Cognitive Performance in the relation between Digital Use and Subjective Wellbeing

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Abstract

The incredible convenience that digital devices offer is suspected to come at a high cost. Researchers have been trying to find out, how the use of digital devices and addictive tendencies affect our health and brains. They found evidence that the dependence on digital devices negatively affects our physical and mental wellbeing, as well as our cognitive skills. To further investigate these relations, this paper analyses the mediating effect of Cognitive Performance in the relation between Digital Use and Subjective Wellbeing. The method applied is a Mediation Model in Structural Equation Modelling, using data from the German Socio-Economic Panel on young adults in 2016 and 2017. The variable Digital Use is measured as time spent on social networks and other surfing on the internet. Cognitive Performance is a latent construct with the indicators Concentration, Efficiency, Thoroughness, Diligence, and Ambition. The results of the analysis are mostly insignificant, which means that no mediating effect is found with the data at hand. As the insignificance might be caused by a gap between the theoretical concept and the available data, the measurability of addictive Digital Use is discussed.

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"The dark side is that being rewarded is sometimes a powerful motivating force at the expense of conscious control."

(Engeser, 2012, p.126)

1. Introduction

When thinking of human existence, wellbeing is perceived as the ultimate goal to work towards (Glatzer, Camfield, Møller, & Rojas, 2015). Nowadays, the high standard of living in western countries allows society to deal with non-existential needs (Glatzer et al., 2015). One of these needs is the desire to be a happy human being. Mental health issues are moving more and more into the focus of society. The WEF global risk report 2019 elaborates that depression, anxiety disorders, and loneliness have been strongly on the rise within the last decade. Indeed, researchers discovered that particularly young adults in the US and in the west; and therefore, countries that have high living standards, suffer from mental health issues (World Economic Forum, 2019). It automatically triggers the question of what differentiates young adults nowadays from young adults of prior generations. Growing up as digital natives, a generation that spent their entire lives surrounded by new technology, they have never known a time prior to being dependent on digital devices (Prensky, 2001). Research shows that digital natives, compared to older generations, are more likely to show addictive phone behaviour (Montag et al., 2015). Despite the convenience and the necessary functions of smartphones, such as communication and navigation, the WEF global risks report 2019 classifies technological addiction as a risk for mental health (World Economic Forum, 2019). The causes for this issue are not accidental but induced by big tech companies, that profit from their users being addicted to their phones. With great concern, some researchers speak of 'intentional manipulation of the mind' and suspect changes in our social, emotional and cognitive environment (Lapowsky, 2018). When unintentionally diving into self-destructive behaviour to the benefit of tech companies, it can no longer be assumed that consumers know what is best for them (Sachs, 2019).

The whole industry of digital devices and content is highly dynamic. Progress in technology generates innovation. Content changes as current users get older and new generations with different interests step into the market. Devices, platforms, target groups, usage behaviour, and content trends change constantly and at a fast pace. To name only one example, a large amount of research on Social Media is conducted on Facebook (Song et al., 2014; Kross et al., 2013; Chen & Lee, 2013). However, the user group of Facebook has shifted drastically within the past five years. While it was initially acclaimed by teenagers, today Facebook is referred to as the "retirement-home" of social networks, as it is most actively used by their parents and grandparents (Heintze, 2018). In the meantime, teenagers have discovered Tik Tok, a social network that might be unknown to most adults (Vodafone Stiftung Deutschland, 2018). Although this paper does not specifically focus on social networks, the example shows that in the field of digital use, consumer preferences shift faster than research can adapt with data gathering. Thus, the causes and effects of addictive digital use change and are difficult to fathom in full depth.

In general, research in this field faces many obstacles, such as the fast pace of change, the complexity due to interdisciplinarity, and the lack of data. The need for research is evident and necessary in order to conduct social interventions. Therefore, it is reasonable to constantly replicate existing research, as well as to find domains for new research. With regard to digital use, researchers still investigate what exactly makes people grab their phones more often than necessary and why people unintentionally spend way too much time staring at it. Also, it has become a matter of subject, how digital use affects our wellbeing. Researchers have found evidence that both physical and psychological aspects partially explain the relation (George & Odgers, 2015; Twenge, Joiner, Rogers & Martin, 2018). For example, it was found that digital use leads to a decrease in social interaction, which in turn decreases subjective wellbeing (Sherman, Michikyan & Greenfield, 2013). Another field of research is how digital use affects cognitive functions. It is hardly surprising for anyone to see that research results confirm the distractive power of smartphones (Stothart, Mitchum & Yehnert, 2015). It has been shown that the mere presence of a smartphone already worsens an individual's performance on a task (Ward, Duke, Gneezy & Bos, 2017). Little is known about how digital use affects an individual's ability to concentrate on a task, work efficiently and stay motivated, and whether this relation might also be related to subjective wellbeing. Therefore, this paper adds to the existing literature by testing the mediating effect of Cognitive Performance in the relation between Digital Use and Subjective Wellbeing. The following research question is investigated: *Is there a mediating effect of Cognitive Performance in the relation between Digital Use and Subjective Wellbeing?* The data used is derived from the Socio-Economic Panel (SOEP), a longitudinal study on private German households. By observing 13-and-14-year-olds in the years 2016 and 2017, this research focusses on the generation of digital natives.

The paper begins with a literature review on mediators in the relation between Digital Use and Subjective Wellbeing. Thereafter, the concepts of Subjective Wellbeing and Digital Use are explained. Cognitive Performance is introduced by proposing theories on how it might be related to the aforementioned concepts. The following analysis is divided into two parts. Firstly, the variable Cognitive Performance is constructed from a variety of measures using Exploratory Factor Analysis. Afterwards, the Mediation Model is built using Structural Equation Modelling. Both the direct effect between Digital Use and Subjective Wellbeing, as well as the indirect effect through Cognitive Performance is shown. The analysis is followed by the description and interpretation of the results. Lastly, the limitations of this research, especially with regard to the measurability of addictive Digital Use, are discussed.

2. Theoretical Framework

2.1 Digital Use and Subjective Wellbeing: Mediators

In social sciences, it is unlikely to prove a direct effect between two variables, as studying humans is very complex and the depth of the research can be increased infinitely. The same holds for the relation between Digital Use and Subjective Wellbeing. Previous papers have investigated potential mediators between the use of smartphones/social media and wellbeing. The goal of research in this field is to understand the psychological benefits of digital devices and also drawbacks both for the physical and mental wellbeing. Researchers try to understand why people suspect happiness in their digital devices and yet do not find it. The results are contradictory, which can mainly be attributed to the fact that various measures are taken to capture Digital Use. Also, smartphone behaviour is heavily dependent on other influencing factors, such as the consumed content, which is difficult to investigate empirically (Verduyn, Ybarra, Résibois, Jonides, & Kross, 2017). In the following, I display what researchers have found so far.

George & Odgers (2015) investigated how mobile technologies influence adolescents in the digital age. The authors divide possible negative effects into safety, social development, cognitive performance, and sleep categories. They deduced that most online behaviours are mirrored offline. For example, individuals with low social interaction offline are also more likely to have little social interactions online. With regard to cognitive performance, they found evidence, that multitasking with new technologies has a negative effects on academic performance (George & Odgers, 2015).

Another factor that has been observed in the relation between Digital Use and Wellbeing are shifts in leisure time spending. Time is a limited resource and taking into account sleep, school and other obligations, leisure time might be especially scarce for young adults. Therefore, research investigated whether or not leisure time is well-spent. High amounts of time spent on digital devices raise the suspicion, that non-screen activities, such as social interaction and exercise, might fall short besides screen activities. This could be related to decreases in wellbeing. Indeed, Twenge, Joiner, Rogers & Martin (2018) found that time spent on new media is associated with mental health issues. Adolescents spending more time on non-screen activities are less likely to report mental health issues. This problem is particularly relevant as the depression rates of 13-to-18-year-olds in the U.S. have risen since 2010. Simultaneously, the mobile phone possession rate increased. The authors conclude that new media screen time is an important modern risk factor for depression and suicide (Twenge et al., 2018).

Closely related to the concept of leisure time shifts is the idea of decreases in social interaction due to increases in electronic communication. Sherman, Michikyan & Greenfield (2013) investigated the effects of different types of communication on the emotional experience of connectedness between friends. They found that in-person communication has the highest level of personal bonding, and that the emotional experience decreases when leaving out the visual and audio components of the communication. Instant messaging, compared to in-person communication, is associated with significantly lower levels of emotional experience (Sherman, Michikyan & Greenfield, 2013).

Many researchers have explored the relation between the use of screen time/ social media and loneliness, anxiety, and wellbeing. However, only few have been analysing causal relations. In this field of research, causal relations are relevant in order to not falsely accuse digital media of being a main cause of low wellbeing. Therefore, researchers investigated, whether digital devices cause negative psychological effects, or lonely individuals are more likely to spend much time using their devices. Song et al. (2014) analysed whether the use of Facebook is associated with loneliness, predicted by shyness and low social support, and also explored the direction of a causal relation. In theory, a causal relation can be argued in both directions. On the one hand, it is reasonable that connections through social media cannot sufficiently substitute human interaction and therefore cause loneliness. However, statistical results by Song et al. (2014) do not support this theory. On the other hand, it is reasonable that lonely individuals are more likely to seek social interaction in social networks, as it is an additional possibility for interaction and might substitute the lack of social interaction in real life. The 'social compensation theory' is supported by the research results of Song et al. (2014). Therefore, the authors conclude that lonely individuals are more likely to use Facebook.

Kross et al. (2013) investigated the effects of social media on subjective wellbeing using the experience-sampling method. This approach allows for instant wellbeing tracking after social media usage. It yields the advantage that the wellbeing data might have more variation and is more closely linked to social media usage. The authors find negative significant correlations both for mood indicators as well as for overall life-satisfaction indicators (Kross et al., 2013).

Researchers suggest that negative effects of digital devices are not proportional to exposure, but rather follow a curvilinear relation. The Goldilocks hypothesis is tested by Przybylski & Weinstein (2017). They argue that moderate levels of device usage do not impact mental wellbeing. Also, they suggest that harmful consumption is different on weekends and during the week. The threshold for harmful effects on wellbeing increases on the weekend compared to weekdays. It means that high amounts of screen time are less harmful on the weekend compared to weekdays. (Przybylski & Weinstein, 2017).

Digital devices, and especially smartphones, give access to real-time information and helpful tools in daily life, which is a curse and a blessing at the same time. As this strive for connectivity can turn into an obsession, negative feelings might occur at times of disconnection. This state of mind is referred to as "fear of missing out" (fomo), which describes an individual's restlessness with digital disconnection. As stated by Scott, Valley & Simecka (2016), the work-related or social fear of missing out on information can trigger anxiety. The direct opposite of fomo is called jomo (joy of missing out), which describes the positive feeling of not being connected and therefore not receiving unlimited amounts of information, most of which is neither necessary nor entertaining (Arana & Baig, 2018). Psychological distress due to social media is also observed by Chen & Lee (2013). The authors investigated the mediating effects of communication overload and self-esteem. They found that Facebook interaction is positively related to psychological distress and communication overload. However, there is no mediating effect of communication overload or self-esteem in the relation between Facebook interaction and psychological distress (Chen & Lee, 2013). However, Vannucci, Flannery & McCauley Ohannessian (2017) found significant correlations between time spent on social media use and anxiety. As measures for anxiety, the researchers investigated feeling terrified, afraid, nervous, tingling, or numb.

The literature review on mediators in the relation between Digital Use and Subjective Wellbeing shows the complexity and interdisciplinarity of research in this field. In order to better understand the definition and determinants of Subjective Wellbeing, as well as the occurrence of addictive Digital Use, both concepts are described in the following.

2.2 Subjective Wellbeing

The terms "happiness", "wellbeing" and "quality of life" are often used interchangeably in literature (Glatzer et al., 2015). According to Diener, Lucas & Oishi (2009), subjective wellbeing (SWB) is defined as an individual's evaluation of his life and can comprise emotions, moods, and life-satisfaction. Veenhoven (1984) defines happiness as *"the degree to which an individual judges the overall quality of his life-as-a-whole favourably"* (Veenhoven, 1984, p.22). The author describes the variability in measuring happiness by stating that individuals might assess their happiness differently in terms of stability, definiteness, time-emphasis, consciousness and appropriateness. For example, for some individuals the perception of their own level of happiness might drastically change from day to day, or individuals might be unconscious of their "true" happiness. However, even though these aspects might be a cause for biased well-being values in the data set, it is in nature that the measure relies on subjective perceptions (Veenhoven, 1984). Diener, Suh, Lucas & Smith (1999) differentiate between the affective and the cognitive component of subjective wellbeing. The affective component refers to an individual's mood and emotion, whereas the cognitive component comprises an individual's overall perception of the life as a whole. The measure used for this paper is as follows: *"How content are you at present, all in all, with your life?"*. The survey participants are asked to state their current "contentment" with life regarding all aspects of it. Thus, in this paper, the cognitive component is used as a measure for subjective wellbeing. A discussion regarding the use of the cognitive component compared to the affective component is provided in the Limitations chapter.

A variety of researchers have looked into determinants of happiness. Frey (2018) divides determinants into the five areas of genetic endowment, economic factors, socio-demographic influences, culture and religion, and political conditions. For instance, the relation between income and life-satisfaction has been investigated intensively. It was found that income has a strong positive correlation with life-satisfaction, but only up to a threshold at which a certain material standard was reached. The consequences of happiness were also investigated. It was found that happiness correlates with productiveness, good health, and a long life. As happiness arises from living a life with meaningful activities and human interaction, humans cannot simply decide to be happy. In order to increase subjective wellbeing, it is therefore necessary to detect and influence happiness-determining parts of life (Frey, 2018).

Farhud, Malmir & Khanahmadi (2014) divide determinants of happiness into endogenic (e.g. biology, cognition) and exogenic aspects (e.g. life-events, economy). Happiness was also investigated on a chemical level. Two neurotransmitters that were found to be related to one's mood are dopamine and serotonin. Serotonin is associated with satisfaction, happiness, and optimism, and, when prevalent in low levels, can be a cause of depression (Farhud, Malmir & Khanahmadi, 2014). Dopamine, however, has been investigated prominently in relation to reward research. Lustig (2017) investigates the causes and effects of addiction on a neurological level. Dopamine is the neurotransmitter for the reward system, which humans can get addicted to. Serotonin, however, is the neurotransmitter that, at very low levels, causes depression. Lustig (2017) explains that dopamine and serotonin are often confused with each other by consumers, as they suspect to find happiness in consumption.

2.3 Digital Use

Individual-level datasets including Digital Use, Cognitive Performance and Subjective Wellbeing are scarce, which is why this research is limited to only one country, namely Germany. As the subsequent analysis is exclusively on German young adults, I want to take a closer look at their digital usage behaviour. Also, the triggers for addictive tendencies are investigated by briefly referring to the intentions of big tech companies, behaviour design and parallels to gambling addiction.

2.3.1 Digital Usage Behaviour

For digital natives, a generation that never knew a time before the internet, the smartphone is the dominant device to access digital services, and therefore the main trigger for addictive digital use. Statistics on the share of teenagers owning a smartphone in Germany show a strong increase from 2011 to 2015, culminating a penetration rate of above 90% in 2015. In 2018 the smartphone penetration rate reached 97% (Medienpädagogischer Forschungsverbund Südwest, 2018). An adoption rate of this magnitude confirms that smartphones have become an integral part of everyday life for German teenagers. Essential functions, such as communication and navigation, have shifted from the analogue to the digital world. A big part of smartphone usage is social media (Global Web Index, 2018). Social Media evolved from pure entertainment content into a serious touchpoint for companies and communication channel for not only private communication, but also advertising, journalism, and politics. Therefore, the type of consumable content is extremely diverse and ranges from entertaining to serious in one scroll. This makes it almost impossible to empirically examine the full range of social media. Yet, researchers have investigated the effects of the amount of screen time and time spent on social media on wellbeing. The following chapter is a brief description of how the usage behaviour of digital natives looks like. Statistics with current figures are difficult to find. The following data is mostly gathered from the market research companies Global Web Index and We Are Social.

The most popular Internet activities on the smartphone in a worldwide survey of 2017 are email, using social media sites and watching movies/videos, reading news and online shopping (Kaspersky Lab, 2018). Therefore, social media sites play an important role when talking about smartphone usage. The most used social network platforms worldwide, as measured by the number of active users, are Facebook, YouTube, WhatsApp, Facebook Messenger, WeChat and Instagram (We Are Social, 2019). The terms ‘social network sites’ and ‘social media’ are not clearly defined and many apps incorporate a large variety of functions, many of which are redundant with one another. For example, WhatsApp might be mostly used for text messages, Snapchat might predominantly be used for sending instant pictures to individuals, while Instagram might be used to present content to a larger audience. Although all of these apps could be used for all three purposes, users chose to use different apps for different purposes. Therefore, the categorisation of different social media apps is increasingly hard and also depends on an individual's way to engage with an app. A survey conducted by Statista (2019) divides the top three types of social media into instant-messengers (e.g. WhatsApp, Facebook messenger), social networking sites (e.g. Facebook), and media sharing platforms (e.g. Snapchat, Instagram, YouTube, Pinterest). As can be seen here, video platforms like YouTube might be considered as a social networking platform.

Germans aged between 16 and 64 spend an average of 4 hours and 52 minutes a day on the internet. Compared to other nations, such as Thailand showing an average time of 9 hours and 38 minutes, Germany is comparatively moderate (We Are Social, 2018). The daily time using mobile internet equals 1 hour and 31 minutes in Germany (We Are Social, 2018). Research among 400,000 Internet users aged 16 to 64, shows that the average time per day spent on social media for German Internet users in 2018 equalled 1 hour and 7 minutes. Among 16-to-24-year-olds, this number increases to 2 hours and 4 minutes. As a reason, the importance of messaging apps is stated (Global Web Index, 2018). In the international comparison, again, Germany is at the lower end. The list is led by the Philippines with an average daily social media usage time of 4 hours and 11 minutes in 2018. Today, social media is mostly used on the phone, while the use of computers decreases (Global Web Index, 2018). Data from the Global Web Index (2018) also reveals that time spent on social media has approached saturation and does not continue to increase with the same rates as in previous years. The Global Social Media penetration rate equalled 42% in 2018. Germany is slightly above average with 46%, while the list is led by the United Arab Emirates, South Korea, and Singapore with 99%, 84% and 83%, respectively (We Are Social, 2018). The global average annual growth of social media users amounts to 15% in Germany and is therefore slightly above the global average of 13%. In international comparisons, Germany is below the international average in most categories when it comes to digital penetration rates (We Are Social, 2018). In conclusion, the data shows clearly that time spent on social media is a big part of overall screen time; especially for young adults.

2.3.2 Triggers for Addictive Tendencies

During the last couple of years, many researchers have claimed that the consumption of both tangible and digital products to an unlimited extent drives our society into a mass-addiction-economy.

Research on the US shows that the country suffers an epidemic of addictions, and refers to a causal relation with decreases in happiness levels (Sachs, 2019). Addictions can be observed in the field of gambling, social media use, video gaming, shopping, consuming unhealthy foods, exercising, engaging in extreme sports, engaging in risky sexual behaviours and many more (Sachs, 2019). Only recently, digital addictions started to gain awareness as a subject to be taken seriously, prominently because it might not only affect a minority, but to some extent all individuals engaging with digital devices. In order to understand the consequences of addictive digital use, it is first necessary to take a closer look at the roots of the problem, which lie in the intentions of big tech companies and the ways they are claimed to manipulate the human brain (Condliffe, 2019).

Companies like Facebook and Google have a strong interest in increasing screen time to a maximum (Alter, 2017). High screen time equals a great amount of attention, which is a scarce resource in the digital age. Increasing the attention to digital devices as much as possible generates profits, for example through data collection and advertising business. Therefore, it is the big tech companies' goal to increase both the number of times someone reaches for his digital device, as well as to increase the actual time spent on the device. As a consequence, tech companies spend huge efforts on research regarding behaviour design. Tristan Harris, a former Design Ethicist at Google, even refers to the man-made problem of addictive digital use as "human downgrading" (Condliffe, 2019).

The Center for Human Technology aims to raise awareness for the negative impacts of technology. According to Harris' theory, "human downgrading" is induced by artificial social systems, overwhelming artificial intelligence, and extractive incentives. Using a framework of ergonomics, he describes the effects of being absorbed by digital devices, while neglecting the needs of human nature (Center for Humane Technology, 2019). Originally, ergonomics is the discipline of designing technology and products in a way so that it fits the users' needs and contributes to more comfort and better usability (SciTechnol, 2019). However, detailed knowledge in this field can also be used to increase usability to a point that it manipulates human behaviour. Harris suspects negative effects in many areas, such as attention spans, relations, civility, community, habits, nuance, critical thinking, mental health, creativity, romantic intimacy, self-esteem, productivity, common ground, shared truth, mindfulness, and governance (Center for Humane Technology, 2019).

The discipline concerned with how design can influence human behaviour, is called behaviour design. It is rooted in the understanding of stimulus and response, which has already been investigated in the 1930s by B. F. Skinner, who saw human behaviour as a function of incentives and rewards (Leslie, 2016). Within the last years, behaviour design became extremely relevant for big tech companies, trying to make users stick to their digital devices, influencing attention spans, and buying decisions. Digital devices are built in a way that they function as a trigger and reward system. The trigger, which for example can be a notification, is followed by a reward, for example a like, that generates dopamine (Leslie, 2016). Experiments with rats have shown, that rewards may only be given irregularly, in order to make them try again and again to get a reward. This principle of variable rewards has been transferred to humans in the interaction with digital devices. People look at their phones at an increasing rate, because they never know if there is a reward (Leslie, 2016). These unconscious impulses are a highly effective way to compel attention, which by some researchers is perceived as the scarcest resource in the information age (Walls, 2010). On average, a person checks his phone 150 times a day, including conscious and unconscious behaviour. Therefore, it is indisputable that big tech companies gain a significant amount of control over people through digital devices (Leslie, 2016).

The insights of addictive digital use in the case of smartphones show parallels to gaming and gambling research. In a paper published by Google, the company describes the digital device as a ‘pocket slot machine’. As individuals have their phones close by at all times, they are able to check it permanently with the subconscious hope for a variable reward to arrive (Arana & Baig, 2018). One common phenomenon in gambling research is the addictive effect of "near misses". A near miss occurs, when an event is close to a win. These outcomes are perceived as the most frustrating, but at the same time also increase the heart rate, subjective arousal and the urge to continue playing. Despite ongoing losses, the feeling of higher chances of winning next time invigorates the play. This kind of trigger is not only applied for slot machines but also for smartphone games, such as Candy Crush (Larche, Musielak & Dixon, 2017). Moreover, it might be a similar mechanism, that makes endless scrolling attractive. Seeing post after post on social media, without the wanted satisfaction might feel like a "near miss", which therefore might increase the urge to scroll further, always with the hope to see something very exciting.

The previous sections have described definitions and determinants of Subjective Wellbeing, as well as the occurrence of addictive Digital Use. Building on this, I add a third concept to investigate one possible explanation for effects of Digital Use on Subjective Wellbeing.

2.4 The Relation of Digital Use and Cognitive Performance

One might perceive the support of digital devices as a form of multitasking; and being able to communicate and operate through digital devices, while focussing on attention requiring tasks, as the ultimate level of efficiency. Schoenberg & Scott (2011) describe concentration as the ability to select stimuli and maintenance to successfully complete a task. The two elements of concentration are sustaining attention on relevant tasks and ignoring irrelevant stimuli (Schoenberg & Scott, 2011). Constant availability through digital devices forces individuals to be reachable, thus, let distraction happen whenever a notification pops up. In fact, users might not benefit from digital content overload, but instead, have an increasingly hard time to control their focus of attention. Media multitasking occurs, when an individual is either engaging in multiple types of media at the same time or engages with media while also engaging in non-media activities. Consequences of media multitasking have been observed in the three domains cognitive control abilities, academic performance, and socioemotional functioning. With regard to consequences on cognitive control, the authors expose two theories, that are relevant for the prevalent research in this paper (Van der Schuur, Baumgartner, Sumter, & Valkenburg, 2015).

The 'scattered attention hypothesis' suggests that adolescents have difficulties in differentiating relevant from irrelevant information, which might lead to distraction and therefore lowers the ability to focus on a relevant task (Ophir, Nass & Wagner, 2009). However, the authors suggest that media multitasking might as well have positive effects on training cognitive processes to filter information more effectively. Underlying measures of cognitive control are the ability to switch between tasks, filter irrelevant information, working memory capacity, sustained attention and response inhabitation (Ophir et al., 2009). Summarized results of several studies show that findings partly support the scattered attention hypothesis when measured with self-report questionnaires. Other performance-based measurement indicators do not find support in research. According to the scattered attention hypothesis, attention is a limited resource. Media multitasking reduces the focus on the primary task (May & Elder, 2018). Similarly, the 'bottleneck theory' suggests, that multitasking does not exist, as the attention can only be allocated to one task at a time (Maslovat et al., 2013). Ophir, Nass & Wagner (2009) also investigated the effects on cognitive performance of media multitaskers. The researchers found evidence, that heavy media multitasking causes irrelevant environmental stimuli and irrelevant representations in memory. They found that both attending multiple input streams as well as simultaneously performing multiple tasks impairs the human cognition (Ophir, Nass & Wagner, 2009). Kushlev & Dunn (2015) investigated the relation between email checking and stress, and found that unlimited email use is associated with higher stress levels than regulated email use. They argue, that increased cognitive loads due to frequent task switching impairs performance, which increases stress. Kushlev, Proulx & Dunn (2016) examined the relation between smartphone notifications and inattention, and confirm that notifications decrease productivity due to higher levels of inattention. Switching tasks requires cognitive efforts additional to the effort necessary to complete the task (Kushlev, Proulx & Dunn, 2016). Stothart, Mitchum & Yehnert (2015) describe how the performance on tasks is lowered by the distraction of smartphone notifications. They found evidence, that attention on a task is interrupted through task-irrelevant thoughts or mind-wandering. Even brief disruptions significantly decrease performance on attention-demanding tasks. They found that notifications disturb attention focused work, regardless of whether it is followed by interaction with the smartphone (Stothart, Mitchum & Yehnert, 2015). Similar results are reported by Sonnentag, Reinecke, Mata & Vorderer (2017), who found a negative relation between perceived interruptions and perceived task accomplishment.

The effects of smartphone addiction on productivity were also investigated by Duke & Montag (2017). In contrast to many other studies, the researchers aimed to investigate the effects of smartphone addiction using a variety of indicators, such as 'number of work hours lost to smartphone use in the past 7 days' and 'average weekly minutes worked without interruption from smartphone'. The authors construct a mediation model with 'daily interruptions' as a mediating variable between 'smartphone addiction' and 'negative impact of smartphone use on work productivity'. The survey questions are quite complicated and inquire estimated values of the participants. Therefore, the authors admit that the data is likely to be biased due to distorted perception and false interpretation of the survey questions. Still, the authors find a significant positive relation between all three variables, and therefore confirm that work productivity is related to interruptions due to smartphone usage. Ward, Duke, Gneezy & Bos (2017) found evidence for the 'brain drain' hypothesis, which suggests that, despite ignoring the smartphone during attention-grabbing tasks, the mere presence of a smartphone is enough to negatively impact one's cognitive performance. Both the working memory and the functional fluid intelligence of the participant are affected, even when the participant neither uses the smartphone nor reports having thought about it. In this study, 'working memory' is measured by the success in solving math problems while remembering a letter sequence, which tests one's 'ability to keep track of task-relevant information while engaging in complex cognitive tasks'. 'Fluid intelligence' represents an individual's 'capacity for understanding and solving novel problems', and is measured by the individual selecting an element that best completes a pattern (Ward, Duke, Gneezy & Bos, 2017).

Due to the necessity of smartphones, it becomes increasingly difficult to be mindfully focussed on a task. Only without distractions, the desired ability to concentrate can be reached. Google, being directly involved with all issues regarding digital use and wellbeing, addressed the issue of cognitive performance in a research paper. Using a qualitative analysis with interviews in Switzerland and the US, they explored reasons why people find it difficult to disconnect from their phones. They found that self-regulation plays a major role, as both internal and external obligations require the use of the device (Arana & Baig, 2018). Self-regulation might be the key to overcome digital addiction. Resisting an urge is very difficult, as it is with all kinds of addictions. The unconscious urge is caused by the constant desire to find pleasure in screens. Research shows that for young adults, car crash incidences are increasingly associated with smartphone usage. It leads to the suggestion that the disturbed self-regulation may be particularly strong for adolescents, as they do not make appropriate decisions about when to give in to the urge of smartphone usage (U.S. Department of Transportation, 2012). The checking habit has been investigated by Oulasvirta, Rattenbury, Ma & Raita (2012), who found that checking behaviours are reinforced by quickly accessible informational rewards. As a result, this impairment of self-regulation might be directly reflected in an individual's subjective perception of the ability to concentrate on a task. Once this ability gets disrupted through smartphone usage, users have a hard time getting off their phones. As explained above, the well thought through behaviour design elements in the user interfaces of smartphones pull users into a world of endless scrolls, recommendations, and binge watching.

2.5 The Relation of Cognitive Performance and Subjective Wellbeing

When distraction due to digital use lowers cognitive performance, an individual might not be able to concentrate fully on certain activities. This idea is closely related to the concept of flow, which is described as the perfect level of concentration and efficiency. The theory of flow has been investigated by Csíkszentmihályi (2014). The researcher describes flow as a state in which high challenges and high skills are matched and therefore, the individual perceives high levels of wellbeing. When in flow, an individual is aware of the current activity but unaware of the awareness itself. Awareness of the flow only becomes conscious again when the flow is interrupted.

"Your concentration is very complete. Your mind isn't wandering, you are not thinking of something else; you are totally involved in what you are doing. Your body feels good. You are not aware of any stiffness. Your body is awake all over. No area where you feel blocked or stiff. Your energy is flowing very smoothly. You feel relaxed, comfortable, and energetic." (Csíkszentmihályi, 2014, p. 139).

Hoenig (2016) describes flow as the merging of action and awareness, strong attention focusing, loss of self-awareness, action control, distorted time perception, and intrinsic motivation and joy in carrying out an activity. Csíkszentmihályi (2014) explains the necessary conditions to get to a state of flow. Firstly, the activity needs a clear set of goals. Secondly, the individual is in a balance between perceived challenges and perceived skills, and lastly, there is clear and immediate feedback to the task. The activity requires full attention, provides a desirable sense of control and is perceived as enjoyable and intrinsically rewarding. This reward makes individuals seek and enjoy new challenges to master. Thus, the ability to completely immerse oneself in an activity might also go along with increased experience of happiness (Csíkszentmihályi, 2014).

2.6 Summary and Hypotheses

The previous chapters have given insights into the relation between Digital Use, Cognitive Performance and Subjective Wellbeing. The scattered attention theory suggests that, against popular opinions, multitasking does not increase cognitive performance. Statistics on smartphone usage behaviour have illustrated the importance and distractive potential. It is therefore likely, that the distraction of smartphones decreases cognitive performance. The brain drain hypothesis further strengthens this theory, stating that negative effects on cognitive performance do not even require interaction with the smartphone. A fully concentrated state, also referred to as flow, can only be achieved without disruptions. The absence of self-regulation due to digital addiciton causes disruptions. Notifications and smartphone sessions cause task-irrelevant thoughts. As flow is perceived as enjoyable and intrinsically rewarding, it might positively affect Subjective Wellbeing.

Based on these theoretical concepts, this research aims to test whether the relation between Digital Use and Subjective Wellbeing can partly be explained through a mediating effect of Cognitive Performance. The hypotheses, that will be empirically examined in the next chapter, are as follows.

H1: Digital Use is negatively associated with Subjective Wellbeing.
H2: Digital Use is negatively associated with Cognitive Performance.
H3: Cognitive Performance is positively associated with Subjective Wellbeing.
H4: Cognitive Performance mediates the relation between Digital Use and Subjective Wellbeing.

3. Data

3.1 Dataset

The data is derived from the Socio-Economic Panel (SOEP), a longitudinal study on private German households. For this research, the SOEP Core Early Youth data set is taken, which is available for the years 2016 and 2017. The survey is headed towards individuals born in 2002 and 2003, and therefore 13-to-14-year-olds at the time of the interview. Individuals in this survey are not observed over time. Thus, the available data only allows for cross-sectional analysis. To increase the number of observations, the data of both surveys (2016 and 2017) is merged. The data set fits the research purpose because it represents digital natives, a generation that grew up with technology. It includes data on life-satisfaction and smartphone usage behaviour, as well as a variety of measures on self-perceived behaviour related to the concept of cognitive performance.

Despite the fact, that there is no prior data available, it serves the research focus to use the most recent data. Firstly, because this paper contributes to existing research, which mostly used data from prior years. Secondly, only within the last few years, addictive digital use has really become a problematic issue. Moreover, the participants surveyed are digital natives, which might deliver particularly undistorted results due to the fact that the smartphone is much more present in everyday situations compared to older generations. Moreover, in this dataset, the use of digital devices is considered in a more differentiated way than in other datasets. Firstly, it differentiates usage behaviours such as streaming, gaming and using social networks. Unlike other data sources, the survey categorizes Youtube as a streaming platform, although it is oftentimes considered a social network. This might indeed be more accurate, as the intention to use Youtube is quite similar to watching TV and therefore deviates from the use of platforms such as Instagram or Facebook. Other studies inquire ‘time spent on digital devices’ as a categorical variable, suggesting daily, weekly or yearly response options. Given the digital dependency of young adults in this day and age, this is not a contemporary approach. The dataset from the SOEP solves this issue by inquiring time spent as a continuous variable. The outcome might give a more realistic picture. However, there are some drawbacks to the dataset, which are further elaborated in the Discussion chapter. Overall, the data set is perceived as comparatively well suited to conduct an analysis on the research question of this paper.

The unedited dataset holds a total of 1,185 observations; 531 from the 2016 survey, and 654 from the 2017 survey. After dropping all of the observations with missing values of the variables used in the analysis, the dataset contains 1,095 observations; 503 from 2016 and 592 from 2017.

3.2 Variables

In this section, the variables are explained in detail. All variables are on an individual level.

Subjective Wellbeing. To assess Subjective Wellbeing, individuals were asked "How content are you at present, all in all, with your life?", measured on an ordinal scale from 0 to 10. A higher value indicates more contentment. The mean of 7.99 shows that the average satisfaction is in the upper third of the scale. The histogram in Figure I displays the variable's distribution, indicating left-skewness.

Digital Use. As a proxy for Digital Use this paper uses self-reported time spent on social networks, inquired as "How long do you spend on average per day with the following activities? – Using online-networks/other surfing on the Internet". The survey participant inserts the average number of hours and minutes per day. The variable is continuous. Outliers are dropped, as it is not perceived realistic for a student to spend on average more than 10 hours a day on this activity. The original dataset differentiates between time spent on social network sites during the week and at the weekend. I have calculated a weighted average to obtain the average daily time spent. For the whole sample, the average roughly equals 83 minutes. Excluding individuals with a value of zero, the average increases to 98 minutes. The distribution can be seen in the histogram in Figure II. Due to a large number of individuals, who are not involved in this activity at all (14.34% of the sample) and many low values, the data is extremely right-skewed. In the theoretical framework it was claimed, that young adults might suffer from addictive digital use. However, given the large number of low values, not all individuals can be considered addicted. Moreover, the threshold from digital use to digital addiction may vary from individual to individual. Therefore, the variable is called Digital Use.

Figure I: *Histogram Subjective Wellbeing*

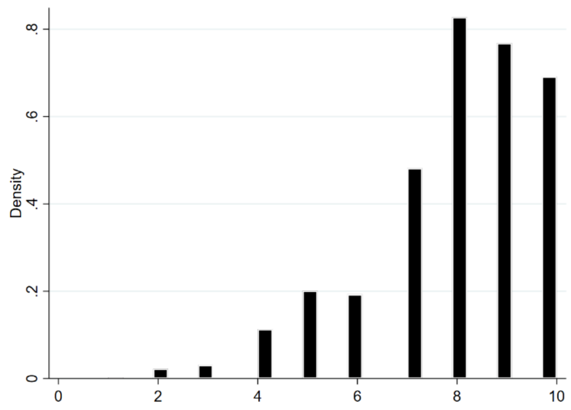
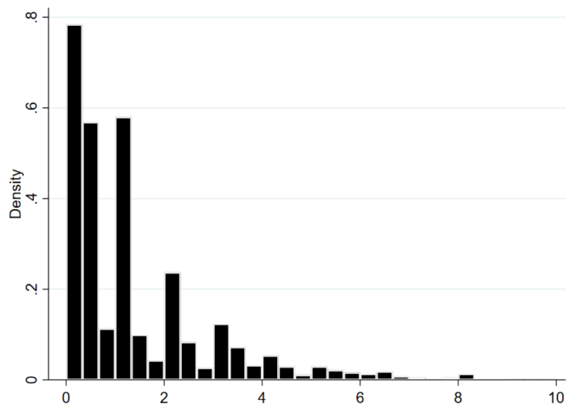


Figure II: *Histogram Digital Use*



Cognitive Performance. This variable is latent, which means that it cannot be measured directly, but is constructed from a number of indicators. In order to assess an individual's Cognitive Performance, I consider the following 10 indicators: Grades, Concentration, Focus, Calm, Stillness, Efficiency, Thoroughness, Diligence, Relaxation, and Ambition. Apart from Grades, all variables are based on subjective assessment of the individual. All of the indicators are described below and should have a positive relation with Cognitive Performance. Thus, a higher value in one of the measures should be associated with higher Cognitive Performance. For this purpose, some of the variables' scales are intentionally reversed.

Grades. The first item is "What Grades did you have in your last report card in the following three subjects? [German, Maths, First Foreign Language]". Based on the Grades in Mathematics, German and a foreign language the average is calculated. If one value is missing in the dataset, an average is built of the remaining two grades. The German grading system takes values from 1 to 6, where 1 is "very good" and 6 is "insufficient". I reversed the scale to increase the intuition of the interpretation. Thus, contrary to the original grading variable, a higher value in the Grades variable means better performance.

Concentration. The second item is evaluated with the statement "What I started, I finish; I can concentrate long enough." and assessed using the 3-item ordinal response option "not true at all"[1], "partially true"[2] or "fully true"[3].

Focus. The third statement is "I am easily distracted; I find it hard to concentrate.". Focus is evaluated on a 3-item ordinal scale with "not true at all"[1], "partially true"[2] and "fully true"[3]. The scale of this variable is reversed. Therefore, the variable Focus indicates a low ability to Focus for the value 1, and a high ability to Focus for the value 3.

Calm. The fourth statement is "I'm often restless, I can't sit still for long", which is evaluated on an ordinal scale with "not true at all"[1], "partially true"[2] and "fully true"[3]. The scale is reversed. Thus, low levels of Calm are indicated by outcome 1, whereas high levels of Calm indicated by value 3.

Stillness. The fifth statement is "I am constantly in motion and fidgety.", which is evaluated on an ordinal scale from "not true at all"[1], "partially true"[2] to "fully true"[3]. The scale is reversed. Thus, low levels of Stillness are indicated by outcome 1, whereas high levels of Stillness indicated by value 3.

Efficiency. The sixth variable is evaluated by the statement "I am someone who performs tasks effectively and efficiently." The ordinary response options range on a 7-item scale from "not true at all"[1] to "fully true"[7].

Thoroughness. This seventh item is evaluated with "I am someone who works thoroughly." The ordinary response options range on a 7-item scale from "not true at all"[1] to "fully true"[7].

Diligence. The eighth item is evaluated with "I am someone who is lazy." The ordinary response options range on a 7-item scale from "not true at all"[1] to "fully true"[7]. The scale is reversed. Thus, low levels of Diligence are indicated by outcome 1, whereas high levels of Diligence are indicated by value 7.

Relaxation. The ninth item is evaluated with "I am someone who gets nervous easily." The ordinary response options range on a 7-item scale from "not true at all"[1] to "fully true"[7]. The scale is reversed. Thus, low levels of Relaxation are indicated by outcome 1, whereas high levels of Relaxation are indicated by value 7.

Ambition. The tenth item is evaluated with "I am someone who tries to solve even the most difficult tasks.". The ordinary response options range on a 7-item scale from "not true at all"[1] to "fully true"[7].

The descriptive statistics of the variables are displayed in Table I, which contains only the variables used for the analysis. The explanation for the selection of these variables is given in the section below.

Table I: *Description and summary of variables*

Variable	Survey Question	Scale	Obs.	Mean	Std. Dev.	Min.	Max.
Subjective Wellbeing (SWB)	"How content are you at present, all in all, with your life?"	ordinal, 10-item likert scale	1,095	7.99	1.72	1	10
Digital Use	"How long do you spend on average per day with the following activities? – Using social online-networks/other surfing on the internet"	continuous, in hours	1,095	1.39	1.58	0	10
Concentration	"What I started, I finish; I can concentrate long enough."	ordinal, 3-item likert scale	1,095	2.27	.60	1	3
Efficiency	"I am someone who performs tasks effectively and efficiently."	ordinal, 7-item likert scale	1,095	4.91	1.31	1	7
Thoroughness	"I am someone who works thoroughly."	ordinal, 7-item likert scale	1,095	4.96	1.34	1	7
Diligence	"I am someone who is lazy."	ordinal, 7-item likert scale (reversed)	1,095	4.07	1.85	1	7
Ambition	"I am someone who tries to solve even the most difficult tasks."	ordinal, 7-item likert scale	1.095	4.84	1.49	1	7

4. Method

The analysis in this research is divided into two parts. First, I assess which of the variables create a reasonable set to describe the concept of Cognitive Performance. Exploratory Factor Analysis is suitable for this purpose. Thereafter, I specify a Structural Equation Model, in which Cognitive Performance is included as a latent construct.

4.1 Exploratory Factor Analysis

Latent variables are unobserved concepts that are constructed through observable measurements, also referred to as indicators. Latent variables are used instead of simply observable variables when several measures are required to fully explain a theoretical concept (Hair, Black, Babin & Anderson, 2014). One of the most frequently cited examples of a latent variable is the intelligence quotient, which cannot be measured directly, but is composed of a large number of indicators. It makes sense to create a latent variable for Cognitive Performance, as it is an unobservable concept for which the dataset contains a series of indicators. Based on theoretical assessment I chose 10 variables, which might contribute information to the concept of Cognitive Performance: Grades, Concentration, Focus, Calm, Stillness, Efficiency, Thoroughness, Diligence, Relaxation, and Ambition. In the following, the words item, indicator, and measure are used synonymously.

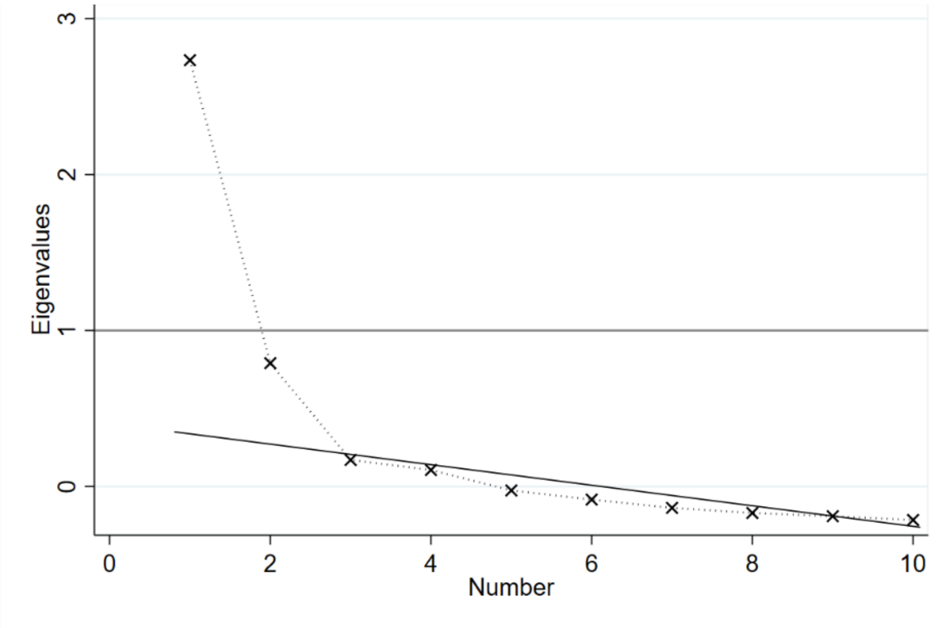
It might not be ideal to include all of these measures. Rather it is advisable to include only those, that are related but still provide unique information to the latent variable. Exploratory Factor Analysis is a method to derive which sets of indicators explain a common factor. The goal is to identify correlated indicators that are members of the same factor and therefore have a similar profile (Hair et al., 2014). To perform Exploratory Factor Analysis, I follow the suggested steps, as described in Brett, Brown & Onsman (2010) and Hair et al. (2014). There are different suggestions with regard to sample size in literature. Hair et al. (2014) suggest that the number of observations should be at least 5 times as high as the number of variables analysed. In this research, I test 10 indicators with a sample size of over 1,000 observations. Therefore, the sample size is sufficient.

At first, I take a look at the correlation matrix, which already gives some meaningful insights into how the items interact with one another. I want to assess whether the data is suitable to perform factor analysis. A certain level of multicollinearity is desired. Hair et al. (2014) suggest to roughly evaluate the correlation matrix on whether there are enough correlations that have a value of about 0.3. Using the pairwise correlation matrix displayed in Appendix A, I can confirm that a substantial number of correlations takes values of about 0.3. Also, there is a strong positive correlation between Efficiency and Thoroughness (0.6086, p=0.00), Stillness and Calm (0.5203, p=0.00), Ambition and Efficiency (0.4651, p=0.00), Efficiency and Concentration (0.4225, p=0.00), and Calm and Focus (0.4070, p=0.00). The correlations are particularly low for Diligence and Stillness (0.0885, p=0.0024), and Ambition and Calm (0.0585, p=0.0452). It was expected that all items are positively correlated. However, there is a negative, but insignificant, value for the correlation between Ambition and Stillness (-0.0056, p=0.8493).

It is necessary to further check the suitability of the data for Exploratory Factor Analysis. Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) (Brett, Brown & Onsman, 2010) are used for this purpose. I start with the Bartlett's test to obtain the significance level showing if the correlation matrix has significant correlations. The test is significant to a 5% significance level (p=0.00) and therefore indicates that the data is suitable (Hair et al., 2014). The Kaiser-Meyer-Olkin-Measure, which measures the shared variance between pairs of variables, exceeds the suggested minimum value for suitability of 0.5 (KMO=0.8168) (Brett, Brown & Onsman, 2010). Regarding the individual items, the Kaiser-Meyer-Olkin-Measure shows higher values for stronger correlations between the variables, which is another indication for the suitability of factor analysis. Appendix B shows that all values exceed 0.8, except Calm (0.7344) and Stillness (0.6722).

In the next step, the factor analysis is carried out. The aim is to assign the individual items to common factors. First, unrotated factor analysis is performed to investigate the factors' eigenvalues. The common factor analysis is the recommended method to identify the items of a latent variable, which is the aim of this analysis (Hair et al., 2014). As suggested by Brett et al. (2010), factors further analysed need to exceed an eigenvalue of 1 (Kaiser criteria). As can be seen in Appendix C, only factor 1 (eigenvalue=2.73) exceeds an eigenvalue of 1. An additional test, mostly based on subjective assessment, is the scree plot of eigenvalues (Figure III), which shows the cumulative percentage of variance extracted. I insert a straight line through the natural bend in the data where the curve flattens out (Costello & Osborne, 2005). Contrary to the Kaiser criteria, factor 1 and factor 2 lie above this straight line, and should, therefore, be taken into account (Hair et al., 2014). I proceed with both factors to obtain the rotated factor loadings in the following step.

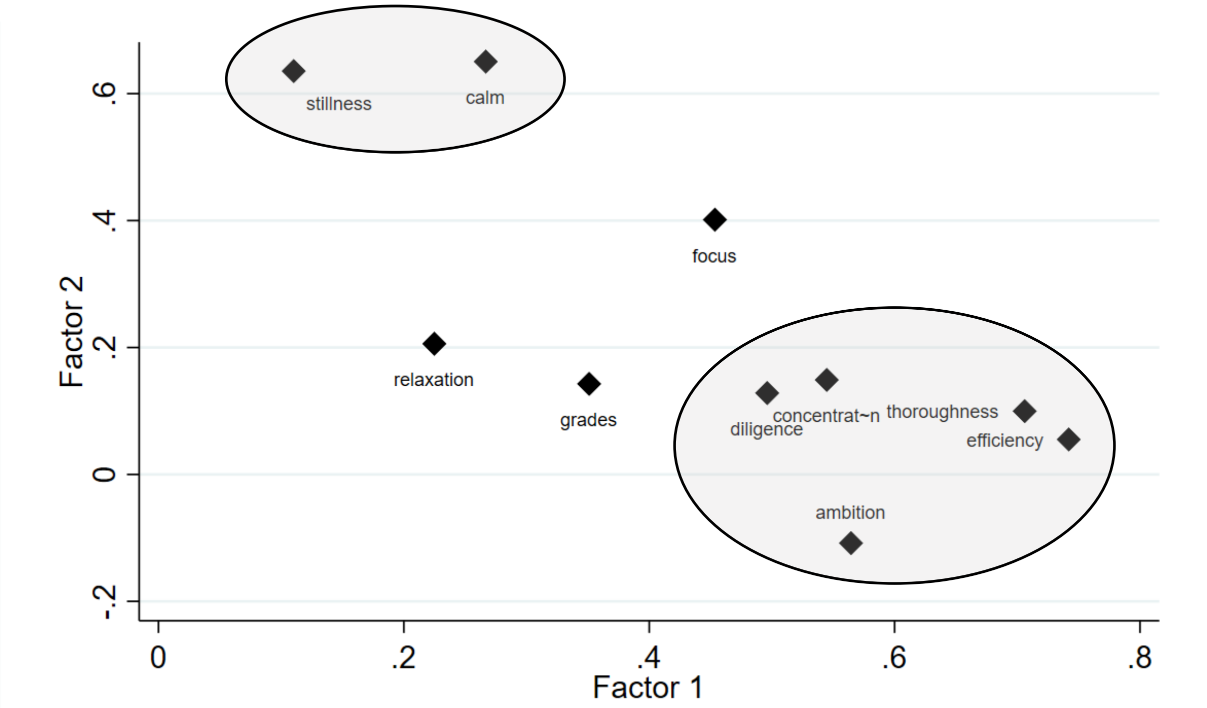
Figure III: *Scree plot of eigenvalues*



A factor loading represents the correlation between an item and a factor (Hair et al., 2014). The rotated analysis provides maximized high factor loadings and minimized low factor loadings, which gives a more interpretable solution compared to the unrotated approach (Brett et al., 2010). The rotation analysis allows the options orthogonal and oblique. Costello & Osborne (2005) suggest using oblique correlation for correlated variables and orthogonal rotation when items are rather uncorrelated. I use orthogonal rotation, because the correlation matrix does not show particularly strong correlations. Moreover, there are different rotation methods to choose from. I chose orthogonal quartimax rotation, which maximizes the factor load on one factor while minimizing it on the other factors (Hair et al., 2014).

Hair et al. (2014) suggest that factor loadings in the range of ±.30 to ±.40 are considered minimal, loadings of ±.50 are significant and loadings exceeding 0.8 are extremely high. The factor loadings of the items are displayed in Appendix D. For factor 1, the rotated factor loadings reach a significant value of about 0.5 or higher for the items Efficiency (0.7419), Thoroughness (0.7060), Concentration (0.5644), Ambition (0.5447) and Diligence (0.4961). According to Costello & Osborne (2005), a solid factor needs to have at least 5 items. This condition is hereby fulfilled. A sixth item, Focus, shows high loadings for both factor 1 (0.4535) and factor 2 (0.4013). It is therefore considered a 'crossloading' item and should not be taken into account (Costello & Osborne, 2005). For factor 2, Calm (0.6506) and Stillness (0.6355) show significant factor loadings. Thus, factor 2 only has two items, Calm and Stillness. Due to low factor loadings for both factors, the items Grades and Relaxation are dropped completely. In line with the results derived from the Table in Appendix D, it can be seen in Figure IV that Stillness and Calm are located in the top left corner, which indicates high values for factor 2 and low values for factor 1. Likewise, the items attributed to factor 1 are situated in the lower right corner. The dropped items, Relaxation, Focus and Grades, are located in the middle, as they have similar factor loadings for both factors.

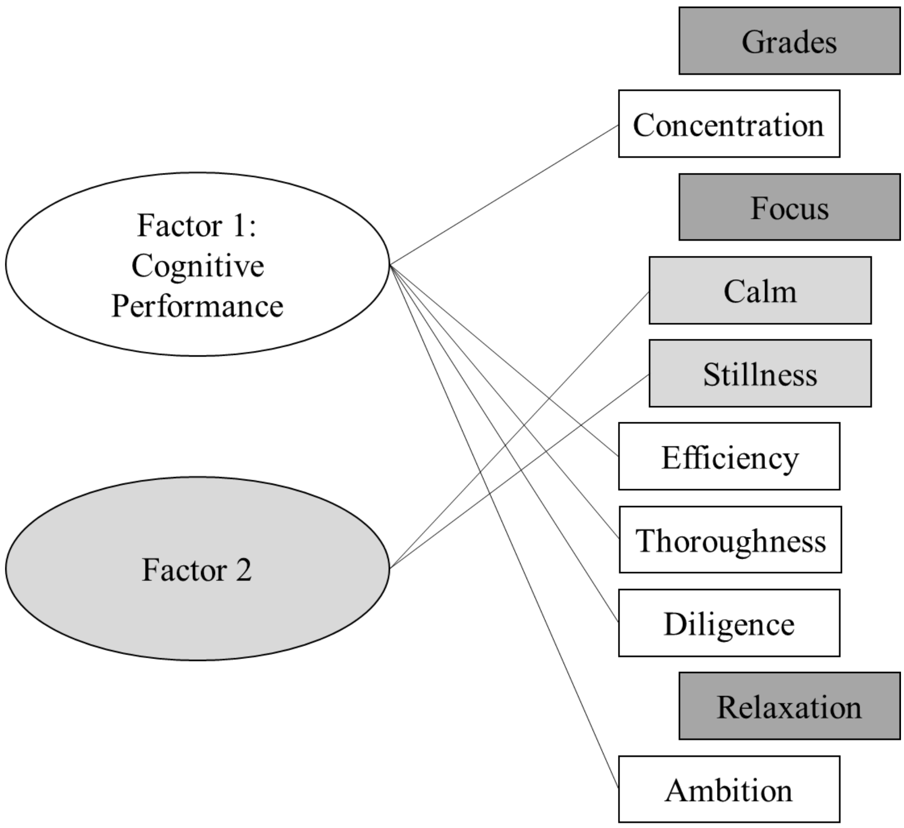
Figure IV: *Factor loadings*



As the last step, the factor analysis must be validated in order to assess the degree of generalizability of the results to the population. To test the scale reliability I use Cronbach's alpha, which should exceed a value of 0.7 (Hair et al., 2014). The reliability can be confirmed with a Cronbach's alpha value of 0.7251 for factor 1. Factor 2 has a reliability of 0.6836, which is slightly below the suggested threshold.

Apart from the empirical analysis, the theoretical and conceptual justification of the items for latent variables is just as important (Brett et al., 2010). The distribution of the kept items shows a clear theoretical separation. The items Concentration, Efficiency, Thoroughness, Diligence and Ambition of factor 1 reflect an individual's ability to work efficiently, concentrated and determined. With the items Calm and Stillness, factor 2 reflects an individual's ability to be rather mindful than fidgety. In the following chapter, I conduct a Structural Equation Model with mediation to test the research question of this analysis. The first obtained factor is used as a mediator, representing the latent variable Cognitive Performance. The underlying indicators are in line with the theoretical framework of this research and the factor has been validated as strong. Therefore, it is well suitable for the subsequent analysis. The second factor will not be considered any further for two reasons. Firstly, the underlying items, Stillness and Calm, are not strongly related to the idea of Cognitive Performance as described in the theoretical framework, and the way in which it might be affected by addictive digital use. Moreover, the second factor has a relatively low value in terms of reliability and only has two items, which indicates weakness of the factor (Hair et al., 2014). The final allocation of the items to the factors derived from the Exploratory Factor Analysis is displayed in Figure V.

***Figure V:** Allocation of the items to the latent construct Cognitive Performance*



4.2 Structural Equation Modelling

Structural Equation Modelling (SEM) is an approach to explain the structure of interrelations of multiple variables (Hair et al., 2014). Compared to normal regressions, Structural Equation Modelling yields the advantage of analysing multiple dependence relations simultaneously. In the analysis of a set of interrelated questions, a variable can be dependent and independent in the same theory. Structural Equation Modelling is the chosen method in this paper for two reasons. Firstly, mediation models can be analysed more easily than through multiple regressions, which is explained in more detail below. Secondly, SEM allows for the use of latent variables. The latent construct Cognitive Performance, that has been derived in the previous chapter, is implemented in the Structural Equation Model. In the following, the SEM model is specified and the concept of mediation is explained. Different assumptions regarding estimation methods are discussed to select a method, which matches the data.

4.2.1 General Model Specification

Structural Equation Models can be displayed graphically, which makes it very easy to understand the relations between several variables. Observable variables are displayed in rectangles, while latent constructs appear in oval shapes. The model constructed in this analysis is fairly simple and displayed in Figure VI. Digital Use is an exogenous variable, which has a path to the endogenous variable Cognitive Performance and another path to the endogenous variable Subjective Wellbeing. Cognitive Performance is a latent variable, that is constructed from the five indicator variables Concentration, Efficiency, Thoroughness, Diligence, and Ambition. Cognitive Performance has a path to Subjective Wellbeing. As can be seen, endogenous variables have additional paths, which represent measurement errors.

4.2.2 Mediation Analysis

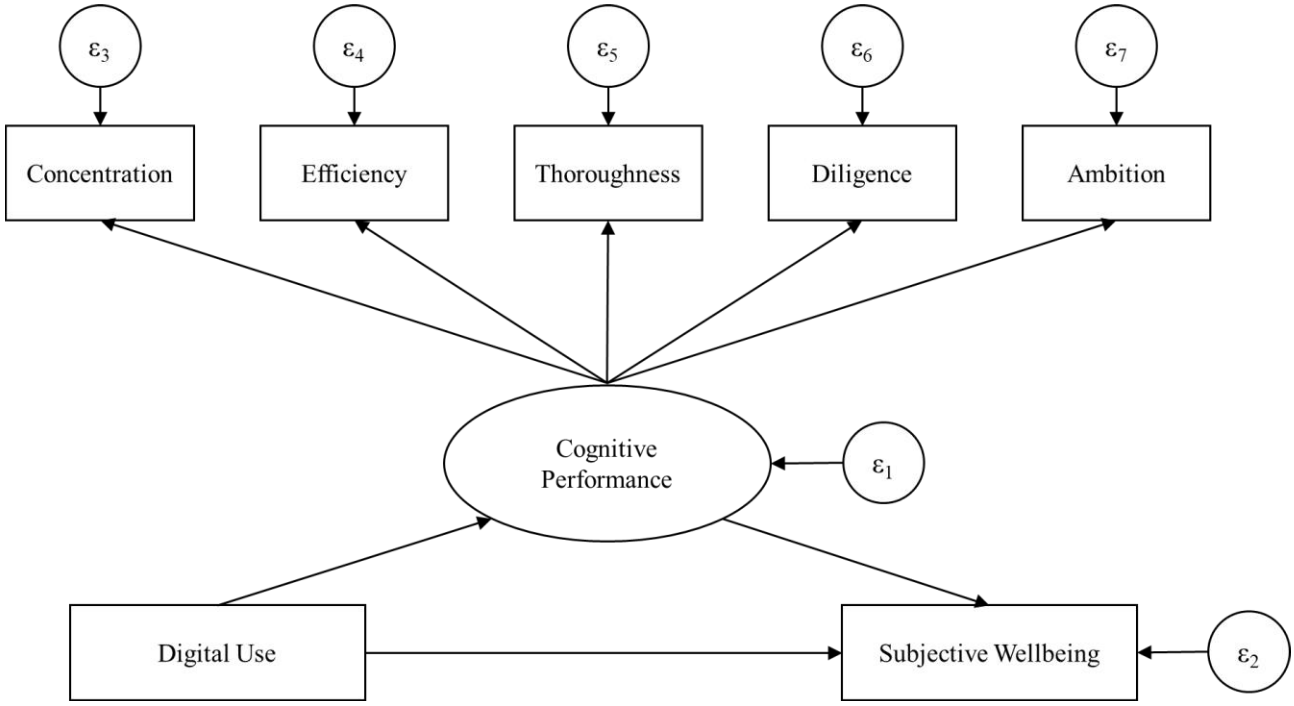
The model constructed in this research is a mediation model, which is a special type of path analysis. A mediation model is used to analyse how an independent variable (X = Digital Use) might affect a dependent variable (Y = Subjective Wellbeing) through a mediator variable (M = Cognitive Performance). Mediation analysis aims to answer the question, whether an effect of an independent variable on a dependent variable is direct, or indirectly explained through a mediating variable (Iacobucci, 2011).

As described in the theoretical framework, researchers have investigated a variety of mediators in the relation between Digital Use and Subjective Wellbeing. They found evidence that both physical and psychological aspects partially explain a relation. As another potential mediator, I investigate Cognitive Performance and expect that there will be a partial mediating effect, if any, but not that Cognitive Performance fully explains the relation.

To test mediation, many researchers use a method developed by Baron & Kenny (1986), who state three conditions. Firstly, the explanatory variable is a significant predictor of the dependent variable. Secondly, the explanatory variable is a significant predictor of the mediator. Lastly, the mediator is a significant predictor of the dependent variable. Thereafter, one can test mediation with the Sobel-z-test (Iacobucci, 2010). However, according to Iacobucci (2010) this rather cumbersome method is outdated as SEM is a statistically theoretically superior method compared to a series of regressions. The reason is that, compared to multiple regressions, simultaneous estimation of all parameters in SEM reduces the standard errors. Especially for the work with latent variables, as it is the case here, SEM perfectly blends the measurement model of the latent variable with the overall structural model (Iacobucci, 2011).

The interpretation of the mediation model in SEM is as follows. A significant X→Y path means that part of the variance in Y is explained by X, which in turn means that M cannot fully mediate the relation between X and Y. If both X→M and M→Y are significant, then M at least partially mediates the relation between X and Y. If only one of the paths (X→M or M→Y) is significant, there is no evidence for mediation (Iacobucci, 2010). Although a mediation model is oftentimes interpreted as causal ("X affects Y through M"), this interpretation needs to be made with caution. Often only a correlation can be confirmed on the basis of the available data (Iacoubcci, 2011). This limitation is addressed again in the Discussion chapter.

Figure VI: *General Model Specification*



4.2.3 Assumptions for Maximum Likelihood Estimation

The use of the default method for Structural Equation Modelling, which is Maximum Likelihood Estimation, requires a set of assumptions, described by Finney & DiStefano (2006). Firstly, observations need to be independent, which is fulfilled if the sample is randomly chosen. As far as known, the study participants of the data set at hand were randomly selected so that the first requirement is fulfilled. Secondly, the sample size needs to be sufficiently large. Hair et al. (2014) suggest that the minimum sample size for SEM should increase as the model gets more complex. The final analysis contains a sample of 1,095 observations. Also, the model constructed in this analysis only contains two observed variables and a latent variable with five indicators, which is fairly simple. For a model of this size, Hair et al. (2014) suggest a minimum sample size of 100 to 150 observations. The sample size is therefore large enough. Moreover, handling missing values is a widely discussed topic in Structural Equation Modelling. All individuals with missing values (89 observations) are dropped, thus, this is not a topic for discussion. Additionally, the model needs to be correctly specified to truly reflect the structure of the population. Lastly, variables should have a multivariate normal distribution and continuous scaling (Finney & DiStefano, 2006). The latter assumptions rarely hold for analyses in social sciences. Very often variables are assessed on likert-scales. Data assessed on likert-scales is neither continuous, nor normally distributed, but simply ordinal data and, therefore, does not hold the assumptions. However, as the number of likert-items increases, the data more closely approximates to continuous data (Finney & DiStefano, 2006). Normality might not be given due to skewness, which is a lack of symmetry in the distribution, or kurtosis, which indicates a peak in the distribution (Razali & Wah, 2011). The Shapiro-Wilk test is considered the most powerful test of normality. A value of 0 leads to rejection of normality; a value of 1 indicates normality. The results of the Shapiro-Wilk test clearly show that neither Digital Use, nor Subjective Wellbeing is normally distributed at a 1% significance level. This result is in line with the descriptions of Subjective Wellbeing and Digital Use in the previous Data chapter. Subjective Wellbeing is left-skewed and assessed on an ordered categorical 10-item-likert scale. The scale might be large enough to treat it as a continuous variable, although this might produce slight underestimation in parameter estimates (Finney & DiStefano, 2006). Digital Use is a right-skewed continuous variable. Overall, I conclude, that the data does not follow a normal distribution and is partially ordered categorically scaled. Thus, the requirements for Maximum Likelihood Estimation are not optimally met, which might lead to errors in the estimated coefficients, standard errors, and model fit indices.

4.2.4 Choice of the Model Estimation Method

The problem with nonnormal and categorical data has been discussed by DiStefano & Finney (2006), who propose a number of different solutions to address this issue. Data in my analysis is not normally distributed and partly based on likert-scales. According literature it is necessary to find a model, that is robust to the assumptions of the Maximum Likelihood Estimator. In the following, I describe two methods used to solve for the fitted parameters, namely Maximum Likelihood Estimation with Satorra-bentler adjusted standard errors and Asymptotic Distribution Free Estimation. For continuous variables, both methods are less efficient than Maximum Likelihood Estimation, but for variables that are categorical and not normally distributed, they might provide more accurate results (DiStefano & Finney, 2006).

Finney & Distefano (2006) still recommend the use of Maximum Likelihood Estimation if continuous data is only slightly non-normal. However, if the multivariate normality assumption is violated, $\chi 2$ does not follow the central $\chi 2$ distribution but inflates as non-normality increases. Moreover, a couple of other model fit indices, such as the Comparative Fit Index (CFI) might be underestimated. This bias becomes more severe, as the univariate skewness and univariate kurtosis levels increase. Over-or underestimation of model fit indicators might lead to falsely discarding plausible models (Finney & DiStefano, 2006). Therefore, when using Maximum Likelihood Estimation for ordinal data, it is necessary to look at adjusted indicators. One possible option is the Satorra-Bentler adjusted measures, which provide standard errors that are robust to nonnormality (Satorra & Bentler, 1994).

The second suggestion proposed in the literature is the use of Asymptotic Distribution Free Estimations (ADF) instead of Maximum Likelihood Estimation (Finney & DiStefano, 2006). ADF makes no assumption of joint normality for observed or latent variables (StataCorp., 2015). One problem with ADF estimation is that model fit indices can be misleading when the sample size is below 5,000 (Finney & DiStefano, 2006). The fit values might be overly optimistic, in which case researchers might fail to reject an incorrectly specified model. These issues become increasingly severe as the non-normality distribution increases (Finney & DiStefano, 2006). Finney & Distefano (2006) do not recommend using the ADF, as it requires a very large sample size and might lead to biased model fit indices. Because the sample size in my dataset only amounts to 1,095 observations, I choose to rather use Maximum Likelihood Estimation with Satorra-Bentler adjusted model fit measures.

5. Results

5.1 Model Fit Adjustments

Before looking at the results of the analysis, I test if the model fits the data well. Therefore, I look at five indicators. $\chi2$, RMSEA and SRMR are badness-of-fit indices, which means that higher values indicate worse fits. CFI and TLI are goodness-of-fit indices, where higher values indicate good fit of the model.

$\chi2$ tests the nullhypothesis that the observed sample is equal to the SEM estimated covariance, which indicates a perfect model fit. A small p-value of the $\chi2$ tests indicates differences in the matrices and therefore a bad model fit (Hair, Black, Babin, Anderson, 2014). Iacobucci (2010) explains that the $\chi2$ test should be interpreted with caution, as it is sensitive to sample size. With an increase in the number of observations, $\chi2$ blows up, making it almost always significant. Therefore, using a large sample size, Iacobucci (2010) suggests that $\chi2$ divided by the degrees of freedom gives a better result. The model shows good fit when $\chi2$/df is smaller or equal to 3. The root mean square error of approximation (RMSEA) is a test of close fit, which corrects for both model complexity and sample size. Thus, it might give better indications than the $\chi2$ statistic, which tends to reject these models (Hair et al., 2014). Hair et al. (2014) do not suggest a strict cut off value but suggest values below 0.5 or 0.8. The Comparative Fit Index (CFI) and the Tucker-Lewis index (TLI) indicate a good fit with a value close to 1 (StataCorp, 2015). The standardized root mean squared residual (SRMR) is a badness of fit index, meaning that it shows good fit for a value lower than 0.09 and close as possible to 0 (Iacobucci, 2010).

The following reported model fit indices are corrected with Satorra-Bentler scaling. The corresponding table is presented in Appendix E. The $\chi2$ statistic ($\chi2(13) = 43.825$, p=.000; $\chi2/df=3.37$) reports significance and $\chi2/df>3$, which indicates a bad model fit. RSMEA equals 0.042, which is slightly below 0.5. The CFI has a value of 0.980 and TLI equals 0.967. Subjectively assessed, both values are close to 1. SRMR equals 0.026 and, therefore, lies below the threshold of 0.09, which also indicates good fit. Overall, the model has a fairly good fit but can possibly still be improved. Therefore, I generate the modification indices and add a covariance to the pair of items that shows the highest value of all modification indices between items. I perform three iterations, for which the model fit indices are displayed in Appendix E. Firstly, I allowed for a correlation between Thoroughness and Efficiency. Thereafter, I added a correlation between Ambition and Efficiency. The final model also contains a correlation between Thoroughness and Concentration. Thus, the final model includes three covariances (Thoroughness ↔ Efficiency, Ambition ↔ Efficiency, Thoroughness ↔ Concentration). The model indicates good fit, as $\chi 2$ is insignificant and $\chi 2/df<3$ ($\chi 2(10) = 11.17$, $p=.3442$; $\chi 2/df=1.12$). RSMEA equals 0.010, which is below value of 0.5. The CFI has a value of 0.999 and TLI equals 0.998; both very close to 1. SRMR equals 0.015, which lies below the threshold of 0.09, also indicating good model fit. Overall, the model fit of the final compared to the initial model has improved due to adding covariances between the items of the latent variable. Various authors suggest to only adjust the model in line with theory. Otherwise, after many adjustments, researchers have a model with a perfect fit that theoretically makes no sense. As I have only allowed for covariances between the items of the latent variable, that should correlate to a certain degree, I am confident that the applied adjustments are in line with theory.

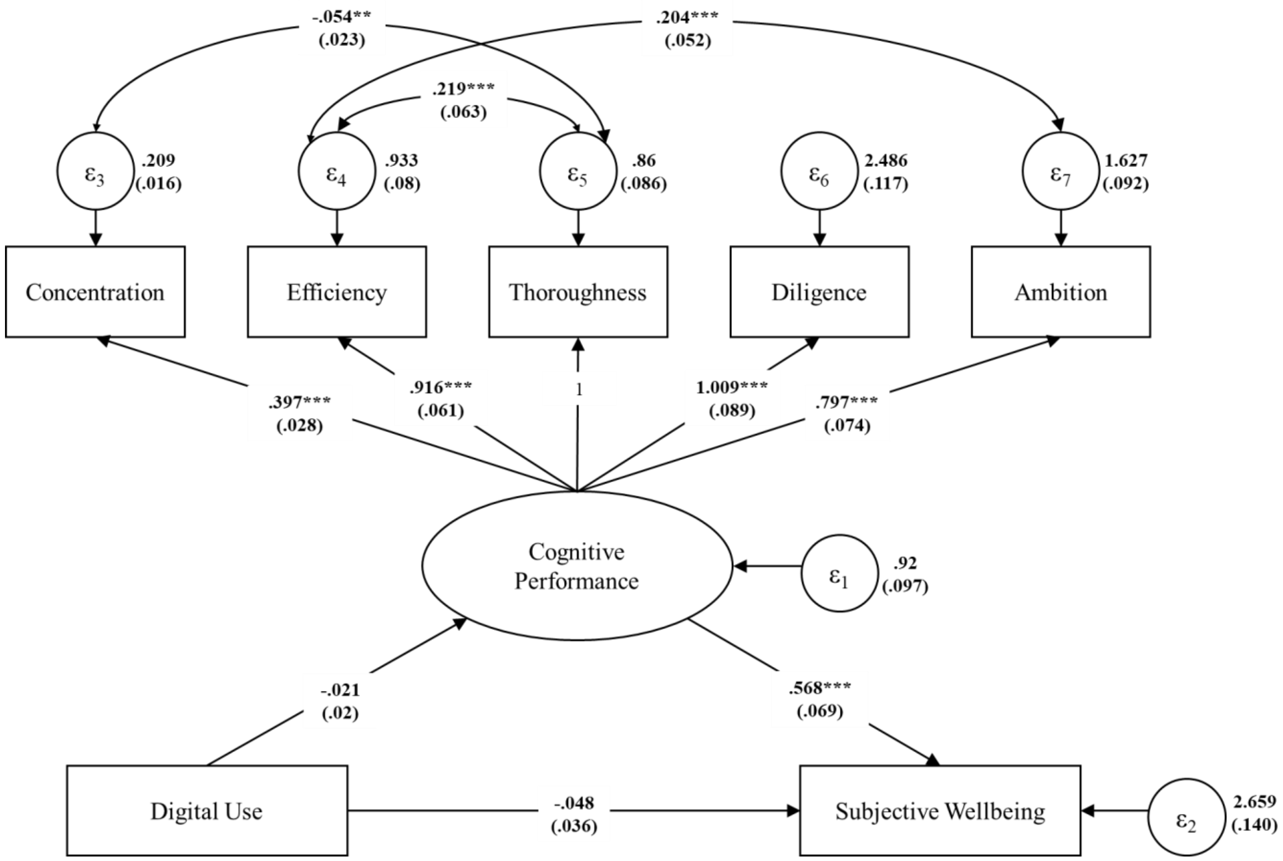
5.2 Results of the Structural Equation Model

The final model has three covariances, shown through curved paths, (Thoroughness ↔ Efficiency, Ambition ↔ Efficiency, Thoroughness ↔ Concentration). The model has a very good model fit and is therefore used to derive the path coefficients. As discussed before, I use Maximum Likelihood Estimation. The results of the analysis are displayed in Figure VII.

The hypotheses proposed in this research are as follows:
H1: Digital Use is negatively associated with Subjective Wellbeing.
H2: Digital Use is negatively associated with Cognitive Performance.
H3: Cognitive Performance is positively associated with Subjective Wellbeing.
H4: Cognitive Performance mediates the relation between Digital Use and Subjective Wellbeing.

__Figure VII:__ SEM Results with Maximum Likelihood Estimation

*(*** p<0.1; ** p<0.05; *** p<0.01, standard errors in parentheses)*



The direct effect of Digital Use on Subjective Wellbeing is negative, but insignificant to a 10% significance level. Therefore, **H1 is rejected**. The effect of Digital Use on Cognitive Performance is also negative, but insignificant to a 10% significance level. Thus, **H2 is rejected**. The effect of Cognitive Performance on Subjective Wellbeing is positive and significant to a 1% significance level. The path coefficient of .56 means that 1 standard deviation difference in Cognitive Performance is associated with a 0.56 standard deviation difference in Subjective Wellbeing. Individuals, who report higher Cognitive Performance also report higher Subjective Wellbeing. Thus, **H3 cannot be rejected**. An additional test shows that the indirect effect, which is the product of the path coefficients from X→M and M→Y, is negative and insignificant to a 10% significance level (-.0117, p=.302). This is consistent with theory by Iacobucci (2010), who states that both X→M (H2) and M→Y (H3) need to be significant for a mediating effect to occur. Thus, there is no mediating effect of Cognitive Performance in the relation between Digital Use and Subjective Wellbeing, and **H4 is rejected**. The total effect, which is the sum of the direct and the indirect effect, is also negative and insignificant to a 10% significance level (-.0597, p=.110).

As discussed in the Method section, there are different estimation methods to choose from. With regard to the given data, the analysis was conducted using Maximum Likelihood Estimation with Satorra-Bentler scaled standard errors. The alternative method presented was Asymptotic Distribution Free Estimation (ADF). Results of the analysis with ADF estimation are shown in the Appendix to see if the chosen method influences the results. Appendix F shows that the chosen covariances between items of the latent variable, again based on the highest value of modification indices, are the same as with Maximum Likelihood Estimation with Satorra-Bentler scaling. The overall fit of the final model is very good ($\chi2(10) = 10.134$, p=.429; $\chi2/df=1.01$; RMSEA=0.003; CFI=1; TLI=0.999; SRMR=0.015). However, the used sample size for ADF estimation is much smaller than recommended in literature. Therefore, the model fit values might be overly optimistic (Finney & Distefano, 2006). Appendix G shows, that there are only some very slight differences in the coefficients of the Structural Equation Model compared to the Maximum Likelihood Estimation. The path from Digital Use to Subjective Wellbeing is insignificant (-0.36, p=0.291), the path from Digital Use to Cognitive Performance is insignificant (-0.24, p=0.225) and the path from Cognitive Performance to Subjective Wellbeing is significant (0.576, p=0.000). In conclusion, it can be said that the chosen estimation method hardly makes a difference in the results of this analysis.

6. Discussion

6.1 Interpretation of the Results

The research question can be answered by saying, that no evidence is found for a mediating effect of Cognitive Performance in the relation between Digital Use and Subjective Wellbeing. The theories put forward cannot be fully confirmed. The direct effect of Digital Use on Subjective Wellbeing is insignificant. Therefore, the evidence found by many other researchers could not be replicated with the data at hand. Moreover, there is no evidence for a negative relation between Digital Use and Cognitive Performance. In line with research on the attentional costs of smartphone notification by Stothart, Mitchum & Yehnert (2015), I have referred to the scattered attention hypothesis and the bottleneck theory. Again, the scattered attention and bottleneck hypothesis suggest that attention is a limited resource, and individuals might not be able to focus their attention on the relevant task, when being interrupted by external factors (Ophir, Nass & Wagner, 2009). In this research, there is no evidence found to confirm this theory. Given that all variables adequately represent the theoretical idea of the used variables, the insignificance of the mediating effect can be explained as follows. Firstly, young adults as digital natives might be used to being surrounded by digital devices and therefore might not be disturbed as much as expected. This is in line with Ophir, Nass & Wagner, (2009), who suggest that media multitasking might as well have positive effects on training cognitive processes to filter information more effectively. Secondly, young adults might be more disciplined than assumed and might successfully ignore their digital devices during tasks that require cognitive performance. Thirdly, the amount of screen time might be too moderate to have a negative effect on Cognitive Performance. This is in line with the Goldilocks hypothesis tested by Przybylski & Weinstein (2017), who argue that moderate levels of device usage do not impact mental wellbeing. The same could also apply for the relation to Cognitive Performance. Lastly, it is likely that 'surfing on the internet' is an activity that requires Cognitive Performance, such as homework. However, the insignificance can also be justified by the fact that the data used does not optimally represent the theoretical basis, which is further elaborated in the next chapter.

This research finds a significant relation between Cognitive Performance and Subjective Wellbeing. As this relation is not connected to Digital Use in any way, it can only be confirmed, that individuals who have higher Cognitive Performance also report higher levels of Subjective Wellbeing. I have explained this relation using the flow theory. Hoenig (2016) explains flow as the merging of action and awareness, strong attention focussing, loss of self-awareness, action control, distorted time perception, and intrinsic motivation and joy in carrying out the activity. Many of these aspects are closely related to the measures, which are used in this research to construct Cognitive Performance (Concentration, Efficiency, Thoroughness, Diligence and Ambition). Therefore, this research might have found evidence, that the concept of flow is related to happiness. This result is in line with Hoenig (2016), who states that immersing oneself completely in an activity goes along with increased experience of happiness. The results are also line with the suggested theory, that a feeling of dissatisfaction, constant waste of time and feelings of inefficiency due to low Cognitive Performance might induce lower levels of Subjective Wellbeing (Csíkszentmihályi, 2014). However, it must be admitted that this might not be a causal relation. As both variables in some way measure the self-assessed state of the mind, the relation might be subject to endogeneity due to omitted variables. It is possible that both Cognitive Performance and Subjective Wellbeing are related to the overall health status of the individual. Moreover, the variables are only assessed once per individual and can therefore not offer the same strength of interpretation as panel data.

Because a significant positive relation between Cognitive Performance and Subjective Wellbeing is found, it would be useful to investigate the whole concept of flow in more detail. Csíkszentmihályi (2014) describes the necessity for society to understand the concept of flow, as it is detrimental for happiness. Especially in this day and age, where everything is supposed to be safe, stable and comfortable, children do not learn to face challenging tasks. Too much comfort, as well as material rewards and passive entertainment, might be a cause for decreases in wellbeing (Csíkszentmihályi, 2014).

6.2 Limitations

In this section, the limitations of the research are addressed, especially with regard to the measurability of addictive Digital Use.

With the data set used, this research does only observe 13-to-14-year olds in Germany. The histogram in Figure II and the daily Digital Use average of 98 minutes, indicate that the digital use in this country might be comparatively low, which is in line with current statistics on social media use for different regions. The Global Web Index published data on 16-64 year old social media users for the year 2018. The statistics shows that daily time spent on social media is highest in Latin America and lowest in Europe (124 min. in Europe; 130 min. in China; 139 min. in North America; 161 min. in Asia Pacific; 188 min. in Middle East & Africa; 210 min. in Latin America) (Global Web Index, 2019). Referring to these statistics, it must be noted that the source includes a much larger age group and, thus, is not directly comparable to the data used in this paper. In any case, it shows that social media use can vary greatly between different regions. Therefore, it would be useful to extend the research to more countries. It is quite possible that stronger addictive behaviour can be seen in Latin American countries. Of course, it is necessary for such an analysis that corresponding data is available, which is mostly not the case. For example, the Latinobarómetro, a yearly long-term socio-economic study for 18 countries, inquires social media usage simply by asking if 'any of the following social networking services' are being used (Latinobarómetro, 2019). As it does not inquire the time spent or any other measure related to addictive behaviour, the data does not sufficiently capture the idea presented in the framework, which makes it impossible to perform a similar analyses as in this paper.

The SOEP dataset includes two variables that are somewhat related to the topic of Digital Use: time spent on 'TV/DVD/Internet-Streams (e.g. Youtube)' and time spent 'using social online-networks/ other surfing on the Internet'. Although these measures much better capture the idea of Digital Use and addictive tendencies, there is criticism to be made. Firstly, neither of the two measures is specified regarding the used device, although the first has a stronger relation to TV and the latter has a stronger relation to the smartphone, which is the reason why the latter is used in this research. Devices might be a crucial distinction, as smartphones are more distracting than computers due to notifications. Unfortunately, messenger apps, which due to notifications might have the strongest distracting effect, are not considered in either of the two variables.

Looking at the questions of the SOEP young adults survey, it becomes evident that questions on Digital Use might not be stated clearly enough. More precisely, the aspect 'surfing on the Internet' is not a term used by young adults in the German Language, which leaves room for interpretation. It might be unclear, which activities (e.g. online shopping, homework related browsing, entertaining content) are meant by 'surfing on the Internet'. If respondents are unsure about survey questions, they might interpret the questions in a different way than intended by the researcher. Inaccuracy in the survey questions leads to measurement errors (Hair, Black, Babin & Anderson, 2014). Especially when answered by young adults, it is even more important to clearly state survey questions. It is therefore advisable for data institutes to constantly check whether the survey questions are contemporary, unambiguous, and generally aim to address issues relevant for research.

Moreover, the self-assessed variable 'time spent on social media/ surfing on the internet' is likely to be biased due to distorted perception. In a study conducted by Montag et al. (2015), self-reported data was compared to directly recorded data. The researchers installed an app on the study participants' phones, which tracks the actual time spent on the device. In addition, the participants were asked to state their perceived time spent. The study reveals that participants overestimated their phone usage. Therefore, it is possible that the Digital Use variable in this research is upward biased.

When research is done on how Digital Use affects Cognitive Performance, total time spent on the devices might not even be crucial, but rather the number of interruptions or the frequency of use (Montag & Walla, 2016). Moreover, a distinction must be made between intentional and unintentional device usage. The used variable combines both social media and surfing on the Internet. Social media might prominently be a leisure time activity and unintentionally conducted, but surfing on the Internet might be more conscious. Thus, it cannot be assumed that surfing on the Internet is a distracting activity, when it really might be the activity the individual tries to focus on. Thus, a negative effect of 'Surfing on the Internet' on Cognitive Performance or Subjective Wellbeing might lack theoretical support.

Overall, it must be admitted that the used variable captures the idea presented in the theoretical framework to some extent. However, it does not perfectly represent the addiction that comes with digital use, which might be a reason for insignificant results. In order to adequately measure addictive Digital Use, a more complex measurement structure would be necessary. A measure that has been used in some studies is the Mobile Phone Problem Use Scale (MPPUS); a scale, which assesses phone usage behaviour using 27 items covering the addictive symptoms tolerance, escape from other problems, withdrawal, craving and negative life consequences (Bianchi & Phillips, 2005). The measure was developed over a decade ago. Considering the fast pace, at which the digital landscape changes, it might not anymore capture addictive Digital Use adequately. For example, taking 'money spent on phone bills' into account is outdated, since people have flat rates. However, the MPPUS scale serves as a good framework to show the complexity of the assessment of addictive Digital Use. A variety of measures is needed instead of a single measure, in order to gain more realistic insights into addictive phone behaviour and empirically investigate its effects on Cognitive Performance and Subjective Wellbeing.

Besides the discussions about the strength of the used variables, causality needs to be addressed. Mediation analysis generally aims to find empirical evidence for causal relations. However, even in the case of significant results, the interpretation of causal effects needs to be well justified, which is difficult given that the data is cross-sectional. In social sciences, data gathered from experiments might be best suited to test causal relations, as it yields the opportunity for the researcher to manipulate the environment (Iacobucci, 2011). Thus, it might be reasonable to adjust the variable Digital Use; for example, by increasing the number of notifications or muting the notifications for a certain time. Ideally, data for the Digital Use variable is directly drawn from the devices. It gives more accurate results, as there is no advantage in self-assessed estimation of time spent on digital devices. An experimental design like this would provide multiple observations for each individual and therefore better justification for causal implications. However, reversed causality cannot be fully ruled out. Reversed causality must be discussed before causalities can be deduced from mediation analysis (Iacobucci, 2011). It is conceivable that a decrease in Subjective Wellbeing, caused by any other external influences, causes both an increase in Digital Use as well as a decrease in Cognitive Performance. Reversed causality between Digital Use and Subjective Wellbeing is supported by Song et al. (2014), who state that lonely individuals seek social interaction in social networks due to a lack of social interaction in real life (Social Compensation Theory).

Just like Digital Use, the variables Cognitive Performance and Subjective Wellbeing can also be measured in many ways. Cognitive Performance could be assessed using regular tests directly on the phone, or alternatively regular queries. Capturing Cognitive Performance right after the use of digital devices would be reasonable to observe that the independent variable occurs right before the dependent variable. Sequential ordering is a necessary factor for causality implications (Iacobucci, 2011). Likewise, Subjective Wellbeing could be assessed more often. As described in the theoretical framework, Subjective Wellbeing can either be assessed by measuring an individual's emotions and mood (affective component) or by measuring an individual's overall satisfaction with life (cognitive component) (Diener et al., 1999). In this paper, the cognitive component was used, as this research aimed to investigate long-term impacts of Digital Use and Cognitive Performance. This way, it can it be observed whether Digital Use has a long-lasting influence, rather than whether possible negative emotions quickly pass by. Although the latter would be an interesting direction for research, the dataset at hand does not contain any variable capturing the affective components. It would be a reasonable suggestion for further research to use panel data, which observes an individual's current emotional state over time. Diener et al. (1999) states that an individual's mood can clearly be differentiated from an individual's life-satisfaction. Therefore, investigating the affective component, or even comparing it to the cognitive component, could give valuable insights.

One of the main issues for research in this field is access to appropriate data on phone usage or social media. This is not due to the absence or immeasurability of data but rather due to the scarce access to it. The data necessary to conduct meaningful research in this field is in the hands of big tech companies (Condliffe, 2019). Researchers do not have access to this data and instead conduct surveys with self-assessed data, which are far less reliable. It becomes clear that responsible companies need to be part of the solution. Based on the evidence of the effect of social network sites on subjective wellbeing, Verduyn, Ybarra, Résibois, Jonides & Kross (2017), give three recommendations to policymakers. Firstly, awareness among users of social media is crucial. Secondly, researchers need to be supported in order to understand the adaptive usage of social media. And thirdly, the providers of social network sites need to be held accountable for rising wellbeing issues. Although these are reasonable recommendations, it underestimates the power and own research capabilities of big tech companies. Google, Facebook and Apple, among others, do not have the incentive to truly demonstrate the impacts addictive Digital Use might have on human behaviour and subjective wellbeing. In fact, implications coming from this, would stand in contrast to what generates more profit, which is increases in screen time. But even then, it is questionable which implications need to be drawn for society, when in the end it all comes down to the self-responsible behaviour of the individual. Alter (2017) might have a valid point saying that more research is not necessarily needed, when individuals are in charge of reflecting their own behaviour in order to make reasonable adjustments to digital device usage and thus, overcome addictive Digital Use.

7. Conclusion

In this paper, I investigated how Digital Use affects Subjective Wellbeing and whether Cognitive Performance mediates this effect. I used data on 13-to-14 year olds in 2016 and 2017 from the German Socio-Economic Panel. Cognitive Performance is constructed as a latent variable with indicators derived through Explanatory Factor Analysis. Based on the analysis results and theoretical reasoning, the variables Concentration, Efficiency, Thoroughness, Diligence and Ambition are taken as indicators for Cognitive Performance. Using Structural Equation Modelling, I built a Mediation Model with Cognitive Performance as the mediating variable between Digital Use and Subjective Wellbeing.

The results are only partially in line with the expected results based on theory. As a significant result, the effect of Cognitive Performance on Subjective Wellbeing was found. The results might provide evidence, that flow, as described by Csíkszentmihályi (2014), is related to wellbeing. However, there is neither a significant effect of Digital Use on Cognitive Performance, nor on Subjective Wellbeing. Thus, the research question '*Is there a mediating effect of Cognitive Performance in the relation between Digital Use and Subjective Wellbeing?'* cannot be affirmed. Due to the fact that there is a variety of literature in which negative effects have been found, the suspicion is obvious that that the Digital Use variable might not perfectly represent the proposed theoretical idea. Therefore, it is discussed what makes measuring addictive Digital Use so difficult and how the variable could be improved. I conclude that the digital landscape is extremely diverse, as devices, platforms, target groups, usage behaviour and content trends constantly change at a fast pace. Therefore, it is difficult to define Digital Use and gather relevant data. However, it is clear that a latent construct gives more reasonable results compared to only using one single measure. A detailed analysis of how this construct might look like would be beyond the scope of this work.

Further research is needed due to the increasing dependence of humans on digital devices and the need to understand both positive and negative consequences, especially with regard to wellbeing. More emphasis should also be placed on interdisciplinarity. Existing research on addictive digital use is conducted in Economics, Psychology, Biology, and Design. Connecting the dots between these domains is crucial to understand the interrelations and identify new research strands. Implications for policy makers seem necessary but are difficult to implement because of humans' dependency on digital devices, the complexity of the problem and the power of big tech companies. Since everyone is responsible for his or her own digital consumption, the greatest lever is to create change in the individual. The simplest way to achieve this is through awareness for responsible use of digital devices.

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Appendix

Appendix A: *Pairwise Correlation Matrix*

Variables	(01)	(02)	(03)	(04)	(05)	(06)	(07)	(08)	(09)	(10)	(11)	(12)
(01) SWB	1.0000											
(02) Digital Use	-0.0517	1.0000										
(03) Grades	0.1163	-0.0507	1.0000									
(04) Concentration	0.2115	-0.0470	0.2576	1.0000								
(05) Focus	0.1944	-0.0299	0.3011	0.3905	1.0000							
(06) Calm	0.0898	-0.0545	0.1758	0.2598	**0.4070**	1.0000						
(07) Stillness	0.0123	-0.0620	0.1354	0.1292	0.3050	**0.5203**	1.0000					
(08) Efficiency	0.1998	-0.0265	0.2695	**0.4225**	0.3277	0.2421	0.1076	1.0000				
(09) Thoroughness	0.2158	0.0078	0.2484	0.3847	0.3205	0.2583	0.1418	**0.6086**	1.0000			
(10) Diligence	0.1905	-0.0586	0.1656	0.3381	0.2956	0.2240	**0.0885**	0.3746	0.3812	1.0000		
(11) Relaxation	0.1410	0.0022	0.1018	0.1961	0.2482	0.2264	0.1668	0.1372	0.1327	0.2672	1.0000	
(12) Ambition	0.1786	-0.0265	0.2541	0.3353	0.2628	**0.0585**	**-0.0056**	**0.4651**	0.3762	0.2548	0.1827	1.0000

Appendix B: *Kaiser-Meyer-Olkin measure of sampling adequacy*

Variable	KMO
Grades	0.8915
Concentration	0.8994
Focus	0.8699
Calm	**0.7344**
Stillness	**0.6722**
Efficiency	0.8014
Thoroughness	0.8162
Diligence	0.8735
Relaxation	0.8144
Ambition	0.8248
Overall	**0.8168**

Appendix C: *Factor Analysis, unrotated*

Factor analysis/correlation	Number of obs = 482
Method: principal factors	Retained factors = 5
Rotation: (unrotated)	Number of params = 40

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	**2.73283**	1.94244	0.9181	0.9181
Factor 2	0.79038	0.62024	0.2655	1.1837
Factor 3	0.17015	0.06476	0.0572	1.2409
Factor 4	0.10539	0.13079	0.0354	1.2763
Factor 5	-0.02540	0.05866	-0.0085	1.2677
Factor 6	-0.08406	0.05311	-0.0282	1.2395
Factor 7	-0.13717	0.03276	-0.0461	1.1934
Factor 8	-0.16993	0.02086	-0.0571	1.1363
Factor 9	-0.21516	0.02416	-0.0641	1.0722
Factor 10	-0.19079	.	-0.0722	1.0000

LR test: independent vs. saturated: chi2(45) = 2454.30 Prob>chi2 = 0.0000

Appendix D: *Rotated Factor Loadings (Pattern Matrix) und Unique Variances, sorted*

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
Efficiency	**0.7419**	0.0551	-0.0754	-0.0469	0.4386
Thoroughness	**0.7060**	0.0997	-0.0773	-0.0921	0.4772
Concentration	**0.5644**	-0.1082	0.0828	0.1356	0.6445
Ambition	**0.5447**	0.1489	0.0915	0.1089	0.6609
Diligence	**0.4961**	0.1283	0.2197	-0.0703	0.6842
Focus	0.4535	0.4013	0.1133	0.1767	0.5892
Grades	0.3510	0.1427	-0.0142	0.2325	0.8022
Calm	0.2668	**0.6506**	0.0082	-0.0320	0.5045
Stillness	0.1102	**0.6355**	-0.0207	0.0009	0.5835
Relaxation	0.2248	0.2059	0.2983	0.0395	0.8165

Appendix E: *Model Fit Indices (Maximum Likelihood Estimation with Satorra-Bentler Scaling)*

method(ml) **vce(sbentler)**	**(1)** no covariances	**(2)** cov (tho., eff.)	**(3)** cov (tho., eff.) cov (amb., eff.)	**(4)** cov (tho., eff.) cov (amb., eff.) cov (tho., conc.)
$\chi 2$	chi2(13) = 43.825 (p = 0.000)	chi2(12) = 30.376 (p = 0.002)	chi2(11) = 18.589 (p = 0.069)	chi2(10) = 11.173 (p = 0.344)
$\chi 2$/df	3.37	2.53	1.69	1.12
RMSEA	0.042	0.034	0.021	0.010
CFI	0.980	0.988	0.996	0.999
TLI	0.967	0.979	0.992	0.998
SRMR	0.026	0.021	0.017	0.015
Modification Indices of covariances of the error terms between items of the latent variable				
	cov (tho., amb.) 7.897 **cov (tho., eff.) 14.104** cov (tho., conc.) 4.675 cov (eff., dilig.) 8.108 cov (dilig., conc.) 9.025	cov (tho., dilig.) 5.827 **cov (amb., eff.) 12.314** cov (amb., dilig.) 8.385	**cov (tho., conc.) 5.715** cov (amb., dilig.) 4.949	-

Appendix F: *Model Fit Indices (Asymptotic Distribution Free Estimation)*

method(adf) **vce(default)**	**(1)** no covariances	**(2)** cov (tho., eff.)	**(3)** cov (tho., eff.) cov (amb., eff.)	**(4)** cov (tho., eff.) cov (amb., eff.) cov (tho., conc.)
$\chi 2$	chi2(13) = 34.911 (p = 0.001)	chi2(12) = 25.344 (p = 0.013)	chi2(11) = 15.769 (p = 0.150)	chi2(10) = 10.134 (p = 0.429)
$\chi 2$/df	2.69	2.11	1.43	1.01
RMSEA	0.039	0.032	0.020	0.003
CFI	0.954	0.972	0.990	1.000
TLI	0.925	0.950	0.981	0.999
SRMR	0.026	0.022	0.018	0.015
Modification Indices of covariances of the error terms between items of the latent variable				
	cov (tho., amb.) 6.346 **cov (tho., eff.) 9.600** cov (amb., eff.) 4.830 cov (eff., dilig.) 4.694 cov (dilig., conc.) 5.237	cov (tho., dilig.) 4.907 **cov (amb., eff.) 9.543** cov (amb., dilig.) 7.144	**cov (tho., conc.) 5.632** cov (amb., dilig.) 4.811	-

Appendix G: *SEM Results with Asymptotic Distribution Free Estimation*

*(**** p<0.1; ** p<0.05; *** p<0.01, *standard errors in parentheses)*