  add_residuals(model1)
data <- data %>%
  add_predictions(model1)
data <- data %>%
  add_residuals(model2)
data <- data %>%
  add_predictions(model2)

modeltest <- lm(Well_being ~ Loneliness)
#1. No multicolllinearity
# --> in this case not necessary, only 1 IV and 1 DV --> no possibility of collinearity

#2. Linear relationship
ggplot(data, aes(x = Loneliness, y = Well_being)) + geom_smooth(method = "lm")

plot(model1, which = 1)
 # --> met, see almost stright red line in Residuals vs. Fitted graph

#3. Normality of residuals assumption
hist(residuals(model1))
hist(residuals(model2))
residuals1 <- resid(model1)
residuals2 <- resid(model2)
shapiro.test(residuals1)
shapiro.test(residuals2)

#Model1 --> not normally distributed, p-value very low, graph shows slight skew to the right
#Model 2 --> same as above

#4. Assumption of equal variance
plot(model1, which = 3)
#slightly uneven line, left side higher than right side
```

```
#Assumption 3 violated, Assumption 4 slightly
#non-parametric tests
#Spearman's rho
library(Hmisc)
rcorr(data$MHC_SF_total, data$Loneliness_total, type = "spearman")
cor.test (data$MHC_SF_total, data$Loneliness_total,method = "spearman", exact =
        FALSE)

##--> results indicate negative relationship between mental wellbeing and loneliness
install.packages("Kendall")
library(Kendall)

Kendall(data$MHC_SF_total, data$Loneliness_total)
#--> results "-0.373" Indicate moderate negative relationship as well

# Based on P-value: Hypothesis 1 can be accepted
summary(model1)
model1 %>%
  tidy(conf.int = TRUE)
##################################################################################
#Hypothesis 2
#H2: Secondly, it is expected that POPC, as well as FoMO act as moderators of the
relationship between loneliness and mental well-being (H2).
# Well-being ~ Loneliness * POPC
# Well-being ~ Loneliness * FOMO
#interaction effect within the models

#Model POPC
modelPOPC <- lm(MHC_SF_total ~ Loneliness_total + OVS_total+
Loneliness_total:OVS_total, data = data)

#model FoMO
modelFoMO <- lm(MHC_SF_total ~ Loneliness_total + FoMOS_total+
Loneliness_total:FoMOS_total, data = data)
```

```
#comined model
modelPOPC_FoMO <- lm(MHC_SF_total ~ Loneliness_total + OVS_total + FoMOS_total+
Loneliness_total:OVS_total + Loneliness_total:FoMOS_total, data = data)
summary(modelPOPC_FoMO)
summary(modelPOPC)
summary(modelFoMO)

modelPOPC_FoMO %>%
  tidy(conf.int = TRUE)
modelPOPC %>%
  tidy(conf.int = TRUE)
modelFoMO %>%
  tidy(conf.int = TRUE)

# create Johnson-Neyman plots
plot_jn(modelPOPC_FoMO, pred = "Loneliness_total", modx = "OVS_total")
plot_jn(modelPOPC_FoMO, pred = "Loneliness_total", modx = "FoMOS_total")

# create Johnson-Neyman plots
plot_jn(modelPOPC, pred = "Loneliness_total", modx = "OVS_total")
plot_jn(modelFoMO, pred = "Loneliness_total", modx = "FoMOS_total")
################################################################################
#assumptions test
data <- data %>%
  add_residuals(modelPOPC_FoMO)
data <- data %>%
  add_residuals(modelPOPC)
data <- data %>%
  add_residuals(modelFoMO)

data <- data %>%
  add_predictions(modelPOPC_FoMO)
data <- data %>%
```

```
  add_predictions(modelPOPC)
data <- data %>%
  add_predictions(modelFoMO)

#1. Linearity
plot(modelPOPC_FoMO, which = 1)
plot(modelFoMO, which = 1)
plot(modelPOPC, which = 1)

#--> Assumption met for all three models, however for model POPC+fomo slight downward skew at the left side
plot(modelPOPC_FoMO$fitted.values, modelPOPC_FoMO$residuals, xlab = "Predicted values", ylab = "Residuals")
abline(h = 0, lty = 2)

#2. Multicolinearity
car::vif(modelPOPC, type = "predictor")
car::vif(modelPOPC_FoMO, type  = "predictor")
car::vif(modelFoMO, type  = "predictor")

# Assumtions met for ModelPOPC and ModelFomo, no issues with multicollineartity as value is 1
# Model POPC and Fomo combined - value greater than 1, some degree of collinearity

#3. Normality of residuals
hist(residuals(modelFoMO))
hist(residuals(modelPOPC))
hist(residuals(modelPOPC_FoMO))

residuals3 <- resid(modelFoMO)
residuals4 <- resid(modelPOPC)
residuals5 <- resid(modelPOPC_FoMO)
shapiro.test(residuals3)
shapiro.test(residuals4)
```

```
shapiro.test(residuals5)
# based on shapiro test: all violate rule, p-value below 0.05 --> but test is really sentitive, check graphs
# Model FoMO --> basically normal, slight right skew
#Model POPC --> slightly skewed to the right
#Model POPC + FOMO -->normal
#4. Equal variance
# Test for equal variance in modelFOMo
data %>% bartlett.test(residuals3 ~ FoMOS_total)
# Test for equal variance in modelPOPC
data %>% bartlett.test(residuals4 ~ OVS_total)

# Test for equal variance in modelPOPC_FoMO

data %>% bartlett.test(residuals5 ~ OVS_total * FoMOS_total)

plot(modelFoMO, which = 3)
plot(modelPOPC, which = 3)
plot(modelPOPC_FoMO, which =3)
#bartell’s test: p-values for all below 0.05 --> assumtpion not met
#graphs: line is not straight for all three models

#Assumptions met. linear relationship, multicollinearity (not for POPC+ FOMO model)
#Violated: Normality of residuals + equal variance

#spearman’s rho --> correlation
library(Hmisc)

rcorr(data$MHC_SF_total, data$Loneliness_total, type = "spearman")
cor.test (data$MHC_SF_total, data$Loneliness_total,method = "spearman", exact =
        FALSE)

# For modelFOMo
x1 <- data$FoMOS_total
```

```
y1 <- residuals(modelFoMO)

# For modelPOPC
x2 <- data$OVS_total
y2 <- residuals(modelPOPC)

# For modelPOPC_FoMO
x3 <- data[, c("OVS_total", "FoMOS_total")]
y3 <- residuals(modelPOPC_FoMO)

# Conducting the Spearman’s rank correlation test
cor.test(x1, y1, method = "spearman")
cor.test(x2, y2, method = "spearman")
cor.test(x3[,1], y3, method = "spearman")
cor.test(x3[,2], y3, method = "spearman")
cor.test(x3, y3, method = "spearman") # Test for the combined effect of OVS_total and
FoMOS_total

x5 <- data[, c("OVS_total", "FoMOS_total")]
y5 <- residuals5
x5_numeric <- as.data.frame(lapply(x5, function(x) as.numeric(as.character(x))))
cor.test(x5_numeric$OVS_total, y5, method = "spearman")
cor.test(x5_numeric$FoMOS_total, y5, method = "spearman")
#NON-Parametric kenall test
install.packages("Kendall")
library(Kendall)

Kendall(data$MHC_SF_total, data$OVS_total, data$Loneliness_total)
install.packages("ppcor")
library(ppcor)
#POPC
data %>%
  dplyr::select(OVS_total, MHC_SF_total, Loneliness_total)%>%
  pcor(method = "kendall")
```

```
cor.test(data$OVS_total, data$MHC_SF_total, method = "kendall")
cor.test(data$OVS_total, data$Loneliness_total, method = "kendall")
cor.test(data$MHC_SF_total, data$Loneliness_total, method = "kendall")
#fomo
data %>%
  dplyr::select(FoMOS_total, MHC_SF_total, Loneliness_total)%>%
  pcor(method = "kendall")

cor.test(data$FoMOS_total, data$MHC_SF_total, method = "kendall")
cor.test(data$FoMOS_total, data$Loneliness_total, method = "kendall")
cor.test(data$MHC_SF_total, data$Loneliness_total, method = "kendall")

##--> results indicate no significant relationship
#Alternative 2
# Load libraries
install.packages("sandwich")
install.packages("lmtest")
library(sandwich)
library(lmtest)

# Fit the model with Huber White estimator
modelHuber1 <- lm(MHC_SF_total ~ OVS_total * Loneliness_total + FoMOS_total *
Loneliness_total, data = data)
vcov_model <- vcovHC(modelHuber1, type = "HC0")
summary(modelHuber1, robust = TRUE, vcov = vcov_model)

#H2:
#Model FOMO --> no significant interaction effect
#Model POPC -->interaction term has a coefficient estimate of 0.0188, a standard error of
0.00954, and a p-value of 0.051 → suggests a weakly significant interaction effect.
#Model POPC + FOMO --> no significant interaction between fomo and loneliness on
mentalwellbeing
################################################################################
```

```
#Hypothesis 3
# Consequently, it is expected, that high scores in online Vigilance are associated with a
worse mental health status (H3).
# Well-being ~ OVS
#Well-being ~ FoMO
# X --> Independent variable OVS/ FoMO
# Y --> Dependent variable Mental Well-being/ MHC_SF

#Visualize the relationship
library(ggpubr)
ggscatter(data, x = "OVS_total", y = "MHC_SF_total",
        add = "reg.line", conf.int = TRUE,
        cor.coef = TRUE, cor.method = "pearson",
        xlab = "Online Vigilance score", ylab = "Mental well-being score")

ggscatter(data, x = "OVS_total", y = "MHC_SF_total",
        add = "reg.line", conf.int = TRUE,
        cor.method = "pearson",
        xlab = "Online Vigilance score", ylab = "Mental well-being score")

ggscatter(data, x = "FoMOS_total", y = "MHC_SF_total",
        add = "reg.line", conf.int = TRUE,
        cor.coef = TRUE, cor.method = "pearson",
        xlab = "FoMO score", ylab = "Mental well-being score")

ggscatter(data, x = "FoMOS_total", y = "MHC_SF_total",
        add = "reg.line", conf.int = TRUE,
        cor.method = "pearson",
        xlab = "FoMO score", ylab = "Mental well-being score")



modelOVS <-lm(MHC_SF_total ~ OVS_total,data = data)
summary(modelOVS)
```

```
model6 <- lm (MHC_SF_total ~ FoMOS_total, data = data)

model6 %>%
  tidy(conf.int = TRUE)
modelOVS %>%
  tidy(conf.int = TRUE)
###### Assumptions check ModelOVS + Model6##########
#preparation for assumption
data <- data %>%
  add_residuals(model6)
data <- data %>%
  add_predictions(modelOVS)
data <- data %>%
  add_residuals(model6)
data <- data %>%
  add_predictions(modelOVS)

#1. No multicolllinearity
# --> in this case not necessary, only 1 IV and 1 DV --> no possibility of collinearity

#2. Linear relationship
plot(model6, which = 1)
plot(modelOVS, which = 1)
# --> met, see almost stright red line in Residuals vs. Fitted graph for both

#3. Normality of residuals assumption
hist(residuals(model6))
hist(residuals(modelOVS))
residuals6 <- resid(model6)
residualsOVS <- resid(modelOVS)
shapiro.test(residuals6)
shapiro.test(residualsOVS)
```

```
#Model6 + Model OVS --> P-value below 0.05 ---> not normally distributed, skewed to the right

#4. Assumption of equal variance
plot(model6, which = 3)
plot(modelOVS, which = 3)
#slightly uneven line, left side higher than right side

#-->Assumption 3 violated,
#non-parametric tests
#Spearman’s rho
library(Hmisc)
rcorr(data$MHC_SF_total, data$FoMOS_total, type = "spearman")
cor.test (data$MHC_SF_total, data$FoMOS_total,method = "spearman", exact =
        FALSE)

rcorr(data$MHC_SF_total, data$OVS_total, type = "spearman")
cor.test (data$MHC_SF_total, data$OVS_total,method = "spearman", exact =
        FALSE)
##--> results indicate negative relationship between mental wellbeing and loneliness
install.packages("Kendall")
library(Kendall)
Kendall(data$MHC_SF_total, data$OVS_total)
Kendall(data$MHC_SF_total, data$FoMOS_total)
#--> results "-0.373" Indicate moderate negative relationship as well

# Based on P-value: Hypothesis 1 can be accepted
summary(model1)
model1 %>%
  tidy(conf.int = TRUE)
##################################################################################
#Hypothesis 4
#difference among age groups
```

```
# T-tests
t.test(data$Loneliness_total ~ data$age_dummy)
t.test(data$MHC_SF_total ~ data$age_dummy)
t.test(data$FoMOS_total ~ data$age_dummy)
t.test(data$OVS_total ~ data$age_dummy)

#convert dummy age to factor
data$age_dummy <- factor(data$age_dummy)
data$Loneliness_total <- factor(data$Loneliness_total)
# ANOVA
anova1 <- aov(data$Loneliness_total ~ data$age_dummy)
summary(anova1)
anova2 <- aov(data$OVS_total ~ data$age_dummy)
summary(anova2)

anova3 <- aov(data$FoMOS_total ~ data$age_dummy)
summary(anova3)

anova4 <- aov(data$MHC_SF_total ~ data$age_dummy)
summary(anova4)
# Post-hoc tests
TukeyHSD(anova1)
TukeyHSD(anova2)
TukeyHSD(anova3)
TukeyHSD(anova4)
# Create a boxplot with ggplot2
ggplot(data, aes(x = Loneliness_total, y = age_dummy, group = age_dummy)) +
  geom_boxplot() +
  labs(y = "Age Group", x = "Loneliness Score") +
  ggtitle("Loneliness Score by Age Group")

ggplot(data, aes(x = MHC_SF_total, y = age_dummy, group = age_dummy)) +
  geom_boxplot() +
  labs(y = "Age Group", x = "MHC_SF Score") +
```

```
  ggtitle("Mental Well-being Score by Age Group")

ggplot(data, aes(x = FoMOS_total, y = age_dummy, group = age_dummy)) +
  geom_boxplot() +
  labs(y = "Age Group", x = "FoMO Score") +
  ggtitle("FOMO Score by Age Group")

ggplot(data, aes(x = OVS_total, y = age_dummy, group = age_dummy)) +
  geom_boxplot() +
  labs(y = "Age Group", x = "Online Vigilance Score") +
  ggtitle("OVS Score by Age Group")

###Assumption check ANOVA's
#1. Outliers
library(car)
outlierTest(aov(Loneliness_total ~ age_dummy, data = data))
outlierTest(aov(FoMOS_total ~ age_dummy, data = data))
outlierTest(aov(OVS_total ~ age_dummy, data = data))
outlierTest(aov(MHC_SF_total ~ age_dummy, data = data))
#-> assumption met
par(mfrow=c(2,2))
plot(anova1, which=1)
plot(anova2, which=1)
plot(anova3, which=1)
plot(anova4, which=1)

#2. Normality assumption
data$age_dummy <- as.numeric(data$age_dummy)
data$Loneliness_total <- as.numeric(data$Loneliness_total
qqnorm(as.numeric(resid(anova1)))
qqline(as.numeric(resid(anova1)))
qqnorm(resid(anova1))

shapiro.test(as.numeric(resid(anova1)))
```

```
#p-value below 0.05 -> not normal
shapiro.test(as.numeric(resid(anova2)))
#p-value below 0.05 ->not normal
shapiro.test(as.numeric(resid(anova3)))
#p-value greater than 0.05 --> normal (p = 0.056)
shapiro.test(as.numeric(resid(anova4)))
#p-value below o.05

shapiro.test(data$Loneliness_total)
shapiro.test(anova1)
qqPlot(data$Loneliness_total)
#p-value below 0.05 --> not normal
shapiro.test(data$MHC_SF_total)
qqPlot(data$MHC_SF_total)
#p-value below 0.05 --> not normal
shapiro.test(data$OVS_total)
qqPlot(data$OVS_total)
#p-value below 0.05 --> not normal
shapiro.test(data$FoMOS_total)
qqPlot(data$FoMOS_total)
#p-value below 0.05 --> not normal

#3. Homogneity of variance#
bartlett.test(Loneliness_total ~ age_dummy, data = data)
#-> p-value above 0.05 --> assumption met
bartlett.test(OVS_total ~ age_dummy, data = data)
#p-value above 0.05 --> assumption met
bartlett.test(FoMOS_total ~ age_dummy, data = data)
#p-value below 0.05 assumption not met ( p = 0.02)
bartlett.test(MHC_SF_total ~ age_dummy, data = data)
#p-value above 0.05 assumption met

#4. Homogeneity of covariances#
library(heplots)
```

```
install.packages("heplots")
box_m(data[, "Loneliness_total", drop = FALSE], data$age_dummy)

#5.Assumption of sphericity#
#-> not relevant --> no two conditions for within design, also between variable
#non parametric test > Wilcoxon rank-sum test
# Load required package
install.packages ("stats")
library(stats)

# Conduct Wilcoxon rank-sum test
wilcox.test(data$Loneliness_total ~ data$age_dummy)

wilcox.test(data$MHC_SF_total ~ data$age_dummy)

wilcox.test(data$FoMOS_total ~ data$age_dummy)
wilcox.test(data$OVS_total ~ data$age_dummy)

############################END#################################################
```

Appendix F

Table: Descriptive Information Regarding the Scales (Mean, Standard Deviation, Minimum, Maximum, compared by Age Groups (n = 167)

	Ages Below 30				Ages Above 30			
Questionnaires	*M*	SD.	Min.	Max.	*M*	SD.	Min.	Max.
OVS	30.8	8.7	14	51	23.7	8.06	12	44
OVS Salience	9.54	3.28	4	19	6.6	2.35	4	14
OVS Monitoring	9.27	3.93	4	18	7.3	3.17	4	18
OVS Reactibility	12.0	3.52	4	18	9.78	4.13	4	20
FoMOS	25.9	8.04	10	44	17.7	6.01	10	35
MHC-SF	33.8	10.9	7	53	40.2	10.2	11	52
MHC-SF Emotion.	7.09	2.61	0	10	8.14	2.27	0	10
MHC-SF Social.	10.2	4.57	0	20	12.9	4.59	1	20
MHC-SF Psy.	26.5	5.07	4	24	19.2	5.07	4	25
UCLA Loneliness Scale	36.2	8.83	23	61	35.8	8.78	23	61

Note. OVS = Online Vigilance scale with its aforementioned Subscales; FoMOS = FoMO Scale; MHC-SF = Mental Health Continuum Short form; M= Mean; SD. = Standard deviation, MHC-SF Emotion. = Subdimension Emotional well-being, MHC-SF = Subdimension Social Well-being, MHC-SF Psy. = Subdimension Psychological Well-being