The impact of Screen Time, Social Media Use and Extraversion on Life Satisfaction among University Students: An extended replication study

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Contents

Abstract

Increased screen time might detrimentally affect well-being and academic performance, lowering life satisfaction. While active social media use seems to increase life satisfaction, passive social media use might have the opposite effect. Extraversion might act as a buffer against the adverse consequences of increased screen time. Thus, the study explores how screen time, social media use (active and passive) and extraversion impact life satisfaction. A convenience sample of 149 students aged 18 to 30 was recruited. First, a multiple linear regression analysis examined the independent effects of screen time, passive and active social media use on life satisfaction. Subsequently, a parallel mediation analysis investigated how extraversion affects life satisfaction via screen time, passive and active social media use. Further, a moderation analysis examined the effect of total screen time on life satisfaction differing among students under the various levels of extraversion. This descriptive, correlational, cross-sectional study collected data via Qualtrics XM and the University of Twente's Test Subject Pool system, with analyses conducted in Rstudio (version 2023.03.1+446). As expected, a significant negative correlation was found between screen time and extraversion. As hypothesised, a significant positive correlation was found between extraversion and life satisfaction. Contrary to expectations, screen time and social media use did not significantly affect life satisfaction. No significant mediating effects in the parallel mediation analysis and no significant moderating effects were found. These findings suggest a need for further exploration of additional factors such as motivations and contexts of use, employing more robust and objective methodologies, such as a tracking device for measuring screen time.

The impact of Screen Time, Social Media Use and Extraversion on Life Satisfaction among University Students: An extended replication study

"People sitting all day for hours looking at a glowing light are bound to get ran over like a deer in headlights" by Richie Norton (*Screen Time Quotes (3 quotes),* n.d.). As this quote suggests, prolonged screen time on computers, smartphones or in front of the television can detrimentally affect mental and physical health. Since the evolution of technology and social media alongside the recent COVID-19 pandemic, an exponential rise in screen time was assessed (Deyo et al., 2023; Singh et al., 2022). Compared to pre-pandemic assessments, during the pandemic, an increase of between 50 and almost 100% was determined worldwide (Singh et al., 2022). Due to the COVID-19 restrictions, education had to take place remotely, explaining parts of the rise in screen time, however, using these devices for entertainment also contributed to this increase (Singh et al., 2022). Particularly, among younger adults and adolescents, digital technologies are popular resulting in high levels of screen time (Hrafnkelsdottir et al., 2018; Sui et al., 2021). These levels are associated with unfavourable academic performance, greater mental issues (Hrafnkelsdottir et al., 2018; Sui et al., 2021) and lower life satisfaction (Bunz, 2021; Hrafnkelsdottir et al., 2018; Iannotti et al., 2009; Kidwell, 2022; Singh et al., 2022; Sui et al., 2021). Possibly explaining how one could be run over like a deer in headlights. Besides, it is assumed that the personality trait of extraversion might impact this relationship since it can predict both life satisfaction and screen time use (Bunz, 2021). Although, the direction and type of the relationship are yet unclear (Bunz, 2021). Thus, the current study aims to investigate the relationship between screen time, social media use, extraversion and life satisfaction among university students.

Target group

The technological evolution brought accessible and widely available devices that are integral to people ‘s lives such as smartphones, computers and TVs (Singh et al., 2022; Stachl et al., 2017). Particularly, during COVID-19, the necessity of these devices increased since education and personal connection were mostly possible via the internet due to restrictions (Deyo et al., 2023; Singh et al., 2022). With this change in people ‘s lives, screen time increased exponentially additionally contributing to worsened mental and physical health along with academic performance (Deyo et al., 2023; Kidwell, 2022). Among young adults and adolescents, the use of these devices is particularly popular (Sui et al., 2021), reaching average screen times between 3 to 7 hours per day (Bunz, 2021; Deyo et al., 2023; Hrafnsdottir et al., 2018). The internationally recommended screen time is two hours a day (Hrafnkelsdottir et al., 2018). Exceeding the recommended screen time can not only impair their health but also negatively impact their evaluation of life satisfaction which can lead to higher screen times (Deyo et al., 2023).

Furthermore, it is assumed that young adults might be more sensitive to using these devices excessively due to biological and psychological factors indicating possible influences from personality (Singh et al., 2022). Besides, according to Kidwell (2022), young adults struggle with increased mental issues compared to the previous years, indicating the need to investigate their screen behaviour and perception of life to tackle this problem through an intervention. For instance, they might scroll through social media excessively while knowing they need to work on a project due to lack of self-control (Kidwell, 2022). In comparison, older adults tend to moderate their use of screens and thus tend to be less influenced by them negatively (Sui et al., 2021). Therefore, this study will investigate screen time, social media use, life satisfaction and extraversion among university students between the ages of 18 and 30 because most attention in research was on older or younger age groups and people of these ages tend to be students along with are at risk of the detrimental effects of prolonged screen time (Kidwell, 2022; Liverpool et al., 2023).

Screen time

Generally, average screen time seems to vary across studies. Nevertheless, the average screen time of the participants always seems to be above the internationally recommended average of two hours per day (Hrafnkelsdottir et al., 2018). In a study by Deyo et al. (2023), the overall screen time of students (aged 18-25) was on average 7 hours. This excludes time spent for educational purposes (Deyo et al., 2023). Similarly, in a study by Hrafnkelsdottir et al. (2018), students spend on average 5.3 hours a day, almost three hours above the internationally recommended average screen time.

Exceeding the recommended screen time is operationalised as prolonged screen time and is associated with various adverse consequences. When screen time overuse starts in childhood until adulthood, it can be responsible for negative health outcomes such as obesity and cardiovascular diseases since it is seen as a sedentary activity (Deyo, et al., 2023; Matin et al., 2016). Furthermore, prolonged screen time might lead to anxiety and addiction related to smartphones (Sui et al., 2021). In alignment, the aforementioned studies by Deyo et al. (2023) and Hradnkelsdottir et al. (2018) concluded adverse health consequences and low levels of life satisfaction possibly associated with high levels of screen time. Thus, suggesting a need for moderation of screen time.

Screen time encompasses the time spent on all activities on a smartphone or other electronic device with a screen such as watching television, playing video games and social media (Matin et al., 2016; Sui et al., 2021). For measurement, some refer to screen time specified on social media as the intensity of social media, whereby the minutes per day spent using social media are measured (Bunz, 2021). Overall screen time can be spent both on education and entertainment, particularly during COVID-19, the increase in screen time could have been partly explained by educational purposes through remote teaching (Singh et al., 2022).

Besides, a distinction is made between active and passive social media use which is a subset of total screen time. In the Netherlands around 25 % of total screen time is spend on social media (Moody & Moody, 2024). Active social media use includes actively spending time on electronic devices for connection, studying, for example using YouTube (Shaikh, 2024), or expression and might impact overall health along with academic performance positively (Singh et al., 2022). Conversely, passive social media use, such as scrolling, is associated with negative outcomes (Marttila et al., 2021; Singh et al., 2022). According to Singh et al. (2022), no particular increase in social media use for communication purposes (active screen time) was determined, it remained that three-quarters use social media for such purposes. Interestingly, the same amount of time is spent on non-communicational activities (passive social media use), like scrolling (Singh et al., 2022). This could explain the other part of the increase in screen time. Since screen time and social media use greatly affect various aspects of life, it is essential to explore how they influence life satisfaction.

Life satisfaction

Being satisfied with life includes the positive "overall evaluation of one's life-as-a-whole" (Kainulainen et al., 2018). It includes not only the presence of positive emotions like happiness and contentment along with the absence of negative ones but also has a cognitive component (Bunz, 2021; Kainulainen et al., 2018). Veenhoven distinguishes between the affective and cognitive components since they contribute to the overall evaluation of life with different levels of strength (Kainulainen et al., 2018). The affective component describes what is felt most of the time while the cognitive component includes the difference one perceives between the ideal and real life (Kainulainen et al., 2018). The first relates to basic needs and overrules the cognitive aspect when evaluating since it more strongly impacts the person if a need is missing (Kainulainen et al., 2018). The second component encompasses the learned wants that one has such as conscious ideas and desirable states (Kainulainen et al., 2018). Because there is ease in recalling the last time of feeling positively, it can outweigh the cognitive aspect for which one needs to weigh events and states according to importance (Kainulainen et al., 2018). Similarly, meeting basic needs can feel like greater success than meeting wants (Kainulainen et al., 2018). This theory aligns with other conceptualisations of life satisfaction such as it being a subset of subjective well-being (hedonic) including positive affect and positive overall evaluation of life (Matin et al., 2016; Sui et al., 2021).

The perception of one's life is impacted and impacts several areas of life. External factors like life events, work and health-related events can impact the overall evaluation of life (Szczęśniak et al., 2019). If life events were negative, the overall evaluation could also be rather negative and vice versa. Since life satisfaction concerns the evaluation of meeting one's needs and wants, it has a direct link to a thriving life (Kainulainen et al., 2018). The higher the life satisfaction, the lower the risk of mortality, mental and behavioural issues, like excess screen time and health implications (Hrafnkelsdottir et al., 2018; Matin et al., 2016; Sui et al., 2021). Thus, life satisfaction seems to be a strong predictor for major effects on human experience and is impacted by these.

Screen time and life satisfaction

Overall, there are mixed results on the impact of screen time on life satisfaction. Many studies found a negative relationship between these two, where the higher the screen time, the lower the life satisfaction (Bunz, 2021; Hrafnkelsdottir et al., 2018; Iannotti et al., 2009; Singh et al., 2022). Few studies found mixed to no associations between the two (Bunz, 2021; Matin et al., 2016). Nevertheless, most found the longer the screen time, the worse health outcomes which might impact the perception of life satisfaction (Matin et al., 2016). Possibly, the different conceptualisations of screen time and investigated factors may explain the inconclusive results with a tendency towards a negative relationship.

One factor possibly influencing the relationship to life satisfaction is the context in which these electric devices are used, so whether one uses these actively or passively. If screen time is used for education, entertainment, communication, news consumption and leisure screen activities like TV watching, no significant effects were determined, however, if there was an increased use of screen time for non-communicational activities, so passive use, like scrolling and social media consumption during COVID-19 compared to pre-pandemic assessment, then there was a significant negative effect on life satisfaction (Singh et al., 2022; Sui et al., 2021). This could be linked to it being less purposeful along with negative social comparison, compared to the other contexts. Despite this increase possibly being explained by the context along with its impact, the existing body of research has only addressed the average change in patterns of screen time use before and during the COVID-19 pandemic. However, the average patterns of screen time use across a day among university students were not yet investigated.

Lastly, the relationship seems to be sensitive to between-person differences (Bunz, 2021). This could be age or even personality. According to Bunz (2021), the older the screen media users, the less likely they are to experience worse health and life satisfaction. Similarly, extraversion might impact the relationship between screen time and life satisfaction which will be further explored in the following.

Extraversion

Extraversion is one of the five continuums of the Big Five personality traits framework by John and Srivasrava (1999) (Bunz, 2021; Lim, 2023; McCabe & Fleeson, 2012). This framework consists of the personality traits Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism. The individual's scores on the Big Five remain mostly stable throughout life (Lim, 2023). Extraversion is associated with outward-oriented energy. People high on extraversion tend to experience heightened positive affect (Schimmack et al., 2004; Szczęśniak et al., 2019) and be seen as outgoing (Stachl et al., 2017; Szczęśniak et al., 2019), warm, cheerful, assertive (Schimmack et al. 2004), expressive, adventurous and communicative (Bunz, 2021; McCabe & Fleeson, 2012). People high on extraversion tend to charge their energy by spending time in company (Lim, 2023). In contrast, people low on extraversion tend to get depleted in such environments and seek solitude (Lim, 2023).

Across studies on personality and screen time, extraversion stands out. First extraversion is both associated with prolonged and almost no screen time (Bunz, 2021). This might be explained by the way they use these devices. Generally, people high on extraversion seem to use screen media in various ways compared to other personality traits (Bunz, 2021; Stachl et al., 2017). Mostly they use these devices for communication, education, personalisation like expressing themselves through wallpaper changes and photographs (Stachl et al., 2017). Similarly, extroverted individuals are more likely to use social media actively to connect with others (Perugini & Solano, 2020) compared to introverts who tend to spend it passively (Kircaburun et al., 2018). Additionally, extroverts tend to make short calls more frequently, presumably to seek external stimulation and might value their social life in regard to quantity over quality (Lim, 2023; Stachl et al., 2017). However, some extroverts do not use screen media but instead spend their time in the natural world (Bunz, 2021). Further, they seem to spend less time passively consuming social media compared to introverts (Kircaburun et al., 2018). Thus, there are mixed results concerning the relationship between screen time and extraversion.

Nevertheless, there seems to be a negative association between extraversion and screen time (Santos & Reeve, 2020).

The big five personality traits can predict life satisfaction. Almost half of the variance in positive and negative affect can be explained by the big five personality traits (Bunz, 2021). Particularly, extraversion is positively correlated with life satisfaction (Bunz, 2021; Schimmack et al., 2004; Singh et al., 2022; Szczęśniak et al., 2019). This might be because the happiness which extroverts tend to experience more often might lead to a higher tendency to recall these feelings when evaluating one's overall life leading to higher life satisfaction. Furthermore, extraversion positively correlates with self-confidence and a positive outlook on life which can further influence the perception of overall life satisfaction (Szczęśniak et al., 2019).

The mediating role of Screen time in the relationship between Extraversion and Life Satisfaction

Though there is some literature on the effects of personality on screen time and life satisfaction, the focus is generally on one of the three relationships: personality and screen time, personality and life satisfaction, or screen time and life satisfaction. The only study that covered these in a multivariate relationship, is the study by Bunz (2021), which investigated social media use, personality and well-being whereby social media use was the mediator between personality and well-being. In this context, social media use was operationalised as the time spent on social media. Therefore, 'social media intensity' refers to this definition to avoid confusion, as 'social media use' in the current paper is otherwise defined as either active or passive participation on social media. In the study by Bunz (2021), extraversion predicted both positive and negative well-being directly. Furthermore, only significant results were found for extraversion positively impacting social media intensity which then negatively affected negative well-being. However, social media intensity seemed to be less strong in predicting positive well-being in this multivariate relationship. Additionally, no significant associations were found between extraversion and positive well-being when social media intensity was the mediator. Thus, mixed support was found for the effects of extraversion on well-being. Only limited (for negative well-being) or no effects (for positive well-being) were found when social media intensity was the mediator.

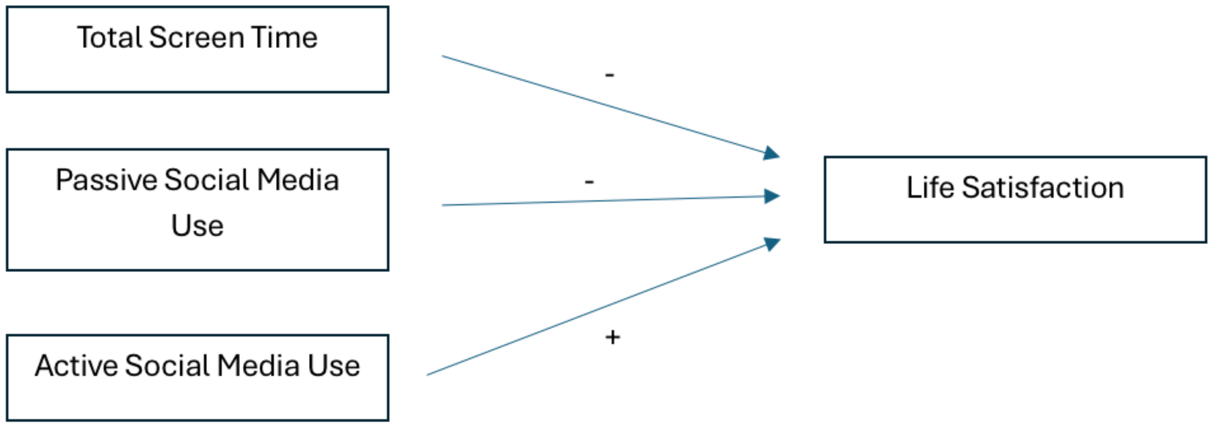
The Present Study

Based on the previous literature review, there seems to be uncertainty about the exact relationship between screen time, active and passive social media use, life satisfaction and the personality trait extraversion. Depending on the aspects of screen time, the relationship seems to change. Looking at overall screen time, there appears to be a negative effect on life satisfaction. When considering extraversion in this equation, no significant effects can be found when social media intensity is the mediator between extraversion and positive well-being (life satisfaction, positive affect) indicating a need for investigation of different types of screen time as mediators between extraversion and life satisfaction and a possible different relationship between the three variables such as moderation for a more comprehensive investigation of the relationship.

When examining the effects of active and passive social media use on life satisfaction. Active social media use such as creating content or connecting with others positively affects life satisfaction while passive screen time such as scrolling through social media and watching TV seems to reduce life satisfaction (Singh et al., 2022). Given the complex nature of these relationships, a multiple linear regression analysis is recommendable because it not only assesses the impact of the various screen time types but also controls for potential confounding variables and offers a holistic understanding of the impact of these variables on life satisfaction. The hypothesised relationship is depicted in **Figure 1**.

Figure 1

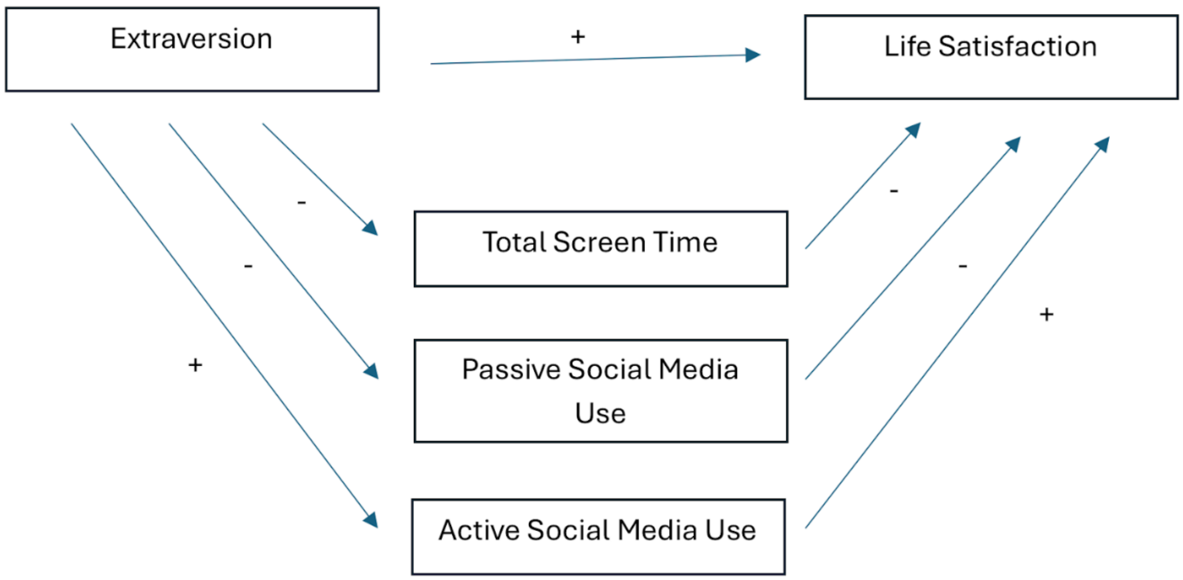
Depiction of the hypothesised relationship between total screen time, passive and active social media use and life satisfaction.



Similarly, by including passive and active social media use as mediators next to screen time in the replicated mediation model by Bunz (2021), a comprehensive understanding of the direct and indirect effects can be yielded. Using a parallel mediation model can account for interrelationships and reduce the risk of variable bias. Thus, it might be insightful to explore this in the current study by extending the mediation model of the study by Bunz (2021) by including active and passive social media use into the model. The hypothesised relationship is depicted in **Figure 2**.

Figure 2

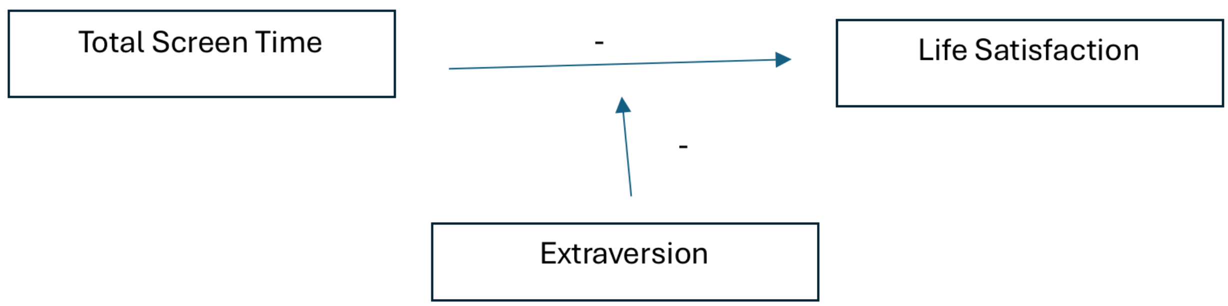
Depiction of the hypothesised relationship between extraversion and life satisfaction along with the mediators of total screen time, passive and active social media use.



As no significant effects were found in the mediation model by Bunz (2021) for positive well-being, but significant effects were observed for negative well-being, it can be hypothesised that the relationship between the variables is not as straightforward as suspected. Given the absence of social media use variables in the mediation analysis by Bunz (2021), the focus will be solely on screen time as a predictor variable for this analysis. Screen time is often associated with passive activities such as scrolling on social media, TV watching and reduced face-to-face interactions which can negatively impact life satisfaction. By examining screen time solely, an alternative perspective to the model proposed by Bunz (2021) is provided to gain insights into the complex interactions between the three variables. Extraverted individuals tend to have higher social interactions and experience positive emotions more frequently than introverted individuals (Szczęśniak et al., 2019). This suggests that extraversion might act as a buffer against the negative influences of screen time on life satisfaction and weaken the relationship. This influence might be particularly striking given the positive correlation between extraversion and life satisfaction (Szczęśniak et al., 2019), suggesting that extraversion enhances well-being, potentially alleviating the adverse effects of prolonged screen time. Since no studies have examined extraversion as a moderator in the relationship between screen time and life satisfaction, testing this hypothesised relationship could enhance the understanding of the conditions under which the effects of screen time on life satisfaction vary. It is assumed that extraversion weakens the relationship between screen time and life satisfaction (see **Figure 3**).

Figure 3

Depiction of the hypothesised relationship between total screen time and life satisfaction under the condition of extraversion.



On this basis, this study aims to investigate the relationships between screen time, social media use, extraversion and life satisfaction in greater detail by first analysing the independent effects of screen time, passive and active social media use on life satisfaction using a multiple linear regression. Then outline the pathways through which extraversion affects life satisfaction via screen time, passive and active social media use and investigate how the effect of total screen time on life satisfaction differs among university students under the various levels of extraversion by utilising both an extended parallel mediation and a moderation analysis. Accordingly, a thorough investigation of this is essential to design focused interventions that improve life satisfaction and have the potential to significantly enhance mental health and educational initiatives. Therefore, the current study aims to investigate how the variables relate to one another among university students in greater detail using an online survey.

Consequently, the following research questions and hypotheses emerge:

Research questions and hypotheses related to the multiple linear relationship between total screen time, active and passive social media use and life satisfaction:

RQ1: “How do total screen time, passive and active social media use each impact life satisfaction among university students, when accounting for them? “

H1a: Total screen time negatively affects life satisfaction when controlling for the effects of active and passive social media use.

H1b: Active social media use positively affects life satisfaction when controlling for the effects of total screen time and passive social media use.

H1c: Passive social media use negatively affects life satisfaction when controlling for the effects of total screen time and active social media use.

Research question and hypothesis related to the replicated and extended parallel mediation analysis:

RQ2: “How does extraversion influence life satisfaction, and to what extent are total screen time, active and passive social media use mediating this relationship simultaneously? “

H2: Extraversion’s direct effect is positive on life satisfaction when accounting for the mediators. It is expected that Extraversion affects total screen time negatively which negatively affects life satisfaction. Simultaneously, it is expected that extraversion positively affects active social media use which positively affects life satisfaction. At the same time, it is expected that extraversion negatively affects passive social media use which negatively affects life satisfaction. It is expected that the mediators partially mediate the relationship between extraversion and life satisfaction.

Research question and hypothesis related to extraversion as a moderator between total screen time and life satisfaction:

RQ3: "To what degree does extraversion moderate the relationship between total screen time and life satisfaction?"

H3: Extraversion weakens the negative relationship between total screen time and life satisfaction.

Methods

Design

This study was approved by the BMS Ethics Committee (request number: 240315) before data collection. The design of the study was descriptive, correlational cross-sectional. The aim of this study is to inspect the relationship between extraversion, total screen time, active and passive social media use along with life satisfaction among university students using an online questionnaire. Since the study took place within the frame of a research group, additional variables such as sleep quality, perceived stress and academic procrastination were assessed but the results of these were not used in the current study. This questionnaire was created using Qualtrics XM and published on SONA, the test subject pool of the University of Twente. In this study, three relationship constellations were tested. In the first relationship, total screen time, passive and active social media use predict life satisfaction. The second constellation consists of extraversion as the direct predictor of life satisfaction and total screen time, active and passive social media use as the mediators. In the last constellation, extraversion is the moderator, total screen time is the independent and life satisfaction is the dependent variable.

Participants

To recruit the participants, convenience sampling was used by distributing the Qualtrics survey on the SONA system and offering the participants 0.25 credits. The link to the study was shared via social media platforms such as WhatsApp and Instagram. A total number of 149 participants were recruited. The inclusion criteria were being students at a university, between the ages of 18 and 30 along with being proficient in English. In **Table 1**, an overview of the participants' characteristics is provided.

Table 1

Characteristics of the participants

Participants	*N* (%)
Total	149 (100)
Gender	
Male	35 (23.5)
Female	99 (66.4)
Non-binary/ other	10 (6.7)
No answer	5 (3.4)
Nationality	
Dutch	56 (37.6)
German	44 (29.5)
Other	43 (28.9)
No answer	6 (4)
Educational Level	
Bachelor student	110 (73.8)
Master student	16 (10.7)
PhD	2 (1.4)
HBO student	14 (9.4)
No answer	7 (4.7)
Age	
18 – 22	92 (61.7)
23 – 27	31 (20.1)
28 – 30	3 (2.1)
No answer	24 (16.1)

Materials

To participate in this study, an electronic device, access to the internet and the survey link were required. Since the survey was conducted within the frame of a research group, the total survey consisted of 133 items, however, for this study, only 65 items were processed comprising of the demographics, adjusted Mini-International Personality Item Pool (Mini-IPIP), self-reported Screen Time, parts of the Social Media Activity Questionnaire (SMAQ), parts of the Social Network Sites (SNS) Questionnaire and the Quality of Life Enjoyment and Satisfaction Questionnaire - Short Form (Q-LES-Q-SF).

Demographics

For the demographics, the participants were asked to indicate their age using a slider from 18 to 30 years, followed by indicating their gender (i.e. „Male“, „Female“ and „Non-binary/other“), nationality (i.e. „Dutch“, „German“ and „Other“) and educational level using the options of „Bachelor student“, „Master student“, „PhD“ and „HBO student“.

Screen time scales

Screen time was assessed using four scales. The first scale is the self-reported ***Total Screen Time*** scale inspired by Montagni et al. (2016) consisting of five items. The scale aims to assess the average daily screen time spent on several screens performing different tasks such as „working on a computer/tablet“ or „watching TV or videos (movies, series, TV programs) on a computer/tablet“. The time is indicated using a 10-point Likert scale ranging from „Not at all “, „30 min. Or less “, „30 min. To 1h“, „1 - 2h“, „2 - 3h“, „3 - 4h“, „4 - 5h“, „5 - 6“, „6 - 7“ and “more than 7h” instead of a 6-point Likert scale for ranging from „1 = Never“ to „6 = more than eight hours“. The range was adjusted since finer granularity was needed for the analyses. The scores in the study by Montagni et al. (2016) were categorised ranging from “very low”, “low”, “high” to “very high”, however, to avoid information and statistical power loss along with the complexity of interpretation, the total scores were summed ranging from 5 to 50. Hereby, the higher the total score, the higher the screen time.

The second scale consists of a part related to the passive use of the Social Media Activity Questionnaire (SMAQ) by Osijek et al. (2023) and is utilised to measure the level of ***Passive Social Media Use***. The passive part includes 10 items. The questionnaire requests an indication of the frequency of using social media for tasks such as reading private messages other users have sent or looking at profiles, newsfeeds or stories of friends or subscriptions. The frequency is indicated using a 5-point Likert scale ranging from “1 = never” to “5 = very often”. The total score is calculated by summing the points for each item, resulting in a total score ranging from 10 to 50, whereby the higher the score, the more passive use was assessed. The internal consistency of the part of the scale is high (α = .85) along with the reliability and validity (Ozimek et al., 2023).

The last scale is the Social Network Sites (SNS) Questionnaire by Orchard et al. (2014) and originally consists of 44 items, however only 8 items were chosen since they measure the ***Active Social Media Use*** to connect with others and maintain social relationships. On a 7-point Likert scale ranging from “1 = Strongly Disagree” to “7 = Strongly Agree”, participants need to indicate to which degree they agree or disagree with statements regarding the purpose of using social media such as for “communicating online” or “to date”. To calculate the total score, summed points on each “new connection”-items and “social maintenance”-items were determined. The higher the score, the higher the active use of social media for connecting or maintaining social relations. For both constructs, the validity and reliability are high (α = .76 - .79) (Orchard et al., 2014).

Personality scale

Personality was assessed using the adapted Mini-IPIP by Donnellan et al. (2006). The Scale was adjusted to the research group's investigated variables such as Neuroticism, Extraversion and Conscientiousness by removing items that do not measure these constructs. Thus, this scale consists of 12 instead of 20 items. For the current study, only the four items related to ***Extraversion*** are relevant. These include "I am the life of the party", "I don't talk a lot (reversed)", "I talk to a lot of different people at parties" and "I keep in the background (reversed)". To indicate the degree of fit with the items, a 5-point Likert scale ranging from "1 = very inaccurate" to "5 = very accurate" was used. To compute the total score, the points on the non-reversed items are added together with the reversed points of the reversed items. Thus, the total score can range from 4 to 20, whereby the higher the score, the higher the level of extraversion. Regarding validity and reliability, the adjusted Mini-IPIP shows "respectable" internal consistency ($\alpha > .60$), high test-retest reliability and validity which is comparable to the 50-item International Personality Item Pool-Five Factor Model (Donnellan et al., 2006).

Quality of Life Enjoyment and Satisfaction Questionnaire - Short Form (Q-LES-Q-SF)

The Q-LES-Q-SF is a 16-item scale and a short form of the original 93-item scale designed to measure ***Life Satisfaction*** and enjoyment in various areas of life including health, work, leisure time and social relations on a 5-point Likert-scale (ranging from "1 = very poor" to "5 = very good") (Riendeau et al., 2018). The last two items are only necessary for clinical purposes and are scored separately from the other 14 items (Riendeau et al., 2018). The lowest total score is 14 (related to lowest level of life satisfaction) while the highest is 70 (= highest level of life satisfaction). These scores are expressed in percentages (0 - 100) (Riendeau et al., 2018). Generally, this scale seems to be unidimensional, shows a high internal consistency (α = .85 - .90), the reliability is high (.90) along with the test-retest reliability (.93) (Riendeau et al., 2018; Stevanović, 2011). However, test-retest reliability is lower for the 15th and 16th items (.75 & .80).

Procedure

Data collection took place from the 18th of March until the 2nd of May 2024. The first step of data collection was completing the survey (see Appendix A). The study took about 15 to 30 minutes to complete and offered 0.25 SONA credits as a reward. The questionnaire started with an informed consent covering agreement on the processing of personal data along with taking part in the study. At the end of the informed consent, the participants were provided with the contact details of the researchers for questions or remarks the participants might have. After giving consent, students were asked to indicate their demographics by age, gender and nationality. Participants were asked to fill out the adjusted Mini-IPIP, self-reported (social media) Screen Time, parts of the Social Media Activity Questionnaire (SMAQ), the Social Network Sites (SNS) Questionnaire, the short - Pittsburgh Sleep Quality Inventory (shortPSQI), Perceived Stress Scale (PSS), Academic Procrastination Scale, the Revised Social Connectedness Scale, and the Quality of Life Enjoyment and Satisfaction Questionnaire - Short Form (Q-LES-Q-SF). At the end of the survey, the participants were thanked for their participation.

Data analysis

Preparing the data

Before conducting the data analyses, the APA 7 theme was applied to the R environment. Using R-studio (version 2023.03.1+446) the data from the Qualtrics survey was imported into R-studio. Before processing the data, the explanatory row and the survey preview were omitted. No participants were excluded based on whether they completed the survey or left items out to ensure that the data is as representative of the population as possible. The demographic data was recoded into numerical values and displayed. The total scores were calculated by first coding the answers numerically and summing the scores on each item of each scale. Items 4 and 10 of the Mini-IPIP were reversed and summed with the other two items to generate the total score for the Mini-IPIP. Since the Mini-IPIP was originally developed in 2006, the importance of re-evaluating its reliability in the context of this study due to potential changes in the population was acknowledged by conducting an internal consistency analysis using the “psych” package and the “cronbach_alpha”-function. Afterwards, the correlation matrix between the five variables was generated.

Analyses conducted

Before each analysis, the assumptions of Linearity, Normality, Homoscedasticity and Independence were checked. For the multiple linear regression, Normality was checked using a histogram (“hist”-function) and Quantil-quantil diagram (“qqnorm”-and “qqline”-functions). Multicollinearity was checked using the variance inflation factor (“vif”-function). Linearity and Homoscedasticity were checked using the “plot”-function and the Breusch-pagan test (“bptest”-function from the “lmtest” package). Lastly, independence was checked using a residual plot and a Durbin Watson test using the “durbinWatsonTest”-function from the “car” package. In the same manner, the assumptions were tested for the moderation analysis, excluding the multicollinearity check. Besides Homoscedasticity and Normality, the assumptions were checked in the same manner for the parallel mediation analysis. Here, the Homoscedasticity and Normality were accounted for in the parallel mediation analysis using bootstrapping (“boot”-function) and robust standard error (“hc=4”-function). The results of the assumptions check for each analysis can be retrieved in Appendix C.

To answer the RQs, the following analyses were conducted. The first RQ was tested using a multiple linear regression, which was conducted using the “lm”-function and “ANOVA”-function. The second and third RQs were tested using a parallel mediation analysis and moderation analysis using PROCESS by Hayes (2018) for R. For the parallel mediation analysis, the fourth model was used and for the moderation analysis the first. Lastly, next to the moderation model, a simple slope analysis was performed and plotted using the “rockchalk” package and the “lm”-and “plotSlopes”-functions if a moderating effect of extraversion was found. In the Appendix B, the full R-script can be retrieved.

Results

Descriptive statistics

As visible in **Table 2**, the total scores of total screen time in this sample are on average 2.6 points higher than the internationally recommended total screen time (total score of more than 20). In total 107 participants reported a total screen time above the internationally recommended screen time. The passive social media use is medium-high and active social media use is on average moderately-high. Concerning the extraversion total scores from the Mini-IPIP, the sample’s level of extraversion is average. Lastly, the sample’s life satisfaction level is three per cent below average since the normal percentage range of total scores lies between 70 and 100.

The reliability of the Mini-IPIP, particularly the subscale of extraversion was tested. In this sample, the Cronbach’s alpha for the extraversion subscale that consisted of 4 items was .82, indicating that the subscale is highly reliable.

Besides, the correlations between the total screen time, social media use (active and passive), extraversion and life satisfaction were investigated. Three correlations were shown to be significant. As expected, the correlation between total screen time and extraversion was negative, small and significant (r = - .29). As expected, for extraversion and life satisfaction, the correlation was small, positive and significant (r = .26). Lastly, the correlation between passive and active social media use was small, positive and significant (r = .27). The remaining correlations did not show to be significant and are displayed in the table below.

Table 2

Descriptive statistics of the five variables total screen time (TST), passive (PSMU) and active social media use (ASMU), extraversion (EX) and life satisfaction (LS) and their bivariate correlations

	M	*SD*	Range	TST	PSMU	ASMU	EX	LS
TST	22.6	4.53	14 - 37	—				
PSMU	28.4	5.89	13 - 44	- .1	—			
ASMU	39.7	7.76	17 - 56	.17	.27*	—		
EX	9.26	3.94	2 - 17	- .29**	.16	-.04	—	
LS	47.1	8.01	27 - 68	- .15	.01	.02	.26*	—

*p < .05, **p < .001

Conducted analyses

Inferential statistics

Multiple linear regression analysis. The multiple linear regression model was constructed and tested to test the first hypotheses (H1a-c) regarding the effect of total, passive and active screen time on life satisfaction. The model was statistically non-significant (F(3,92) = 0.9, p = .44), indicating that no predictor significantly affects and the model does not explain a significant portion of the variance in life satisfaction. The adjusted R^2 of -0.0 further illustrates that the model does not account for the variance in life satisfaction.

Parallel Mediation analysis. The parallel mediation model was constructed using PROCESS “model = 4”. The mediation model was tested with extraversion as the independent variable, total screen time, active and passive social media use as the mediators and life satisfaction as the dependent variable. Concerning the direct effects of Extraversion on Total Screen Time, Active and Passive Social Media Use, only the direct effect on Total Screen Time was negative and significant [B = -0.41, SE = 0.12, t (1, 94) = -3.38, p < .05]. Regarding the direct effects of Extraversion when controlling for the indirect path, Total Screen Time, Active and Passive Social Media Use on Life Satisfaction, only extraversion resulted in a close to significant and positive effect [*B* = 0.48, *SE* = 0.25, *t* (4, 91) = 6.48, *p* = .06]. The indirect effects of Extraversion on Life Satisfaction through Total Screen Time, Passive and Active Social Media Use were all weak and not significant since the bootstrapped confidence interval includes 0. The remaining direct and indirect effects are displayed in **Table 3**. The overall model fit was not significant, indicating a model misfit [*F* (4, 91) = 1.52, *p* = .2]. Thus, the hypothesis was rejected.

Table 3

Outcome of the parallel mediation analysis

Direct effects of Extraversion on:				
Variables	*B*	*SE*	*T*-value	*p*-value
TST	-0.41	0.12	-3.38	.001*
PSMU	0.28	0.19	1.51	.14
ASMU	-0.12	0.21	-0.59	.56
Direct effects of Extraversion, Total Screen Time, Active and Passive Social Media Use on Life Satisfaction:				
EX	0.48	0.25	1.89	.06
TST	-0.16	0.18	-0.91	.36
PSMU	-0.09	0.15	-0.64	.53
ASMU	0.08	0.11	0.68	.5
Indirect effects of Extraversion on Life Satisfaction through:				
Variables	*B*	*BootSE*	*BootLLCI*	*BootULCI*
Total Indirect effect	0.03	0.1	-0.15	0.24
TST	0.07	0.08	-0.07	0.25
PSMU	-0.03	0.05	-0.16	0.05
ASMU	-0.01	0.03	-0.08	0.04

Moderation analysis. A moderation analysis, using PROCESS "model = 1", was conducted, whereby the total screen time was the independent variable, extraversion the moderator and life satisfaction the dependent variable. Following running the model, no significant effect of total screen time on life satisfaction was observed which confirms the result of the multiple linear regression analysis [$B = -0.09$, $SE = 0.19$, $t\ (3, 94) = -0.47$, $p = .64$]. When only investigating the effect of extraversion on life satisfaction, there was as expected a significant positive effect [$B = 0.49$, $SE = 0.21$, $t\ (3, 94) = 2.34$, $p < .05$]. Furthermore, as expected, no significant effect was observed for the interaction effect between extraversion and total screen time on life satisfaction [$B = 0.03$, $SE = 0.04$, $t\ (3, 94) = 0.66$, $p = .51$]. Overall, the model fit was significant and explained 8% of the variance in Life Satisfaction [$F\ (3, 94) = 2.65$, $p < .05$]. Consequently, the last hypothesis was accepted since extraversion did not moderate the relationship between total screen time and life satisfaction.

Discussion

Theoretical reflection and implications

The current study aimed to investigate the relationships between screen time, social media use (active and passive), extraversion and life satisfaction in greater detail. For this, first the independent effects of each total screen time, passive and active social media use on life satisfaction when controlling for the remaining independent variables via a multiple linear regression were analysed. Counter to expectation neither total screen time nor active or passive social media use independently predicted life satisfaction. The same has been discovered for the direct effects of screen time and social media use in the replicated and extended parallel mediation analysis.

Since almost 72% of the participants' screen time exceeded the internationally recommended two hours a day, it was expected that screen time would significantly reduce life satisfaction but in the current study no significant correlations between the two were detected. These effects are generally not in line with the current literature (Bunz, 2021; Hrafnkelsdottir et al., 2018; Iannotti et al., 2009; Singh et al., 2022). Since in the current study, besides the multiple linear regression, screen time did not seem to significantly affect life satisfaction in any way and there was no trend towards a significant effect, it can be assumed that the various types of screen time might have played a significant role. However, when comparing the studies and the conceptualisations of screen time, the same effects as expected can be observed. Regardless, of whether the focus mainly lied on TV watching or all screen devices, these devices seemed to reduce life satisfaction, the more time was spent using them (Bunz, 2021; Chen et al., 2022; Hrafnkelsdottir et al., 2018; Iannotti et al., 2009; Singh et al., 2022). Thus, it might be that the purpose of screen use might affect life satisfaction. Notably, there is limited research on this topic and existing studies mainly focus on internet and social media use. This indicates a need to investigate whether motivations or intentions behind the use of general screen devices make a difference in their effect on life satisfaction and could explain the lacking association within the current study.

Concerning the passive and active use of social media, the sample showed medium-high social media consumption behaviours and moderately high active connection seeking and maintaining behaviours. Accordingly, it is assumed that the higher the passive use of social media the lower the life satisfaction while on the contrary, higher active use might enhance life satisfaction. However, these dynamics were not discovered in the current study since the associations were close to zero and neither active nor passive screen time seemed to predict life satisfaction when accounting for the remaining independent variables. This has been shown to be partly in line with the current research (Valkenburg et al., 2021). Though there is the active-passive dichotomy hypothesis, in which it is expected that active social media use enhances life satisfaction and passive social media use decreases it, contrary effects have been observed in multiple studies in a systematic literature review by Valkenburg et al. (2021). Possible reasons for this may lie in the specific context of social media use of each individual in which consuming enjoyable and interesting content might heighten life satisfaction even though it is considered to be passive social media use which normally was associated with negative impact (Valkenburg et al., 2021). Similarly, an individual might actively engage with content that is disturbing, such as negative feedback, which might decrease life satisfaction (Valkenburg et al., 2021). Thus, due to the current study not accounting for such individual context, it might be that this has impacted the predictions of active and passive social media use on life satisfaction by cancelling the effects out. Moreover, it might be that the associations between social media use and life satisfaction have been weak due to being diluted across a sample that might experience social media use in various ways (Valkenburg et al., 2021). For example, the motivation behind social media use might impact how individuals engage with these media (Perugini & Solano, 2020). Whereby individuals who are intrinsically motivated might seek enjoyable content more often compared to extrinsically motivated individuals who might focus more on their public appearance leading to increased social comparison which might result in decreased life satisfaction (Perugini & Solano, 2020). In both cases, individuals engage actively with social media but the outcomes on life satisfaction vary.

Next to investigating the independent effects of each screen time measure on life satisfaction via multiple linear regression, this study also explored how extraversion affects life satisfaction through the variables. Additionally, it examined how screen time's impact on life satisfaction differs among students under the various levels of extraversion. This was done by using both a parallel mediation and a moderation analysis. Regarding the replicated and extended mediation of the study by Bunz (2021), no indirect effects were found which is in line with the study by Bunz. Though in the study social media intensity was the mediator between extraversion and positive well-being, changing the variables to total screen time as a mediator and life satisfaction as the outcome variable did not yield different results. Furthermore, after including two additional variables such as active and passive social media use, no mediating effects were detected either which was not surprising since there were no direct effects of total screen time, active and passive social media use on life satisfaction. This could be due to active and passive use of social media being subject to multiple factors such as context of use and individual motivation (Valkenburg et al., 2021). Nonetheless, similarly to the study by Bunz (2021), extraversion seems to positively impact life satisfaction, indicating that extraversion might enhance life satisfaction possibly due to the tendency to experience positive emotions more often and recall them when evaluating one‘s life (McCabe & Fleeson, 2012; Schimmack et al., 2004; Szczęśniak et al., 2019). Moreover, as expected, extraversion predicts total screen time, however, instead of increasing extraversion levels leading to increased screen time, in the current study, the higher the extraversion level, the less time is spent on screens. This might be because there is a tendency in extroverts to prefer traditional face-to-face interaction over internet interaction (Kuhlman et al., 2014). Besides, neither active nor passive social media use was predicted by extraversion. This is inconsistent with current research and counter to expectations (Kircaburun et al., 2018; Perugini & Solano, 2020). It was assumed that extraversion was positively associated with active social media use to enhance contact with others (Kircaburun et al., 2018), though they seem to prefer in-person over screen-based interactions (Bağcı & Horzum, 2022; Kuhlman et al., 2014). Furthermore, in current research, extraversion was negatively associated with passive social media use due to introverts spending more time consuming social media compared to extroverts (Kircaburun et al., 2018). Accordingly, similar to social media predicting life satisfaction, the individual motivations behind social media use among extraverts might impact how extraverts interact with social media, possibly explaining the inconsistency in research and the current study.

Lastly, concerning the moderation analysis, no significant moderating effects of extraversion on screen time and life satisfaction were found which is counter to the expectation whereby extraversion would act as a buffer for the negative impacts of screen time on life satisfaction. Thus, in this sample, no difference in extraversion significantly strengthens or weakens the relationship between screen time and life satisfaction. However, this is not in accordance with current literature in which extraverts might be protected from the potential negative effects of screen time by focusing on social interactions and support (Kuhlman et al., 2014). Nevertheless, similarly, as for social media use, there might be varying associations between extraversion and screen time depending on the context of screen time or the motivation behind using it. For example, using screen time to procrastinate or to advance personal interest might have contradictory effects on life satisfaction, possibly explaining the lack of moderating effect of extraversion.

Strengths and limitations of the current study

One of the strengths is that this study contributed to the scientific knowledge about screen time, active and passive social media use, extraversion and life satisfaction by not only investigating the influencing factors of life satisfaction among university students but also by extending and replicating the study by Bunz (2021). Prior to the current study, the focus of research mainly lay on the effects of screen time and social media use among children or middle-aged adults and not on young adults that are confronted with screens daily.

Besides, the current study was able to provide evidence for Bunz’s study that besides social media intensity, general screen time and social media use (passive and active) do not mediate the relationship between extraversion and life satisfaction. Regardless, there seem to be direct positive effects of extraversion on life satisfaction which are in line with current research (Bunz, 2021; McCabe & Fleeson, 2012; Schimmack et al., 2004; Szczęśniak et al., 2019).

Lastly, a strength of this study lies in the comprehensive approach to analysing the effects of screen time, active and passive social media on life satisfaction. Though it seems intuitive to consider active and passive social media as main components of total screen time, potentially resulting in concerns about multicollinearity, this study evaluated this factor to ensure robustness of the findings. By conducting bivariate correlations and checking for multicollinearity, it was confirmed that the variables were not excessively interrelated, thus validating their inclusion as distinct predictors and mediators in the multiple linear regression and parallel mediation models. Consequently, this methodological rigor provided nuanced insights into the relationship and emphasised the importance of considering specific contexts behind screen use.

Though this study showed some strengths, there were several limitations. The first limitation of this study includes difficulty in generalising the results due to convenience sampling. Since the sample consisted predominantly of females, young adults and bachelor students, the results cannot be generalised to all ages, educational levels and young adults who use screens and social media.

Due to the use of three different scales for the screen time measures, there might be limited validity. Active and passive social media use are related specifically to social media and not to general screen time. Here, active social media use was only related to connecting with others and passive social media use to consuming social media. Similarly, total screen time is not limited to social media but also includes the use of computers and tablets for work, playing video games, watching TV or videos and using the smartphone. Therefore, it might be that effects could vary depending on the conceptualisation of screen time and social media use.

Regarding the screen time measures, the total screen time scale was inspired by Montagni et al. 's (2016) existing scale but adapted since there was a need for finer granularity for the analyses. However, by doing this, the validity and reliability were not ensured and need testing. Furthermore, since this self-report scale is based on recall instead of an objective measure of screen time such as a screen time tracking app, the reported screen time might not be as specific and valid because young adults tend to under- or overestimate their screen time (Hodes & Thomas, 2021). This might explain why the average total screen time in this sample is very low. Accordingly, it is advisable to utilise an objective measure for screen time for the most precision in the prediction of its impact.

Lastly, the sample might have not been big enough to detect possible significant effect sizes due to missing values which were automatically removed from the analyses. Though some significant effects were detected for extraversion on screen time and life satisfaction, for the multiple linear regression no significant effects were observed. This might be due to a too-small sample size to detect small effects. In comparison, studies that detected effects used at least a sample size of 300 (Bunz, 2021; Hrafnkelsdottir et al., 2018; Iannotti et al., 2009; Singh et al., 2022). For the current study, using the “G*Power 3” tool by Faul et al. (2007) and a G-power of at least .8, for medium effect sizes around 77 complete cases are necessary. Since no medium effect sizes were detected for a sample size of 92, a sample size of 550 complete cases might be necessary to observe small effect sizes. Comparably, using the same software, for the moderation analysis to detect medium effect sizes for the interaction term, a sample size of 55 would have been necessary. However, no significant effects were observed for the interaction term with a sample size of 94. Accordingly, to detect small effect sizes for the interaction term, using a G-power of .8, a sample size of 395 would be required. Similarly, for the parallel mediation analysis, no significant mediating effects were discovered. Using the “Monte Carlo Power

Analysis for Indirect Effects"-Software by Schoemann et al. (2017) and a G-power of .8, for the parallel mediation to detect expected effect sizes, a minimum sample size of 310 would be necessary. Thus, it would be recommended to replicate this study and the models using a sample size of at least 550 to ensure detection of small effect sizes.

Further recommendations

In the future, it would be recommendable to replicate this study with a bigger sample size to ensure enough complete cases for the analyses since in most analyses around 50 participants were excluded due to missing data. By using a bigger sample, the marginally significant results might become detectable as significant results such as for the direct effect of extraversion on life satisfaction in the parallel mediation when accounting for the direct effects of the screen time measures. Further, utilitising a bigger sample size of around 550, might enable the analyses to detect small effects sizes of each variable on life satisfaction that were not observed with the current sample size varying between 91 and 94.

Moreover, to ensure precise estimations of the effects of screen time on life satisfaction, it is advisable to objectively measure screen time via a screen time tracking app or guided self-assessment of screen time. By using an objective over a measure based on recall, biases related to potential wrong estimations or unreliability can be excluded, contributing to more precise testing of screen time effects.

Besides, using different methods such as repeated measures to determine the direction of the relationship between screen time, social media use, extraversion and life satisfaction might yield insights into causation between the variables. Since this study was of cross-sectional nature, no assumptions regarding causality can be made with confidence. Moreover, using an experimental or repeated measure design, the effect of time could be examined in regard to its effects on the different relationships. Since life satisfaction is very subjective, it might vary across short periods of time (Heller et al., 2006). Similarly, screen time and social media use might vary across time, thus might differently affect life satisfaction.

Next, when replicating the mediation and moderation analyses, it would be recommendable to include confounding variables such as age, gender and educational level to investigate to which degree they impact the relationships since in the current study their impact was not accounted for. Furthermore, when replicating these analyses, it might be insightful to differentiate between different types of screen time not only in regard to social media use (active and passive) but also more generally such as each TV, gaming, social media, and other screen time types to, for example for the moderation, better differentiate the various influences of extraversion on them. Comparably, different types of screen time might differentially mediate the effects of extraversion on life satisfaction, thus might need further exploration. Moreover, the context in which the screens are used and the motivations behind using them should be explored to allow clear understanding of their influence on life satisfaction. Based on these, an opportunity might arise for precise intervention creation to improve life satisfaction and reduce certain screen related activities.

A further recommendation for future studies might be investigating the different mediating effects of screen time and social media use along with moderating effects of extraversion on the relationship between screen time and negative well-being. In the current study the focus was mainly on the influences of these variables on life satisfaction which is related to positive well-being. In accordance with the study by Bunz (2021), no significant mediating effects were detected. Compared to this study, the current study did not investigate the effects of these variables on negative well-being. Accordingly, replicating the study by Bunz (2021), by including negative well-being as an outcome variable might yield insights into the effects of screen time and social media use in regard to ill-being. In a similar manner, exchanging the outcome variable of the moderation analysis in the current study to negative well-being might yield insights into the effects of screen time on negative well-being among various levels of extraversion. Since ill-being is not the opposite of well-being but can co-occur (Valkenburg et al., 2021), investigating these effects not only in regard to life satisfaction but also to negative well-being might help in the future in designing interventions for improving well-being by addressing factors that might contribute to decreasing it.

Lastly, looking into what factors are relevant for life satisfaction might be impactful for creations of models and in the future of interventions to improve life satisfaction. Based on the insignificant correlations in the current study, it could be hypothesised that other factors that more profoundly impact life satisfaction might be different from social media use or screen time. According to Matin et al. (2016), physical activity was a better predictor for life satisfaction than screen time. Accordingly, it might be insightful to conduct a qualitative study on the important factors that are considered in the evaluation of one's life. Possibly, if prolonged screen time is seen as detrimental in one's life, one would incorporate this issue as an influencing factor in the evaluation of life while not perceived problematic screen time might be unrelated to life satisfaction. Subsequently, it might be insightful to quantitatively investigate the different factors impacting life satisfaction to design effective interventions for improving life satisfaction among young adults.

Conclusion

In the beginning of this study, people who spend all day in front of screens were compared to deers bound to be run over in headlights (Screen Time Quotes (3 quotes), n.d.). This analogy underlines the urgency of understanding potential negative impacts of screen time on life satisfaction and well-being. However, the findings of the current study suggest that the situation may not be as simple as previously assumed since neither total screen time nor active or passive social media use independently predicted life satisfaction. Thus, the context and individual motivations behind screen time and social media use may play a critical role in explaining these dynamics and thus should be investigated in future research. Though, this study’s replication and extension of Bunz’s (2021) work provides broader understanding of these variables, it would be recommendable to replicate the current study with a larger, more diverse sample and objective measures of screen time. Further, including additional confounding variables and using a sample size of at least 550 samples allows for detection of small effect sizes within both the parallel mediation and moderation analysis. Following this approach may provide comprehensive insights for future intervention targeted at university students to enhance their life satisfaction through moderation of their screen time and social media use.

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Appendix A

Qualtrics survey: Screen-Time among university students

Informed consent

Thank you for participating in our study centred around screen time, personality, and aspects of student life. Participation in this study is completely voluntary, and it is possible to withdraw from this study at any point without giving an explanation. While participating in this study you will be asked several questions that are related to (Social Media) Screen Time, Personality, Sleep Quality, Procrastination, Life Satisfaction, and Perceived Stress.

There are no known safety risks related to participation. The estimated time to complete this questionnaire is 15-30 minutes. If you are a student participating through the SONA system, completing this study will reward you with 0.25 SONA point (s).

The data that is collected will be anonymised and will only be available to the researchers. Since the data is anonymised, even the researchers will not be able to identify you from your personal information. So please answer all questions as honestly as possible. Once the research is concluded, the data will be disposed of in accordance with the guidelines of the University of Twente. If there are any questions or remarks, please feel free to contact the researchers:

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I read the informed consent and agree to participate in this study.

- Yes
- No

Demographics

What is your age?

What is your gender?

- Male
- Female
- Non-binary/other

What is your nationality?

- Dutch
- German
- Other

What is your study level?

- Bachelor student
- Master student

- PhD
- HBO student

Adjusted Mini-IPIP

Please indicate on a range of very inaccurate to very accurate how much the statements suit you as a person.

	Very inaccurate	Moderately inaccurate	Neither inaccurate nor accurate	Moderately accurate	Very accurate
I am the life of the party	○	○	○	○	○
I get chores done right away	○	○	○	○	○
I have frequent mood swings	○	○	○	○	○
I don't talk a lot	○	○	○	○	○
	Very inaccurate	Moderately inaccurate	Neither inaccurate nor accurate	Moderately accurate	Very accurate
I often put things back in their proper place	○	○	○	○	○
I am relaxed most of the time	○	○	○	○	○
I talk to a lot of different people at parties	○	○	○	○	○
I like order	○	○	○	○	○

	Very inaccurate	Moderately inaccurate	Neither inaccurate nor accurate	Moderately accurate	Very accurate
I get upset easily	○	○	○	○	○
I keep in the background	○	○	○	○	○
I make a mess of things	○	○	○	○	○
I seldom feel blue	○	○	○	○	○

Screen Time

For the next questions, please indicate the average time you spend in a day in front of these different screens. If you can, indicate the accurate measure by using the "screen time" option in the settings of the device. If not, try to estimate the time as good as possible. What is the average time in a day spent...

	Never	30 min or less	0.5 - 1 h	1 - 2 h	2 - 3 h	3 - 4 h	4 - 5 h	5 - 6 h	6 - 7 h	More than 7h
...working on a computer/tablet.	○	○	○	○	○	○	○	○	○	○
...playing video games on a computer/tablet.	○	○	○	○	○	○	○	○	○	○
...surfing the internet on a computer/tablet.	○	○	○	○	○	○	○	○	○	○
	Never	30 min or less	0.5 - 1 h	1 - 2 h	2 - 3 h	3 - 4 h	4 - 5 h	5 - 6 h	6 - 7 h	More than 7h
...watching TV or videos (movies, series, TV programs) on a computer/tablet.	○	○	○	○	○	○	○	○	○	○
...using a smartphone.	○	○	○	○	○	○	○	○	○	○

What is your estimated daily screen time across all devices in hours?

(text box)

Social Media Screen Time. Please indicate for each social media platform how much time you spend on a daily average. For this please follow these steps on your phone:

Apple: Settings -> Screentime -> See All App & Website Activity -> Week (on top of the screen) -> click on each social media platform you used -> Daily Average

Android: Settings -> Digital Wellness and Parental Control -> click on each social media platform you used

-> Weekly (on top of the screen) -> Daily Average (...h ...min/day)

If this does not work or if you cannot find this information, take a guess at how much time on an average day in the past week you spent on each of the social media platforms you use (or look in the apps directly).

(Remember that if you fill this out at the beginning of a new week, the analysis only shows data from one or two days. In that case please look in your settings at the last week. If you do not find this, then just take a guess at how much you used the social media platform in the last week on average.)

With that information, please fill out the next items. Please also keep in mind the time on other devices (laptop, iPad, etc.) you use social media on (i.e., YouTube or Twitch).

	Not at all	30 min. or less	0.5 - 1 h	1 - 2 h	2 - 3 h	3 - 4 h	4 - 5 h	5 - 6 h	6 - 7 h	More than 7h
Instagram	○	○	○	○	○	○	○	○	○	○
Snapchat	○	○	○	○	○	○	○	○	○	○
WhatsApp	○	○	○	○	○	○	○	○	○	○
TikTok	○	○	○	○	○	○	○	○	○	○
	Not at all	30 min. or less	0.5 - 1 h	1 - 2 h	2 - 3 h	3 - 4 h	4 - 5 h	5 - 6 h	6 - 7 h	More than 7h
Pinterest	○	○	○	○	○	○	○	○	○	○
Facebook	○	○	○	○	○	○	○	○	○	○
YouTube	○	○	○	○	○	○	○	○	○	○
Twitter/X	○	○	○	○	○	○	○	○	○	○
	Not at all	30 min. or less	0.5 - 1 h	1 - 2 h	2 - 3 h	3 - 4 h	4 - 5 h	5 - 6 h	6 - 7 h	More than 7h
Reddit	○	○	○	○	○	○	○	○	○	○
Twitch	○	○	○	○	○	○	○	○	○	○
Others	○	○	○	○	○	○	○	○	○	○

For each statement please indicate how often you engage in said activity online when using social media on an average day, during the last 7 days.

	Never	Rarely	Sometimes	Often	Very Often
1. I look at the photo albums of other users.	○	○	○	○	○
2. I look at the profiles/pages of other users or read through them.	○	○	○	○	○
3. I look at the stories of my friends/ my subscriptions.	○	○	○	○	○
4. I read private messages that other users send me.	○	○	○	○	○
5. I read entries on the chronicles and personal pages of other users.	○	○	○	○	○

	Never	Rarely	Sometimes	Often	Very Often
6. I read through the comments on other users' pictures.	○	○	○	○	○
7. I read the comments on my own pictures.	○	○	○	○	○
8. I look at links or video clips posted on other people's profile pages (e.g., YouTube).	○	○	○	○	○
9. I look at the profile pages of my relatives.	○	○	○	○	○
10. I look at the "newsfeed" to see the latest activities of other users (e.g., if they have new friends).	○	○	○	○	○

For each statement please indicate whether you agree or disagree that you use social media to...

	Stongly Disagree	Disagree	Somewhat Disagree	Neither Disagree nor Agree	Somewhat Agree	Agree	Strongly Agree
1. ... communicate online.	○	○	○	○	○	○	○
2. ... communicate with those I don't know.	○	○	○	○	○	○	○
3. ... make new friends.	○	○	○	○	○	○	○
4. ... to date.	○	○	○	○	○	○	○
	Stongly Disagree	Disagree	Somewhat Disagree	Neither Disagree nor Agree	Somewhat Agree	Agree	Strongly Agree
5. ... keep in touch.	○	○	○	○	○	○	○
6. ... communicate with distant friends.	○	○	○	○	○	○	○
7. ... communicate with those I know offline.	○	○	○	○	○	○	○
8. ... maintain social contact.	○	○	○	○	○	○	○

Short - Pittsburgh Sleep Quality Inventory

During the past month, when have you usually gone to bed?

- Before 21:00
- 21:00 - 23:00
- 23:00 - 01:00
- Later than 01:00

During the past month, how long (in minutes) has it taken you to fall asleep each night?

(Text box)

During the past month, when have you usually gotten up in the morning?

- Before 06:00
- 06:00 - 08:00
- 08:00 - 10:00
- 10:00 - 12:00

- Later than 12:00

During the past month, how many actual hours of sleep did you get at night? (This may be different than the number of hours you spend in bed.)

(Text box)

During the past month, how often have you had trouble sleeping because you…

	Not during the last month	Less than once a week	Once or twice a week	Three or more times a week
Cannot get to sleep within 30 minutes	○	○	○	○
Wake up in the middle of the night or early morning	○	○	○	○
Cannot breathe comfortably	○	○	○	○
Cough or snore loudly	○	○	○	○
	Not during the last month	Less than once a week	Once or twice a week	Three or more times a week
Feel too hot	○	○	○	○
Have bad dreams	○	○	○	○
Have pain	○	○	○	○

During the past month, how often have you had trouble staying awake while driving, eating meals, or engaging in social activity?

- Not during the last month
- Less than once a week
- Once or twice a week
- Three or more times a week

During the past month, how much of a problem has it been for you to keep up enthusiasm to get things done?

- Not during the last month
- Less than once a week
- Once or twice a week

- Three or more times a week

Perceived Stress Scale

The questions in this scale ask you about your feelings and thoughts during the last week. In each case, you will be asked to indicate how often you felt or thought a certain way.

	Never	Almost Never	Sometimes	Fairly Often	Very Often
1. In the last week, how often have you been upset because of something that happened unexpectedly?	○	○	○	○	○
2. In the last week, how often have you felt that you were unable to control the important things in your life?	○	○	○	○	○
3. In the last week, how often have you felt nervous and "stressed"?	○	○	○	○	○
4. In the last week, how often have you felt confident about your ability to handle your personal problems?	○	○	○	○	○
5. In the last week, how often have you felt that things were going your way?	○	○	○	○	○

	Never	Almost Never	Sometimes	Fairly Often	Very Often
6. In the last week, how often have you found that you could not cope with all the things that you had to do?	○	○	○	○	○
7. In the last week, how often have you been able to control irritations in your life?	○	○	○	○	○
8. In the last week, how often have you felt that you were on top of things?	○	○	○	○	○
9. In the last week, how often have you been angered because of things that were outside of your control?	○	○	○	○	○
10. In the last week, how often have you felt difficulties were piling up so high that you could not overcome them?	○	○	○	○	○

Academic Procrastination Scale

These questions are about your procrastination tendencies, meaning how quickly you get things done or whether you tend to put them off. Please indicate your answer to the questions on a scale of Disagree to Agree.

	Disagree	Somewhat disagree	Neither agree or disagree	Somehwat agree	Agree
I usually allocate time to review and proofread my work.	○	○	○	○	○
I put off projects until the last minute.	○	○	○	○	○
I have found myself waiting until the last day before to start a big project.	○	○	○	○	○
I know I should work on schoolwork, but I just don't do it.	○	○	○	○	○
When working on schoolwork, I usually get distracted by other things.	○	○	○	○	○
I waste a lot of time on unimportant things.	○	○	○	○	○
I get distracted by other, more fun, things when I am supposed to work on schoolwork.	○	○	○	○	○

	Disagree	Somewhat disagree	Neither agree or disagree	Somehwat agree	Agree
I concentrate on schoolwork instead of other distractions.	○	○	○	○	○
I can't focus on schoolwork or projects for more than an hour until I get distracted.	○	○	○	○	○
My attention span for schoolwork is very short.	○	○	○	○	○
Tests are meant to be studied for just the night before.	○	○	○	○	○
I feel prepared well in advance for most tests.	○	○	○	○	○
"Cramming" and last minute studying is the best way that I study for a big test.	○	○	○	○	○
I allocate time so I don't have to "cram" at the end of the semester.	○	○	○	○	○

	Disagree	Somewhat disagree	Neither agree or disagree	Somehwat agree	Agree
I only study the night before exams.	○	○	○	○	○
If an assignment is due at midnight, I will work on it until 23:59.	○	○	○	○	○
When given an assignment, I usually put it away and forget about it until it is almost due.	○	○	○	○	○
Friends usually distract me from schoolwork.	○	○	○	○	○
I find myself talking to friends or family instead of working on schoolwork.	○	○	○	○	○
On the weekends, I make plans to do homework and projects, but I get distracted and hang out with friends.	○	○	○	○	○
I tend to put off things for the next day.	○	○	○	○	○

	Disagree	Somewhat disagree	Neither agree or disagree	Somehwat agree	Agree
I don't spend much time studying school material until the end of the semester.	○	○	○	○	○
I frequently find myself putting important deadlines off.	○	○	○	○	○
If I don't understand something, I'll usually wait until the night before the test to figure it out.	○	○	○	○	○
I read the textbook and look over notes before coming to class and listening to a lecture or teacher.	○	○	○	○	○

Revised Social Connectedness Scale

On a scale of disagree very strongly to agree very strongly please indicate how much the statements apply to you as a person

	Disagree very strongly	Disagree strongly	Disagree	Agree	Agree strongly	Agree very strongly
I feel comfortable in the presence of strangers	○	○	○	○	○	○
I am in tune with the world	○	○	○	○	○	○
Even among my friends, there is no sense of brother/sisterhood	○	○	○	○	○	○
I fit in well in new situations	○	○	○	○	○	○
I feel close to people	○	○	○	○	○	○
I feel disconnected from the world around me	○	○	○	○	○	○
Even around people I know, I don't feel that I really belong	○	○	○	○	○	○

	Disagree very strongly	Disagree strongly	Disagree	Agree	Agree strongly	Agree very strongly
I see people as friendly and approachable	○	○	○	○	○	○
I feel like an outsider	○	○	○	○	○	○
I feel understood by the people I know	○	○	○	○	○	○
I feel distant from people	○	○	○	○	○	○
I am able to relate to my peers	○	○	○	○	○	○
I have little sense of togetherness with my peers	○	○	○	○	○	○
I find myself actively involved in people's lives	○	○	○	○	○	○

	Disagree very strongly	Disagree strongly	Disagree	Agree	Agree strongly	Agree very strongly
I catch myself losing a sense of connectedness with society	○	○	○	○	○	○
I am able to connect with other people	○	○	○	○	○	○
I see myself as a loner	○	○	○	○	○	○
I don't feel related to most people	○	○	○	○	○	○
My friends feel like family	○	○	○	○	○	○
I don't feel I participate with anyone	○	○	○	○	○	○

Life satisfaction scale

Taking everything into consideration, during the past week how satisfied have you been with your…

	Very Poor	Poor	Fair	Good	Very Good
... physical health?	○	○	○	○	○
... mood?	○	○	○	○	○
... work?	○	○	○	○	○
... household activities?	○	○	○	○	○
... social relationships?	○	○	○	○	○
... family relationships?	○	○	○	○	○
	Very Poor	Poor	Fair	Good	Very Good
... leisure time activities?	○	○	○	○	○
... ability to function in daily life?	○	○	○	○	○
... sexual drive, interest and/or performance?	○	○	○	○	○
... economic status?	○	○	○	○	○
... living/housing situation?	○	○	○	○	○
... ability to get around physically without feeling dizzy or unsteady or falling?	○	○	○	○	○

	Very Poor	Poor	Fair	Good	Very Good
... your vision in terms of ability to do work or hobbies?	○	○	○	○	○
... overall sense of well being?	○	○	○	○	○
... medication? (If not taking any, leave this item blank.)	○	○	○	○	○
... How would you rate your overall life satisfaction and contentment during the past week?	○	○	○	○	○

End of survey

We thank you for your time spent taking this survey.

Your response has been recorded.

Appendix B

Full R-script:

```
##Data analyses of Bachelor thesis

##Sara von Pruski

##2.05.24


###apply APA 7 theme:###

.First <- function() {

  # Load packages

  library(tidyverse)

  library(interactions)


  # Set theme

  apa_theme <- theme(

    plot.margin = unit(c(1, 1, 1, 1), "cm"),

    plot.background = element_rect(fill = "white", color = NA),

    plot.title = element_text(size = 22, face = "bold",

                              hjust = 0.5,

                              margin = margin(b = 15)),

    axis.line = element_line(color = "black", size = .5),

    axis.title = element_text(size = 18, color = "black",

                              face = "bold"),

    axis.text = element_text(size = 15, color = "black"),

    axis.text.x = element_text(margin = margin(t = 10)),
```

```
    axis.title.y = element_text(margin = margin(r = 10)),
    axis.ticks = element_line(size = .5),
    panel.grid = element_blank(),
    legend.position = c(0.20, 0.8),
    legend.background = element_rect(color = "black"),
    legend.text = element_text(size = 15),
    legend.margin = margin(t = 5, l = 5, r = 5, b = 5),
    legend.key = element_rect(color = NA, fill = NA)
  )

  theme_set(theme_minimal(base_size = 18) +
            apa_theme)
}
usethis::edit_r_profile()




###load all necessary packages:###
install.packages("dplyr")
library(dplyr)
library(tidyverse)
library(janitor)
library(table1)
library(ggplot2)
```

```
install.packages("car")

library(car)

library(modelr)




###prep data for analyses:###

#open and view data:

rawd <- readxl::read_excel("Screen-
Time+among+university+students_May+2,+2024_07.33.xlsx")


#remove first row that is not an observation but explanation:

prodata <- rawd

prodata <- prodata[-c(1, 2),]


#create subset with necessary variables:

prodata <- prodata[c("Age_1","Gender","Nationality","Education",  "Mini-IPIP _1", "Mini-IPIP
_4", "Mini-IPIP _7", "Mini-IPIP _10", "Screen Time_1","Screen Time_2", "Screen Time_3",
"Screen Time_4", "Screen Time_5", "Q49_1", "Q49_2", "Q49_3", "Q49_4", "Q49_5", "Q49_6",
"Q49_7", "Q49_8", "Q49_9", "Q49_10", "Q51_1", "Q51_2", "Q51_3", "Q51_4", "Q51_5",
"Q51_6", "Q51_7", "Q51_8", "Life satisfaction _1","Life satisfaction _2", "Life satisfaction _3",
"Life satisfaction _4", "Life satisfaction _5", "Life satisfaction _6", "Life satisfaction _7", "Life
satisfaction _8", "Life satisfaction _9", "Life satisfaction _10", "Life satisfaction _11", "Life
satisfaction _12", "Life satisfaction _13", "Life satisfaction _14")]
```

```
#re-code values to numeric values for items Gender, Nationality, Education,:
prodata$Gender <- factor(prodata$Gender, levels = c("Male", "Female", "Non-binary/other"),
ordered = TRUE, labels = c(0,1,2))
levels(prodata$Gender)

prodata$Nationality <- factor(prodata$Nationality, levels = c("Dutch", "German", "Other"),
ordered = TRUE, labels = c(0,1,2))
levels(prodata$Nationality)

prodata$Education <- factor(prodata$Education, levels = c("Bachelor student", "Master student",
"PhD", "HBO student"), ordered = TRUE, labels = c(0,1,2,3))
levels(prodata$Education)

  #screen-time related:
col_TST <- paste0("Screen Time_", 1:5)
response_mappingTST <- c("Never"=1, "30 min or less"=2, "0.5 - 1 h"=3, "1 - 2 h"=4, "2 - 3 h"
=5, "3 - 4 h" =6, "4 - 5 h" =7, "5 - 6 h" = 8, "6 - 7 h" =9, "More than 7h" = 10)
prodata[col_TST] <- lapply(prodata[col_TST], function(x) response_mappingTST[x])

col_PST <- paste0("Q49_", 1:10)
response_mappingPST <- c("Never"=1, "Rarely"=2, "Sometimes"=3, "Often"=4, "Very
Often"=5)
prodata[col_PST] <- lapply(prodata[col_PST], function(x) response_mappingPST[x])
```

```
col_AST <- paste0("Q51_", 1:8)

response_mappingAST <- c("Stongly Disagree"=1, "Disagree"=2, "Somewhat Disagree"=3,
"Neither Disagree nor Agree"=4, "Somewhat Agree"=5, "Agree"=6, "Strongly Agree"=7)

prodata[col_AST] <- lapply(prodata[col_AST], function(x) response_mappingAST[x])


  #Extraversion related:

col_EX <- paste0("Mini-IPIP _1")

response_mappingEX <- c("Very inaccurate" = 1, "Moderately inaccurate" =2, "Neither
inaccurate nor accurate"=3, "Moderately accurate"=4, "Very accurate"=5)

prodata[col_EX] <- lapply(prodata[col_EX], function(x) response_mappingEX[x])


col_EX <- paste0("Mini-IPIP _4")

response_mappingEX <- c("Very inaccurate" = 1, "Moderately inaccurate" =2, "Neither
inaccurate nor accurate"=3, "Moderately accurate"=4, "Very accurate"=5)

prodata[col_EX] <- lapply(prodata[col_EX], function(x) response_mappingEX[x])

  #reverse the scores for item 4:

prodata$`Mini-IPIP _4` <- 5 - prodata$`Mini-IPIP _4`


col_EX <- paste0("Mini-IPIP _7")

response_mappingEX <- c("Very inaccurate" = 1, "Moderately inaccurate" =2, "Neither
inaccurate nor accurate"=3, "Moderately accurate"=4, "Very accurate"=5)

prodata[col_EX] <- lapply(prodata[col_EX], function(x) response_mappingEX[x])
```

```
col_EX <- paste0("Mini-IPIP _10")

response_mappingEX <- c("Very inaccurate" = 1, "Moderately inaccurate" =2, "Neither inaccurate nor accurate"=3, "Moderately accurate"=4, "Very accurate"=5)

prodata[col_EX] <- lapply(prodata[col_EX], function(x) response_mappingEX[x])

  #reverse the scores for item 10:

prodata$`Mini-IPIP _10` <- 5 - prodata$`Mini-IPIP _10`


  #life satisfaction related:

col_LS <- paste0("Life satisfaction _", 1:14)

response_mappingLS <- c("Very Poor"=1, "Poor"=2, "Fair"=3, "Good"=4, "Very Good"=5)

prodata[col_LS] <- lapply(prodata[col_LS], function(x) response_mappingLS[x])




###demographic data displayed in a table:###

library(table1)

library(janitor)

prodata%>%

  tabyl("Age_1")

prodata%>%

  tabyl("Gender")

prodata%>%

  tabyl("Nationality")

prodata%>%
```

```
  tabyl("Education")
```

###compute total scores for each sub-scale and total sample means (Total, passive and active Screen Time, Extraversion and Life Satisfaction):###

```
prodata<-prodata%>%
  mutate(TSTTotalScore = as.numeric(prodata$`Screen Time_1`) + as.numeric(prodata$`Screen Time_2`) + as.numeric(prodata$`Screen Time_3`) + as.numeric(prodata$`Screen Time_4`) + as.numeric(prodata$`Screen Time_5`),
         PSTTotalScore = as.numeric(prodata$Q49_1) + as.numeric(prodata$Q49_2) + as.numeric(prodata$Q49_3) + as.numeric(prodata$Q49_4) + as.numeric(prodata$Q49_5) + as.numeric(prodata$Q49_6) + as.numeric(prodata$Q49_7) + as.numeric(prodata$Q49_8) + as.numeric(prodata$Q49_9) + as.numeric(prodata$Q49_10),
         ASTTotalScore = as.numeric(prodata$Q51_1) + as.numeric(prodata$Q51_2) + as.numeric(prodata$Q51_3) + as.numeric(prodata$Q51_4) + as.numeric(prodata$Q51_5) + as.numeric(prodata$Q51_6) + as.numeric(prodata$Q51_7) + as.numeric(prodata$Q51_8),
         EXTotalScore = as.numeric(prodata$`Mini-IPIP _1`) + as.numeric(prodata$`Mini-IPIP _4`) + as.numeric(prodata$`Mini-IPIP _7`) + as.numeric(prodata$`Mini-IPIP _10`),
         LSTotalScore = as.numeric(prodata$`Life satisfaction _1`) + as.numeric(prodata$`Life satisfaction _2`) + as.numeric(prodata$`Life satisfaction _3`) + as.numeric(prodata$`Life satisfaction _4`) + as.numeric(prodata$`Life satisfaction _5`) + as.numeric(prodata$`Life satisfaction _6`) + as.numeric(prodata$`Life satisfaction _7`) + as.numeric(prodata$`Life satisfaction _8`) + as.numeric(prodata$`Life satisfaction _9`) + as.numeric(prodata$`Life
```

```
satisfaction _10`) +  as.numeric(prodata$`Life satisfaction _11`) + as.numeric(prodata$`Life satisfaction _12`) + as.numeric(prodata$`Life satisfaction _13`) + as.numeric(prodata$`Life satisfaction _14`)
  )




###descriptive statistics:###
#calculate means, sd's, ranges and medians for each variable and add it into a table:
table1::label(prodata$TSTTotalScore) <- "Total level of total Screen time"
table1::label(prodata$PSTTotalScore) <- "Level of passive Screen time"
table1::label(prodata$ASTTotalScore)<-"Level of active Screen time"
table1::label(prodata$EXTotalScore)<-"Level of Extraversion"
table1::label(prodata$LSTotalScore)<-"level of Life satisfaction"
table1::table1(~ TSTTotalScore + PSTTotalScore + ASTTotalScore + EXTotalScore + LSTotalScore, data = prodata)

#testing how many above recommended amount of total screen time (total score above 20 for TST):
participants_above_20<-prodata[prodata$TSTTotalScore > 20,]
num_part_ab_20<-nrow(participants_above_20)
print(num_part_ab_20)

#calculate Cronbach's Alpha for this sample for the MINI-IPIP:
```

```
library(psych)
MINIIPIPitems <- prodata[c("Mini-IPIP _1", "Mini-IPIP _4", "Mini-IPIP _7", "Mini-IPIP _10")]
cronbach_alpha<-alpha(MINIIPIPitems)
print(cronbach_alpha)

#create data-set only with the 5 variables:
justtot<- select(prodata, TSTTotalScore, PSTTotalScore, ASTTotalScore, EXTotalScore,
LSTotalScore)

#correlations between the 5 variables:
library(Hmisc)
rcorr_result <- rcorr(as.matrix(justtot[, c("TSTTotalScore", "PSTTotalScore", "ASTTotalScore",
"EXTotalScore", "LSTotalScore")]), type= "pearson")
rcorr_result$r
rcorr_result$P

###multiple linear regression:###
#create a multiple linear model + run an anova:
mlmodel<- lm(LSTotalScore~TSTTotalScore+PSTTotalScore+ASTTotalScore, data= justtot)
summary(mlmodel)

#test assumptions for multiple linear regression:
```

```
  #get model residuals and plot the result to test normality:
mlmodel_res<-mlmodel$residuals
hist(mlmodel_res)
qqnorm(mlmodel_res)
qqline(mlmodel_res)

  #multicollinearity assumption check:
library(car)
vif_values <- vif(mlmodel)
print(vif_values)

  #Testing Linearity and Homoscedasticity:
plot(mlmodel, 1)
install.packages("lmtest")
library(lmtest)
bptest(mlmodel)

  #Testing Independence:
cor_matrix <- cor(justtot[, c("TSTTotalScore", "PSTTotalScore", "ASTTotalScore")])
print(cor_matrix)
library(modelr)
prodata %>%
  add_residuals(mlmodel) %>%
  add_predictions(mlmodel) %>%
```

```
  mutate(obs_numb = row_number()) %>%
  ggplot(aes(x = obs_numb, y = resid)) +
  geom_point() +
  labs(x = "Number of observations", y = "Residuals")
library(car)
durbinWatsonTest(mlmodel)



###inferential statistics###
#load PROCESS for R version 4.3.1 by Andrew F. Hayes using download link on
www.processmacro.org
##testing the assumptions for parallel mediation analysis:
#comprehensive test:
  #replicate model used in Process for mediation:
    #EX on TST, PST and AST:
model.m1<- lm(TSTTotalScore~EXTotalScore, data= justtot)
summary(model.m1)
model.m2 <-lm(PSTTotalScore~EXTotalScore, data=justtot)
model.m3 <- lm(ASTTotalScore~EXTotalScore, data=justtot)
#all predictors on LS:
modeldir<-lm(LSTotalScore~EXTotalScore, data= justtot)

  #testing linearity (linearity is already checked for mediators on LS in MLR above):
```

```
plot(model.m1, 1)

plot(model.m2, 1)

plot(model.m3, 1)

plot(modeldir, 1)

bptest(modeldir)


#Testing Multiple collinearity:

medmodel<- lm(LSTotalScore~EXTotalScore+TSTTotalScore+PSTTotalScore+ASTTotalScore,
data= justtot)

summary(medmodel)

library(car)

vif_valuesmed <- vif(medmodel)

print(vif_valuesmed)


##parallel mediation analysis (Homoscedasticity and Normality are accounted for in this):

process(data = justtot, y="LSTotalScore", x="EXTotalScore", m=c("TSTTotalScore",
"PSTTotalScore", "ASTTotalScore"), model=4, describe =1, stand =1, contrast=1, modelbt=1,
boot = 10000, seed = 424272, hc=4)


##Testing the assumptions for moderation analysis:

#create dataset for moderation including only totalscores from Total Screen Time, Extraversion
and Life Satisfaction:
```

```
MODDATA<- select(prodata, TSTTotalScore, EXTotalScore, LSTotalScore)


#create a linear model + run an anova:
outmod <-lm(LSTotalScore~TSTTotalScore+EXTotalScore+TSTTotalScore:EXTotalScore,
data= MODDATA)
summary(outmod)
anova(outmod)%>%
  tidy()


#get model residuals and plot the result to test normality:
modmodel_res<-outmod$residuals
hist(modmodel_res)
qqnorm(modmodel_res)
qqline(modmodel_res)


#Testing Linearity and Homoscedasticity:
MODDATA%>%
  ggplot(aes(x=TSTTotalScore, y=LSTotalScore, color= EXTotalScore))+
  geom_point() +
  labs(x= "Total Screen Time", y ="Life Satisfaction", z="Extraversion")
plot(outmod, 1)
library(lmtest)
bptest(outmod)
```

```
#Testing Independence:
library(modelr)
MODDATA %>%
  add_residuals(outmod) %>%
  add_predictions(outmod) %>%
  mutate(obs_numb = row_number()) %>%
  ggplot(aes(x = obs_numb, y = resid)) +
  geom_point() +
  labs(x = "Number of observations", y = "Residuals")
library(car)
durbinWatsonTest(outmod)

##moderation analysis:
process(data = justtot, y="LSTotalScore", x="TSTTotalScore", w="EXTotalScore", model=1,
center=2, describe=1, stand=1, jn=1, moments = 1, modelbt = 1, boot = 10000, seed = 424272)

#plot Simple Slopes:
library(rockchalk)
my_fit <- lm(LSTotalScore ~ TSTTotalScore * EXTotalScore, data = justtot)
summary(my_fit)
plotSlopes (my_fit, plotx ="TSTTotalScore" , modx = "EXTotalScore", modxVals = "std.dev." )
```

Appendix C

Assumptions check of the multiple linear regression:

Before performing the multiple linear regression, the assumptions of Linearity, Normality, Homoscedasticity, Independence and multicollinearity were checked. All assumptions were met. For Homoscedasticity, Independence and multicollinearity, additional tests were performed. Homoscedasticity was tested using the Breusch-Pagan test and homoscedasticity was met since the no significant p-value was found (p = 0.56). Independence was checked using the Durbin Watson test and the Durbin Watson statistic was close to 2 and significant, indicating a small autocorrelation in the residuals (*D-W Statistic* = 2.42, p = 0.04). However, since the D-W Statistic of 2.42 lies within the boundaries of 1.5 to 2.5, there is no potentially serious autocorrelation problem. Multicollinearity was examined using the variance inflation factor (vif). Since the vif-values all were below 2 (1.08 for TST, 1.13 for PST and 1.15 for AST), no multicollinearity was assessed.

Assumptions check of the parallel mediation:

Before performing the parallel mediation analysis, the assumptions of Linearity and multicollinearity were checked. All assumptions were met. The assumptions of Homoscedasticity and Normality were accounted for using bootstrapping and robust standard error in the modelling of the mediation. Same as with the multiple linear regression, multicollinearity was examined using the variance inflation factor (vif). Since the vif-values all were below 2 (1.17 for EX, 1.2 for TST, 1.16 for PST and 1.16 for AST), no multicollinearity was assessed.

Assumptions check of the moderation:

Prior to performing the moderation analysis, the assumptions of Linearity, Normality, Homoscedasticity and Independence were checked. All assumptions were met. Independence was additionally checked using the Durbin Watson test and the Durbin Watson statistic was close to 2 (*D-W Statistic* = 2.29, p = .13).