MASTERARBEIT / MASTER'S THESIS

Titel der Masterarbeit / Title of the Master‘s Thesis

„Digital divide in well-being“

verfasst von / submitted by

Anastasia Čepelova

angestrebter akademischer Grad / in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien, 2023 / Vienna 2023

Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet:	UA 066 550
Studienrichtung lt. Studienblatt / degree programme as it appears on the student record sheet:	Masterstudium Communication Science
Betreut von / Supervisor:	Univ.-Prof. Hajo Boomgaarden, PhD

Abstract

The notion of digital divide is a previously well studied topic, this study however aims to take the current state of the research a step further and explore it from the perspective of well-being. Is there a digital divide in well being? Previous research in the field of digital divide has primarily focused on defining the different levels of it (access, skills and outcome divides), well-being research in connection to technology has merely studied whether there is a relationship between usage and well-being or not. In connecting these two fields, this study sheds some light into the socioeconomic perspective of the technology use. As self control is the key determinant in the effect of technology use on well-being, it is used as a key measure in this study. The relationship between digital divide and well-being was therefore studied through measuring self-control of its respondents and then using linear regression to explore the relationship between self-control index and the sociodemographic backgrounds of respondents. The study also included a segment dedicated to self-control strategies, to explore if the sociodemographic groups differ in their choice of self-control strategy. Fortunately, the analysis has found no previously unknown connection between common sociodemographic factors and levels of trait self-control, and only minor differences among the differences in strategy use. Subsequently, it can be inferred that there is no digital outcome divide in how technology is affecting our well-being.

Introduction

Smartphones are surrounding all of our lives. Being constantly online and having several streams of ongoing conversations at different levels (personal live conversations and mediated online conversations) is something that many consider a default (Reinecke et. al, 2018). However, this default is potentially having negative effects both on us as individuals and us as a society. The consensus on whether social media or media use in general is bad for our health is yet to be reached (Valkenburg, 2022; Meier & Reinecke, 2021), there is however a general agreement on the fact that media use is not the same across all socio-demographic groups, i. e. there exists a digital divide between different segments of our society (Brandtzæg et al., 2011). This study aims to unveil if this digital divide also affects the well-being of people who fall behind on internet access, skills or general outcomes of usage.

The digital divide describes the difference between certain groups of people in terms of access, skills or outcomes tied to ICT knowledge and computer usage. Previous research has shown that this is mainly determined by socioeconomic factors - those with lower income or lower education are more at risk to be less skilled in their usage (Livingstone et al., 2021). As smartphones are now accessible to almost anyone (in western societies at least), the gap in terms of access has been almost bridged. Yet the divide in the use itself (Van Deursen and Van Dijk, 2011) and its outcomes of it (Wei et al., 2011) is still intact. Outcomes may represent anything from being more successful at finding a job through the internet, or simply being able to use the technology for one's own benefit (ibidem).

Social media can be an effective way to regulate one's emotions and inner states (Robinson, & Knobloch-Westerwick, 2016) or to stay in touch with loved ones. Hence usage itself is not inherently unhealthy. But the amount of attention and time attributed to social media may be. Given the addictive nature of digital technologies, it might be hard for a person to strike a healthy balance in their approach to technology usage. One of the key determinants of successful use is therefore the ability to regulate one's own use (Reinecke et al., 2022), self-control.

The digital divide has many potentially dangerous impacts on our society, from affecting political participation to enlarging the canyon between the rich and the poor (Wei, 2012). Given the rise of the business model of attention economy (Bhargava & Velasquez, 2020) and internet addiction (ibidem), it is important to ask ourselves, if there also might be a connection between the digital divide and well-being. Thus, if people who come from socially weaker backgrounds (low income, low education etc.) have their well-being affected more or not. Given the fact that the mediator of technology usage is self-control, the question is, if there is a difference in the level of self-control among different sociodemographic groups.

Stemming from this, the main research question this study will focus on is whether there is a digital outcome divide in well-being or not, using self-control as the mediating variable. This study aims to determine whether there is a relationship between the proposed two components (socioeconomic background and self-control regarding smartphone use) by conducting a cross-sectional online survey on a representative sample of young adults in the Czech Republic. The survey used the well-validated Brief Self-Control Scale (Tangney et al.,2004) and strategies for self-control (Brevers & Turel, 2019) to determine the ability to self-control technology usage, and different socioeconomic factors to determine the placement of individuals in terms of the digital divide (such as income, education, parent's education (cite all three, from further paragraphs).

Literature review

Digital divide

Digital divide describes a phenomenon in our society when the introduction of new technologies reproduces the societal inequalities that people face in their offline lives into the online world and then in turn also negatively affects their lives. Originally the term was proposed by the US government and was used to solely describe the discrepancy between physical access to internet hardware and software among different social groups (Calderon Gomez, 2021). The meaning of the term has evolved with the progression of the research focused on this topic. Currently, the term is used to describe the gap between individuals in terms of their Internet access, usage, outcomes of or attitudes towards internet usage (OECD, 2001, Van Deursen & van Dijk, 2014, Wei et al., 2011).

The operalization of the term had several iterations, usually described as “grades” of the divide. The first-grade digital divide research focused on determining which groups of people had access to the Internet, which groups did not have it, and how it was affecting their lives. Early studies, therefore, mainly focused on researching the causes and factors in its creation. Access to the internet was then determined by socioeconomic factors (OECD, 2001), as both internet connection and the hardware used to access the internet were costly. Early research has shown low-income groups, women and older generations to be most at risk (Van Dijk, 2009) of falling behind the digital divide. In this paradigm, measuring the gap was fairly simple - the number of access lines per 100 inhabitants was the greatest indicator (OECD, 2001).

Shortly, many scholars noticed that simply enabling people to access the web was not enough to close the gap, as the way people spend their time on it was fairly different. This has given rise to a new term - the so-called “second-grade digital divide” (Brandtzæg et al., 2011), alternatively also coined as “skills divide” (Van Deursen and Van Dijk, 2011). Extensive research done by van Dijk (2005, 2009, 2011, 2014) has shown that specific classes and groups have different usage patterns. Even though people with lower levels of education actually spend more time on the internet than their higher-educated peers (refuting the access approach), they use the internet in more general and superficial ways (Van Dijk, 2005), such as gaming or communicating with friends (Van Deursen & Van Dijk, 2014). Higher-educated people usually use the internet for more “capital-enhancing” activities (Harittai & Hinnant, 2008), such as reading news or searching for information (Van Deursen & Van Dijk, 2014).

This is especially interesting as it mirrors how these people spend their free time besides internet usage and therefore further supports the notion that the internet only reflects how society works in the real world (ibidem). People with lower incomes tend to spend their time in a more passive manner, f. e. by watching more TV and reading less. They consequently spend less time on activities promoting personal growth or enhancing their digital capital (ibidem).

The third-grade divide, also called the “digital outcome divide”, was initially proposed by Wei et al. (2011), as a prolonged hand of the second-grade divide, refocusing the attention from the skills and usage (as descriptives of the problem) to the inequality of outcomes of internet use (the consequences). Wei et al. also confirmed that there is a relationship between the divides - f. e. if a student can not afford to have a computer at home (first-grade divide), they subsequently also have worse computer skills (second-grade divide) and that translates into their knowledge outcome (they learn worse) (2011). Furthermore, if a person has better skills and is able to use the internet more productively, the gain they achieve will enhance their social or digital capital and therefore reinforce the divide (DiMaggio et al., 2004).

Digital divides have been mainly studied because of the dire consequences they might lead to, as it can be viewed as a policy issue that might be a threat to our democracy (Hacker & van Dijk, 2000). The digital divide is intervined with the concept of the knowledge gap as better skilled and equipped users will be able to achieve and retrieve information faster than the unprivileged ones, therefore gaining another advantage (Van Deursen & van Dijk, 2014, Wei & Hindman, 2011). This may also lead to the exacerbation of current social issues (Livingstone & Helsper, 2007) and may also affect political participation, as using the internet for only basic applications is associated with lower political participation (Wei, 2012). Given the changing labor market and the onset of the fourth industrial revolution, digital skills will gain importance as unskilled positions can get automated (Vasilescu et al., 2020).

Individual level factors contributing to the digital divide

As operalizations of the digital divide evolve, so do the factors that influence people to fall behind on Internet usage. Scholars have previously described several factors that may have an impact on one's internet usage, skills or outcomes.

Age has been considered one of the most important determinants of digital division (van Deursen & van Dijk, 2009), with a negative linear relationship between age and the use of social media networks and smartphones (Serrano-Cinca et al., 2018). Friemel (2016) has shown that even in Europe, where internet penetration approaches 90 %, older seniors above 70 are still being excluded. However, it must be said that the linear relationship between age and divide is the strongest in the access divide, it can not be generally stated that the younger the person, the more digitally skilled they are, as socioeconomic factors come into play (Livingstone & Helpser, 2007; Harris et al., 2017).

The financial situation of internet users seems to play a key role in determining their digital exclusion. Firstly, a person's financial situation is connected to the ability to purchase and use various devices freely. Knowing that opportunities for online use are closely linked to more advanced digital skills (Livingstone et al., 2021), the consequence of a lower income is a lower level of digital literacy. As smartphones and other smart devices became more accessible, some may argue that the financial situation may not be a factor anymore, as anyone could afford to buy a device that has internet access. However, the rising number of smartphone owners does not help this situation either, as Donner et al. (2011) has concluded that a smartphone may not fully replace a computer, especially in situations such as creating a CV. He stresses that smartphones were created in the Global North to serve as complementaries to computers, not as their replacements.

Another commonly described factor influencing digital divide is education. Korrup & Szydlik have already confirmed in 2004, that higher education is connected to more common use of computers for personal purposes. This may be attributed to the fact, that people with lower education generally have less access to the Internet (Van Dijk, 2009). This may have changed since 2009, yet a difference in skills and usage persisted. Low education is still connected to change in usage patterns - as Van Deursen and van Dijk have confirmed in their 2014 study, people with lower education tend to spend more time on the internet, but they are spending it in less beneficial ways compared to their higher educated peers.

Gender has initially been shown to also be a factor in internet use (Helsper, 2010), where women would be underprivileged compared to men. Further research has unveiled that this is due to other factors accompanying gender (such as income and education) and the difference has disappeared when research has controlled for education, income, technical interest etc. (Friemel, 2016). Furthermore, the gender gap seems to be closing with younger generations (Van Dijk, 2009).

Finally, living in urban versus rural conditions may also be a factor in the level of a person's digital divide. Studies on this topic have been scarce, but for example, a study by van Deursen & van Dijk (2014) has shown that people living in urban areas tend to use the internet for socialization more often than those living in rural areas.

Well-being

One of the possible outcomes of the third-grade digital divide may also be a difference in the impact technology has on a person's well-being. Of course, the digital divide may affect one’s well-being simply in terms of quality of life (for example if someone gets a better job position due to better digital skills and therefore has better access to healthcare etc.). However, it is also important to explore if there is a difference in the usage effects on mental well-being as well. Especially since the recent onset of critique of social media which has been present in the mainstream media through TV shows like Black Mirror or The Social Dilemma.

Technology has certainly reshaped the way we interact with our peers, the outer world and ourselves (Reinecke et al., 2018). We are able to maintain connections with people whom we do not see often, and even create parasocial relationships with people who we do not know at all, such as singers or influencers (Bi & Zhang, 2022). We are also able to mindlessly distract ourselves from whatever is currently happening in our mindscape (Robinson, & Knobloch-Westerwick, 2016). But this also takes a toll as the internet may also distract us when we try to focus on something important, such as writing a master thesis or even listening to a friend (Valkenburg, 2022).

Hence, these changes to how we function as individuals have been influenced not only by the technology itself but mostly by the people and companies who make it. There is currently a whole business fraction of so-called “attention economy”, which is built on generating revenue by capturing the user's attention and showing them as many advertisements as possible (Bhargava & Velasquez, 2020). This model incentivizes users to stay online as much as possible, even going as far as using our brain's liabilities and weak self-control (Brevers & Turel, 2019) to create an addiction and generate even more income (Bhagrava & Velasquez, 2020). This may come at the expense of users, as they may experience a negative effect on their well-being from this usage (either by directly postponing other tasks to be online or by other psychological effects (Meier et al., 2016). The question proposed by this study is, whether different groups in society experience different effects on their well-being, i. e. if there is a digital outcome divide in well-being as well.

RQ: Is there a digital outcome divide in well-being?

What is well-being?

Well-being can be defined from different perspectives. It can be a momentary affect, for example when we experience pleasure from being on our phones, which drives the hedonic (subjective) well-being (Vanden Abeele, 2021). In this definition, well-being is a transient emotional state. You are well, if you feel well, and you are not well when you are feeling bad (Hofman, Reinecke & Meier, 2016). In terms of technology use this may be experienced when a person is playing a game on their smart phone.

It can also be viewed from the perspective of eudaimonic (cognitive) well-being, which is experienced when an activity adds meaning to our lives (Lukoff et al., 2018) and improves "the appraisal of the relative quality of our lives" (Hofman et al., 2016). This may also include situations when we are not exactly feeling "well" in the pleasurable sense of the world, but we are experiencing a deeper more ling lasting satisfaction. When it comes to technology use, this might be for example driven by the ability to connect to our peers through online mediated communication, or simply be able to study online.

How are these two dimensions affected by how we use technology? A vast array of both negative and positive effects the attention economy has on well-being have been studied. Some say that intense social media use may have negative effects on academic success (Uzun & Kilis, 2019), it may induce depressive symptoms (Hancock et al., 2019), increase anxiety (ibidem), worsen both well-being and ill-being (Huang, 2020), lower the life satisfaction (ibidem), interfere with social activities (McDaniel & Drouin, 2019), lead to procrastination (Meier & Reinecke, 2018). On the other hand, Appel & Gnams (2020) have found no potentially devastating effects of social media on school achievements. Most of the meta-reviews conducted on such topics concluded that the findings from studies on these topics are often conflicting (Valkenburg, 2022) and most only report weak (Meier & Reinecke, 2021) or no associations (George et al., 2018).

Measuring well-being and phone usage

One of the potential reasons for the disagreement on the consequences of technology usage is that both measuring technology usage (or social media usage) and well-being presents a methodological and operationalizational challenge.

There are many ways to measure social media and smartphone use, one option is to use self-reports of the overall usage time. Self-reports have however proven to be very unreliable as shown in a study conducted by Sewall et al. (2020), participants misestimated the weekly overall use by 19.1 hours on average. Another is to get actual log data from the time spent on SNS, or even content-based log data to examine what the user truly does. As for the content-based approaches, there is the notion of a difference between active and passive use, with active use having more positive effects on well-being (Valkenburg & Beyens, 2022). This has however been debunked in a recent meta-review, which concluded that the findings of most studies on these topics are highly inconsistent and show conflicting results (Valkenburg, 2022). Furthermore, there have been some doubts raised about the categorisation of online media use, as some studies seem to confound problematic use with intense use (ibidem) and over-pathologize everyday usage (Kardefelt‐Winther et al., 2017). Another metric sometimes used by scholars to define usage is the size of one's social network.

Well-being raises the same questions about the measurement as social media use. Firstly, well-being presents an operationalizational challenges, as there seems to be a frequent confoundment of well-being and lack of symptoms of ill-being (Valkenburg, 2022). The construct also seems to overlap with outright mental-health issues, as the questions aiming to measure the decrease in well-being also measure mental illnesses (ibidem).

One of the most common methods is cross-sectional self-reporting when participants fill in a battery of questions about their well-being which is then used to create a "well-being index". This has however been proven to be ineffective, as Schwarz has shown in his continuous work. The responses of respondents are affected by a number of heuristics (to paraphrase Kahneman, when you ask someone a cognitively difficult question, they tend to answer another, simpler question (Kahneman, 2013)). One example is the mood-as-information heuristic when people tend to assess their life more positively on sunny days (Schwarz & Clore, 1983).

Another often-used method is experience sampling, which consists of collecting daily instant assessments of one's state or mood over a longer period of time, which can tell researchers more about participants' overall sentiment (Hoffman et al., 2012). This method is however very costly and time-intensive, hence not many researchers opt for it.

The presented challenges are the potential reasons for the difficulty in achieving consistent results on the effects of technology use on well-being. Furthermore, this is the reason why the relationship between the digital divide and well-being is not examined in this study in a direct way, as direct well-being measurement methods are either too unreliable or too costly for this particular study.

Trait self-control

The current media environment is a trap for our attention and therefore is more challenging for self-control. Specifically, media affordances such as notifications (that work as instant gratifications) or overall experience design tend to support habitual use and increase distraction (Reinecke et al., 2022). Fear of missing out on something also contributes to the temptations of social media (Milyavskaya et al., 2018), and so does the social pressure to be constantly available (Halfamann, 2019). These factors together also help to bring instant gratification from using the phone, which reinforces the need to use the phone (Du, Kerkhof & van Koningsbruggen, 2019). Finally, another important factor supporting common self-control failure is the ubiquity of phone usage, which encompasses many of the activities we have to perform in the offline world (ibidem).

One of the ways to shed light on the confusion about online presence and well-being while surpassing the measurement challenges is to look at the determinants that may predict the individual outcomes of such usage. Previous research has shown that (trait) self-control (Reinecke et al., 2022, Brevers & Turel, 2019; Panek, 2014) and mindfulness may be explanatory moderators of online media use (Bauer et al. 2017). Being able to realize what one is feeling and taking action to maintain or create inner balance may be key to supporting well-being (Vanden Abeele, 2021).

Trait self-control is defined as the “ability to override or change one’s inner responses” (Tangney et al., 2004, p. 274), which also is trans-situational (Reinecke et al., 2021). The trans-situational aspect is important as self-control can also be described as a muscle, meaning it has limited resources and can be trained (Baumeister et al., 1998). It is therefore not a fixed yes-or-no trait, it can be improved over time. It can also get depleted - there is a limited amount of self-control one can execute in a day (Duckworth et al., 2016).

The term is sometimes used interchangeably with self-regulation; it is however important to note that self-control refers to the personality trait and self-regulation is the act or behavior of implementing self-control (Bayer et al., 2016). Self-regulation may also be defined as a “dynamic process of determining the desired end state (i.e., a goal) and then taking action to move toward it while monitoring progress along the way” (Inzlich et al., 2021, p. 321).

Trait self-control has been previously linked to an array of positive outcomes. It enables individuals to forgo short-term pleasure in exchange for a long-term goal, which in many cases is better for them (Hofman et al., 2016). It can have a positive effect on physical health (as individuals may be better at controlling impulses to eat unhealthy food or skip exercise) (Moffitt et al., 2011), academic success (Gaudreau et al., 2014), improves the ability to regulate emotion (Reinecke et al., 2021), better sleep (Cain & Gradisar, 2010) and also a healthy approach to media use. In predicting school performance, TSC is more important than IQ (Duckworth & Seligman, 2005). Finally, trait self-control is also positively related to affective well-being (Hoffman et al., 2014).

Several studies have however concluded that successful control over media use is key to avoiding these pitfalls (Blachnio & Przepiora, 2016). Individuals with lower self-control are more prone to use the SNS excessively (ibidem), on the other hand, people with higher self-control generally use social media sites less (Brevers & Turel, 2019).

One of the common failures of self-control is procrastination, postponing something important to do something pleasurable, otherwise defined as an irrational delay of an intended task (Steel, 2007). Apart from consequences stemming from skipping important tasks, procrastination is linked to impaired post-exposure well-being (Reinecke, Hartmann et al., 2014). Evidence furthermore suggests a link between procrastination and self-control (Meier, Reinecke & Meltzer, 2016).

A challenge that researchers often face when it comes to self control studies is the measurement of this construct. Obviously, a direct measurement of the strength of will would be the best and most accurate measruement, this is not usually available given the funding and timing. Luckily, Tangney et al. have developed a scale, in which respondents self-asses their own ability to control their impulses (2004). They first developed a 36-item Self control scale, in which people would judge their own self-control skills on a five point Lickert scale.

The scale produced reliable and consistent results. They further proceeded with creating a shorter version - Brief self control scale, which they tested on the same respondents as the first scale three weeks later. The results of the Brief self control scale were consistent with the ones generated from the first battery of questions. The scale they created is now often used for measuring self control (Brevers & Turel, 2019; Sriran, Glanzer & Allen, 2018 Meier et al., 2016).

In the context of studying the digital divide, it would be beneficial to see if self-control is connected to any socioeconomic factors. Obviously, higher trait self-control is linked with higher achieved education (Gaudreau et al., 2014), it can be therefore inferred that people with higher education will be better at controlling their phone usage and therefore have greater well-being. The relationship between trait self-control and other socioeconomic factors has previously not been studied, which means the relationship between the digital divide and well-being has yet to be confirmed. A hypothesis to support or refute this is therefore proposed:

H1: Lower educated people will be reporting lower levels of trait self-control.

H2: Low-income people will be reporting lower levels of trait self-control.

Strategies for self-control

One of the ways to tackle the current attention-grabbing climate is to create effective strategies for controlling one’s media and phone usage. As was previously mentioned, self-control can be likened to a muscle and therefore can get quickly depleted. Creating an environment where one has to use the muscle less, or not at all, is one of the ways to tackle distractions (Duckworth et al., 2016). It is an interesting factor to count in when it comes to well-being and the digital divide, as it is a tool that may help the less controlled people tackle their weaknesses, avoid attention depletion and improve their trait self control in the long run.

Not all control strategies have been created equally, some of them were proven to be more effective than others. The key determinant of effectiveness (e. g. how much energy it costs to execute the strategy) is when the strategy takes place in the impulse-generation process (Brevers & Turel, 2019). The sooner the strategy comes into play, the more effective it is. Therefore most effective strategies are those that stop the cycle before it even happens, Duckworth et al. have called them situation selection strategies (2016)*,* for example when a person puts their phone into another room, so they are not tempted to use it. It is especially beneficial in saving up the energy of the attention muscle and also maintaining attention. Duckworth et al. (ibidem) have also described other four types of strategies for self-control. Another family of strategies is called situation modification and these modify some of the other factors in distractions, such as turning off notifications. This method is less effective than the previous one but can still be beneficial in certain cases, especially as it stops certain triggers (notifications) from happening. Another type of method is attentional deployment, simply trying to focus on something else. People also use cognitive change strategies, which is when they try to imagine the tempting object to be something else, or to reframe the situation to try to stay motivated. The last strategy is called response modulation and it entails using willpower to overcome the urge to do something, f. e. use a certain device or app. These may include setting a limited time frame to use a device or using self-talk to motivate oneself from using the phone. These are the least effective, as the self-control muscle gets tired after some time and therefore this leads to attention depletion.

Brevers & Turel (2016) have applied similar strategies to self-control regarding mobile phone use, and described six families of self-control strategies:

1. "No strategy – little need to control: the individual has no (or very low) interest in social media (e.g., "never had social media").

2. No strategy – little motivation to control: the individual is interested in and uses social media, but does not want to control access to it (e.g., “I don’t want to control my social media use”).
3. Prevent access – full: in this type of strategy, the individual creates or chooses a context that prevent any physical or perceptual access to social media (e.g., “Spend two days in an area with no service and limited Wi-Fi”).
4. Prevent access – partial: in this type of strategy, the individual creates or chooses a safe context, but with self-selected potential access to social media (e.g., “I put my phone to charge 15 ft away from me”).
5. Modify a feature on the device: in this type of strategy, the individual modifies a feature on the device to allow better control over social media use (e.g., “I put my phone on airplane mode”).
6. Delimit a specific time of use: in this type of strategy, the individual associates a specific context with a preventive or controlled use over social media (e.g., “I plan to stop using social media after 11 pm”).
7. Self-talk: in this type of strategy, the individual uses thinking or mental imagery to reflect on his/her longterm goals and in order to resist to social media use (e.g., “tell myself that there is an important test coming up”).
8. Straightforward self-control: in this type of strategy, the individual resists directly to SNS use and continues the task at hand “finish important tasks before checking my phone.”’

(Brevers & Turel, 2016), p 555-556)

This study proposes to examine the usage of these strategies in terms of trait self-control digital divide.

H3: Lower-educated people will be using fewer and less effective self-regulation methods.

H4: Low-income people will be using fewer and less effective self-regulation methods.

H5: People with higher trait self-control are using more effective strategies than those with a lower one.

Research gap

To summarize, digital divide is a thoroughly studied topic, which intervines notions of internet usage, digitall skills, digital outcomes and the sociodemographic aspects of these measures. Special attention was given to the mere operationalization of the term “digital divide”, the so-called grades of the digital divide (Van Deursen & van Dijk, 2014; Vasilescu et al., 2020). Scholars explored wether it is only a question of access, digital skills or the outcomes it leads to. Further research also studied the sociodemographic factors that lead to the grades, to see how to determine which people are being disadvantaged and which are not (Brandtzæg et al., 2011; Friemel, 2016; Calderon Gomez, 2021). One area that has been left unexplored is the connection between the divide and its effect on well-being. However, the well-being difference between groups is not a new divide in itself, it is just an extension of the outcome divide (the 3rd-grade digital divide), as the potential impact on well-being is a consequence (outcome) of usage.

Well-being in terms of technology use is a very salient topic in the last decades, as many scholars try to use communication research methods to see if technology is a plague to our society or not (Valkenburg, 2022). Plague might be a harsh word to use, however, the approaches to the impacts are various and sometimes extreme. As it usually is with such vast and abstract topics, the consensus on whether there is a relationship is yet to be reached (ibidem), most metareviews conducted on this topic report conflicting and inconsistent findings. Few studies however suggest that this relationship depends on the individual skills, specifically on their ability to control their usage and to be mindfull (Reinecke et al., 2022).

Most of the studies trying to explore the sociodemographic factors behind smartphone usage effects on well-being only aim to explore the directional relationship. None of the studies however tried to see if there is a relationship between sociodemographic factors (or the digital divide) and self-control. This study aims to fill in the blank spaces in this research area and explore the connection between sociodemographic factors and self-control and the subsequent potential effect on well-being.

Methodology

The proposed method to answer these research questions and their sub-questions is to conduct a cross-sectional quantitative online survey. Both of the fields involved in these questions (connection of media use to well-being and digital divide) are already thoroughly studied - the study does not have to confirm whether the digital divide exists or if self-control is essential for one's well-being. The goal is to confirm if these constructs have a relationship.

Sample

Data collection took place in September 2022 via a Czech panel Trendaro. The panel has a good representative sample of the online Czech population, it contains around 30.000 respondents. Respondents for the panel are recruited via the snowball method, usually either by acquaintances who already are in the panel, or by various online channels such as ads or social networks. The questionnaire was created via Trendaro's own internal system. The questionnaire was not incentivized - people had been completing it for free. Other questionnaires are usually incentivized on this platform.

The questionnaire focused only on the younger population, i. e. only people 18-24 years old. The reason behind this is that the youngest generation is the most impacted by the effects of technology on our well–being, so the sample was narrowed down only to them. The sample was stratified into several categories - gender, income, education, city size, living location and voting behavior. The sizes of different groups were taken from the Czech statistical office and the percentage of the people in different categories in the sample was approximately the same as in the Czech population. Income was defined by calculating household income per person and then placing it within three groups depending on current official data about incomes - low income, medium income and high income.

Measures

First, respondents filled in the Brief self-control scale (Tangney et al., 2004). The survey contained 12 items on the scale, respondents had to choose on a 7-point Lickert scale if the statements presented in the questions resembled how they feel or act, or not at all. The order of the items was randomized in two batches. Both the statements and the scale had to be translated into Czech, which was done with a help of an English - Czech translator.

The next questions were focused on different self-control strategies. First, a model situation was presented to the respondents so they all had the same notion of what is asked. ("The next questions will ask you about situations in which you need to focus on something and do not want to be distracted by your smartphone. Try to imagine this kind of situation. For example when you study for an exam or do an important task."). Respondents also had the option to say that they do not use a smartphone and this situation, therefore, does not apply to them. These people were then filtered out from the questions focusing on the self-control strategies.

This was followed by seven questions, which first contained a description of a self control strategy and the respondents had to choose on a four point semantic scale how often do they use this particular strategy. The most extreme options were: "I do this always when I need to focus." and "I never do this.". The answers were then coded to a scale of 1 to 4, with 1 meaning the most intense usage and 4 meaning not using this strategy at all. A more standardized time based scale (f. e. daily, weekly, monthly) was not not used as this would not reflect the differences in lifestyle people might have. Respondents with certain occupations such as students might have to focus daily and other people may have to focus in this way more scarcely, so this type of scale better reflects the actual importance of strategy than the mere frequency.

The descriptions of strategies were similar to the ones provided by Brevers & Turel (2016), but concretized, so respondents had a more specific notion of what the strategy means and to avoid confusion. The strategies were these:

- **Prevent access – full**
  - In this type of situation, how often do you go somewhere where there is no internet when you wish not to be distracted by your phone?
- **Prevent access – partial**
  - In this type of situation, how often do you put your phone further away when you want to focus, so it is more difficult for you to distract yourself?
- **Feature modification**
  - In this type of situation, how often do you turn on or turn off some kind of function to make your phone distract you less? (For example, you turn off sound and notifications or turn on the plane mode…)
- **Self-control**
  - In this type of situation, how often do you just leave your phone by your side and try to ignore it as much as possible?
- **Time limit**
  - In this type of situation, how often do you put a limit on the time you can use your phone? (For example, "I will use the phone only for fifteen minutes and then I will work.")
- **Self-talk**

- In this type of situation, how often do you remind yourself of the reason why you need to focus? (For example by reminding yourself of what happens when you finish the task. Or you imagine, what will it be like when you achieve your long term goal that the task helps to achieve).

- **No strategy**
    - In this type of situation, how often do you do nothing out of the methods presented in the previous questions?

A vast database of information about the respondents was acquired with the data, so most of the socioeconomic factor variables did not have to be included in the questionnaire itself. The only socioeconomic factor included in the questionnaire was parental education - respondents chose the highest education achieved by either of their parents from a list of the grades of education in the Czech republic.

Data Analysis

The data was analyzed using SPSS 20. Five steps had to be taken to test the introduced hypotheses. The first step of the analysis aimed to create a trait-self-control index out of the 12 questions of the Brief self-control scale. First, questions 1, 5, 7 and 10 had to be recorded, as they were positively phrased, whereas the other questions were phrased negatively, so the Lickert scale was reversed. Then principal component analysis with varimax rotation was used to identify the underlying factors. The analysis revealed 3 possible factors, two of them overlapped, so items which loaded onto both of these factors were excluded. Factor loadings were used above 0.5. Three items did not load into any of the factors. Cronbach's Alpha reliability test was performed on both of the extracted factors. Values were above 0.6, so the reliability was acceptable. Two self-control measures were then created, one for both of the factors.

Then the analysis proceeded with preparing the sociodemographic data. First, the question about parental education was recoded from string values to numeric, so it can be used in further analysis. Then, all the other sociodemographic variables had to be altered from string to numeric, as some contained missing values, which were put in as string variables, which would obstruct further analysis.

Furthermore, the sociodemographic data for education, income, religion, city size (urban vs rural) and voting behavior were obtained as 0 or 1 dummy variables, so they had to be combined into one variable. This was done by creating a new variable for each socio-economic factor, and then recoding it accordingly using the dummy variables. The variables were coded so the numbers would serve as a scale and not as a category - therefore lowest education or income would be a 1, and the highest would be a 4.

Then, a series of linear regressions were performed on each of the socioeconomic factors separately. The goal of this analysis was to determine if there is a relationship between self-control and various socioeconomic factors, therefore if there possibly exists a digital outcome divide in self-control and therefore in well-being as well. The factors were used as an independent variable, self-control index was used as a dependent variable. Then a multiple linear regression analysis was done on all sociodemographic factors at once. This was then performed on the second self-control index as well. All these regressions fulfilled the requirements for regressions - Gauss-Markov assumptions. Next, ANOVA had to be performed on voting behaviour, as it is a categorical variable.

The last step of the analysis focused on determining if various socioeconomic groups are using different self-control strategies and if people with higher trait self-control use different strategies. A T-test was performed on the dichotomous variables (gender and religion) and then an ANOVA was performed on the other variables. The socioeconomic factors were used as independent variables (factors) and a usage scale (1 - every time, 4 - never) was used as a dependent variable.

Results

Respondents

Given the fact that the questionnaire was not incentivized, the response rate was lower than one would usually expect - only 42 %. 1035 respondents were targeted with the questionnaire, 432 people have filled it in and a randomly chosen stratified sample of 300 people was picked out of the 432 completed questionaires.

The stratification was done according to the latest data provided by the Czech statistical office, several categories were given percentages (or quota) that the sample had to meet, randomized respondent choice was than used to create a balanced sample. The criteria for stratification were city size, work position (full time, part time, maternity leave, student, unemployed), education, income, place of living (which district of the Czech Republic they live in) and gender. The quotoas were interconnected, meaning there was equal parts of all of the groups in each of the segment.

The only liability of the sample lies in the gender - for some reason women have responded to the questionnaire in greater numbers than men, therefore the sample contains more women than men (56 % women, 44 % men). This may have introduced some inconsistencies when performing test which need equal group size.

Table 1 Demographic profile

	N	%
Gender		
Male	133	44 %
Female	167	56 %
Education		
Basic education	57	19 %

Basic without a diploma	44	15 %
Basic with a diploma	154	51 %
University degree	45	15 %
City size		
City size up to 2 thousand inhabitants	69	23 %
City size 2 - 10 thousand inhabitants	74	25 %
City size 10 - 50 thousand inhabitants	61	20 %
City size over 50 thousand inhabitants	96	32 %
Income		
Low	125	42 %
Middle	100	33 %
High	75	25 %

Self-control index

To explore if there is a relationship between self-control and socioeconomic factors, self-control scale first had to be created. The scale was computed out of the 12 questions of the Brief self-control scale (Tangney et al., 2004). First, items which had a positive formulation had to be recoded into the reverse of the original 7-point Lickert scale. This means, that the higher the score, the less trait self-control a person has.

A principal component factor analysis was then performed on the 12 questions. Values below .5 were suppressed. The KMO measure of sampling adequacy was .76, which was adequate, as the minimum acceptable value is .5. The analysis revealed three factors. The eigenvalue of the first one is 3.12, the factor explained 26 % of the variance. The second eigenvalue is 1.45 and it explained 12.1 % of the variance. The last factor had an eigenvalue of 1.34 and explained 11.13 % of the variance.

As per the factor loading of the items, the third factor had to be excluded, because it contained only two items. The other factors contained five and three items each, which all had factor loadings above .5, which makes them acceptable to use.

The explained variance of the individual factors is generally not sufficient as usually only values above 50 % are accepted. However, the entire solution approaches explaining 50 % of the variance, plus the eigenvalues are above 1, which is the usually acceptable minimum, therefore the factors will be used.

A reliability test was then performed on both of the extracted factors, they showed $\alpha=.67$ and $\alpha=.64$, which is an acceptable value to compute a factor with. Two created factors are in line with previous findings. Even though the Brief self control scale authors originally proposed it as a single factor measure, further studies have described two underlying factors in the scale (Maloney et al., 2011) - restraint and impulsivity. Two index scales were therefore created with the factors - *sc_index1* (which potentially reflects the notion of a persons impulsivity) and *sc_index2* (which might describe the ability to restrain one's impulses).

Table 2. Rotated factor matrix of the factors

Factor	Items	Factor loadings
1	I am lazy.	.55
	I say inappropriate things.	.61
	I have trouble concentrating.	.63
	Sometimes I can't stop myself from doing something, even if I know it is wrong.	.64
	I often act without thinking through all the alternatives.	.66
2	I am good at resisting temptation. (recoded)	.64
	People would say that I have iron self- discipline. (recoded)	.79
	I am able to work effectively toward long-term goals. (recoded)	.74

The Brief self control scale is a well validated scale used numerous times since its' creation in 2004, it is therefore surprising to see such a low explained variance in a factor analysis. The reason for such a dip in the value might be in the translation. The questions were translated and well verified with an experienced translator, however, the meaning of certain phrases can change within languages, plus some of the formulations may be archaic even for today's English.

Interestingly enough, all of the recoded items loaded into one factor, which might also suggest some kind of an influence of the recoding process. One of the potential explanations might be that people are simply more likely to answer in a more positive way when the question is phrased positively, and negatively when the question is put negatively. This may have introduced some biases into the research, however, this topic would have to be explored in more detail, which the current dataset does not allow.

Exploring the relationship between self-control and socio-economic factors

Using the self-control scales created in the previous step, a linear regression was executed. Firstly, a linear regression was done on all socioeconomic factors. Parental education, living area (urban vs rural), income, religion and gender did not show any significant relationship between the factor and either of the self-control indexes.

Table 3 The coefficients table of regression of socioeconomic variables on self control

Independent variable	Dependent variable	*b*	sig.
parental education	sc_index1	-.083	.123
living area	sc_index1	-.147	.250
income	sc_index1	-.054	.443
gender	sc_index1	.156	.244
religion	sc_index1	-.144	.273
parental education	sc_index2	.05	.369
living area	sc_index2	-.156	.242
income	sc_index2	-.011	.877
gender	sc_index2	.011	.935
religion	sc_index2	-.167	.219

The only significant result was in education. The regression shows a significant negative relationship between self-control and education (*b*=-.146, p=.009). This is not a surprise as it was previously shown that people with higher self-control have better academic achievements, this is therefore in line with previous research.

Table 4. The coefficients table of regression of education on self-control

	Unstandardized Coefficients		Standardized Coefficients		
Model	**B**	**Std. Error**	**Beta**	**t**	**Sig.**
(Constant)	4.498	0.148		30.477	0
education	-0.146	0.056	-0.15	-2.624	0.009**

a Dependent Variable: sc_index

Next, a regression model containing all of the socioeconomic variables included was tested. The results were however insignificant for both self-control indexes.

Table 5. The coefficients table of regression of all socioeconomic factors on self-control

	Unstandardized Coefficients		Standardized Coefficients		
Model	**B**	**Std. Error**	**Beta**	**t**	**Sig.**
(Constant)	4.624	.283		16.356	0
parent_education	.011	.06	.012	.189	.85
education	-.176	.074	-.155	-2.389	.018*
income	-.013	.084	-.009	-.149	.881
gender	.127	.138	.057	.921	.358
religion	-.137	.142	-.059	-.961	.337
living area	-.058	.137	-.026	-.426	.67

Dependent Variable: sc_index1

Lastly, an ANOVA was conducted on voting behavior, as this is not an ordinal scale, but a categorical variable. There is no relationship between voting behavior and either of the self-control indexes ($F(4, 2)=1.861$, $p =.117$; $F(4, 2)=2.191$, $p =.07$).

This, therefore, supports the first hypothesis (H1), lower educated people do show lower levels of trait self-control. At the same time this refutes the second hypothesis (H2), low-income individuals do not have lower levels of trait self-control.

Frequency of usage of self-control strategies

Next, the analysis focused on the various self-control strategies. To get an overview of the strategies, frequency tables were made. 5 % of respondents stated they do not use a smartphone, they were therefore filtered out from the data about the frequency of usage.

The most commonly used method for self-control was mere self-control (willpower), it is the preferred method of choice for 32 % of people. 29 % of people use feature modification, and 25 % always use self-talk. On the other hand, the most scarcely used methods are access prevention, both full and partial, as 50 % of respondents stated that they never use this method. This is one of the more grim findings, as previous research has shown that these two methods are among the most effective ones (Duckworth et al., 2016).

Table 6. Frequencies of usage

	Every time	**Only when it is important**	**Sometimes**	**Never**
Prevent access – full	7 %	21 %	22 %	50 %
Prevent access – partial	9 %	17 %	24 %	50 %
Feature modification	29 %	23 %	29 %	19 %
Self-control	32 %	20 %	34 %	14%
Time limit	18 %	20 %	23 %	39 %
Self talk	25 %	28 %	31 %	16 %
No strategy	18 %	23 %	46 %	13 %

Relationship between socioeconomic factors and self-control strategies

Next, the analysis proceeded with focusing on the next three hypotheses regarding the self-control strategies being used. The aim was to determine if the intensity of usage and choice of strategy depends on either socioeconomic factors or on self-control index.

First, T-tests for independent samples had to be performed on religion, gender and living area variables, as they are dichotomous. The nonparametric test showed that the data about strategies were normally distributed (p was between .37 and .99 for all variables) and therefore the T-test is an appropriate method of testing.

A series of T-tests were then conducted to explore the relationship between the dichotomous socioeconomic variables and the intensity of strategy usage (on a scale of 1 to 4, 1 being most intense usage a 4 being no usage at all). This analysis has shown three significant results, two regarding gender and one regarding religion. Men ($M = 3$, $SD = 1.105$) are using the time limit strategy significantly less often than women ($M = 2.69$, $SD = 1.130$) ($t(265) = -2.256$, $p = .025$). Men ($M = 2.55$, $SD = .997$) also tend to use the self talk strategy less often than women ($M = 2.3$, $SD = 1.04$) ($t(265) = -2.05$, $p = .042$). As per self talk, religious people ($M = 2.28$, $SD = .996$) use this type of strategy significantly more often than non-religious people ($M = 2.57$, $SD = 1.06$) ($t(284) = -2.379$, $p = .018$). Other than this, none of the results was significant.

Table 7 Results of the T-tests

Strategy	**Independent variable**	**t**	**p**
Prevent access – full	religion	-1.049	.295
	gender	-1.45	.149
	living area	1.046	.297
Prevent access – partial	religion	.8	.42
	gender	-1.17	.243
	living area	1.012	.312

Feature modification	religion	-.305	.761
	gender	-1.05	.29
	living area	-.481	.631
Self-control	religion	-.117	.907
	gender	-.430	.668
	living area	-.207	.836
Time limit	religion	-.738	.461
	gender	-2.26	.025*
	living area	.824	.411
Self-talk	religion	-2.379	.018*
	gender	-2.047	.042*
	living area	-.965	.335
No strategy	religion	.914	.361
	gender	.109	.913
	living area	1.404	.161

Next, other socioeconomic variables were tested to see if people falling into different groups were using different self-control strategies. Out of four variables (education, income, parental education and voting behavior), only parental education yielded a significant result. It showed that parental education can have a significant effect on the frequency of usage of the "Prevent full access" strategy ($F(4, 281) = 2.509$, $p = .042$. 34 % of the variance can be explained by parental education. Post-Hoc test with Dunnett-T3 (as the variance is not equal among the groups) shows that the difference is especially significant between people with parents having a high school education with a diploma and without it ($p = .045$). The differences between other groups are not significant. The table shows the rest of result of the ANOVAs for all the other sociodemographic groups and other strategies.

Table 8 Results of the ANOVA

Strategy	Independent variable	F	p

Prevent access – full	education	1.75	.140
	income	.194	.901
	parental education	2.509	.042*
	voting	1.812	.127
Prevent access – partial	education	.690	.599
	income	.591	.621
	parental education	.475	.754
	voting	.941	.441
Feature modification	education	.396	.818
	income	.657	.579
	parental education	1.270	.282
	voting	1.755	.138
Self control	education	2.110	.08
	income	1.311	.271
	parental education	1.291	.274
	voting	.621	.648
Time limit	education	.896	.466
	income	.886	.449
	parental education	.693	.597
	voting	1.630	.167
Self-talk	education	.928	.448
	income	.551	.648
	parental education	1.507	.2
	voting	.066	.992
No strategy	education	.413	.761
	income	1.779	.151
	parental education	2.445	.047*
	voting	1.778	.133

Based on these results we can therefore reject both the hypotheses 3 and 4. Neither education nor income play a role in the method selection for self control. The analysis has however shown that religion, gender and parental education may play a role in the strategy choice. The role however is only partial as this is true only for certain strategies.

Relationship between self control index and self control strategies

At last, a series of regressions was conducted to see if people with higher self control are also using different strategies to those with a lower self control. I therefore did a regression on the effect of self control index on the frequency of usage of each strategy, using both indexes created in the first step. The analysis has shown only one significant result - people with higher self control index two (sc_index2) are using the self talk strategy more often than people with lower self control index. Other than that, there is no relationship between the level of self control and the choice of self control strategy, which refutes the hypothesis H5.

Table 9 Results of regression of self control on frequency of strategy usage

Dependent variable (strategy)	**Independent variable (self-control index)**	**b**	**p**
Prevent access – full	sc_index1	.021	.687
	sc_index2	.075	.141
Prevent access – partial	sc_index1	.064	.246
	sc_index2	.000	.994
Feature modification	sc_index1	.060	.945
	sc_index2	.040	.478
Self-control	sc_index1	.057	.530
	sc_index2	.079	.151
Time limit	sc_index1	.061	.417
	sc_index2	.106	.07
Self-talk	sc_index1	.061	.278
	sc_index2	.118	.027*
No strategy	sc_index1	-.009	.855
	sc_index2	.045	.352

These results lead to the conclusion that the last hypothesis, H5, is refuted as well. People with higher trait self-control are not using different strategies than people with a lower one, nor are they using more efficient strategies.

Discussion

The answer to the original research question, whether there is a digital outcome divide in well-being, stemming from this study is simple: Luckily, no. This study did not confirm a relationship between the typical sociodemographic factors and self-control, which subsequently implies a relationship between digital divide and well-being cannot be confirmed. Analysis has however brought forth interesting significant findings - it replicated previously confirmed positive relationship between education and self-control and unveiled few unknown differences in usage of different self control strategies. To summarize, this research was not successful in terms of confirming the hypotheses presumed at the beginning of the process, but the absence of significant findings is an optimistic message for the state of our society.

First, this research focused on the relationship between sociodemographic variables underlying digital divide (such as education, income, gender and living area (Livingstone et al., 2021; van Deursen & van Dijk, 2014; Helsper, 2010; Van Dijk, 2009)) and trait self-control. Trait self control was previously shown to be the key determinant in successful digital use management and therefore also in maintaining well-being (Reinecke et al., 2022, Brevers & Turel, 2019; Panek, 2014).

Two self-control index measures were created based on the Brief self-control scale (Tangney et al., 2004), which were used for later analysis. It is however important to note that the analysis stumbled upon certain issues during the creation of these indexes. All of the 12 items of the scale are supposed to load into only one factor, which was not true for this factor analysis, where three factors were revealed by the principal component analysis. Previous research of Brief self control scale has however suggested there might be two constructs in this scale - impulsivity and restraint, which is in line with the questions involved in the indexes (Maloney et al., 2011).

Furthermore, these factors individually did not explain over 50 % of the variance. Given the fact that they did explain over 50 % when combined, the factors were still used for further analysis, but still, this should be taken into account. This error can be mainly attributed to the translation, as all the other requirements for the use of this scale were fulfilled.

Two of the factors were then used to create two self-control indexes. A series of linear regressions of the relationship between self-control (represented by each of the self control factors) and sociodemographic variables (education, income, city size, gender, parental education). Only one of the factors has been shown to have a significant relationship with self-control, which was education. This is however not unexpected, as Gaudreau et al. has already proven this relationship in 2014. This study therefore did not uncover new significant factor influencing self control, but it potentially does prove that there is no relationship between the sociodemographic factors and self-control. In turn, given the effects self-control has on well-being, this may also unveil that technology is not affecting the well-being of digitally less skilled people in greater amounts than those who are digitally skilled.

Another branch of the research focused on the self-control strategies used by different socio demographic groups. The analysis revealed some interesting findings - sadly, generally speaking, people tend to use the strategies that are most effective (either full or partial access restriction) less often than the less effective ones (self-control or self-talk). Furthermore, women more often tend to use strategies such as self-talk and time limit than men, religious people also tend to use self-talk more often than non-believers. People with parents with higher education also tend to use the strategy of access restriction more often.

Lastly, the analysis explored the relationship between trait self-control and strategy usage. Interestingly, people with higher trait self-control more often opt to use the “self-talk” strategy - they remind themselves why the task they need to finish is important and what is the good they get out of it. The aforementioned strategy is not among the most effective ones, yet in the case of strategy usage, any strategy is better than none.

These findings are novel and shed some light on the strategy usage, but also help to explore the original research question in more depth. The key message that these results send is that all sociodemographic groups and groups of people with the same trait self-control use the strategies mostly in a similar way (with a few exceptions). Thus, none of the groups is executing self-control in a more efficient way, which implies that the digital outcome divide in well-being may not be deepened by the choice of strategy.

To conclude, the presented research did not find any indication of the potential for a digital outcome divide in the form of a worsened impact on well-being in disadvantaged socio demographic groups. The presented findings are however based on the presumption that self-control is indeed an important mediator in well-being and it was studied as the main measure for this study. In further research, a direct study of the phenomena presented (the relationship digital divide and well-being) may be beneficial, for example by direct assessment of well-being and connecting that to a measure for niveau of digital divide.

Furthermore, this study relied mainly on sociodemographic factors as indicators for the digital divide. This is a very narrow manner of defining the divide, which focuses on the cause (income, education etc.) and not the consequence (actual digital skills or the amount of disadvantage faced by individuals). Perhaps creating a tool to measure actual digital skills or subsequent lack of knowledge in individuals and then using this to explore the potential dire consequences these people face would be another mean to explore the phenomena of the digital divide and its subsequent consequences for us as a society in a greater depth.

Bibliography

Appel, Marker, C., & Gnambs, T. (2020). Are Social Media Ruining Our Lives? A Review of Meta-Analytic Evidence. Review of General Psychology, 24(1), 60–74. https://doi.org/10.1177/1089268019880891

Bauer, Loy, L. S., Masur, P. K., & Schneider, F. M. (2017). Mindful Instant Messaging. Journal of Media Psychology, 29(3), 159–165. https://doi.org/10.1027/1864-1105/a000225

Bayer, Dal Cin, S., Campbell, S. W., & Panek, E. (2016). Consciousness and Self-Regulation in Mobile Communication. Human Communication Research, 42(1), 71–97. https://doi.org/10.1111/hcre.12067

Bhargava, V. R., & Velasquez, M. (2021). Ethics of the Attention Economy: The Problem of Social Media Addiction. Business Ethics Quarterly, 31(3), 321–359. https://doi.org/10.1017/beq.2020.32

Bi, & Zhang, R. (2022). “I will buy what my ‘friend’ recommends”: the effects of parasocial relationships, influencer credibility and self-esteem on purchase intentions. Journal of Research in Interactive Marketing. https://doi.org/10.1108/JRIM-08-2021-0214

Błachnio, A., & Przepiorka, A. (2016). Dysfunction of selfregulation and self-control in Facebook addiction. The Psychiatric Quarterly, 87(3), 493–500. doi:10.1007/s11126-015-9403-1

Brandtzæg, P. B., Heim, J., & Karahasanović, A. (2011). Understanding the new digital divide—A typology of Internet users in Europe. International Journal of Human-Computer Studies, 69(3), 123–138. https://doi.org/10.1016/j.ijhcs.2010.11.004

Brevers, & Turel, O. (2019). Strategies for self-controlling social media use: Classification and role in preventing social media addiction symptoms. Journal of Behavioral Addictions, 8(3), 554–563. https://doi.org/10.1556/2006.8.2019.49

Cain, N., & Gradisar, M. (2010). Electronic media use and sleep in school-aged children and adolescents: A review. Sleep Medicine, 11, 735–742. doi: 10.1016/j.sleep.2010.02.006

Calderon Gomez, D. (2021). The third digital divide and Bourdieu: Bidirectional conversion of economic, cultural, and social capital to (and from) digital capital among young people in Madrid. New Media & Society, 23(9), 2534–2553. https://doi.org/10.1177/1461444820933252

Claro, M., Preiss, D. D., San Martín, E., Jara, I., Hinostroza, J. E., Valenzuela, S., Cortes, F., & Nussbaum, M. (2012). Assessment of 21st century ICT skills in Chile: Test design and results from high school level students. Computers and Education, 59(3), 1042–1053. https://doi.org/10.1016/j.compedu.2012.04.004

DiMaggio, P, Hargittai, E, Celeste, C. (2004) From unequal access to differentiated use: a literature review and agenda for research on digital inequality. In: Neckerman, K (ed.) Social Inequality. New York: Russell Sage Foundation, pp. 355–400.

Donner, J., Gitau, S., & Marsden, G. (2011). Exploring Mobile-only Internet Use: Results of a Training Study in Urban South Africa. International Journal of Communication, 5, 574–597.

Du, Kerkhof, P., & van Koningsbruggen, G. M. (2019). Predictors of Social Media Self-Control Failure: Immediate Gratifications, Habitual Checking, Ubiquity, and Notifications. Cyberpsychology, Behavior and Social Networking, 22(7), 477–485. https://doi.org/10.1089/cyber.2018.0730

Duckworth, & Seligman, M. E. P. (2005). Self-Discipline Outdoes IQ in Predicting Academic Performance of Adolescents. Psychological Science, 16(12), 939–944. https://doi.org/10.1111/j.1467-9280.2005.01641.x

Duckworth, White, R. E., Matteucci, A. J., Shearer, A., & Gross, J. J. (2016). A Stitch in Time: Strategic Self-Control in High School and College Students. Journal of Educational Psychology, 108(3), 329–341. https://doi.org/10.1037/edu0000062

Friemel, T. N. (2016). The digital divide has grown old: Determinants of a digital divide among seniors. New Media & Society, 18(2), 313–331. https://doi.org/10.1177/1461444814538648

Gaudreau, Miranda, D., & Gareau, A. (2014). Canadian university students in wireless classrooms: What do they do on their laptops and does it really matter? Computers and Education, 70, 245–255. https://doi.org/10.1016/j.compedu.2013.08.019

George M. J., Russell M. A., Piontak J. R., Odgers C. L. (2018). Concurrent and subsequent associations between daily digital technology use and high-risk adolescents' mental health symptoms. Child Development, 89(1), 78–88.

Hacker, K. L., & van Dijk, J. A. G. M. (2000). Digital Democracy. SAGE Publications.

Halfmann A, Rieger D: Permanently on call: the effects of social pressure on smartphone users' self-control, need satisfaction, and well-being. J Computer-Mediated Commun 2019, 24:165–181, https://doi.org/10.1093/jcmc/zmz008.

Hancock, J. T., Liu, X., French, M., Luo, M., & Mieczkowski, H. (2019, May). Social media use and psychological well-being: a meta-analysis. In 69th Annual International Communication Association Conference (pp. 24-28).

Hargittai, E., & Hinnant, A. (2008). Digital Inequality. Communication Research, 35(5), 602–621. https://doi.org/10.1177/0093650208321782

Harris, C., Straker, L., & Pollock, C. (2017). A socioeconomic related 'digital divide' exists in how, not if, young people use computers. PloS One, 12(3), e0175011–e0175011. https://doi.org/10.1371/journal.pone.0175011

Helsper, E. J. (2010). Gendered Internet Use Across Generations and Life Stages. Communication Research, 37(3), 352–374. https://doi.org/10.1177/0093650209356439

Hofmann, Baumeister, R. F., Förster, G., & Vohs, K. D. (2012). Everyday temptations: An experience sampling study of desire, conflict, and self-control. Journal of Personality and Social Psychology, 102(6), 1318–1335. https://doi.org/10.1037/a0026545

Hofmann, Luhmann, M., Fisher, R. R., Vohs, K. D., & Baumeister, R. F. (2014). Yes, But Are They Happy? Effects of Trait Self-Control on Affective Well-Being and Life Satisfaction. Journal of Personality, 82(4), 265–277. https://doi.org/10.1111/jopy.12050

Hofmann, Reinecke, L., & Meier, A. (2016). Of sweet temptations and bitter aftertaste: Self-control as a moderator of the effects of media use on well-being. In The Routledge Handbook of Media Use and Well-Being: International Perspectives on Theory and Research on Positive Media Effects (pp. 211–222). https://doi.org/10.4324/9781315714752

Huang, C. (2020). A meta-analysis of the problematic social media use and mental health. International Journal of Social Psychiatry, 0020764020978434.

Inzlicht M, Werner KM, Briskin JL, Roberts BW: Integrating models of self-regulation. Annu Rev Psychol 2021, 72: 319–345, https://doi.org/10.1146/annurev-psych-061020-105721

Kahneman, D. (2013). Thinking, Fast and Slow (1st ed.). Farrar, Straus and Giroux.

Kardefelt‐Winther D., Heeren A., Schimmenti A., van Rooij A., Maurage P., Carras M., Billieux J. (2017). How can we conceptualize behavioural addiction without pathologizing common behaviours? Addiction , 112(10), 1709–1715. doi:10.1111/add

Korrup, & Szydlik, M. (2005). Causes and Trends of the Digital Divide. European Sociological Review, 21(4), 409–422. https://doi.org/10.1093/esr/jci030

Livingstone, S., & Helsper, E. (2007). Gradations in digital inclusion: children, young people and the digital divide. New Media & Society, 9(4), 671–696. https://doi.org/10.1177/1461444807080335

Livingstone, S., Mascheroni, G., & Stoilova, M. (2021). The outcomes of gaining digital skills for young people's lives and wellbeing: A systematic evidence review. New Media & Society, 146144482110431. https://doi.org/10.1177/14614448211043189

Lukoff, K., Yu, C., Kientz, J., & Hiniker, A. (2018). What makes smartphone use meaningful or meaningless? Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 2(1), 1–26.

Maloney, Grawitch, M. J., & Barber, L. K. (2012). The multi-factor structure of the Brief Self-Control Scale: Discriminant validity of restraint and impulsivity. Journal of Research in Personality, 46(1), 111–115. https://doi.org/10.1016/j.jrp.2011.10.001

McDaniel, B. T., & Drouin, M. (2019). Daily technology interruptions and emotional and relational well-being. Computers in Human Behavior, 99, 1–8. doi:10.1016/j.chb.2019.04.027

McGillivray, D., & Mahon, J. (2021). Distributed digital capital: digital literacies and everyday media practices. Media Practice and Education, 22(3), 196–210. https://doi.org/10.1080/25741136.2021.1899628

Meier, & Reinecke, L. (2021). Computer-Mediated Communication, Social Media, and Mental Health: A Conceptual and Empirical Meta-Review. Communication Research, 48(8), 1182–1209. https://doi.org/10.1177/0093650220958224

Meier, Reinecke, L., & Meltzer, C. E. (2016). "Facebocrastination"? Predictors of using Facebook for procrastination and its effects on students' well-being. Computers in Human Behavior, 64, 65–76. https://doi.org/10.1016/j.chb.2016.06.011

Milyavskaya M, Saffran M, Hope N, Koestner R: Fear of missing out: prevalence, dynamics, and consequences of experiencing FOMO. Motiv Emot 2018, 42:725–737, https://doi.org/ 10.1007/s11031-018-9683-5.

Moffitt, Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., Houts, R., Poulton, R., Roberts, B. W., Ross, S., Sears, M. R., Thomson, W. M., & Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. Proceedings of the National Academy of Sciences - PNAS, 108(7), 2693–2698. https://doi.org/10.1073/pnas.1010076108

OECD (2001-01-01), "Understanding the Digital Divide", OECD Digital Economy Papers, No. 49, OECD Publishing, Paris. http://dx.doi.org/10.1787/236405667766

Panek. (2014). Left to Their Own Devices. Communication Research, 41(4), 561–577. https://doi.org/10.1177/0093650213499657

Reinecke, Gilbert, A., & Eden, A. (2022). Self-regulation as a key boundary condition in the relationship between social media use and well-being. Current Opinion in Psychology, 45. https://doi.org/10.1016/j.copsyc.2021.12.008

Reinecke, Hartmann, T., & Eden, A. (2014). The Guilty Couch Potato: The Role of Ego Depletion in Reducing Recovery Through Media Use. Journal of Communication, 64(4), 569–589. https://doi.org/10.1111/jcom.12107

Reinecke, Klimmt, C., Meier, A., Reich, S., Hefner, D., Knop-Huelss, K., Rieger, D., & Vorderer, P. (2018). Permanently online and permanently connected: Development and validation of the Online Vigilance Scale. PloS One, 13(10), e0205384–e0205384. https://doi.org/10.1371/journal.pone.0205384

Reinecke, & Meier, A. (2021). Media Entertainment as Guilty Pleasure? In The Oxford Handbook of Entertainment Theory. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190072216.013.12

Robinson, & Knobloch-Westerwick, S. (2016). Mood management through selective media use for health and well-being. In The Routledge Handbook of Media Use and Well-Being: International Perspectives on Theory and Research on Positive Media Effects (pp. 65–79). https://doi.org/10.4324/9781315714752

Schwarz, & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. Journal of Personality and Social Psychology, 45(3), 513–523. https://doi.org/10.1037/0022-3514.45.3.513

Serrano‐Cinca, C., Muñoz‐Soro, J. F., & Brusca, I. (2018). A Multivariate Study of Internet Use and the Digital Divide. Social Science Quarterly, 99(4), 1409–1425. https://doi.org/10.1111/ssqu.12504

Sewall, Bear, T. M., Merranko, J., & Rosen, D. (2020). How psychosocial well-being and usage amount predict inaccuracies in retrospective estimates of digital technology use. Mobile Media & Communication, 8(3), 379–399. https://doi.org/10.1177/2050157920902830

Sriram R., Glanzer, P. L., & Allen, C. C. (2018). What Contributes to Self-Control and Grit?: The Key Factors in College Students. Journal of College Student Development, 59(3), 259–273. https://doi.org/10.1353/csd.2018.0026

Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. Psychological Bulletin, 133(1), 65e94. http://dx.doi.org/10.1037/0033-2909.133.1.65.

Tangney, Baumeister, R. F., & Boone, A. L. (2004). High Self-Control Predicts Good Adjustment, Less Pathology, Better Grades, and Interpersonal Success. Journal of Personality, 72(2), 271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x

Uzun, & Kilis, S. (2019). Does persistent involvement in media and technology lead to lower academic performance? Evaluating media and technology use in relation to multitasking, self-regulation and academic performance. Computers in Human Behavior, 90, 196–203. https://doi.org/10.1016/j.chb.2018.08.045

Valkenburg. (2022). Social media use and well-being: What we know and what we need to know. Current Opinion in Psychology, 45. https://doi.org/10.1016/j.copsyc.2021.12.006

Valkenburg, van el, I. ., & Beyens, I. (2022). The associations of active and passive social media use with well-being: A critical scoping review. New Media & Society, 24(2), 530–549. https://doi.org/10.1177/14614448211065425

Van Deursen, A. J. A. ., & van Dijk, J. A. G. . (2009). Using the Internet: Skill related problems in users' online behavior. Interacting with Computers, 21(5-6), 393–402. https://doi.org/10.1016/j.intcom.2009.06.005

Van Deursen, A. J. A. M., & van Dijk, J. A. G. . (2011). Internet skills and the digital divide. New Media & Society, 13(6), 893–911. https://doi.org/10.1177/1461444810386774

Van Deursen, A. J. A. M., & van Dijk, J. A. G. . (2014). The digital divide shifts to differences in usage. New Media & Society, 16(3), 507–526. https://doi.org/10.1177/1461444813487959

Van Dijk, J. A. G. M. (2005). The Deepening Divide. In The Deepening Divide: Inequality in the Information Society. SAGE Publications. https://doi.org/10.4135/9781452229812

Van Dijk, J. A. (2009). " One Europe, Digitally Divided." Pp. 288 – 305 in A. Chadwick and P. N. Howard, eds., Routledge Handbook of Internet Politics. Abingdon : Routledge.

Van Laar, E., van Deursen, A. J. A. ., van Dijk, J. A. G. ., & de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. Computers in Human Behavior, 72, 577–588. [https://doi.org/10.1016/j.chb.2017.03.010]

Vanden Abeele. (2021). Digital Wellbeing as a Dynamic Construct. Communication Theory, 31(4), 932–955. https://doi.org/10.1093/ct/qtaa024

Vasilescu, M. D., Serban, A. C., Dimian, G. C., Aceleanu, M. I., & Picatoste, X. (2020). Digital divide, skills and perceptions on digitalisation in the European Union - Towards a smart labour market. PloS One, 15(4), e0232032–e0232032. https://doi.org/10.1371/journal.pone.0232032

Wei, L., & Hindman, D. B. (2011). Does the Digital Divide Matter More? Comparing the Effects of New Media and Old Media Use on the Education-Based Knowledge Gap. Mass Communication and Society, 14(2), 216–235. https://doi.org/10.1080/15205431003642707

Wei, K. K., Teo, H. H., Chan, H. C., & Tan, B. C. Y. (2011). Conceptualizing and Testing a Social Cognitive Model of the Digital Divide. Information Systems Research, 22(1), 170–187. https://doi.org/10.1287/isre.1090.0273

Wei. (2012). Number Matters: The Multimodality of Internet Use as an Indicator of the Digital Inequalities. Journal of Computer-Mediated Communication, 17(3), 303–318. https://doi.org/10.1111/j.1083-6101.2012.01578.x

Abstract

The notion of digital divide is a previously well studied topic, this study however aims to take the current state of the research a step further and explore it from the perspective of well-being. Is there a digital divide in well being? Previous research in the field of digital divide has primarily focused on defining the differents levels of it (access, skills and outcome divides), well-being research in connection to technology has merely studied whether there is a relationship between usage and well-being or not. In connecting these two fields, this study sheds some light into the socioeconomic perspective of the technology use. As self control is the key determinant in the effect of technology use on well being, it is used as a key measure in this study. The relationship between digital divide and well-being was therefore studied through measuring self-control of its respondents and then using linear regression to explore the relationship between self-control index and the sociodemographic backgrounds of respondents. The study also included a segment dedicated to self-control strategies, to explore if the sociodemographic groups differ in their choice of self-control strategy. Fortunately, the analysis has found no previously unknown connection between common sociodemographic factors and levels of trait self-control, and only minor differences among the differences in strategy use. Subsequently, it can be inferred that there is no digital outcome divide in how technology is affecting our well-being.

Abstract

Der Begriff der digitalen Kluft ist ein bereits gut untersuchtes Thema. Diese Studie zielt jedoch darauf ab, den aktuellen Stand der Forschung einen Schritt weiter zu bringen und ihn aus der Perspektive des Wohlbefindens zu untersuchen. Gibt es eine digitale Kluft beim Wohlbefinden? Die bisherige Forschung auf dem Gebiet der digitalen Kluft hat sich in erster Linie darauf konzentriert, die verschiedenen Ebenen dieser Kluft zu definieren (Zugang, Fähigkeiten und Ergebnisse), während die Forschung zum Wohlbefinden im Zusammenhang mit der Technologie lediglich untersucht hat, ob es eine Beziehung zwischen Nutzung und Wohlbefinden gibt oder nicht. Durch die Verbindung dieser beiden Bereiche wirft diese Studie ein Licht auf die sozioökonomische Perspektive der Technologienutzung. Da die Selbstkontrolle die entscheidende Determinante für die Auswirkungen der Technologienutzung auf das Wohlbefinden ist, wird sie in dieser Studie als Schlüsselmaßstab verwendet. Die Beziehung zwischen der digitalen Kluft und dem Wohlbefinden wurde daher durch die Messung der Selbstkontrolle der Befragten und die anschließende Verwendung einer linearen Regression untersucht, um die Beziehung zwischen dem Selbstkontrollindex und dem soziodemografischen Hintergrund der Befragten zu untersuchen. Die Studie umfasste auch ein Segment, das den Selbstkontrollstrategien gewidmet war, um zu untersuchen, ob sich die soziodemografischen Gruppen in ihrer Wahl der Selbstkontrollstrategie unterscheiden. Erfreulicherweise hat die Analyse keinen bisher unbekannten Zusammenhang zwischen gemeinsamen soziodemografischen Faktoren und dem Niveau der Trait-Selbstkontrolle und nur geringe Unterschiede bei der Verwendung von Strategien ergeben. Daraus lässt sich ableiten, dass es keine digitale Kluft bei der Auswirkung der Technologie auf unser Wohlbefinden gibt.