Investigating the associations between digital technology, executive function, and sleep quality

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DECLARATION

This thesis is the result of my own work. The material contained in the thesis has not been presented, nor is currently being presented, either wholly or in part for any other degree or qualification.

Signed: Rewarsaw

Dated: 7/10/22

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Abstract

While there is substantial amount of research into the potential relationships between digital technology, executive functioning, and sleep, the majority of this research is inconclusive or mixed. This thesis aimed to investigate whether digital technology use was associated with executive functions, and sleep quality using a mixed-methods approach and open science practices. Methods included a systematic review, observational epidemiology, an online study, and qualitative focus groups.

The systematic review examined a total of eight papers and five aspects of executive functioning. Although there was mixed evidence of associations between smartphones and video gaming, and executive functions, the identified overall evidence base was of poor quality. Methodological issues included an over-reliance on retrospective self-report measures, a lack of longitudinal studies, and homogeneity of groups.

Studies were conducted to attempt to address these methodological issues. Data from the Millennium Cohort Study was used to examine cross-sectional and longitudinal associations between three types of screen media use (social media, playing video games, and watching TV, DVDs, or videos) at age 14, with decision-making and sleep quality at age 14 and age 17 in UK adolescents. Multiple imputation was used to try to account for attrition bias. There was no evidence of associations between adolescent screen use, decision-making, and sleep quality.

An online study aimed to empirically examine the impact of smartphone exposure specifically, with the increased objectivity of behavioural measures of four facets of executive functioning: inhibition, working memory, attention, and decision-making. A UK sample of 217 young adult participants were scored on their smartphone use, sleep quality, and a short battery of executive function tasks. There was a negative association between smartphone use behaviours and sleep quality, and no evidence of associations between smartphone use and any of the four executive functions.

Finally, to anticipate the future direction of objective measurement of these relationships, focus groups explored the practicalities of smartphone use, and the acceptability of monitoring applications and wearable technology to objectively measure participants' smartphone use behaviours, sleep quality, and other sleep-related outcomes in an ecologically valid way. Four themes were identified from the data; 'Functional use', 'Connection', 'Attachment' and 'Distraction and disruption'. Mobile devices were seen as handy tools, useful for everything from document access at work, to navigation and entertainment; however, they also brought the expectation to always be available, leading to detrimental consequences. Wearable technology was viewed favourably for health and connectivity, and as a potential research measurement device.

The studies presented here add incremental evidence to the lack of associations between digital technology, executive function, and sleep; however, they should be interpreted with caution. Future research should focus on longitudinal experiments using comprehensive, objective measures of all constructs to further our knowledge and enable stronger conclusions.

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Chapter 1: General Introduction

Digital technology has grown and advanced tremendously in the last decade. However, cyclic concerns about its potential associations, either positive or negative, with executive functioning and sleep-related outcomes have also grown (Exelmans & Van den Bulck, 2015, 2016; He, Xiao, Su, Tang, & Tu, 2020; Hysing *et al.*, 2015; Orben, 2020a; Pardo & Minda, 2021; Ward, Duke, Gneezy, & Bos, 2017; Woods & Scott, 2016). Investigations into these relationships have primarily been of poor quality and inconclusive (Warsaw *et al.*, 2021). For example, they have lacked longitudinal or objective, experimental designs, which would provide stronger evidence of any associations. With scaremongering articles centred around the impact of digital technology becoming more common within the public domain mass media (Greenfield, 2015; Hari, 2022), and specifically sensationalising the potential for effects on children and adolescents, now is the time for scientific, rigorous examinations (Etchells, 2017; Orben, Etchells, & Przybylski, 2018). This thesis aims to further our understanding of the associations between digital technology, executive functioning, and sleep in adolescents and young adults using a variety of methodologies with increased rigor and conceptual reliability than the existing literature.

1.1 Digital technology

The last decade has seen the rapid growth and development of digital technologies. They have become an integral part of our everyday lives, offering connectivity, education, employment, and leisure functionality. Digital technologies include: social media, smartphones, tablets, smart watches, and electronic video gaming. As of 2019, 88% of UK adults owned a smartphone, 65% owned a tablet, and 78% owned a laptop (Lee & Calugar-Pop, 2019). While the adoption of laptops remained relatively steady in the 7 years prior to this, smartphone ownership increased by 36% and tablet use increased by 49% since 2012. Video game adoption has also grown; in 2020 there was an estimated 3 billion gamers worldwide (Stojanovic, 2022). On average, gamers are ~30 years old, with around 40% being females (GWI, 2021; formerly Global Web Index), outgrowing the widely-held stereotype of gamers being adolescent boys. Recent market research has found that 86% of internet users play games on electronic devices (GWI, 2021); accessing content through their mobile devices and laptops as well as dedicated games consoles. Smart watches have also seen a substantial rise in popularity, with reported users increasing from 6.7 million in 2014, to 29.6 million in 2019 (Fitbit, 2020). This popularity is expected to continue, with projections of 280 million units being shipped globally by 2024 (Arkenberg, Loucks, Silverglate, & Arbanas, 2021).

With almost every adult and adolescent in possession of a smartphone, they are arguably the most ubiquitous of these digital technologies. Smartphones enable a wealth of multi-purpose capabilities and bring unprecedented connectivity, functionality, and user engagement opportunities. Average users tend to spend approximately three hours and fifteen minutes on their phones every day, increasing to almost five hours for those in the top twenty percent (MacKay, 2019), and interacting with their phones between 58 to 85 times (Andrews, Ellis, Shaw, & Piwek, 2015; MacKay, 2019). Interactions in this study referred to when the phone screen was activated, such as unlocking the phone for text message retrieval, or for longer durations such as phone calls and browsing the internet (Andrews *et al.*, 2015). Given the myriad of uses, services, and functionality accessed through these devices, from the operating system itself (e.g., communication and navigation) to the wealth of third-party applications they can be personalised with, their ubiquity in our lives is unlikely to change on any large scale. Smartphones have advanced from simple communication devices to portable personal computers, which allow individuals access to a plethora of opportunities and information (Duggan & Smith, 2013). This immediacy can be beneficial, for ease of information access, maintaining relationships (Lundquist, Lefebvre, & Garramone, 2014), and reducing social isolation (Cho, 2015).

A wide variety of these devices are used daily, with many enabled for internet connectivity. Many activities that would have once been associated with specific devices (e.g., accessing the internet on a computer) are now capable through all mediums (e.g., accessing the internet on smartphones, tablets, and even games consoles). Smartphones may even be the preferred method for browsing online, with UK adults spending twice the amount of time doing so than on a computer (Harrison, 2016). This convergence of technology has led to academic and research circles using the umbrella term, 'screen time'; defined as the length of time spent engaging with screen-based devices and activities (Oxford English Dictionary, 2020). The primary ways of measuring this include hours or frequency of use as a continuous variable, measuring excessive use scores on an existing self-report scale, or by categorising high versus low users often using the polarised extremes of either the usage hours or scores. This has become the convenient composite measure of digital technology and device use. While this is useful and commonly used, it reduces the complexities and nuances of digital technology use, and removes individuals' contexts from the narrative (Orben *et al.*, 2018).

Although the use of technology is functional in everyday life, there is a heavy focus in the literature on understanding this from perspective of excessive/problematic use, which some researchers refer to as smartphone addiction. Although not recognised as an official addiction, smartphone use may meet at least some criteria of an addictive disorder, as outlined by the Diagnostic and Statistical Manual (DSM-5; American Psychiatric Association, 2013). Academics have sought to evaluate, label, and quantify screen media use and specifically smartphone use behaviours through the development and administration of many measurement scales. These include, for example, the Mobile Phone Problem Use Scale (MPPUS) (Bianchi & Phillips, 2005), Smartphone Addiction Inventory (SPAI) (Lin *et al.*, 2014), and the Smartphone Addiction Scale (SAS) (Kwon *et al.*, 2013).

The MPPUS was developed to measure problematic use from constructs such as personality traits, gender, and age. In this instance, problematic use includes situational behaviours, such as individuals continued mobile phone use while driving despite increased legislative and societal controls. Items include: '*I find it difficult to switch off my mobile phone*' and '*I have received mobile* *phone bills I could not afford to pay*'. The scale had a Cronbach's alpha of 0.93. However, the data was collected in 2003, four years prior to mobile phones' advancement to smartphones which came with the introduction of the iPhone in 2007. This is important to note as the way in which smartphones are used ubiquitously, with internet access and a plethora of content instantly available, is different from how mobile phones were used in 2003. The SPAI was developed based on features of internet addiction to identify individuals addicted to their smartphone and predicted that smartphone addiction would have aspects similar to internet and substance addiction. The scale is comprised of four factors: compulsive behaviour, functional impairment, withdrawal, and tolerance. The scale had a Cronbach's alpha of 0.94 and acceptable test-retest reliability. The SAS was developed as a self-diagnostic tool to identify smartphone addiction based on the Korean program for internet addiction (K-scale) and the smartphone's features. The scale had a Cronbach's alpha of 0.97 and is comprised of six factors: daily-life disturbance, positive anticipation, withdrawal, cyber-space-oriented relationship, overuse, and tolerance. Items include: '*Missing planned work due to smartphone usage*', and '*My life would be empty without my smartphone*'. The SPAI and the SAS are particularly common self-reported measures of smartphone addiction within the literature and while they seek to measure the same concept and may have similar items, each is based on a different original measurement.

However, an abundance of self-report measurement scales does not effectively characterise or define what 'problematic' smartphone use is; the incongruence between the measurements and insufficient research has left the concept yet to be firmly established (Harris, Regan, Schueler, & Fields, 2020). A recent systematic review by Harris *et al.* (2020) examined 78 existing scales measuring problematic smartphone use developed in the preceding 13 years. However, the most efficient, or "gold standard" of measurement scales could not be identified; the majority of these scales employed criteria from the DSM, despite controversy over whether problematic smartphone use should be considered an 'addiction'. Moreover, with no validated cut-off scores established, the abundance of measurement scales cannot be accurately compared.

The rapid advancements of digital technologies and the adoption of diverse screen uses have led to societal concern and research interest in their effects (Burnett, 2016; Etchells, 2017; Hari, 2022; Orben *et al.*, 2018), in general and on vulnerable populations such as children (Bell, Bishop, & Przybylski, 2015; Kardefelt-Winther, 2017). Recently, these interests have focused on the potential for impact on aspects of cognitive functioning and sleep outcomes in adults and adolescents. However, this is not a new phenomenon; similar concerns were once shared about the radio and television (Preston, 1941). The emergence of each new technology in the last century or so has provoked similar worries in a cyclic manner, as can be seen in Figure 1 (Orben, 2020a). Personal and parental concerns are raised about a new technology infiltrating lives and minds, leading to media scaremongering and panic creation. Politicians capitalise on the panic to pursue their own gains but outsource finding solutions to scientists. Researchers are looked towards to provide solutions, and research interest increases in an attempt to determine the effects (either positive or negative) and present any valid evidential basis for the concerns. However, the lack of methodological and theoretical frameworks leaves scientists to start from scratch (wheel reinvention). This reduced research efficiency is too slow to effectively guide policymakers, and the arrival of the next new technology restarts the cycle (Orben, 2020a). As desired academic answers to these concerns may have lagged behind technological advancements throughout the last century, research has tended to have to start from scratch with each new digital technology introduced. As a consequence of this, and in the context of more recent technological advancements, the research conducted to provide these desired academic answers may be of a reduced quality from the reduce theoretical underpinnings. This is examined more closely in a systematic review in Chapter Two.

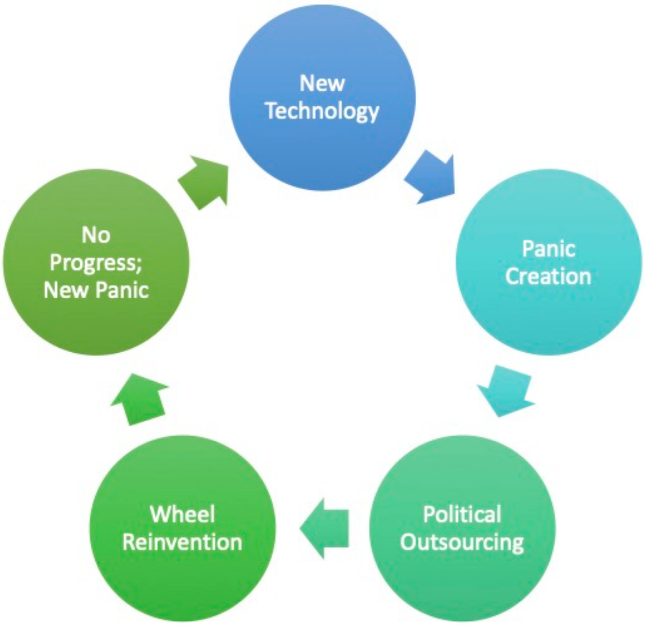

Figure 1: The Sisyphean Cycle of Technology Panics, as outlined by (Orben, 2020a).

It is contested whether individuals can become addicted to smartphones, or the services available through them. These services are often referred to as ‘affordances’ and indicate the functional capabilities smartphones allow access to, either through the device itself (e.g. instant messaging, SatNav), or specific third-party applications or platforms (e.g. Facebook, mobile banking). For instance, social media (Marino, Gini, Vieno, & Spada, 2018; Sun & Zhang, 2021) and gambling (James, O'Malley, & Tunney, 2017; James, O’Malley, & Tunney, 2019) can be accessed through smartphones, indicating that perhaps smartphones act more as a portal to particular content, with the content itself being that which may be used in a problematic way. A core part of smartphone use content is the internet itself, which was first introduced as an addictive concept over twenty years ago (Young, 1998, 2004). However, it is important to note that research focusing on ‘addiction’ to digital technologies and smartphones in particular only relate to a small percentage of everyday users. Therefore, it does not increase our understanding of usage more generally, and consequently how use may be related to health-related behaviours. The advancement of the internet into our daily lives over the last two decades does not predetermine it causing the problematic use and functional impairment that would qualify as an addiction. It is perhaps more accurate to suggest that the internet, however it may be accessed, acts as a facilitator to enable access to other ‘addictive’ constructs.

Another concern which had been raised and promoted is the notion that screen use, for instance the general internet and computer games, may have harmful effects on mental and social wellbeing (review: Bell *et al.*, 2015; Greenfield, 2015). These claims are often made within the mass media (rather than scientific peer-reviewed journals) and provide anecdotes as evidence, drawing sensationalist parallels with global climate change and neurodevelopmental conditions (Bell *et al.*, 2015; Etchells, 2019, pp. 197 - 205). There are a number of theories which seek to explain the relationship between digital technology use and wellbeing; for example the Displacement Hypothesis (Neuman, 1988), which suggests that technology engagement and online communication negatively impacts wellbeing by replacing the time spent on other activities (Valkenburg & Peter, 2007); and the opposing Stimulation Hypothesis, which suggests that digital technology is engaged with to positively affect and facilitate these relationships, thereby stimulating wellbeing (Valkenburg & Peter, 2007).

The application of better theoretical underpinnings has improved digital technology research, enabling each cycle of interest to build on the knowledge base, rather than starting from scratch. This, therefore, increases our understanding of the motivations underpinning digital technology adoption and the impact this has on humans and our behaviours. In 2022, primary motivations for using the internet were cited as for “finding information”, “staying in touch with friends and family”, and “keeping up-to-date with news and events” (Kemp, 2022). Understanding the motivations or reasons why individuals use digital technology is crucial for differentiating between each of these uses and the individual impacts each use may have on our behaviours. The Uses and Gratifications Theory (UGT; Katz, 1959; Katz & Blumler, 1974) states that users and consumers of media and communications play an active role in their own usage; to fulfil a need and to accomplish something. According to this theory, there are four media purposes: 1) 'diversion or entertainment' as a form of escapism; 2) 'personal relationships', as a substitute for real-life interpersonal interaction; 3) 'personal identity', to associate with characters both in written and visual formats; and 4) 'surveillance', for information gathering. This theory differs from other media effect theories by focusing on "what do people do with media", as opposed to "what does media do to people" (Katz, 1959, p. 2).

Since its proposal and the formation of theoretical foundations, the UGT has gained interest and research has extended its use to apply to new forms of digital and screen-based media (Ruggiero, 2000). For instance, during the height of its popularity, research examined the psychological motivations underlying engagement with the augmented reality (AR) mobile game, *Pokémon Go* (Rauschnabel, Rossmann, & tom Dieck, 2017). Underpinned by the UGT, users' engagement with playing the AR game was driven by enjoyment, physical activity, flow, nostalgia, and image. Additionally, the wide variety of uses of mobile phones and smartphones lead to many gratifications and motivations behind their use; including, for instance, affection, entertainment, and psychological reassurance. However, given that there is content which can be accessed through smartphones too, the UGT extends to the motivations for using the general internet and social media (Leung, 2013). A recent study by Menon (2022) identified seven drivers behind the short-form videos feature of Instagram Reels; social rewarding self-promotion, entertainment, escape, surveillance, novelty, documentation, and trendiness. These motivations and socio-psychological traits were associated with certain Instagram behaviours (e.g. content production vs consumption). While this was a novel study focusing on a specific aspect of one social media platform, Instagram Reels, it is important these drivers and motivations receive further investigation using more comprehensive, objective measures or exploratory qualitative methods. This is particularly important during a time when social media platforms are developing similar features to compete with one another, therefore the results may be more widely applicable that initially thought.

An additional theory underpinning digital technology adoption is the Technology Acceptance Model (TAM) (Davis, 1985), which proposes that the rate of uptake of new technologies can be predicted through its perceived ease of use (the effort required), and perceived usefulness (the degree to which it may enhance an individual's life). Joo and Sang (2013) investigated the factors which influence technology and smartphone adoption and use. They suggest that the TAM and the UGT would benefit from being merged into an integrated model. While the TAM focuses on extrinsic motivations of technology use, such as how it is adding value or ease, the UGT focused on intrinsic motivational factors, such as for escapism, leisure and entertainment.

More recently, the move towards open access, reproducible science in this area resulted in the proposal of the Digital Goldilocks Hypothesis (Przybylski & Weinstein, 2017). This predicts that moderate levels of technology use is not intrinsically harmful (Etchells, Gage, Rutherford, & Munafò, 2016; Parkes, Sweeting, Wight, & Henderson, 2013), and may even be advantageous. The authors state this as "empirically derivable balance points" that may be optimal for young people. Participants were identified and recruited from the National Pupil Database and used a large-scale survey to be the first to test for curvilinear relations between screen time and wellbeing. The design also accounted for additional contextual factors when it comes to technology use (activity and day of the week). Results suggest that after a certain threshold of screen time having no impact, the small negative effect size accounted for ≤1% of variability in wellbeing. This posits that there is an optimal amount of screen time, at which digital technology engagement is not intrinsically harmful to wellbeing. Too little or too much exposure could therefore have a negative impact, demonstrating an inverted U shape of a curvilinear relationship. Similarly, a recent large scale longitudinal analysis examined the social media use and life satisfaction of UK adolescents (Orben, Przybylski, Blakemore, & Kievit, 2022). According to this, there may be sex-specific time periods of developmental sensitivity to social media whereby higher estimated social media use predicted decreased life satisfaction ratings a year later, and vice versa. For males, this was between 14-15 and at 19 years old, and for females between 11-13 and at 19 years old. Going forwards, the Uses and Gratifications

Theory, and the Digital Goldilocks Hypothesis may be the most applicable to how digital technology, both established and emerging, may be used, and future research should strengthen and advance these theories appropriately.

1.2 Executive function

Executive Functions (EF) are a selection of effortful and deliberate cognitive processes that are responsible for goal attainment and attentional orientation (Diamond, 2013). They are required in times of concentration and assist with time management and organisation, attention, and focus, and withholding predominant actions. It has been suggested that there are three core components of executive functions; updating (monitoring, addition, and deletion from working memory), shifting (flexible mental switching), and inhibition (withholding predominant responses) (Miyake *et al.*, 2000). While there is separation between these processes, there are also some overlap; this led to the development of the Unity and Diversity Framework (Miyake & Friedman, 2012). This suggests that while all tasks measuring EFs load onto a common latent variable of executive function (unity), the shifting and updating aspects of EF are nested within this, with some tasks loading onto each aspect respectively (diversity). From this, higher-order EFs (such as problem solving, planning, and reasoning), are developed (Collins & Koechlin, 2012). In this model, inhibition is removed after it was almost perfectly correlated with the common EFs in accordance with the unity framework (Friedman, Miyake, Robinson, & Hewitt, 2011; Friedman *et al.*, 2008). This concept has been supported further by evidence that inhibition is subsumed by working memory and varies based on individual differences in working memory capacity (Tiego, Testa, Bellgrove, Pantelis, & Whittle, 2018).

Executive functions can be measured using subjective self-reported questionnaires to identify and quantify behaviours. For example, the Barratt Impulsiveness Scale (BIS) is designed to measure the behavioural construct of impulsiveness and has been condensed to an 11-item measure for ease of administration with good validity (Patton, Stanford, & Barratt, 1995). Questionnaire measures exist for a range of EF, including attention (Attention-Related Cognitive Errors Scale) (Cheyne, Carriere, & Smilek, 2006), and delay discounting (Monetary Choice Questionnaire; MCQ) (Nigro & Cosenza, 2016). Objective behavioural task measures of EF are also used within the literature. These tasks often simulate scenarios in interactive formats to enable true behavioural representations of EFs. For example, inhibition is often measured using the Stop Signal task (Verbruggen *et al.*, 2019; Verbruggen & Logan, 2008), which requires participants to press a keyboard response to specific stimuli as quick as possible. However, this response must be withheld on the presentation of the stop signal (either visual or auditory) a varying number of milliseconds after the stimulus presentation. Participant's successful response withholdings and reaction times provide information on inhibitory control conflict, with increased reaction times denoting reduced inhibition. Behavioural measures of risk taking include the Balloon Analog Risk Task (BART) (Lejuez *et al.*, 2002), whereby risky decisions to a certain threshold yield a reward. The task involves a simulation of a balloon and a pump, with each click on the pump accumulating 5 cents in a temporary bank, which must be collected and transferred to a permanent bank before the balloon explodes. If the money is not transferred, the participant loses the money accumulated from that balloon. This is a small selection of the various measures of EF across the literature.

A distinction can be made between 'hot' and 'cool' executive functions; hot EFs are driven by emotion and the dissonance of instant gratification versus long-term rewards (Zelazo, Qu, & Müller, 2005), whereas cool EFs involve conscious control of thoughts and actions using logic and critical thought (Rubia, 2011). Evidence suggests cool EFs are associated with academic performance, and hot EFs are related to emotional difficulties (Poon, 2018). EFs are essential for the development and maintenance of mental and physical health, academic and general life success, and development (Diamond, 2013). Reduced executive functioning may be as a result of neurodiversity, such as Attention Deficit Hyperactivity Disorder (ADHD) or autism, or caused by conditions such as dementia and depression (Goodman, 2021). Impaired executive functions are associated with addiction (Baler & Volkow, 2006), depression, (Tavares *et al.*, 2007), and interpersonal problems (Eakin *et al.*, 2004). Whereas improved EFs, such as self-control, can lead to academic success (Borella, Carretti, & Pelegrina, 2010), weight-loss attainment (Crescioni *et al.*, 2011), and increased overall quality of life (Brown & Landgraf, 2010). However, executive functions are also trainable across the life course (Diamond, 2013) in the absence of neurodevelopmental conditions (e.g. Attention Deficit Hyperactivity Disorder or dementia) and can be improved upon at any age with repeated practice. In sum, executive functions operate towards successful self-regulation through attentional control, active suppression of unconscious behaviours, and flexible switching between goals (Hofmann, Schmeichel, & Baddeley, 2012).

1.2.1 Digital technology and Executive Function

Currently, the focus of much of this research is on the potential impact on cognition, specifically executive functioning. As digital technology and particularly mobile phones have become 'smart', these devices have gained services and functionalities which can support our cognition. For example, smartphones as assistive technology, perhaps for the purpose of socially acceptable memory aids in children and adolescents with acquired brain injury (Plackett, Thomas, & Thomas, 2017), or even general everyday assistance (e.g. contact details, navigation, and mathematics). However, sensationalist media articles also raise the question of whether reliance on digital technology may harm cognitive functioning; suggesting that as technology advances, so does its capability to supersede our mental processes (Greenfield, 2015; Hari, 2022). However, research remains inconclusive. Deficits in the inhibitory control subcomponent of EFs have been associated with problematic smartphone use (Hartanto & Yang, 2016; Tang, Eachus, Szeto, & Royle, 2018; Wilmer, Sherman, & Chein, 2017). Chen, Liang, Mai, Zhong, and Qu (2016) sought to examine the effect of smartphone use on inhibitory control through its associated neural electrophysiological components. Participants were categorised into excessive use and control groups (16 per groups) using the Smartphone Addiction Inventory (SPAI) and completed a novel Go-NoGo task, which had three visual cue contexts, blank, neutral, and smartphone-related, surrounded by a coloured frame to indicate trial type. They were asked to respond with or withhold (inhibit) a keyboard response based on the cue context and whether it was a 'go' trial (red) or a 'no-go' trial (green). Results demonstrated a general deficit in inhibition in the excessive smartphone use group. There was an increased negative N2 amplitude in NoGo trials for excessive smartphone users compared to 'normal' smartphone users. N2 is the ERP component which may reflect conflict monitoring and inhibitory neural processes (Falkenstein, Hoormann, & Hohnsbein, 1999; Randall & Smith, 2011). Therefore, an increased negative N2 amplitude may indicate increased conflict in inhibitory processes for excessive smartphone users during NoGo trials as they attempted to withhold responses. Although there was some electrophysiological evidence, this study did not provide any behavioural evidence as there was no difference between groups for inhibition accuracy or reaction time as measured by the Go-NoGo task (Chen *et al.*, 2016). These results should be interpreted with caution too as the groups were only comprised of sixteen participants each, which is too few to state findings with any certainty.

Video games have an array of genres available, including learning and education, strategy, simulation, role-play, and action (e.g. first-person shooter) gameplay (Adams, 2013); and each genre may have differential effects on executive functions (Bediou *et al.*, 2018b; Jiwal, Jain, & Jain, 2019). Players of First Person Shooter (FPS) games displayed reduced inhibition capabilities compared to players of other online games (Deleuze, Christiaens, Nuyens, & Billieux, 2017). This study controlled for appropriate confounding variables (e.g. age, impulsive personality traits, and depressive symptoms). However, it only examined male online video game players, perhaps perpetuating stereotypes in the video game community, which are often sexist (Kuss, Kristensen, Williams, & Lopez-Fernandez, 2022). Although, a strength of the Deleuze *et al.* (2017) study is that it was designed as a pilot study, and presents a good basis for future research into specific video game genres. In contrast, Miedzobrodzka, Konijn, and Krabbendam (2021) examined adolescent video game players inhibitory control using a stop-signal task with emotional recognition stimuli. Greater habitual exposure to violent video games was associated with improved inhibitory control. Inhibition also improves throughout early adolescence to early adulthood (Constantinidis & Luna, 2019), suggesting the capacity for these skills to be honed through practice and developmental maturation. Video gaming has been associated with improved working memory (Waris *et al.*, 2019) and attention (Jiwal *et al.*, 2019). Video games have also been associated with improved learning by enhancing attentional and executive control to tend to task relevant information (Green & Bavelier, 2012), which if tailored appropriately may have substantial applications for real-world training and rehabilitation.

This variation in findings is evident across various executive functions. Exposure to digital technology may benefit task switching performance (Alzahabi & Becker, 2013), working memory (Huang, Young, & Fiocco, 2017), and attentional control (Green & Bavelier, 2012). Conversely, exposure may also be related to reduced task switching capability, (Ophir, Nass, & Wagner, 2009), decreased attentional capacity (Marty-Dugas, Ralph, Oakman, & Smilek, 2018; Moisala *et al.*, 2016; Ralph, Thomson, Cheyne, & Smilek, 2014), impaired multi-tasking ability (Donohue, James, Eslick, & Mitroff, 2012), and working memory deficits (Cain, Leonard, Gabrieli, & Finn, 2016; Hartanto & Yang, 2016; He *et al.*, 2020; Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013; Uncapher, Thieu, & Wagner, 2016). Marty-Dugas *et al.* (2018) examined the relationship between general smartphone use (e.g. how frequently participants sent and received messages, used social media etc.) and absent-minded smartphone use (e.g. using their phone without a specific purpose in mind) and everyday inattention. Their findings demonstrated that absent-minded smartphone use drove the associations between smartphone use and increased lapses in attention. However, this study relied on self-reported questionnaires to quantify inattention and smartphone use, without validating their smartphone use questionnaire first, or using an existing developed and validated one from the plethora of scales available. It is likely that there are discrepancies between behavioural measures and self-reported measures, with participants under- or overestimating their own behaviours (Buchanan, 2016; Hodes & Thomas, 2021; Lee, Ahn, Nguyen, Choi, & Kim, 2017; Lee, Tse, Wu, Mak, & Lee, 2021; Reinholdt-Dunne, Mogg, & Bradley, 2013), either consciously as result of social desirability bias, or unconsciously. The validity of self-reported versus objectively measured smartphone use has been studied across a seven-day monitoring period. Self-report estimates exceed the objective data by an average of 760 minutes per week (Lee *et al.*, 2021). While social networking, messaging, and gaming app use estimates were positively correlated, self-reported and objectively measured overall smartphone use was not related, supporting the idea of discrepancies between self-reported and real-world behaviours. However, this validity study focused on smartphone use as measured in minutes in both conditions, falling into the reductionist notion of 'screen time' without regard to the affordances or activities participants' may have engaged in using their smartphones. Measuring smartphone use behaviours by the content and functionality engaged in would assist in the development of monitoring methods for objective data collection and help conceptualise and focus this area of the literature.

Fewer articles demonstrate no association between digital technologies and executive function, this may be due to publication bias (Kühberger, Fritz, & Scherndl, 2014), which entails null results often not being published. Due to this, a lack of relationship between these two constructs may be more common than we are led to believe. Frost *et al.* (2019) examined whether smartphone use had lingering effects on cognition. Participants were assigned into lower (≤ 2hrs) and higher (≥ 5.5hrs) smartphone use groups and completed measures of delayed gratification and problem solving. There were no group differences in delayed gratification or problem-solving ability. However, these executive functions were measured by self-reported questionnaires, rather than behavioural tasks which would have provided increased objectivity and reliability for real-world behaviours for delaying gratification and problem solving. Additionally, these groups were split solely based on usage time, which is a poor concept for smartphone use when their functionality is so varied. Instead, groups could have been divided based on services and functionality; one group could have been restricted to using only the basic communication functions (e.g. calls, texts, and instant messaging services), and the second groups allowed to use the full functionality of their smartphone.

There may also be no group differences between video game players and non-players in multi-tasking ability. Donohue *et al.* (2012) examined players of First Person Shooter (FPS) video games compared to non-players of FPS on multi-tasking ability. Participants had to complete visually demanding tasks with and without a dual-task component of answering unrelated trivia questions. Video games players and non-players did not differ in their performance, with each group suffering dual-task costs. Therefore, engagement in First Person Shooter video games did not offer protection or immunity from dual-task costs; however, this only accounted for one genre of video gaming (Donohue *et al.*, 2012).

The contradictory and often inconclusive evidence on the nature of these associations may be due to the methodological approaches taken throughout the body of research. Throughout this field, there is a tendency towards cross-sectional studies and a reliance on self-reported questionnaires to quantify smartphone use behaviours, executive functioning, and sleep (Frost *et al.*, 2019; He *et al.*, 2020; Marty-Dugas *et al.*, 2018; Tang, Zhang, Yan, & Qu, 2017). This is further examined in Chapter Two. Although self-report is a useful form of data collection, it is worthwhile specifying the nuances behind this method. It can be used for various types of data, such as in the moment reporting (e.g., Ecological Momentary Assessment (EMA) and diaries), reporting averagely (e.g., "on average how many hours a day do you watch TV?"), or retrospectively estimating use over a specific period (e.g., "how many hours did you watch TV last week?"). However, the methods which capture data averagely or retrospectively are generally poorer, perhaps a consequence of biases in autobiographical memory, which can vary between different populations (e.g., healthy vs depressed individuals) (Hitchcock *et al.*, 2020).

Additionally, the concept of digital technology remains undefined. There is a wide variety of conceptualisations for what digital technology includes, but no clear guidelines on what features constitute digital technology, nor how to accurately measure them in an ecologically valid and useful manner to inform and strengthen future research (Kaye, Orben, Ellis, Hunter, & Houghton, 2020). This has resulted in researchers urgently attempting to fill the gaps in the literature where public concern and the need for evidence-based policy guidelines intercepts. Even then, research around the associations of new and emerging technology and human behaviour is selectively engaged with and often sensationalised by the mass media (Etchells, 2017). Therefore, now more than ever there is a need for clear conceptualisation and measurement guidelines to be developed; perhaps in collaboration with technology developers and policymakers. Only with these guidelines being accepted and used by researchers across the field can we move towards strengthening this body research alongside the new and emerging technologies and conduct applicable, transparent science with increased strength of evidence and conclusions.

1.3 Sleep

Sleep is a restorative state of altered consciousness, which occurs daily in a cyclic process and is prompted by an internal circadian rhythm (Krueger, Frank, Wisor, & Roy, 2016; Patel, Reddy, & Araujo, 2021). Circadian rhythms are the physical, mental and behavioural changes that follow a twenty-four-hour cycle, and respond primarily to light and darkness cues. They are controlled by the suprachiasmatic nucleus, the ‘biological clock’ of the brain, which activates the secretion of melatonin to signal the time for sleep (Walker, 2017). Sleep stages can be divided between Rapid Eye Movement (REM) and non-Rapid Eye Movement (NREM) sleep (Suni & Vyas, 2022). REM sleep is characterised by temporary muscle paralysis and increased brain activity, heart rate, and blood pressure, compared to non-REM sleep. REM sleep is crucial for cognitive functions, such as memory and learning (Ellenbogen, Payne, & Stickgold, 2006; Maquet, 2000). By comparison, NREM sleep is characterised by a reduction in brain activity, body temperature, and heart rate. Between four and five sleep cycles happen each night, each lasting around 90 minutes and oscillating between REM and non-REM sleep. Van Dongen, Maislin, Mullington, and Dinges (2003) conducted an experiment on chronic sleep deprivation and restricted the sleep of 48 participants for two weeks, allocating each to one of three sleep conditions, 4, 6, or 8 hours in bed per night. Total sleep deprivation involved an additional 3 nights without sleep. A dose-dependent effect of sleep was found, with insufficient sleep (≤6hrs) associated with deficits in cognitive performance in domains of attention and working memory (Van Dongen *et al.*, 2003). Regardless of the mode of insufficient sleep, either by restriction or complete deprivation, the threshold at which the lapses in cognition and alertness began was when continuous wakefulness reached in excess of fifteen hours.

There is conflicting evidence regarding sleep duration requirements across the lifespan. Evidence indicates adolescents need an increased number of hours of sleep compared to adults, with suggestions of between eight to ten hours (Paruthi *et al.*, 2016) to support the maturation of their cognitive development (Tarokh, Saletin, & Carskadon, 2016b). However, there is also evidence that sufficient sleep duration is steady across the life course and perhaps even curvilinear, and inverted u-shape relationship suggestive of an optimum amount of sleep. Richards *et al.* (2017) demonstrated that, regardless of age, cognitive performance across arithmetic, working memory, and visuospatial memory was optimised by achieving seven hours sleep; indicative of an optimal-dose model of sleep (Li *et al.*, 2022; Richards *et al.*, 2017).

While 24-hour circadian rhythms control essential functions such as the sleep process (Sollars & Pickard, 2015), which is initiated by the release of melatonin (Walker, 2017), the introduction of artificial light can interrupt this natural cycle. Artificial light sources include the first lightbulb, to electric lights, and light emitting diodes (LED). Light falls on the visible light spectrum, ranging from warm yellow light emitted by the old incandescent lightbulbs to the cooler hues of blue light emitted by LEDs. It is this blue light which has the most impact on circadian rhythms (Walker, 2017). The light receptors in the eyes are most sensitive to short-wave blue light from the visible light spectrum, an evolutionary remnant from our distant marine ancestors (Walker, 2017). Although most blue light is derived from sunlight and can improve alertness (Vandewalle, Maquet, & Dijk, 2009), blue light is also emitted from the screens of digital technology and other electronic devices.

1.3.1 Digital technology and Sleep

The rise of screen-based devices and digital technology has introduced new sources of artificial light to our lives, specifically the blue light found to inhibit melatonin secretion (Chellappa *et al.*, 2013); as a consequence, evening electronic device use may be detrimental to sleep quality. However, wearing amber-tinted blue light blocking lenses prior to bed-time may mitigate these effects compared to clear placebo lenses (Shechter, Kim, St-Onge, & Westwood, 2018). However, although this was a randomised within-subjects trial, the evidence may be thought of as a pilot study, as there were only fourteen insomniac participants. In future, a larger scale replication is needed.

Screen-based device use is associated with increased sleep-wake disturbances and reduced sleep quality (Alonzo, Hussain, Stranges, & Anderson, 2021; Carter, Rees, Hale, Bhattacharjee, & Paradkar, 2016; Hisler, Hasler, Franzen, Clark, & Twenge, 2020a; Woods & Scott, 2016). Hisler *et al.* (2020a) utilised a large sample of ~10,000 children to investigate how screen-based media devices were associated with sleep. Typical weekend and weekday use of a variety screen media (TV, video, video gaming, social media, texting, and video chat) was reported by the children, and symptoms of sleep-wake disturbance were parent-reported. Higher TV, video, and video game use was associated with reduced sleep duration, increased sleep latency (time to fall asleep), increased sleepiness and insomnia. However, this cross-sectional survey design may have been weakened by the incongruence of self-reported data sources; parent-reported sleep estimates may lead to inaccurate data, as parents tend to overestimate their children's sleep experiences (Lam, Mahone, Mason, & Scharf, 2011). Although the inclusion of an objective measurement for sensitivity purposes would have been ideal, an adjustment factor (e.g. subtract 30-minutes from parent estimated sleep duration) may be added to parent-reported data to increase accuracy (Nelson *et al.*, 2014). Moreover, Alonzo *et al.* (2021) conducted a systematic review of the associations between social media use, sleep quality, and negative mental health outcomes (anxiety, depression, and psychological distress) in young adults (aged 16 - 25). The 42 articles included global populations, with representative samples of youth in Europe and Asia, and included cross-sectional and longitudinal research designs. Studies found that frequent social media use was associated with poor sleep quality, and suggested a complex interplay between social media use, mental health outcomes, and sleep quality (Alonzo *et al.*, 2021). In future, this research would be further advanced by a meta-analysis to provide a comprehensive weighted mean value of the associations between these complex variables.

When used in proximity to bedtime, exposure to blue light from smartphone use is associated with reduced sleepiness (Heo *et al.*, 2017), and smartphone use in general may have a detrimental impact across sleep-related domains, including poor sleep quality, increased sleep latency (time to fall asleep), increased sleep disturbance and insomnia, and more daytime dysfunction and fatigue (Exelmans & Van den Bulck, 2016). This is supported by cross-sectional evidence, which found a moderate positive correlation between the Smartphone Addiction Proneness Scale, which rates responder's non-clinical risk of smartphone addiction, and the Pittsburgh Sleep Quality Index (PSQI), which measures sleep disturbances and quality over the last month (Haripriya, Samuel, & Megha, 2019). However, the survey design and correlational analysis does not produce causal evidence and therefore precludes any certainty in this evidence.

Playing video games is also associated with increased sleep-wake disturbances, including reduced sleep duration and increased sleep onset latency, the time it takes to fall asleep at bedtime (Carter *et al.*, 2016; Hisler *et al.*, 2020a). A recent study by Hisler, Twenge, and Krizan (2020b) used the nationally representative Millennium Cohort Study (MCS) to examine the associations between sleep and a variety of screen-based media, including social media use, video games, television viewing, and general internet use. Those who spent more time using screen-based media took longer to fall asleep (sleep latency) and experienced more mid-sleep disturbances, with the effect being more pronounced in associations with social media and general internet use compared to video gaming or television viewing. Although this study did differentiate between the different screen uses, the control variables did not include key confounding variables which may have impacted the associations between technology use and sleep-related outcomes and were available in the MCS data sweep used for this cross-sectional research. Socioeconomic status (Anders, Breckenkamp, Blettner, Schlehofer, & Berg-Beckhoff, 2014), mental health (Fang, Tu, Sheng, & Shao, 2019; Patalay & Gage, 2019), and substance use (Kwon, Park, & Dickerson, 2019) have been associated with deficits in sleep-related outcomes and should therefore be included in large-scale cohort studies and experimental designs.

The underlying mechanism behind these associations between screen use and sleep may be that these digital technologies provide psychologically stimulating content and affordances, which may prime the user into a state of heightened psychological arousal, inhibiting sleep onset (Cain & Gradisar, 2010). Another mechanism may be the impact of blue light emitting diodes on all of these screen-based digital technologies (Shechter *et al.*, 2018; Vandewalle *et al.*, 2009). Research has found blue light exposure to have a dose-dependent suppression of melatonin (West *et al.*, 2011); where increased irradiance (brightness) resulted in increased melatonin suppression, leading to the consequence of reduced alertness and impaired performance. Many devices operating systems now have the option for reducing these self-luminous displays through Night Shift, which adjusts the spectral composition and increases the orange hue of the light emitted from the screen, in an attempt to counterbalance the effects of blue light on melatonin secretion. However, there is evidence which indicates this function may not be effective. For example, an experimental study has found that the activation of Night Shift mode was insufficient as protective action on melatonin secretion, unless the overall screen brightness was also reduced (Nagare, Plitnick, & Figueiro, 2019), and even then may vary between devices (Calvo-Sanz & Tapia-Ayuga, 2020). Although there is support for both arguments, this is still an area of debate which is worthy of continued longitudinal empirical studies, perhaps with biological measurement components such as blood hormone measurement.

1.4 Sleep and Executive Function

Sleep is essential for effective executive function. Maintaining regular sleep attainment is crucial for wellbeing, general day-to-day activities, and educational and workplace performance (MacKinnon, 2020; Okano, Kaczmarzyk, Dave, Gabrieli, & Grossman, 2019). Insufficient sleep can differentially impair a variety of executive functions, including decision-making (Aidman, Jackson, & Kleitman, 2019; Harrison & Horne, 1999, 2000; Killgore, Balkin, & Wesensten, 2006), attention (Thomas *et al.*, 2000), problem solving, working memory, and inhibitory control (Satterfield & Killgore, 2019). The Yerkes-Dodson Law (Teigen, 1994; Yerkes & Dodson, 1908) proposes an inverted U-shaped relationship between arousal and performance. This may be related to sleep and cognitive performance, with the reduced arousal portion of the curve perhaps being that of increased sleepiness as a consequence of sleep deprivation or loss (Jackson & Van Dongen, 2011). This is supported by findings which suggest an optimal-dose model of sleep across the life course (Richards *et al.*, 2017; Tai, Chen, Manohar, & Husain, 2022), functioning as a protective factor against cognitive decline and age-related neurodegenerative conditions such as dementia (Eide, Vinje, Pripp, Mardal, & Ringstad, 2021; Sabia *et al.*, 2021; Spira, Chen-Edinboro, Wu, & Yaffe, 2014).

García, Del Angel, Borrani, Ramirez, and Valdez (2021) conducted a between-subjects experiment to identify the specific EF components susceptible to the consequences of sleep deprivation. Compared to a free-sleeping control group, the sleep deprivation group demonstrated significantly reduced alertness, selective and sustained attention, and inhibition. Additionally, previous research of a dose-dependent model of sleep found insufficient sleep (≤6hrs) was associated with reduced attention and working memory performance (Van Dongen *et al.*, 2003).

Furthermore, wearable technology devices were utilised to examine the associations between multiple measures of sleep and class performance in 88 university students (Okano *et al.*, 2019). Greater sleep duration, better quality, and longer consistency were associated with better academic performance, accounting for almost 25% of the variance in performance (Okano *et al.*, 2019). Research into sleep loss and deprivation is often based on a short temporal period, perhaps one to two days of deprivation (Lim & Dinges, 2010) or a week or two of limited rest (Van Dongen *et al.*, 2003). This would suggest short-term impacts of insufficient sleep on cognitive functioning, and the almost immediate restorative nature of regained sleep. However, the evidence presented by Okano *et al.* (2019) of the beneficial properties of sleep consistency perhaps suggests longer-term benefits to the restorative nature of sufficient sleep.

Although the duration of sufficient sleep is thought to remain constant over the life course, adolescents are an at-risk group for chronic insufficient sleep due to being biologically driven towards later bedtimes, while rise times for the start of school remain unchanged (Tarokh, Saletin, & Carskadon, 2016a). Therefore, ensuring sufficient, restorative sleep in adolescence is important in supporting learning and memory, attention, cognition, and emotional processing in a crucial period of neurodevelopmental maturation (Tarokh *et al.*, 2016a). In addition to adolescents, individuals who have insomnia may be at increased risk of reduced executive functioning performance. A combined systematic review and meta-analysis demonstrated small to moderate deficits in EF in individuals with insomnia (Ballesio, Aquino, Kyle, Ferlazzo, & Lombardo, 2019). However, it is possible that these deficits may be compensated for by insomniacs through increased cognitive effort (Ballesio, Cerolini, Ferlazzo, Cellini, & Lombardo, 2018; Schmidt, Richter, Gendolla, & Van der Linden, 2010), facilitated by the hyper-arousal that characterises the brain activity of individuals with insomnia (Riemann *et al.*, 2010). Therefore, those at risk for sleep loss and subsequent EF decline may be suitable targets for sleep interventions.

Although sleep and executive functioning are inherently related, a prerequisite of understanding their possible combined associations with digital technology is to clarify their associations with digital technology respectively. Therefore, the studies within this thesis present these two concepts as separate outcomes. To advance a complex and niche field, a step back needs to be taken to establish the fundamental relationships first. The intricacies of the associations between EF and sleep combined with digital technology is outside the scope of this thesis.

1.5 Summary

Overall, while there is a substantial amount of research into the potential relationships between digital technology and executive functioning, and digital technology and sleep, much of this research is inconclusive or mixed. Furthermore, little of this research considers digital technology, sleep, and executive function in the same study. There is a methodological reliance on cross-sectional analyses using retrospective self-reported quantitative data, which may be unreliably estimated (Andrews *et al.*, 2015; Barnhart & Buelow, 2017; Buchanan, 2016), and prevents causal or longitudinal associations from being investigated.

Further, the prevalence of such a vast diversity of digital technologies in our everyday lives has made the concept increasingly difficult to consistently conceptualise. While 'screen time' is a commonly used composite measure, it removes the nuance and contextual factors that may arise from differentiating between screen uses and devices. This conceptual difficulty has led to between-group experiments using arbitrary splits of participant groups and the development of many retrospectively self-report measurement scales (this is further detailed in Chapter One). Furthermore, debate surrounding digital technology use has resulted in the development of theories behind the motivations and implications of digital technology use. The Uses and Gratifications Theory (UGT) (Katz, 1959; Katz & Blumler, 1974) and the Technology Acceptance Model (TAM) (Davis, 1985) detail the motivations behind media and technology use, and the Digital Goldilocks Theory (Przybylski & Weinstein, 2017) suggests an optimal-dose type model of exposure to technology.

Research in this field has a need for robust, reproducible studies with increased objectivity to increase the strength of evidence and prevent it from faltering. This is particularly true at a time of increasingly sensationalist media articles, which at best communicate the society-wide concerns, and at worst needlessly alarm the public. Therefore, now more than ever is the time for researchers in this field to be conducting high-quality investigations with scientific rigor to reduce the ambiguity surrounding digital technologies.

This thesis aims to investigate the associations between digital technology use, executive function, and sleep quality within the same studies, a novelty compared to the existing literature. It was hypothesised that (H1) digital technology use would be associated with executive functioning, and (H2) digital technology use would be negatively associated with sleep quality. This approach will also utilise mixed methods and lay the foundations towards the robust, objective science needed in this field. Using a combination of methodologies may increase validity and provides a more comprehensive study of complex phenomena (Doyle, Brady, & Byrne, 2009), such as those that may have less conceptual stability like digital technology.

1.6 Overview of thesis

1.6.1 Significance of the research

To investigate the associations between digital technology, executive functions, and sleep quality I used a mixed-methods approach, including: a systematic review, observational epidemiology, an online experiment, and qualitative focus groups. This use of mixed methods provides triangulation of evidence to allow a number of essential research questions to be examined which cannot be answered by one method alone (Creswell & Plano Clark, 2007), while attempting to address the methodological and conceptual issues within the remit of the topic. These issues are examined in more depth in Chapter One.

The influx of research and media articles into this area is indicative of what an important and pertinent topic it is. The role of digital technology on human behaviours is one of vital importance to understand. This is especially true in relation to executive functioning and sleep as intrinsically interlinked health-related behaviours (Wilckens, Woo, Kirk, Erickson, & Wheeler, 2014). They are important for overall life success across every age group, with sufficient sleep contributing to optimal cognitive processes crucial for academic, social, and health development (Borella *et al.*, 2010; Brown & Landgraf, 2010; Eakin *et al.*, 2004; Tavares *et al.*, 2007).

1.6.2 Organisation of the thesis

The variety of methodologies employed to study these relationships produce a varied examination. To supplement this, chapter-specific literature reviews introduce each study. Firstly, a systematic review was conducted to examine the existing literature on the relationship between mobile technology and executive function. The methodologies and quality of the evidence provided by the published articles was assessed. Chapter Three used data from a large, nationally representative UK birth cohort (Millennium Cohort Study; Connelly & Platt, 2014), and took an epidemiological approach to examining the associations between different types of screen uses on the decision-making facet of executive function and sleep quality. This was examined in terms of both cross-sectional and longitudinal associations to determine whether any relationship persisted in the long term. Chapter Four detailed an online cross-sectional study, using objective measures of executive function. This method is in contrast to a number of experiments in the existing literature that measure behavioural outcomes, such as aspects of executive functions, using self-reported methods (Marty-Dugas *et al.*, 2018; Tang *et al.*, 2017), which may not be comparable to actual behaviours (Barnhart & Buelow, 2017; Buchanan, 2016). Finally, qualitative focus groups were conducted to gain participants' insights on expanding the role of objective measures of smartphone use and sleep quality in an ecologically valid way. I explored the acceptability and feasibility of using existing monitoring features built into smartphone operating systems, as well as health-related wearable technology, which is gaining popularity and traction, for objectively measuring smartphone use behaviours and sleep-related outcomes in future research.

Chapter 2: Mobile technology use and its association with executive functioning in healthy young adults: a systematic review

This chapter closely reflects: *Warsaw, R. E., Jones, A., Rose, A. K., Newton-Fenner, A., Alshukri, S., Gage, S. H. (2021). Mobile Technology Use and Its Association with Executive Functioning in Healthy Young Adults: A Systematic Review. Frontiers in Psychology, 12, doi.org/10.3389/fpsyg.2021.643542*.

2.1 Abstract

2.1.1 Introduction:

Screen-based and mobile technology has grown at an unprecedented rate. However, little is understood about whether increased screen-use affects executive functioning (EF), the range of mental processes that aid goal attainment and facilitate the selection of appropriate behaviours. To examine this, a systematic review was conducted.

2.1.2 Method:

This systematic review is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement. A comprehensive literature search was conducted using Web of Science, MEDLINE, PsycINFO and Scopus databases to identify articles published between 2007 and March 2020, examining the use of mobile technologies on aspects of EF in healthy adults aged 18-35 years. In total 6079 articles were screened by title, and 39 screened by full text. Eight eligible papers were identified for inclusion. Our methods were pre-registered on the PROSPERO international prospective register of systematic reviews.

2.1.3 Results:

A total of 438 participants were included across the eight studies. Five of the eight studies examined more than one EF. Five studies measured inhibition, and four studies measured decision-making. Smartphone use was negatively associated with inhibition and decision-making. Working memory performance was found to be improved by increased time engaging in video games and by refraining from smartphone use prior to bedtime. Quality assessments indicated high risk of methodological biases across the studies and a low quality of evidence for determining the relationship between technology use and executive functioning.

2.1.4 Conclusions:

This review highlights the scarcity of the literature in this area. It presents a call for rigorous and objective research to further our understanding of the impact of mobile technology on different aspects of executive function.

Key words: Mobile technology, Mobile devices, Smartphones, Executive Function, Cognition, Brain

2.2 Introduction

Mobile devices have become integral to people's lives by offering a myriad of functions from communication, internet connectivity and the capacity to support additional applications (Heo, Ham, Park, Song, & Yoon, 2009; Lee & Calugar-Pop, 2019). Ownership of mobile devices has grown rapidly across the globe. For smartphones in particular, usage is high across developed countries. There is an estimated 851 million smartphone users in China, 345 million users in India, and 260 million users in the United States of America; the three largest markets of smartphone users as of September 2019 (O'Dea, 2020). Given their ubiquity, it is necessary to understand the potential impact of mobile devices on user's executive functioning.

To date, the research literature on the relationship between mobile device technology and executive functioning is equivocal. Some studies suggest a benefit of exposure, including improved task switching (Alzahabi & Becker, 2013) and attentional control (for review see: Green & Bavelier, 2012). Conversely, research has also demonstrated a negative relationship, including reduced task switching ability (Ophir *et al.*, 2009); decreased attentional capacity (Moisala *et al.*, 2016; Ralph *et al.*, 2014) and working memory deficits (Cain *et al.*, 2016; Sanbonmatsu *et al.*, 2013; Uncapher *et al.*, 2016). Moreover, smartphone use has been found to impair inhibition and working memory through inducing separation anxiety (Hartanto & Yang, 2016). Excessive smartphone use may also be related to reduced brain functional connectivity in regions associated with cognitive control: the orbitofrontal cortex (OFC), nucleus accumbens (NAcc) and midcingulate cortex (MCC) (Chun *et al.*, 2018). Despite evidence of interesting and complex associations, there is a shortage of experimental longitudinal research in this area of the literature. This may be due to technological advancements in the industrial sector happening so quickly, that rigorous scientific and academic pursuits struggle keep up.

A previous review (Wilmer *et al.*, 2017) examined the existing literature with a focus on three facets of executive function: attention, memory and delay of gratification. Although the included evidence suggests a negative relationship between smartphone use and executive function, this may be unsubstantiated as methods were primarily correlational and made use of self-report data. Therefore, the literature lacks the longitudinal evidence needed to support claims of a detriment to memory or reward processing (Wilmer *et al.*, 2017). With varying evidence across the literature, a clearer picture is needed on the association between mobile technology exposure and users' executive functions.

Executive functions (EF) are effortful mental processes which aid in the attainment of goals (Diamond, 2013). There are three core executive functions; inhibition and interference control, working memory, and cognitive flexibility (Diamond, 2013; Miyake *et al.*, 2000). Inhibition and interference control contribute to regulation of one's behaviour, attention, thoughts, or emotions to respond to stimuli in an appropriate manner by overruling habitual or dominant responses. Working memory is the ability to hold information in the forefront of the mind after it is not perceptually present. Cognitive flexibility builds on the previous two EFs, enabling one to change their perspective, either spatially or interpersonally, allowing problems to be addressed in a new way or another's perspective to be understood. Taken together, these skills are essential for social (Mann, Hund, Hesson-McInnis, & Roman, 2017) and academic success (Borella *et al.*, 2010), and good health (Miller, Barnes, & Beaver, 2011). Executive functions facilitate a range of goal-appropriate behaviours, including attending to important information (Psouni *et al.*, 2019) and problem solving (Miller, Avila, & Reavis, 2020).

Given the saturation of screen-based and mobile devices in society, objective scientific research into the effects of exposure on a variety of populations is needed to inform public policy. This review aimed to address the question of how exposure to mobile technology affects executive functioning in healthy young adults. This was achieved by examining the existing peer-reviewed literature which investigated mobile device use and executive function in healthy adult samples, aged 18 to 35 years.

2.3 Method

This systematic review is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Moher, Liberati, Tetzlaff, & Altman, 2009) (see *Appendix A*, *Table 5*). An *a priori* protocol was published on the PROSPERO international prospective register of systematic reviews (CRD42019127003; https://www.crd.york.ac.uk/PROSPERO/).

2.3.1 Eligibility Criteria

To qualify as eligible for inclusion, *s*tudies were required to investigate the use of mobile, or portable, technology, including but not limited to smartphones, video games and tablets. They had to include either between subject comparisons (e.g. groups with different extents of usage) or within participant comparisons (e.g. measures of any changes in usage between time points). The outcome measure of one or more aspects of executive function had to be independently assessed using validated self-reported or experimental methods (e.g. Diamond 2013). Participants had to be healthy adults, aged between 18-35 years old, recruited from the general population. This age group was chosen as they are less likely to be in cognitive decline (Murman, 2015; Salthouse, 2009), and this is in line with the NIHR's focus on children and young people. Any peer-reviewed published articles from between 2007 and March 2020 inclusive were considered. The start date was chosen as 2007 was the year *Apple* first introduced the *iPhone*. This marked a pivotal innovation as the features offered by the iPhone were more advanced than other devices and created the foundations of media consumption and mobile data use as we know it (Murphy, 2008).

2.3.2 Information Sources and Search

The main search took place in April 2020, using four databases: Web of Science, MEDLINE, PsycINFO, and Scopus. Search terms were designed using scoping searches and adapted for suitability to each of the four databases; they included key words for different mobile technologies and aspects of executive function (see Table). The search strategy was piloted using Web of Science in March 2020. Scoping searches indicated that the inclusion of eligibility criteria, such as 'healthy adults', as a search term excluded some potentially relevant articles. Therefore, the search strategy was kept specific to technology and executive function terms, and the resulting literature was screened by hand for other eligibility criteria. RW performed the searches.

2.3.3 Study Selection

Three authors were responsible for the evaluation of articles for inclusion. RW screened titles and abstracts, with a random sample of 20% of the screenings cross-checked by AN-F and SA; there were no disagreements. Full texts of articles were screened by RW to identify those that met the eligibility criteria.

2.3.4 Data Collection

Data was initially extracted by RW and cross-checked by AN-F and SA. In instances where required data was not reported in the publication, corresponding authors were contacted to request this. Data extractions included country of origin, participants, mobile technology exposure (intervention), comparison, and executive function outcome (see *Table 1).*

2.3.5 Risk of Bias Assessment

The quality of the included papers was assessed using the Newcastle-Ottawa Scale (NOS) (Wells *et al.*, 2000) adapted for cross-sectional studies. NOS was designed to evaluate the quality of nonrandomised studies for inclusion in systematic reviews and meta-analyses. Studies were judged on three criteria: group selection, group comparability, and determination of the outcome of interest.

Table 1: Search strategy terms.

#	Search Strategy
1	“mobile technolog*” OR smartphone OR “mobile phone*” OR “cell phone*” OR “screen time” OR touchscreen*
2	"executive function*" OR "executive control" OR cogniti* OR "self-regulation" OR "self-control" OR attention OR "working memory" OR "fluid intelligence" OR inhibit* OR impulsi* OR "impulse control" NOT biolog* OR "task switching" OR "problem solving" OR multitask* OR "delay of gratification" OR "delayed gratification" OR "delay discounting"
3	1 AND 2

2.3.6 Quality of cumulative evidence assessment

The Grading of Recommendation, Assessment, Development and Evaluations (GRADE) framework was used to assess the quality of the body of evidence (Guyatt *et al.*, 2011). Each study was assessed against downgrading and upgrading criteria within the domains of: factors which may decrease the quality of the evidence (e.g. methodological quality, directness of the evidence, heterogeneity, precision of reported results, and publication bias), and factors which may increase the quality (e.g. magnitude of effect, plausible confounds, and dose-response gradient). The results provided a rating of confidence in estimated effects within the studies, and therefore for the association between mobile technology and the measured aspect of executive function.

2.4 Results

2.4.1 Study Selection

Once duplicates were removed, a total of 6079 articles were identified from the searches. After screening, eight articles were identified as meeting the eligibility criteria (Chen *et al.*, 2016; Donohue *et al.*, 2012; Fortes *et al.*, 2020; Fortes *et al.*, 2019; Frost *et al.*, 2019; He *et al.*, 2020; Huang *et al.*, 2017; Tang *et al.*, 2017). The study selection process is outlined in Figure 2.

2.4.2 Study Characteristics

The number of participants in each study ranged from 20 (Fortes *et al.*, 2019) to 125 individuals (Tang *et al.*, 2017) , with an average of 54. Participants were largely sampled from primarily student and university affiliated populations. All participants were aged between 18 and 35 years and had no reported history of any psychiatric or neurological disorders. Five articles assessed smartphones, two examined video games, and one article included both smartphones and video games (see Table 1).

2.4.3 Risk of Bias in Included Studies

The cross-sectional adaptation of the Newcastle-Ottawa Scale (NOS) was used to screen for risk of methodological bias. Of the eight included studies, four were rated as 'good', and four as 'satisfactory' based upon the three assessment areas: selection, comparability, and outcome (see Table 3). According to the NOS, five of the included studies (Fortes *et al.*, 2020; Fortes *et al.*, 2019; Frost *et al.*, 2019; He *et al.*, 2020; Huang *et al.*, 2017) obtained comparable groups based on study design or analysis, by including valid control groups or reporting adjustments made for confounding variables. The remaining three articles (Chen *et al.*, 2016; Donohue *et al.*, 2012; Tang *et al.*, 2017) did not report any adjustments to account for confounds.

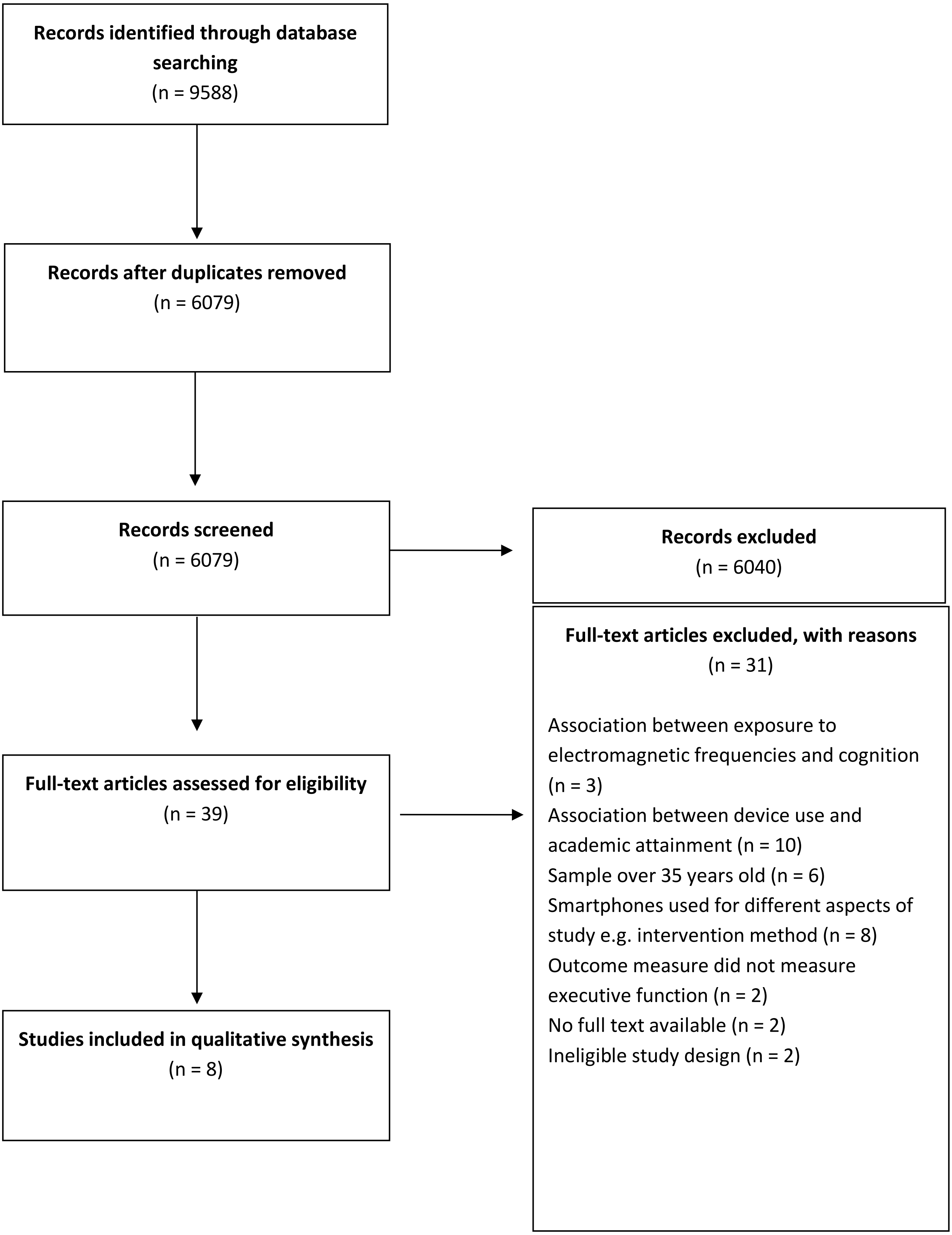

Figure 2: Flowchart of the selection of studies.

Table 1: Summary of study characteristics

Author(s)	Title	Country	Participants	Mobile Technology	Comparison	Executive Function
Chen *et al.* (2016)	General Deficit in Inhibitory Control of Excessive Smartphone Users: Evidence from an Event-Related Potential Study	China	32 Excessive: n = 16 (7 males). Age: M = 19.50 ± 1.27. Normal: n = 16 (9 males). Age: M = 19.69 ± 1.30.	Smartphones	Between-subjects, Excessive smartphone use group Vs Normal use group Categorised by SPAI scores	Inhibitory control
Donohue *et al.* (2012)	Cognitive pitfall! Videogame players are not immune to dual-task costs	USA	60 Video Game Players (VGP): n = 19 (no females). Non VGP: n = 26 (7 females). Overall age: M = 20.2, SD = 3.5. 52 males, 8 females.	Video games	Between-subjects, Video game players Vs Non-video game players	Multi-tasking

Fortes *et al.* (2019)	Effect of exposure time to smartphone apps on passing decision-making in male soccer athletes	Brazil	20 All male. Age: M = 24.7 ± 3.6 years	Smartphones	Within-subjects, all participants took part in 4 conditions	Decision-Making Inhibition
Fortes *et al.* (2020)	The effect of smartphones and playing video games on decision-making in soccer players: A crossover and randomised study	Brazil	25 All male. Age: M = 23.4 ± 2.8 years	Smartphones Video games	Within-subjects, all participants took part in 3 conditions	Decision-Making Inhibition
Frost *et al.* (2019)	An examination of the potential lingering effects of smartphone use on cognition (study 2)	USA	50 M = 20.73. 14 males, 36 females.	Smartphones	Between-groups Higher vs lower smartphone use	Delayed gratification, Problem solving

He *et al.* (2020)	Effect of restricting bedtime mobile phone use on sleep, arousal, mood, and working memory: A randomized pilot trial	China	38 Intervention group: n = 19. Age: M = 20.95 ± 2.07. 12 males, 7 females. Control group: n = 19. Age: M = 21.37 ± 2.63. 14 males, 5 females.	Smartphones	Between-subjects, Intervention group Vs Control group	Working Memory
Huang *et al.* (2017)	The Association Between Video Game Play and Cognitive Function: Does Gaming Platform Matter?	Canada	88 (50 females). VGP: n = 59. NVGP: n = 29. Age: M = 21.11, SD = 3.21.	Video games	Between-subjects, Video game players, Vs Non-video game players	Working memory Inhibition
Tang *et al.* (2017)	Time Is Money: The Decision Making of Smartphone High Users in Gain and Loss Intertemporal Choice	China	125 (52 males). Age: M = 19.92, SD = 1.20.	Smartphones	Between-groups, Low vs Medium vs High smartphone users, categorised from SPAI scores	Decision-Making Delay discounting Impulsivity

Table 2: Summary of Newcastle-Ottawa Scale ratings and findings by article

Study	Newcastle – Ottawa Scale Rating	Findings
Chen *et al.* (2016)	Good	ERP N2 mean amplitude was larger for excessive smartphone users (upper 30% of SPAI scores), compared to controls (lower 30% of SPAI scores), $F(1,30) = 11.67$, $p < 0.005$, $\eta^2 p = 0.28$. Demonstrates an electrophysiological inhibition deficit. No behavioural main or interaction effects of group were found.
Donohue *et al.* (2012)	Satisfactory	No interaction effects. VGP (played First Person Shooter [FPS] games in last 6 months, >average expertise) & NVGP (FPS games never played / not played in last 6 months, <average expertise) did not differ in multi-tasking/dual-task costs. VGP not protected from this through experience.
Fortes *et al.* (2019)	Good	There was a significant difference between smartphone exposure condition on Decision-Making Index (DMI) scores ($F = 30.5$, $p < .001$). DMI scores were significantly reduced at 30 mins ($M = 53.8$, $SD = 8.6$) and 45 mins ($M = 51.4$, $SD = 10.1$) compared to 15 mins and control. An inhibition response time interaction was found (F = 21.4, p = .01). Inhibition was significantly impaired after 30 mins (M = 6.2, SD = 1.4) and 45 mins (M = 7.0, SD = 1.8) of smartphone use, compared to 15 mins and control.

Fortes *et al.* (2020)	Satisfactory	There was a significant difference between smartphone or video game exposure on decision-making performance (F = 23.6, p = .01, ES = 0.5). Both 30 mins smartphone use (M = 57.2, SD = 9.1) and 30 mins video game use (M = 60.7, SD = 9.6) had a detrimental effect on decision-making compared to control. There was a significant difference in inhibition response time (F = 32.5, p = .02), with 30 mins smartphone use (M = 0.9, SD = 0.4) and 30 mins video game use (M = 1.0, SD = 0.3) reducing inhibition performance compared to the control condition (M = 0.3, SD = 0.2).
Frost *et al.* (2019)	Satisfactory	Study 2: No difference between higher smartphone use group (≥ 5.5 hrs daily) and lower use group (≤ 2 hrs daily) was found for Delay of Gratification or problem solving.
He *et al.* (2020)	Satisfactory	Compared to the control group, intervention group demonstrated improved working memory performance after refraining from pre-bedtime smartphone use. Main effect of time in task accuracy found. Significant difference between intervention and control groups at post-test in the 1-back task (*F* = 5.02, *p* = .046) and 2-back task (*F* = 7.17, *p* = .036).
Huang *et al.* (2017)	Good	VGP (>5 hrs/week) had enhanced working memory compared to NVGP (<5 hrs/week), *F*(9, 72) = 3,77, p = 0.001, $\eta^2 p$ = 0.32. No effect on inhibition.

Tang *et al.* (2017)	Good	Participants categorised into high, medium and low groups using SPAI scores. Correlation between SPAI and BIS scores (r = 0.22, p = 0.01). High users showed irrational decision-making bias toward immediate rewards ($F(2,122) = 6.76$, $p = 0.002$, $\eta^2 p = 0.100$), and later penalties ($F(2,122) = 3.335$, $p = 0.039$, $\eta^2 p = 0.052$) compared to low users. High and medium users similar; suggesting a critical amount of smartphone usage to impact choices.

2.4.4 GRADE Assessment

The body of evidence provided by the included articles for each outcome measure of executive function was GRADE assessed by one author (RW). Three of the included studies were rated ‘moderate’, three rated as ‘low’, and two rated as ‘very low’ (see Table 3). Therefore, the evidence from these studies is likely to be weak regarding the associations between mobile technology and executive function.

Table 3: GRADE rating results for each Executive Function outcome.

Outcome	**Number of Studies**	**GRADE**	
		Rating	**Reason**
Inhibition	5	Low	Imprecision of results. Exposure-response gradient.
Multi-tasking	1	Very Low	Imprecision of results. Design limitations.
Working Memory	2	Moderate	Imprecision of results. Exposure-response gradient.
Decision-Making	4	Low	Imprecision of results. Indirectness of evidence. Exposure-response gradient.
Problem Solving	1	Low	Imprecision of results.

2.4.5 Inhibition

Five studies examined the association between mobile technology use and inhibition (Chen *et al.*, 2016; Fortes *et al.*, 2020; Fortes *et al.*, 2019; Huang *et al.*, 2017; Tang *et al.*, 2017). Chen *et al.* (2016) used behavioural and electrophysiological measures to assess inhibition in a total of 32 excessive and normal smartphone users (16 per group). Participants completed a novel Go-NoGo task, which had three cue contexts: blank, neutral and smartphone-related. Behavioural findings from the Go-NoGo revealed no group differences between excessive and normal users. However, there was an electrophysiological inhibition deficit between excessive and normal users (see Table 2).

Reduced inhibition was demonstrated by Tang *et al.* (2017), who used the Barratt Impulsiveness Scale (BIS) to assess impulsivity, and the Smartphone Addiction Inventory (SPAI) to divide 125 participants into high, medium and low usage groups. SPAI and BIS scores were positively correlated (r = 0.22, p = 0.01), suggesting increased smartphone use is associated with higher impulsivity. Further analysis demonstrated high smartphone users were more impulsive compared to low users, and that medium smartphone users were more impulsive compared to low users. No difference in impulsivity was found between high and medium use groups.

Fortes *et al.* (2019) assessed the effect of smartphone use on player's inhibition prior to a football match. Inhibition was quantified using the Stroop Task. Over four weeks, four conditions were completed: 0 (control), 15, 30 and 45 minutes of smartphone use exposure. Using a smartphone for 30 minutes or 45 minutes was found to induce mental fatigue and impair inhibition, compared to the control and 15 minute conditions.

The literature has also examined the association between video gaming and inhibition. Fortes *et al.* (2020) examined the impact of 30 minutes of video game use and smartphone use on inhibition performance, measured using the Stroop Task. Compared to the control of watching advertisement videos, 30 minutes of either video game play or smartphone use significantly increased response times to the Stroop Task, demonstrating reduced inhibition. In addition to this, Huang *et al.* (2017) used a Go-NoGo task to assess whether video game players (VGP) and non-video game players (NVGP) differed in inhibition. However, although VGPs demonstrated faster reaction times on average (~11 ms) there was no association between video game play and inhibition.

2.4.6 Decision Making

Tang *et al.* (2017) examined decision making in a sample of 125 participants. A delay discounting task assessed the decision-making process in high, medium, and low groups of smartphone users, categorised by SPAI scores (see above). All participants completed both a gain and a loss task condition. In the gain condition, a choice had to be made between receiving smaller monetary rewards in the short term, or larger monetary rewards after a longer time delay. In the loss condition, a choice was made between whether to take the penalty sooner, or delay the loss. Participants in the high usage group and the medium usage group, respectively, had an increased preference for immediate rewards and postponed punishment, compared to the low usage group who chose delayed gratification in the gain condition, and to take penalties sooner in the loss condition.

Frost *et al.* (2019) used a self-report measure of delayed gratification to quantify the associations with smartphone use. In study two of their paper, participants were divided into lower (≤ 2hrs) and higher (≥ 5.5hrs) smartphone use groups and asked to ensure they met their assigned group's limit criteria. After one week of tracked smartphone use, they completed the Delayed Gratification Inventory (DGI-10), which scores across five domains: food, physical pleasure, social interaction, money, and achievement. However, no difference of delayed gratification was found between lower and higher smartphone use groups.

In contrast, Fortes *et al.* (2019) investigated decision making during football matches. They used a within-subjects design to understand the effect of smartphone use exposure prior to a football match on passing decisions. Over four weeks, four conditions were completed: 0 (control), 15, 30 and 45 minutes of smartphone use exposure. Participants then completed a short Stroop task to measure their mental fatigue before playing a full football match. The game was video recorded and each pass was independently coded as appropriate or inappropriate by two researchers, who were blinded to the experimental conditions, to calculate a Decision-Making Index (DMI) score. At least 30 minutes of smartphone exposure was found to impair decision making; both 30 and 45 minutes exposure before game play reduced decision-making performance compared to 15 minutes and no exposure control.

Fortes *et al.* (2020) extended this research further to examine the effect of 30 minutes of exposure to smartphone or video game use on passing decisions in a football match. A third, control condition involved passively watching advertisement videos for 30 minutes. Twenty-five male football players took part in each of the three conditions, completing a short Stroop Task pre- and post- to the exposure condition, before playing a full football match. As before, the game was recorded and passing decisions independently coded to calculate a Decision-Making Index (DMI) score. Compared to the control condition, thirty minutes of exposure to either smartphones or video games was associated with significantly lower DMI scores, demonstrating impaired decision-making.

2.4.7 Problem Solving

Frost *et al.* (2019) investigated the relationship between smartphone use and problem solving. As previously, participants were divided into lower (≤ 2hrs) and higher (≥ 5.5hrs) smartphone use groups and asked to complete a self-report questionnaire on problem solving using the Modified Means End Problem Solving (MEPS). Independent judges rated participant's proposed solutions to hypothetical problems. However, there was no statistically significant group difference for problem solving (d = 0.08, p = .73).

2.4.8 Multi-tasking

Donohue *et al.* (2012) examined the association between mobile technology use and multi-tasking, in a sample of 60 participants. The authors aimed to determine whether video game players

(VGP) were better at multi-tasking than non-videogame players (NVGP). Participants were grouped based on their experience with First Person Shooter (FPS) games. All participants completed three tasks under single and dual-task conditions; computer simulated driving, multiple object tracking, and image search. The dual-task condition involved answering trivia questions while engaging in each task. There was no association between video gaming status and dual-task performance in any of the three tasks.

2.4.9 Working Memory

The association between video gaming and working memory (WM) performance was assessed by Huang *et al.* (2017), with a sample of 88 participants. Participants were grouped in to video game players (VGP) and non-video game players (NVGP) according to self-reported playing hours, and the Motivation for Video Game Use scale. WM was assessed using the N-Back task, which involved participants indicating whether a stimulus was presented in the same orientation as in a previous trial. The *N* refers to how many trials back they have to refer to, with difficulty increasing with each higher *N*. VGPs demonstrated increased task performance on the 1-Back and 2-Back trials, respectively, suggesting increased working memory performance compared to NVGPs.

The *N*-Back task was also used by He *et al.* (2020) to assess the impact of restricted mobile phone use prior to sleep. Participants completed baseline measurements before being divided into two groups. An intervention group had to refrain entirely from using their mobile phone for 30 minutes before their average bedtime. This was achieved either by parental control settings or, where these were unavailable on participant's phones, by instructions to turn their phone off 30 minutes prior to their bedtime. This was followed up by a researcher calling at any time to ensure compliance. A control group received no instructions regarding their phones. Post-test measures were then completed after four weeks. The intervention group demonstrated improved working memory performance in both the 1-Back and 2-Back trials compared to controls.

2.5 Discussion

This systematic review aimed to assess the literature on mobile technology exposure and the association with executive function in healthy adults aged 18 to 35. A total of eight papers examining five aspects of executive functioning were eligible for inclusion. Inhibition, decision-making, and working memory were outcome measures in more than one paper.

Increased smartphone use was found to be negatively associated with inhibition (Chen *et al.*, 2016; Fortes *et al.*, 2020; Fortes *et al.*, 2019; Tang *et al.*, 2017) and decision-making (Fortes *et al.*, 2020; Fortes *et al.*, 2019; Frost *et al.*, 2019; Tang *et al.*, 2017). According to Tang *et al.* (2017), there could be a critical threshold of device use, and use beyond this threshold contributes to impaired delayed gratification. In the present culture of information on demand, the instant access and connection enabled by smartphones is perhaps acclimatising heavy smartphone users to expect immediate fulfilment of their commands, therefore reducing their capacity to delay gratification. Increased working memory performance was associated with refraining from smartphone use before sleep (He *et al.*, 2020) and with playing video games (Huang *et al.*, 2017). Video gaming was not associated with multitasking (Donohue *et al.*, 2012). Contradicting evidence was found for video gaming and inhibition (Fortes *et al.*, 2020; Huang *et al.*, 2017).

A major issue of the identified evidence base is the poor quality of the studies. Three studies did not report any adjustments for confounding variables to ensure the comparability of groups (Chen *et al.*, 2016; Donohue *et al.*, 2012; Tang *et al.*, 2017). Therefore, although the articles were rated as ‘good’ or ‘satisfactory’, we are not able to determine the association between smartphones or video games and executive function from the evidence provided. The articles were also assessed using the GRADE criteria (Guyatt *et al.*, 2011), which rated the body of evidence for each outcome as between ‘very low’ and ‘moderate’. Articles primarily met downgrading criteria, such as: imprecise results reporting from an absence of confidence intervals (Chen *et al.*, 2016; Donohue *et al.*, 2012; Fortes *et al.*, 2020; Fortes *et al.*, 2019; Frost *et al.*, 2019; He *et al.*, 2020; Huang *et al.*, 2017; Tang *et al.*, 2017); comparability issues, such as potentially homogenous groups (Chen *et al.*, 2016; Donohue *et al.*, 2012; Huang *et al.*, 2017); and a reliance on self-report questionnaires (Frost *et al.*, 2019; Tang *et al.*, 2017).

A methodological issue in three of the eligible articles was homogeneity of groups (Chen *et al.*, 2016; Donohue *et al.*, 2012; Huang *et al.*, 2017). Donohue *et al.* (2012) divided participants into two groups, Video Game Players and Non-Video Game Players, based on their expertise in playing First Person Shooter (FPS) video games in the last six months. Using this arbitrary grouping, players of any other type of game may have been categorised as non-video game players, therefore diluting the comparison group. This may partly explain why there was no difference in dual-task costs between the two groups. Similarly, Huang *et al.* (2017) defined VGPs as playing for more than 5 hours a week, and NVGP as playing less than 5 hours per week. Although they collected duration of game play per week, no mean duration game play for each group is reported. Therefore, the difference between these two groups could be minimal, which may invalidate the positive association between frequent video gaming and improved working memory. In general, dichotomising groups as high vs low exposure on a continuous variable is not recommended and can bring about misleading conclusions (Altman & Royston, 2006).

Chen *et al.* (2016) divided their participants into normal and excessive smartphone use groups using the self-report SPAI and a monitoring app installed on participant's smartphones. However, given the ubiquity of smartphones in daily life, 'normal' and 'excessive' use is hard to define. Although by all intentions the normal use participants were the comparison group, they still had access to and use of their smartphones. Therefore, the normal and excessive groups could have been too similar to examine the behavioural association between smartphone use and inhibition. Frost *et al.* (2019) also divided participants by extent of phone use, however their smartphone use groups were clearly distinct from one another (≤ 2 hrs and ≥ 5.5 hrs) to examine the relationship with delayed gratification and problem solving.

A crucial methodological issue throughout is the reliance on self-report measures. Tang *et al.* (2017) quantified smartphone use and impulsivity using the SPAI and BIS respectively, finding a negative association. However, self-reported and behavioural impulsivity have been demonstrated to be different to one another (Barnhart & Buelow, 2017; Christiansen, Cole, Goudie, & Field, 2012). Furthermore, self-reported estimates may lead to underreporting of negatively perceived behaviours, e.g. video game play (Kahn, Ratan, & Williams, 2014), and in relation to executive functioning, correlate poorly with behavioural measures (Buchanan, 2016).

Frost *et al.* (2019) also quantified delay of gratification and problem solving using self-reported measures. The Delayed Gratification Inventory (DGI-10) is scored on a five-point Likert scale and covers five domains; food, physical pleasure, social interaction, money, and achievement. Scores have been found to be associated with relevant behaviour tendencies (Hoerger, Quirk, & Weed, 2011). Additionally, the Modified MEPS focuses on social problems, asking participants to provide solutions to social issues posed to them in small vignettes. It is possible that this limits the applications of these findings to only be applicable to social problem solving, rather than a wider variety of problem solving scenarios.

A strength of this review is that it is founded upon the existing literature and presents findings by the outcome measures they were intended to be contextualised with. The Miyake *et al.* (2000) framework of three core EFs was included at the beginning of this review (inhibition and interference control, working memory, and cognitive flexibility). It was a purposeful choice for the structure of the results to differ from this, to accurately reflect the complexity of the associations. However, this review is not without limitations. The included articles were of varying methodological quality, which should be kept in mind during interpretation. Additionally, there may be additional cognitive processes effected by mobile technology exposure, aside from executive functioning and, therefore, outside the remit of this paper.

Two of the five executive function outcomes reported here are only supported by one study (Donohue *et al.*, 2012; Frost *et al.*, 2019). The included studies are at risk for methodological bias. This collection of studies and inconclusive findings suggest that, at a point of increasing public concern about the associations between mobile technology and executive function, there was a gap in the literature to address. The urgency to fulfil this deficit perhaps resulted in studies of reduced quality. It is worthwhile to note that the quality of studies has improved over time, as the four more recent studies (Fortes *et al.*, 2020; Fortes *et al.*, 2019; Frost *et al.*, 2019; He *et al.*, 2020) are conducted to a higher standard than the four earlier studies. They contain a pilot study for a randomised control trial (He *et al.*, 2020), discrete groups of smartphone use (Frost *et al.*, 2019) and repeated measures within-subject investigations (Fortes *et al.*, 2020; Fortes *et al.*, 2019) to clarify the associations between smartphone and executive functions. This indicates that the literature in this area is improving in terms of methodological quality and, therefore, the reliability of estimates.

This systematic review highlights the inconclusive nature of the literature to date and acts as a call for rigorous and objective research on the association between mobile devices and executive functions.

Chapter 3: Examining the cross-sectional and longitudinal associations between type of screen use, decision making, and sleep in UK adolescents: an MCS Study

3.1 Abstract

Introduction:

This chapter aimed to determine whether screen use in early adolescence (age 14) was associated with executive function (decision making), and sleep quality respectively at age 14 and 17.

Method:

This was examined using the Millennium Cohort Study (MCS), a national birth cohort study which initially followed 19,000 participants. Screen use was measured using Time Use Diaries (TUD) at age 14 and delineated between three discrete categories: social media, video gaming, and watching content on TV, DVDs and videos. Decision making was measured using the Cambridge Gambling Task (CGT) and a risk and time preference questionnaire. Sleep quality was assessed through self-reported answers of how often participants woke during the night. A number of pre-birth and childhood confounds were included in sample weighted analyses. Multiple imputation methods were used to reduce the attrition bias of missing data, and analyses comprised of either hierarchical, linear, or logistic regressions.

Results:

Complete case analysis found evidence of weak associations between all three screen uses and increased quality of decision making at age 14, and longitudinally between playing video games

and reduced sleep quality at age 17. There was no evidence of further relationships found in the complete case analyses. No evidence of associations was found in the imputed analyses.

Discussion:

Implications suggest that there were no robust relationships between leisure focused screen-based media use and decision making or sleep quality in the present sample. However, current analyses were limited by an underpowered sample size for the epidemiological methods, and attrition bias despite efforts to address and minimise this.

3.2 Introduction

To help address the gap in the literature the systematic review identified, studies of increased quality and rigor are needed across the field. To contribute towards this, secondary data analysis of a birth cohort study was utilised. I examined the cross-sectional and longitudinal relationships between screen uses, decision-making, and sleep quality in UK adolescents.

Adolescence is an important period of growth and development across neurological, cognitive and behavioural domains (Blakemore & Mills, 2014; Griffin, 2017). Subsequently, it is pivotal for the adoption and maintenance of vital health and wellbeing behaviours to sustain into adulthood (Raphael, 2013). One such health behaviour is sleep. Adolescents need an increased amount of sleep compared to adults, with suggestions of between eight to ten hours (Paruthi *et al.*, 2016), compared to approximately seven hours in adults (Watson *et al.*, 2015). Sufficient sleep is essential for the adolescent maturational development of brain structure and function, as well as to support cognitive functions, such as emotional regulation, learning and memory, and decision making which includes risk taking (Arain *et al.*, 2013; Tarokh *et al.*, 2016b). Sleep deprivation and deficiency can produce excessive daytime sleepiness, cognitive performance decline, increased impulsivity, and irritability (Tarokh *et al.*, 2016b).

Additionally, there is evidence to suggest the relationship between sleep duration and cognitive performance is curvilinear. Richards *et al.* (2017) studied the association between age, average sleep duration and performance in a range of game-like online cognitive training tasks measuring working memory, visuospatial memory, and arithmetic. Participants ranged between 15 to 75 years old, and were grouped into ten-year age groups (e.g., 15 to 24, 25 to 34, and so on). Peak cognitive performance was demonstrated at 7 hours of sleep for all age groups, with the most pronounced curvilinear relationship in adolescents to middle-aged participants. Shorter (6hrs) and longer sleep duration (>7hrs) was associated with decreased performance in all three cognitive tasks. This suggests an optimal-dose model of sleep requirements for adolescents (Van Dongen *et al.*, 2003).

The prevalence of screen use has increased rapidly in the last decade. This is particularly true for adolescents; as of 2017, 83% of 12 to 15 year olds have their own smartphone, and 55% have their own tablet (Ofcom, 2017). This rapid growth has prompted societal conversation on the impacts of these devices and subsequently resulted in an urgency to understand the relationship between screen uses, cognition, and sleep, especially regarding the impact on adolescents. Although there is some evidence of negative associations between screen time and adolescent well-being (Twenge, 2019; Twenge & Campbell, 2018), recent reviews and meta-analyses conclude that the current evidence base presents mixed findings (Odgers & Jensen, 2020; Orben, 2020b).

There is some evidence to suggest sex differences in the use of different screen-based activities (Leonhardt & Overå, 2021; Soares, de Oliveira, Wehrmeister, Menezes, & Gonçalves, 2021). Social media is more frequently used by females, whereas video games are perceived to be a male pursuit. However, some evidence suggests otherwise. Within the broad range of video games available, females tend to opt for creative, fantasy-based, and intellectual games, whereas males prefer action orientated games (Jiwal *et al.*, 2019; Trisolini, Petilli, & Daini, 2018). Playing video games have been associated with enhanced working memory (Soares *et al.*, 2021; Waris *et al.*, 2019), inhibition (Liu, Liao, & Dou, 2019; Miedzobrodzka *et al.*, 2021), attention (Jiwal *et al.*, 2019), and learning (Green & Bavelier, 2012). However, video gaming may also be associated with impaired decision-making (Fortes *et al.*, 2020) and inhibition (Deleuze *et al.*, 2017).

Additionally, while there is evidence that commercial, off-the-shelf video games may have no relation to executive function performance, focused and tailor-made games designed to provide scenarios to repeatedly practice a specific executive functioning skill may show promise (Mayer, Parong, & Bainbridge, 2019). Homer, Plass, Raffaele, Ober, and Ali (2018) used a custom-designed learning game developed to target the executive function subskill of shifting. Participants aged between 14 and 18 years had to engage with the game for a minimum of thirty minutes across 6 sessions. The intervention successfully improved participants shifting skills, with EF post-test measures predicted by in-game performance. Furthermore, computer use has been found to have a positive association with the neurocognitive domains of language, memory and learning, and social perception, whereas watching television was negatively related to visuospatial processing and attention in addition to these cognitive domains (Rosenqvist, Lahti-Nuuttila, Holdnack, Kemp, & Laasonen, 2016).

Evidence also suggests that the rise of screen-based media and devices may be reciprocally associated with insufficient sleep and sleep-related problems in adolescents (Alonzo *et al.*, 2021; Johnson, Cohen, Kasen, First, & Brook, 2004; Mac Cárthaigh, Griffin, & Perry, 2020; Poulain *et al.*, 2018; Woods & Scott, 2016). Paiva, Gaspar, and Matos (2016) refer to these screen-based devices as 'sleep stealers' (p.8) and suggest that increased use of these devices reduces adolescent sleep duration. Their results demonstrated that media device use was more prevalent in sleep deprived adolescents, however the study design raises methodological concerns. Firstly, although some effort was made to differentiate between screen uses by producing two categories of 'screen time' to denote computer use (e.g., 'standard', games, internet, social networks, emails), and 'TV and mobile phone use', each of these were still reductionist composite measures, which group together different types of screen-based media use and assuming each use has the same impacts. Secondly, each measure was transformed into dichotomous data for analyses to consider only high frequency versus low frequency / absence of the behaviour in further composite binary analyses.

Research by Hisler *et al.* (2020b) examined the associations between sleep and specific screen-based media activities using a nationally representative cohort study. Social media use, video games, television viewing, and general internet use was examined in relation to sleep duration and rise times on weekdays and weekend days. Those who used increased amounts of screen-based media were less likely to sleep well, especially on school nights. Additionally, compared to video gaming or television viewing, there was stronger evidence for these negative sleep associations for social media and general internet use. The use of a representative cohort study increases the power of analyses for this examination of the associations between screen-based media and sleep; however, these findings are somewhat limited by the cross-sectional design.

Further examination of this relationship using more statistically advanced methods has demonstrated that although there is a negative association between digital technology use and adolescent well-being, the effect is negligible (Orben, 2020b; Orben & Przybylski, 2019). Although studies posit that the nuanced effects of different types of 'screen time' should be examined more closely, few go so far as to put that into practice. In their review, Kaye *et al.* (2020) detailed how the evidence is based on predominantly low quality cross-sectional studies and relies on self-reported measures and poor conceptualisation (Kaye *et al.*, 2020; Warsaw *et al.*, 2021).

The aggregate measure of 'screen time' is not an appropriate manner of measuring these activities. Given that different devices and content are likely to have different outcomes, the nuance of screen-based activities should be divided into the composite individual types to gain a complete picture of the impact they may have on adolescents' cognition and sleep. As such, the term 'screen use' has been suggested, to take into account the activities, uses, and affordances these devices offer (Kaye *et al.*, 2020). In addition to this, the variability of individuals' life contexts and socio-demographics should be taken into consideration to control for the impacts of these on cognition and sleep (Kardefelt-Winther, 2017).

Using the Millennium Cohort Study, this study aimed to determine whether screen use at age 14, in 3 discrete categories (e.g., time spent on social media, video gaming, and passively watching content on TV, DVDs and videos) was associated with executive function (decision making) and sleep quality respectively at age 14 and 17. Based on this research question, the hypotheses were:

1. Social media use and watching TV, DVDs, and videos at age 14 will each be negatively associated with decision-making at age 14.
2. Playing video games at age 14 will be positively associated with decision-making at age 14.
3. Social media use and watching TV, DVDs, and videos at age 14 will each be negatively associated with decision-making at age 17.

4. Playing video games at age 14 will be positively associated with decision-making at age 17.
5. Social media use, video gaming, and watching TV, DVDs, and videos at age 14 will each be negatively associated with sleep at age 14.
6. Social media use, video gaming, and watching TV, DVDs, and videos at age 14 will be negatively associated with sleep at age 17.

3.3 Method

3.3.1 Data

The research questions were explored using data from the Millennium Cohort Study (MCS); a longitudinal birth cohort of 19,244 children born in England, Scotland, Wales and Northern Ireland between September 2000 and January 2002. The MCS was constructed to be nationally representative. The sampling approach included over-sampling specific sub-groups of the population to represent harder to reach populations and ensure sufficient sample sizes for analyses of these sub-groups (e.g., children living in disadvantaged areas or children of ethnic minority backgrounds). Sampling weights attribute variable worth to values and account for the stratified clustered design and oversampling of sub-groups. Therefore, analysis of MCS data was adjusted using sampling weights to ensure accurate prevalence estimates (Connelly & Platt, 2014). The MCS has seven data sweeps currently available when cohort members were aged 9 months, and at ages 3, 5, 7, 11, 14 and 17. The current study obtained covariate data from the sweeps at 9 months, age 7, and 11, and exposure and outcomes variables were obtained from ages 14, and 17. Attrition by age 14 was predicted by being male, of Black ethnicity, lower occupational and educational level, and single-parent family (Mostafa & Ploubidis, 2017). More information about this cohort study can be found here: https://cls.ucl.ac.uk/cls-studies/millennium-cohort-study/.

3.3.2 Participants

Cohort members were considered eligible for inclusion in the present study if they were the first cohort member for each MCS family, which randomly selects one participant from families with multiple cohort members, such as twins or triplets, and if they had complete data for each outcome variable from the age 14 and 17 data sweeps. The age 17 Complete Case Analysis returned a sample of 576 participants.

3.3.3 Measures

Exposure: Age 14 Screen Use Time

Variables measuring screen use were derived from the Time Use Diaries (TUD) data from the sixth sweep, when participants were aged 14. Participants documented two days of activities, a weekday and a weekend day, in ten-minute time slots between 04:00 to 03:59 the following day. Three separate numerical codes were used to denote the different types of screen related activities of interest. The number of times each activity was reported in the TUD was frequency counted across the two documented days and divided by six to produce variables denoting time by whole hours and part of hours in decimals (e.g., 2.66 = 2 hours, 40 minutes) on each screen use activity. This produced three individual exposure variables of different types of screen-based activities:

- Social Media Use (e.g., Twitter, Facebook, BBM, Snapchat)
- Playing video games
- Watching TV, DVDs, Videos

For the purposes of supplementary analyses, additional variables specifying total screen time as a whole and total time for each screen-based activity on the weekday and weekend day respectively were also calculated using the variable that denoted the documented days of the week.

Outcome variables: Sleep Quality

Sleep quality at both age 14 and age 17 was derived based upon the National Sleep Foundation's suggestion of poor sleep quality being categorised by increased wakeful periods during the night (National Sleep Foundation, 2020). Measures of wakeup periods differed slightly at each data sweep; therefore, for the purposes of harmonisation across time points, participant's wakeful periods were dichotomised into 'poor' and 'good' sleep quality. At age 14, self-reported data was available on participant's bed times and wake times on weekdays and weekends, how long it takes them to fall asleep (latency), and how often participants woke up in the night (quality). An outcome variable for sleep quality was derived from participant answers to how often they awakened during sleep and had difficulty falling back to sleep. Answers between 1 (all of the time) and 3 (a good bit of the time) were transformed to 0 = poor quality. Answers between 4 (some of the time) and 6 (none of the time) were coded as 1 = good sleep quality.

At age 17, sleep quality was measured by a single self-reported item rated on a four-point categorical scale from (1 = 'very good', 2 = 'fairly good', 3 = 'fairly bad', 4 = 'very bad'). 'Fairly bad' and 'very bad' were recoded as 0 = poor sleep quality, and 'fairly good' and 'very good' were recoded as 1 = good sleep quality. This had the benefit of being harmonious with the age 14 data to allow for interpretation of findings.

Outcome variables: Decision-Making

At age 14, the Cambridge Gambling Task (CGT) was used to measure decision-making and risk-taking behaviour. Participants were asked to bet from a bank of points on which a target token would be hidden behind from a selection of red and blue boxes. If they were correct, the number of points they risked would be added to the total, and if they were wrong they would be deducted. This produced six performance variables: quality of decision making, risk adjustment, risk taking, delay aversion, overall proportional bet, and deliberation time. Quality of decision-making score represented the proportion of times the participant placed their bet on the most likely outcome. This score became the outcome variable and was measured on a continuous scale with increased scores indicating increased quality of decisions.

At age 17, decision-making was measured through a delay discounting task which accounted for individuals' risk and time preferences respectively (Dohmen *et al.*, 2011). The task was grouped by preference, and participants selected their preferred option of two choices for 10 items per preference. Previous research has found negative relationships between risk and time preferences (Ferecatu & Önçüler, 2016), and risk and time preferences with cognitive ability (Dohmen, Falk, Huffman, & Sunde, 2010). Therefore, these two constructs were kept separate as outcome variables to allow for the differences to be represented.

In the risk section, a choice had to be made between a 50-50 chance of receiving £240, or receiving reducing increments of less money for certain. The switching point, the choice at which participants prefer the lottery option over the safe option, provides information about an individual's attitude to risk; risk adverse, or risk loving. This variable was scored between 0 to 10, with 10 indicating an increased proclivity to take risks.

In the time section, the choice was between £50 in two months, or receiving a value of money equal to or greater than £50 in four months. Participants indicated which choice they would prefer, with the switching point providing information on attitudes to patience; patient or impatient. This variable was scored between 0 to 10, with 10 indicating increased impatience.

Although the cohort data used different measures of decision-making at each data sweep, the distinct outcomes of decision-making and delay discounting have been found to be related constructs. For instance, Nigro and Cosenza (2016) compared decision making and delayed discounting in adolescent gamblers and non-gamblers while controlling for alcohol consumption. Compared to their counterparts, the gamblers performed worse on the Iowa Gambling Task (IGT) and demonstrated steeper delay discounting. Their evidence was the first to suggest associations between gambling, maladaptive decision-making, and increased delayed discounting in adolescents. Furthermore, Callan, Shead, and Olson (2011) examined the psychological mechanisms of the relationship between personal relative deprivation (a social comparison belief that one is deprived of desired or deserved outcomes compared to others) and gambling behaviour. Across four studies, empirical evidence demonstrated that steeper delay discounting (or the decreased willingness to delay gratification) was associated with increased gambling behaviour. Therefore, although the change in MCS measures was not ideal for cross-time point harmonisation and inferences, each was a related measure of decision-making.

Potentially Confounding Variables

Sex:

Participant sex was extracted from the first data sweep at 9 months. This was controlled for as sex differences have been demonstrated in smartphone use (Andone *et al.*, 2016), video gaming, and social media (Leonhardt & Overå, 2021). The variable was kept binary as it was collected (1 = male, 2 = female).

Ethnicity:

Ethnicity was extracted from sweep 1 data and contained an 8-category parent-reported answer (1 = White, 2 = Mixed, 3 = Indian, 4 = Pakistani, 5 = Bangladeshi, 6 = Black Caribbean, 7 = Black African, 8 = Other Ethnic Group (including Chinese, Other). As the majority of the participants were White and there was less viable data for specific ethnic minority groups (see Table 4), for the purpose of including this as a covariate in analyses ethnicity was recoded as 1 = white and 2 = non-white (Thornton, Patalay, Matthews, & Bannard, 2021).

Socioeconomic Status:

Socioeconomic Status was adjusted for as there is evidence of an association between SES and screen use; lower income and socioeconomic status families tending to spend more time in front of screens compared to their wealthier counterparts (Carson, Spence, Cutumisu, & Cargill, 2010; Männikkö, Ruotsalainen, Miettunen, Marttila-Tornio, & Kääriäinen, 2020). SES was controlled for using four variables extracted from sweep 1: income, occupational class, parental education, home ownership. UK OECD income weighted quintiles were used as an indication of household income (1 = highest, 5 = lowest). Occupational status was derived from the paid work status of the main parent respondent and scores ranged between 1 to 4 (1 = currently doing paid work, 2 = has a paid job but on leave, 3 = has worked in the past but no current paid job, 4 = never had a paid job). Parental education ranged between higher degrees to none of the formal qualifications listed (1 =

degree or higher, 5 = none of these qualifications). Home ownership was collapsed into three categories; 1 = owning the home, either outright or through a mortgage or loan, 2 = renting, from a local authority, housing association or privately, or 3 = other, which included shared equity, living rent free or with parents, squatting, or other. The variables were ordered categorically and added with the other pre-birth confounds (sex and ethnicity) to produce partially adjusted models.

Age 7 emotional difficulties:

Sweep 4 data on parent reported Strengths and Difficulties Questionnaire was used to generate an age 7 emotional difficulties variable (Muris, Meesters, & van den Berg, 2003). Although age 11 is the data sweep prior to the exposure measures of different screen use, by age 11 (~2011) participants may have had increased access to screens already. Therefore, adjusting for age 7 emotional difficulties was deemed more appropriate. The SDQ contains subscales of emotional, conduct, hyperactivity and peer problems. The emotional symptoms subscale was used as a continuous variable to control for emotional difficulties with increased scores demonstrating increased difficulties.

Age 7 physical activity:

Physical activity (PA) is associated with screen use, decision making, sleep respectively (Fomby, Goode, Truong-Vu, & Mollborn, 2021; Lang *et al.*, 2013; Sofis, Carrillo, & Jarmolowicz, 2017). Participants wore the uniaxial ActiGraph GT1M accelerometer around their waists for 7 days to collect objective measures of physical activity and sedentary behaviour. Sedentary time was defined as <100 counts per minute, light PA (LPA) as 100–2241 and moderate to vigorous (MVPA) as >2241 (Pulsford *et al.*, 2011). A derived variable of total time in minutes spent in MVPA was controlled for in analyses.

Family Structure:

There is prior evidence of adolescents in two-parent households spending significantly less time on screen-based activities (television, computer use and video gaming) than their counterparts in single-parent households (Hofferth, Flood, & Sobek, 2018) or reconstituted households (Langøy, Smith, Wold, Samdal, & Haug, 2019). Based on these findings, a binary family derived variable summarising the parents/carers was used to denote single or dual adults in a household.

Substance Use:

Youth substance use is related to sleep (Pasch, Latimer, Cance, Moe, & Lytle, 2012) and decision making (Dom, Sabbe, Hulstijn, & Van Den Brink, 2005). An alcohol, smoking or substance use variable was derived from the age 14 young person questionnaire. Participants were asked 'Have you ever had five or more alcoholic drinks at a time? A drink is half a pint of lager, beer or cider, one alcopop, a small glass of wine or a measure of spirits' and 'Have you ever tried any of the following things: Cannabis (also known as weed, marijuana, dope, hash or skunk); Any other illegal drug? (such as ecstasy, cocaine, speed)'. Responses to these questions were binary (1 = yes and 2 = no). Participants were also asked to select which of 6 statements best described their smoking habits: 1 = I have never smoked, 2 = I have only tried smoking cigarettes once, 3 = I used to smoke sometimes but I never smoke a cigarette now, 4 = I sometimes smoke cigarettes now but I don't smoke as many as one a week, 5 = I usually smoke between one and six cigarettes a week, 6 = I usually smoke more than six cigarettes a week. If participant responded as statement 4, 5, or 6, this was coded as 1 = smoking. If they responded 1, 2, or 3, it was coded as 0 = non-smoking.

A total substance use variable was derived from the sum of their answers to these four substances: alcohol, smoking, cannabis, and any other illegal drug. This was derived as a score between 0 and 4, with a point given for each substance a participant reported using (Gage & Patalay, 2021). Higher scores would indicate more risky substance use behaviour.

Missing Data

When the MCS was first implemented it had a UK representative sample of around 19,000 cohort members. After data cleaning my sample, there were 10,782 cohort members who had demographic variables.

Although effort was made to reduce bias when designing the Millennium Cohort Study, through over-recruiting under-represented populations for example, bias can be introduced due to attrition. As the number of data sweeps increases, so does the number of opportunities for missing data as cohort members refuse to answer questions or drop out of the continued follow-ups completely. This type of missingness in data is likely to be 'missing not at random' (MNAR), whereby certain types or groups of individuals are more likely to have dropped out than others (Graham, 2009). This is considered nonignorable missingness, as MNAR data and analyses can yield biased estimates (Graham, 2009). For the current data, the sweep 7 complete case analysis was a sample of 576. This represents ~5% of the MCS sample at sweep 7, and ~3% of the originally recruited MCS sample. This is a substantial loss of power. Therefore, my strategy to deal with this attrition bias was to use Multiple Imputation and include auxiliary variables in my model to address the MNAR data to make it suitable for analysis (Graham, 2009).

Multiple Imputation Justification

Multiple Imputation (MI) is a robust and popular method handling missing data by estimating plausible missing values based upon observed values either directly related to the variable with missing data, or on other variables in the dataset (Graham, 2009). It produces multiple datasets each with varying data points based on the probability of the likelihood of that value. Standard analysis methods are then applied to each of the completed datasets and the resulting estimates for variables of interest are combined using Rubin's rules (Rubin, 1987) to produce one set of inferential statistics. Through estimating missing values, insufficient sample sizes are improved upon and, therefore, the power of analyses. The MI models were specified through a process of trial and error to troubleshoot issues that would cause a breakdown in the model algorithm (Nguyen, Carlin, & Lee, 2021). An example of such instances include collinearity, whereby covariates in the imputation model were highly correlated, resulting in the algorithm having difficulty estimating separate effects. The adverse effects of multicollinearity in regression analyses is well documented, and can result in unstable standard errors and p-values (Vatcheva, Lee, McCormick, & Rahbar, 2016). I resolved this breakdown in the model by removing variables from the model in turn, and examining the correlations between variables in the model to ensure any correlations were appropriate. I removed a sweep 6 ordinal variable which measured how often participants woke up during sleep, which had been interfering with my regression models for MI.

It was deemed to be statistically unwise to impute the data for the outcome variables of decision-making and sleep quality (Sterne *et al.*, 2009). The number of cohort members who had complete data for the age 14 and age 17 outcome measures was calculated, and the data was imputed up to that number.

Multiple Imputation was conducted using the multivariate normal regression (MVN) method for both the age 14 cross-sectional data and the age 17 longitudinal data. The MVN method functions on the assumption that the variables with missing values to be imputed are continuous and follow a multivariate normal distribution (Schafer, 1997). A total of ten datasets were imputed for each age. The total achieved sample sizes were 3224 for age 14, and 2328 for age 17.

Data Analysis

Data cleaning and analysis was carried out using STATA version 14.1. The association between each screen time exposure variable (e.g. social media use, watching TV or videos, and playing video games), decision-making and sleep were examined. Data was analysed accounting for potential demographics and health behaviour-related confounding variables. An overall measure of screen use time was purposefully not used for any analysis as the concept of the umbrella term of screen time is problematic (Orben *et al.*, 2018).

Primary analyses were conducted using either hierarchical or logistic regression analyses as appropriate; cross-sectional analyses at age 14, and longitudinal analyses between age 14 and age 17. Hierarchical regressions comprised of 3 steps; the first entered the exposure variable to predict the outcome variable to comprise the unadjusted model. The second step added pre-birth confounding variables taken from sweep 1 of the data at 9 months (sex, ethnicity, socioeconomic status, and family environment) to comprise the partially-adjusted model. The third and final step included health-related behaviour confounds at age 14 (e.g. substance use) and age 7 (e.g. emotional difficulties and physical activity) to comprise the fully adjusted model. This was repeated for the age 17 outcome measures from the seventh sweep, whilst controlling for life course and age 14 and age 7 confounds, to examine the possible longitudinal associations.

Supplementary Analyses

Additional sensitivity analyses were conducted on the age 14 Complete Case Analysis (CCA) data to explore the reliability of the screen use exposure variables derived from the Time Use Diaries at age 14. As data was collected from one weekday and one weekend day, the mean difference between the two days measures was examined for each type of screen use activity. Additionally, the sweep 6 cohort member questionnaire reports single item data of hours spent watching TV and playing video games on weekdays. This was compared with the derived TUD data for watching TV and playing video games respectively on weekdays. Paired t-test statistics and Cohen's d effects sizes are reported.

3.4 Results

3.4.1 Descriptives

Participants in the complete case analyses (age 14: *n* = 834; age 17: *n* = 576) and in the imputed data (age 14: *n* = 3224; age 17: *n* = 1929) were majority white and female (see Table 4). They had a mean total of ~6 hours of screen time per day, primarily watching TV, DVDs or videos (Social media: *M* = 1 hour. Video gaming: *M* = 1.8. TV, DVDs, Videos: *M* = 3 hours). In both samples, the majority of participants were from dual parent/carer households (CCA: 93%. Imputed: .84) and did an average of 30 minutes moderate to vigorous physical activity a day (*M* = 30.9). Compared to the original sweep 7 of the MCS data, there is less ethnic representation of the United Kingdom in the CCA sample and the imputed sample (see Table 4).

3.4.2 Complete Case Analysis

Complete Case Analysis (CCA) numbers were calculated for the cross-sectional and longitudinal data respectively. In cross-sectional analyses, three hierarchical regressions were conducted to examine the associations between decision-making and three different types of screen-based activities; social media, video gaming, and watching TV, DVDs or videos (see Table 5). A further three hierarchical logistic regressions examined the associations between screen-based activities and sleep quality (see Table 6). Full results tables including all covariates can be found in Appendix A.

Table 4: % (N), proportions or mean (SD) of descriptive, exposure, and outcome variables in the longitudinal age 17 CCA and age 17 imputed sample, with comparison to MCS Sweep 7.

Variable			Complete Case Analysis (age 17: *n* = 576) Percentage or *M* (SD)	Multiple Imputation (*n* = 2,378) Proportion or *M* (SD) [95% CI]	MCS Sweep 7 (*n* = 10,782) Percentage or *M* (SD)
Demographics	Sex				
		Male	46.70%	.455	52.61%
		Female	53.30%	.545	47.39%
	Ethnicity				
		White	96.18%	.919	87.23
		Mixed	2.60	.033	3.22
		Indian	0.69	.015	1.71
		Pakistani	0	.006	2.68
		Bangladeshi	0	<.001	0.91
		Black Caribbean	0	.007	1.45
		Black African	0.35	.009	1.53
		Other inc. Chinese	0.17	.009	1.28
Exposure *M* (SD)	Social media use * (hours) (Range = 0, 18.83)		1.07 (1.83)	.99 (.07) [.84, 1.14]	.93 (1.73)

		Playing video games* (hours) (Range = 0, 21.33)	1.89 (3.39)	1.79 (.12) [1.55, 2.03]	1.71 (3.31)
		Watching TV, DVDs, or videos * (hours) (Range = 0, 20.83)	3.35 (3.18)	3.02 (.12) [2.77, 3.26]	2.92 (3.12)
Outcome *M* (SD)	Decision-making				
		Cambridge Gambling Task (age 14) * (Range = 0.29, 1)	0.91 (0.11)	.91 (.003) [.89, .90]	.89 (.13)
		Risk Preferences (age 17) (Range = 0, 10)	2.22 (3.18)	2.07 (.17) [1.74, 2.41]	2.02 (2.94)
		Time preferences (age 17) (Range = 0, 10)	4.86 (2.64)	5.00 (.10) [4.80, 5.21]	5.01 (2.72)
	Sleep quality				
		Sleep quality (age 14) *	0.84 (0.37)	.79 (.01) [.77, .81]	.77 (.42)
		Sleep quality (age 17)	0.69 (0.46)	.64 (.02) [.61, .68]	.67 (.47)
Covariates	SES				

	Parent academic qualification	Degree or higher	30.56%	.189	13.36%
		A/AS/S Levels	20.66%	.193	17.55%
		GCSE A-C	35.42%	.358	35.47%
		GCSE D-G	7.64%	.126	14.00%
		None of these	5.73%	.134	19.62%
	Home ownership	Own	80.21%	.638	55.14%
		Rent	15.80%	.300	38.14%
		Other	3.99%	.062	6.72%
	Occupational status	Current paid work	62.33%	.504	44.84%
		Paid job but on leave	2.95%	.017	2.46%
		Worked previously	33.51%	.400	42.18%
		Never had paid job	1.22%	.079	10.52%
	Income weighted quintiles		3.46 (1.29)	3.04 [2.90, 3.18]	2.71 (1.41)
Family structure	Two parents / carers		92.88%	.841	80.07%
	One parent / carer		7.12%	.160	19.93%

Substance use *	.19 (.49)	.269 [.231, .306]	.36 (.71)
Emotional difficulties (age 7)	1.22 (1.61)	1.39 [1.34, 1.44]	1.46 (1.73)
Physical activity (mins) (age 7)	30.94 (12.11)	30.93 [30.01, 31.85]	31.14 (11.18)

Note: Proportions, means and SDs of the multiple imputation data are pooled across 10 imputed datasets and sample weighted. * denoted the variable was measured at age 14.

3.4.3 Cross-sectional analyses

Decision-making – age 14

A hierarchical regression (*n* = 834) examined the association between decision-making at age 14 and social media use at age 14, accounting for several pre-birth and childhood confounders. There was no evidence of an association in the unadjusted model (β = .05, *p* = .11). After adjustment for pre-birth covariates of sex, ethnicity, SES and family structure, there was a weak association (β = .081, 95% CI = .001, .009, *p* = .02). In the fully adjusted model (*F* (11, 822) = 4.57, *SE* = 0.12, *p* <.001, R^2 = .07), which accounted for the additional covariates of age 7 physical activity, age 7 emotional difficulties, and age 14 substance use, a weak association between decision-making and social media remained (β = .08, 95% CI = .001, .009, *p* = .02) (see Table 5).

A second hierarchical regression examined the association between decision-making and time spent on video games. In the unadjusted model, there was a weak association, (β = .07, 95% CI = <.001, .005, *p* = .04). After taking pre-birth confounds into consideration, including sex, ethnicity, SES and family structure, a weak association remained (β = .09, 95% CI = <.001, .005, *p* = .02). The fully adjusted model added in the childhood covariates and found a weak association between age 14 decision-making quality and video game play (β = .10, 95% CI = <.001, .01, *p* = .02).

A third hierarchical regression examined the association between decision-making at age 14 and total time spent watching TV, DVDs, or videos. The unadjusted model presented a weak association between decision-making and time spent watching TV (β = .097, 95% CI = .001, .006, *p* = .005). After pre-birth covariates were included in the partially adjusted model, the weak association remained (β = .101, 95% CI = .001, .006, *p* = .004). Additional childhood covariates were added into the fully adjusted model and a weak association between decision-making and watching TV, DVDs or videos remained (β = .11, 95% CI = .001, .006, *p* = .006).

Table 5: Hierarchical multiple regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs or videos) at age 14 and decision making at age 14 in the age 14 CCA (n = 834)

	Social Media			Video Games			Watching TV, DVDs, Videos		
Model	*B*	95% CI	P value	*B*	95% CI	P value	*B*	95% CI	P value
Unadjusted	.003	-.001, .007	.11	.002	<.001, .01	.04	.004	.001, .006	.005
Partially adjusted	.005	.001, .009	.02	.003	<.001, .005	.02	.004	.001, .006	.004
Fully adjusted	.004	.001, .009	.02	.003	<.001, .006	.02	.004	.001, .006	.006

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 14 quality of decision making based on the Cambridge Gambling Task (CGT)

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties and age 7 physical activity).

Table 6: Hierarchical logistic regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs or videos) at age 14 predicting sleep quality at age 14 in the age 14 CCA (n = 834)

	Social Media			Video Games			Watching TV, DVDs, or Videos		
Model	Odds Ratio	95% CI	P value	Odds Ratio	95% CI	P value	Odds Ratio	95% CI	P Value
Unadjusted	0.98	.88, 1.09	.81	1.03	.95, 1.11	.47	1.02	.95, 1.11	.63
Partially adjusted	1.01	.89, 1.14	.91	1.02	.94, 1.10	.67	1.02	.95, 1.10	.61
Fully adjusted	1.02	.90, 1.14	.75	1.01	.94, 1.11	.75	1.02	.95, 1.10	.58

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 14 quality of decision making based on the Cambridge Gambling Task (CGT)

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties and age 7 physical activity)

Sleep Quality – age 14

A hierarchical logistic regression examined the association between sleep quality at age 14 and social media use at age 14. There was no evidence of an association in the unadjusted, partially adjusted, nor the fully adjusted models (fully adjusted: OR = 1.02, 95% CI = .90, 1.15, p = .75) (see Table 6).

A hierarchical logistic regression was used to examine the association between sleep quality at age 14 and playing video games at age 14. There was no evidence of an association in the unadjusted, partially, or fully adjusted models (fully adjusted: OR = 1.01, 95% CI = .94, 1.101, p = .75).

A hierarchical logistic regression was used to examine the association between sleep quality at age 14 and watching TV, DVDs, or videos. There was no evidence of an association in the unadjusted, partially, or fully adjusted models (fully adjusted: OR = 1.02, 95% CI = .95, 1.10, p = .58).

3.4.4 Longitudinal associations

The longitudinal associations between type of screen use at age 14 and the effect on decision making and sleep quality at age 17 were also examined. There were 576 participants with complete exposure, outcome, and covariate data.

Decision-making – age 17

Two hierarchical regressions were conducted to examine the association between social media use at age 14 and later risk/time preferences at age 17 (see Table 7). For risk decision making, there was no evidence of an association in the unadjusted, partially adjusted or fully adjusted models (fully adjusted: β = .06, 95% CI = -.09, .305, p = .31). For the association between time preferences at age 17 and social media use at age 14, there was no evidence of an association in the unadjusted, partially adjusted or fully adjusted models (fully adjusted: β = .03, 95% CI = -.09, .16, p = .59).

A second set of hierarchical regressions was used to examine the respective associations of risk and time preferences in decision-making and playing video games. In regard to the risk preferences, there was no evidence of an association in the unadjusted, partially adjusted or fully adjusted models (fully adjusted: β = -.023, 95% CI = -.14, .092, *p* = .71). In regard to the time preferences, there was no evidence of an association between decision-making and playing video games in the unadjusted, partially adjusted or fully adjusted models (fully adjusted: β = .02, 95% CI = -.071, .095, *p* = .75).

Two hierarchical regressions were conducted to examine the association between risk preferences and time preferences in decision-making respectively at age 17 from watching TV, DVDs or videos at age 14. In regard to the risk preferences, there was no association found in either the unadjusted, partially, nor fully adjusted models (fully adjusted: β = -.028, 95% CI = -.121, .063, *p* = .54). In regard to time preferences, there was no association found in neither the unadjusted, partially, nor fully adjusted model (fully adjusted: β = -.003, 95% CI = -.080, .075, *p* = .95).

Sleep Quality – age 17

A hierarchical logistic regression was used to examine the association between age 17 sleep quality from age 14 screen use (see Table 8). The relationship between sleep quality and social media use was examined in the same steps as above. No evidence of an association was found in either the unadjusted, partially, nor fully adjusted model (fully adjusted: OR = .941, 95% CI = .84, 1.06, *p* = .304).

The relationship between sleep quality at age 17 and video games was examined using a hierarchical logistic regression. In the unadjusted model, there was weak evidence for an association between playing video games at age 14 and sleep quality at age 17, (OR = .919, *SE* = .028, 95% CI = .867, .975, *p* = .005). After the inclusion of pre-birth covariates in the partially adjusted model, there was evidence of a weak association, OR = .902, *SE* = .031, 95% CI = .843, .966, *p* = .003. The addition of childhood covariates, including age 7 physical activity and emotional difficulties and age 14 substance use, were included in the fully adjusted model. There was weak evidence for an association between age 17 sleep quality and age 14 video gaming (OR = .889, *SE* =.032, 95% CI = .838, .954, *p* = .001).

A third logistic regression was conducted predicting age 17 sleep quality from time spent watching TV, DVDs, or videos. No evidence of an association was found in neither the unadjusted, partially, nor fully adjusted model (fully adjusted: OR = 1.049, 95% CI = .979, 1.13, *p* = .176).

3.4.5 Supplementary Analyses

Paired t-tests were conducted to examine the mean difference between weekday and weekend hours of use for each type of screen use in the age 14 CCA. The method for calculating Time Use Diaries screen use was that each instance was frequency counted across the two documented days and divided by six to produce variables denoting time by whole hours and part of hours in decimals. For instance, 2.66 = ~2 hours, 30 minutes. For social media use, there was no difference between weekday and weekend use (*t* (833) = -1.81, 95% CI = -.16, .01, *p* = .07, *d* = .07). There was a significant difference between time spent playing video games on weekdays and weekends (*t* (833) = -4.06, 95% CI = -.46, -.16, *p* <.001, *d* = .15). Participants spent more time (~1hr 10mins) playing video games on the weekend day (*M* = 1.13, 95% CI = .97, 1.28) compared to the weekday (*M* = .81, 95% CI = .69, .94) (~40mins). There was a significant difference between time spent watching TV, DVDs, or Videos on weekdays and weekends (*t* (833) = -7.04, 95 CI = -.74, -.42, *p* <.001, *d* = .29). Participants spent more time (~1hr 50mins) watching TV, DVDs, or Video on the weekend day (*M* = 1.92, 95% CI = 1.77, 2.07) compared to the weekday (*M* = 1.34, 95% CI = 1.22, 1.46) (~1hr 20mins).

Paired t-tests were also conducted to examine the difference between the screen use time reported in 10 minute intervals in the TUD and the self-reported hours spent using screen media from the sweep 6 cohort member questionnaire. Participants were asked about their video game use and the time spent watching TV, DVDs, or Videos on weekdays. The questionnaire did not include an item on social media. There was a significant difference between TUD and questionnaire reported time spent playing video games (t (833) = -38.91, 95% CI = -3.26, -2.95, p <.001, d = 1.52). TUD estimates suggested video games were played for an average of 50 minutes on weekdays (M = .81, 95% CI = .69, .94), whereas the questionnaire reported time was near 4 hours (M = 3.92, 95% CI = 3.77, 4.07). There was also a significant difference between TUD and questionnaire reported time spent watching TV, DVDs, or Videos (t (833) = -50.58, 95% CI = -4.10, -3.81, p <.001, d = 2.41). TUD estimates suggested television was watched for an average of an hour and 20 minutes on weekdays (M = 1.34, 95% CI = 1.22, 1.46), whereas the questionnaire reported time was over 5 hours (M = 5.29, 95% CI = 5.19, 5.39). This suggests that when asked directly about their use on weekdays, participants may have overestimated the amount of time engaging with video games or watching TV, DVDs, or Videos.

Table 7: Hierarchical multiple regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs or videos) at age 14 and decision making at age 17 in the age 17 CCA (n = 576)

		Social Media			Video Games			Watching TV, DVDs, Videos		
Model		*B*	95% CI	P value	*B*	95% CI	P value	*B*	95% CI	P value
Unadjusted	Risk	.08	-.15, .30	.51	.05	-.05, .15	.32	-.04	-.13, .06	.46
	Time	-.01	-.15, .12	.84	.07	<-.001, .14	.05	-.01	-.09, .07	.87
Partially adjusted	Risk	.12	-.09, .32	.26	-.03	-.14, .09	.64	-.03	-.12, .07	.58
	Time	.03	-.10, .15	.70	.02	-.07, .11	.71	<-.01	-.08, .07	.91
Fully adjusted	Risk	.11	-.09, .31	.31	-.02	-.14, .09	.71	-.03	-.12, .06	.54
	Time	.04	-.09, .16	.59	.01	-.07, .09	.75	<-.01	-.08, .08	.95

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 17 decision making

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties, and age 7 physical activity)

Table 8: Hierarchical logistic regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs or videos) at age 14 predicting sleep quality at age 17 in the age 17 CCA (n = 576)

	Social Media			Video Games			Watching TV, DVDs, or Videos		
Model	Odds Ratio	95% CI	P value	Odds Ratio	95% CI	P value	Odds Ratio	95% CI	P Value
Unadjusted	.93	.83, 1.03	.16	.92	.87, .97	.005	1.05	.98, 1.12	.15
Partially adjusted	.92	.82, 1.04	.18	.90	.84, .97	.003	1.05	.98, 1.12	.21
Fully adjusted	.94	.84, 1.06	.30	.89	.83, .95	.001	1.05	.98, 1.12	.18

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 17 sleep quality

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties, and age 7 physical activity)

3.4.6 Imputed Sample

3.4.6.1 Cross-sectional analyses

Decision-making – age 14

Multiple linear regressions were conducted to examine the associations between types of screen use and decision-making at age 14 in 10 imputed datasets of 3224 individuals with outcome data. There was no evidence in the unadjusted, partially or fully adjusted models of an association between social media use at age 14 and decision-making at age 14 (fully adjusted: B **=** <.001, 95% CI = -.003, .004, p = .83) (see Table 9).

A second linear regression examined the relationship between decision-making at age 14 and playing video games. There was no evidence of an association between time spent playing video games and decision-making quality in the unadjusted, partially or fully adjusted models (fully adjusted: B <.001, 95% CI = -.002, .003, p = .64).

The relationship between decision-making and time spent watching TV, DVDs, or videos was examined by a third linear regression. There was no evidence of an association (B = .001, 95% CI = -.001, .003, p = .47), suggesting that time spent passively watching TV at age 14 did not have an effect on decision-making quality at age 14.

Sleep quality – age 14

A logistic regression was used to examine the association between social media use at age 14 and sleep quality at age 14 in the imputed sample (see Table 10). There was no evidence of an association in the unadjusted, partially, or fully adjusted models (fully adjusted: OR = 1.01, 95% CI = .93, 1.09, p = .83).

A logistic regression was used to examine the association between playing video games at age 14 and sleep quality at age 14 in the imputed sample. In the unadjusted model, there was weak evidence of a positive association (OR = 1.06, 95% CI = 1.01, 1.12, p = .01). However, this did not remain in the partially and fully adjusted models, where confidence intervals overlapped with the null (fully adjusted: OR = 1.02, 95% CI = .96, 1.08, p = .59).

A logistic regression was used to examine the association between watching TV, DVDs, or videos at age 14 and sleep quality at age 14 in the imputed sample. There was no evidence of an association in the unadjusted, partially, or fully adjusted models (fully adjusted: OR = 1.03, 95% CI = .98, 1.09, p = .19). The narrow range of values in the confidence intervals demonstrate that these findings provide more reliable support for the lack of evidence of associations found in the CCA analyses.

Table 9: Multiple regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs or videos) at age 14 and decision making at age 14 in the age 14 imputed sample (n = 3224)

	Social Media			Video Games			Watching TV, DVDs, Videos		
Model	*B*	95% CI	P value	*B*	95% CI	P value	*B*	95% CI	P value
Unadjusted	<-.001	-.005, .003	.64	.001	-.001, .003	.32	.001	-.001, .003	.31
Partially adjusted	<.001	-.003, .004	.87	<.002	-.002, .002	.61	<.001	-.001, .003	.45
Fully adjusted	<.001	-.003, .004	.83	<.001	-.002, .003	.64	.001	-.001, .003	.47

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 14 quality of decision making based on the Cambridge Gambling Task (CGT)

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties, and age 7 physical activity).

Table 10: Logistic regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs or videos) at age 14 and sleep quality at age 14 in the age 14 imputed sample (n = 3224)

	Social Media			Video Games			Watching TV, DVDs, Videos		
Model	*OR*	95% CI	P value	*OR*	95% CI	P value	*OR*	95% CI	P value
Unadjusted	.97	.91, 1.05	.48	1.06	1.01, 1.12	.01	1.04	.99, 1.11	.10
Partially adjusted	1.02	.94, 1.12	.65	1.02	.96, 1.08	.52	1.04	.99, 1.09	.11
Fully adjusted	1.01	.93, 1.09	.83	1.02	.96, 1.08	.59	1.03	.98, 1.09	.19

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 14 sleep quality.

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties, and age 7 physical activity).

3.4.6.2 Longitudinal analyses

Decision-making – age 17

Multiple regressions were conducted to examine the associations between type of screen use at age 14 and decision-making at age 17. Risk and time preferences of decision-making were kept as separate constructs as before in the complete case analyses (see Table 11).

There was no evidence of an association between risk preferences and social media use (fully adjusted: B = .05, 95% CI = -.05, .16, p = .34), suggesting that time spent on social media was not related to risk-based decision-making. There was also no evidence of an association between time preferences and social media use (fully adjusted: B = .015, 95% CI = -.08, .11, p = .75), suggesting that social media use was not related to time-based decision-making either.

The association between playing video games and decision-making preferences was examined using a multiple linear regression. Regarding risk preferences, there was no evidence of an association in the unadjusted, partially, or fully adjusted models (fully adjusted: B = -.008, 95% CI = -.08, .06, p = .81). Regarding time preferences, there was no evidence of an association with playing video games in the unadjusted, partially, or fully adjusted models (fully adjusted: B = .02, 95% CI = -.04, .08, p = .47).

The association between risk preference in decision-making and time spent watching TV, DVDs, or videos was examined using a multiple linear regression. There was no evidence of an association in the unadjusted, partially, or fully adjusted models (fully adjusted: B = .02, 95% CI = -.05, .09, p = .55). Regarding time preferences, there was no evidence of an association with watching TV, DVDs, or videos in the unadjusted, partially, or fully adjusted models (fully adjusted: B = .001, 95% CI = -.06, .06, p = .97). The lack of evidence of an association between the different types of screen-based activities and decision-making is in accordance with the findings of the CCA analyses.

Table 11: Multiple regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs, or videos) at age 14 and decision making at age 17 in the age 17 imputed sample (n = 1929)

		Social Media			Video Games			Watching TV, DVDs, Videos		
Model		*B*	95% CI	P value	*B*	95% CI	P value	*B*	95% CI	P value
Unadjusted	Risk	.019	-.09, .12	.73	.03	-.03, .09	.27	.007	-.05, .07	.82
	Time	-.01	-.10, .08	.81	.05	-.002, .10	.06	-.008	-.07, .05	.79
Partially adjusted	Risk	.06	-.05, .17	.26	-.01	-.08, .05	.72	.008	-.05, .07	.79
	Time	.01	-.08, .11	.76	.02	-.04, .08	.54	-.006	-.06, .05	.82
Fully adjusted	Risk	.05	-.05, .16	.34	-.008	-.08, .06	.81	.02	-.05, .09	.55
	Time	.015	-.08, .11	.75	.02	-.04, .08	.47	.001	-.06, .06	.97

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 14 quality of decision making based on the Cambridge Gambling Task (CGT)

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties, and age 7 physical activity).

Table 12: Logistic regression of three types of screen-related activities (social media, video gaming, and watching TV, DVDs or videos) at age 14 and sleep quality at age 17 in the age 17 imputed sample (n = 1929)

	Social Media			Video Games			Watching TV, DVDs, Videos		
Model	*OR*	95% CI	P value	*OR*	95% CI	P value	*OR*	95% CI	P value
Unadjusted	.96	.89, 1.03	.22	.99	.95, 1.03	.61	1.01	.97, 1.06	.54
Partially adjusted	.96	.89, 1.04	.30	.97	.93, 1.02	.20	1.01	.97, 1.06	.56
Fully adjusted	.97	.89, 1.05	.39	.96	.92, 1.00	.08	1.02	.97, 1.07	.48

Unadjusted model – Age 14 screen use time, split into the type of screen use, by age 14 sleep quality.

Partially adjusted model – as the unadjusted, with additional adjustment for pre-birth confounders (sex, ethnicity, socioeconomic status, family structure)

Fully adjusted model – as partially adjusted, with additional adjustment for childhood confounders (age 14 substance use history, age 7 emotional difficulties, and age 7 physical activity).

Sleep quality – age 17

Logistic regressions were conducted to examine the associations between types of screen-based activities at age 14 and sleep quality at age 17 in the imputed sample of 1929 (see Table 12). The relationship between social media use at age 14 and sleep quality at age 17 was examined. In accordance with the CCA analysis, there was no evidence of an association in the unadjusted, partially, or full adjusted models (fully adjusted: OR = .97, 95% CI = .91, 1.05, p = .39).

The relationship between playing video games at age 14 and sleep quality at age 17 was examined by a second logistic regression. In contrast to the findings of the complete case analysis, there was no evidence of an association in the unadjusted, partially, or fully adjusted models (fully adjusted: OR = .96, 95% CI = .92, 1.00, p = .08).

A third logistic regression examined the association between watching TV, DVDs, and videos at age 14 and sleep quality at age 17. In accordance with the CCA analysis, there was no evidence of an association in the unadjusted, partially, or full adjusted models (fully adjusted: OR = 1.02, 95% CI = .97, 1.07. p = .48). These results suggest that time spent on social media, video gaming, or watching TV at age 14 was not related to the quality of sleep achieved at age 17.

3.5 Discussion

This study aimed to determine whether screen use at age 14, in 3 discrete categories (time spent on social media, video gaming, and passively watching content on TV, DVDs and videos) was associated with executive function (decision making), and sleep, respectively, at age 14; and whether this endures longitudinally to age 17. It was hypothesised that social media use and watching TV at age 14 would be negatively associated with decision-making at age 14, and that it would endure to age 17; that playing video games at age 14 will be positively associated with decision-making at age 14, and that it would endure to age 17; and that social media use, video gaming, and watching TV, DVDs, and videos at age 14 will each be negatively associated with sleep quality at age 14, and remain negatively associated at age 17. Analyses were carried out on both the complete case analysis sample (age 14: n = 834; age 17: n = 576) and on an age 14 imputed sample (n = 3224) for cross-sectional analyses, and an age 17 imputed sample (n = 1929) for longitudinal analyses.

In the complete case analyses, there was weak evidence of associations between social media use, playing video games, and watching TV at age 14 and decision-making quality at age 14 in the fully adjusted models. This suggests that even after controlling for pre-birth and childhood confounds, there was a small positive relationship between each of the different types of screen use and decision-making. However, this did not endure to age 17. For sleep quality, playing video games at age 14 was negatively associated with sleep quality at age 17. There were no further associations between the three types of screen use and decision-making or sleep. However, the evidence for weak associations did not remain in the imputed sample analyses, for which there was no evidence of associations between social media, video gaming, and watching TV, and decision-making or sleep quality. The current findings should be interpreted with caution as the sample sizes and effect sizes were small, with effect sizes being almost negligible, and the cross-sectional analysis precludes causal inferences. The demonstrated longitudinal evidence of a negative association between playing video games and later sleep quality in the complete case data may hint at causality. Given the consistent existing evidence that this relationship may exist (Altintas, Karaca, Hullaert, & Tassi, 2019; Kristensen, Pallesen, King, Hysing, & Erevik, 2021) and the coherent plausibility that exposure to video games is related to reduced sleep quality via an explanatory mechanism (e.g. blue light exposure (Heo *et al.*, 2017) or psychological arousal), this observed association may have the potential to match the Bradford Hill criteria for causal inferences (Fedak, Bernal, Capshaw, & Gross, 2015; Hill, 1965). There was some overlap between the estimated confidence intervals for both the complete case analyses and the imputed analyses. Therefore, while the imputed data had a smaller range of possible values for the estimated effect size, it is unlikely that there is a statistically significant difference in the true estimate of effect between the complete case and imputed data. This implies support for the imputed analysis as it has increased reliability, suggesting that the null hypothesis should be accepted. To further this, methodologically rigorous experimental designs are now needed to examine these associations to claim any causal inferences with greater certainty than I can ascertain from these associations.

3.5.1 Implications

Decision-making

The weak positive association between each screen use and decision-making at age 14 in the CCA analyses is in accordance with previous research. Playing video games may improve decision-making and other related executive functions (Bediou *et al.*, 2018a, 2018b; Buelow, Okdie, & Cooper, 2015; Huang *et al.*, 2017; Mayer *et al.*, 2019; Reynaldo, Christian, Hosea, & Gunawan, 2021; Waris *et al.*, 2019). Improved executive functions, including decision-making, inhibition, and cognitive flexibility, were found in highly-ranked video game players compared to average-ranked players with similar experience, and therefore may be due to gaming skill rather than amount of gameplay experience (Li, Huang, Li, Wang, & Han, 2020). Similar findings have been reported in children, with experienced video game players performing better in inhibitory control tasks than non-gamers (Liu *et al.*, 2019). Additionally, video game genre is an important factor; over a six-week intervention, focused video game play may develop adolescents' executive function skills in shifting and inhibition (Homer *et al.*, 2018). Although, the mechanisms underlying the association between playing video games and improved decision-making are likely to be complex and bidirectional, especially given the inconsistent findings often reported (e.g. Buelow *et al.*, 2015; Fortes *et al.*, 2020; Jiwal *et al.*, 2019; Trisolini *et al.*, 2018).

The result of watching TV demonstrated a weak association with improved decision making in the complete case analysis. Previously, watching TV has been associated with improved executive functioning in children, however this was specific to working memory, inhibition, and planning abilities (Yang, Chen, Wang, & Zhu, 2017). There is variable evidence on this association, with some suggesting that background television exposure may negatively impact executive functions (Nichols, 2022), perhaps through a mechanism of behavioural modelling and observation (Kulman, 2022). For children especially, it is the content consumed which is important, rather than the screen-based device or length of time. Performance on working memory and delayed gratification measures has been shown to improve after engaging with an interactive educational app, rather than passively watching cartoons (Huber, Yeates, Meyer, Fleckhammer, & Kaufman, 2018).

However, this research often finds conflicting evidence. There may be no association between screen-based device use and executive functions. As detailed in Chapter Two, playing video games may not be related multi-tasking ability (Donohue *et al.*, 2012), and neither smartphone, tablet, TV, or computer use was related to children's inhibition, working memory, or shifting (Jusienė, Rakickienė, Breidokienė, & Laurinaitytė, 2020). In addition to this, there was no evidence of a relationship between using more than one screen-based device at a time, known as Media Multitasking, and executive functions, including inhibition, working memory, and cognitive flexibility (Seddon, Law, Adams, & Simmons, 2018). However, despite the mixed results presented in published studies and the sheer quantity of research into this relationship, evidence of an absence of association between screen-based devices and executive function is sparse. This supports the notion of the publication bias in the literature (Kühberger *et al.*, 2014).

Sleep quality

There is evidence to suggest screen-based device use is associated with increased sleep-wake disturbances and reduced sleep quality (Carter *et al.*, 2016). In accordance with the current complete case longitudinal findings, there is evidence that video games are associated with reduced sleep quality (Brunetti, O'Loughlin, O'Loughlin, Constantin, & Pigeon, 2016; Dworak, Schierl, Bruns, & Strüder, 2007; Exelmans & Van den Bulck, 2015). Increased video games use is associated with sleep-wake disturbances, specifically decreased sleep duration and increased sleep onset latency and sleep disturbances (Hisler *et al.*, 2020a; Hisler *et al.*, 2020b).

Hisler *et al.* (2020b) also used the MCS to examine the associations between sleep and a variety of screen-based media, including social media use, video games, television viewing, and general internet use. Whereas the current study derived time spent on three types of screen use from the Time Use Diaries, Hisler *et al.* (2020b) derived screen media use from participant interviews, which asked about the number of hours spend watching TV, playing electronic video games, general internet use outside of school, and on social networking sites. Sleep duration and onset latency was also calculated in an alternative way, using interview responses detailing the time participants went to bed and woke up on school and non-school days, and the average time it took them to fall asleep. Hisler *et al.* (2020b) found that those who spent more time using screen-based media took longer to fall asleep (sleep latency) and experienced more mid-sleep disturbances, with the effect being more pronounced in associations with social media and general internet use compared to video gaming or television viewing. Therefore, whereas the finding of greater video game use was associated with reduced sleep in both studies, the incongruence of other findings may be due to the alternative ways the derived variables were calculated. However, another explanation for the difference in findings may be as a result of the confounding variables. Hisler *et al.* (2020b) did not account for key confounding variables which may have impacted the associations between technology use and sleep-related outcomes and were available in the MCS data sweep used for this cross-sectional research. Socioeconomic status (Anders *et al.*, 2014), mental health (Fang *et al.*, 2019; Patalay & Gage, 2019), and substance use (Kwon *et al.*, 2019) have been associated with deficits in sleep-related outcomes and should therefore be included in large-scale cohort studies and experimental designs.

Interestingly, there may be a desensitising effect of amount of video game exposure on the relationship with sleep. After playing a violent or non-violent game before bedtime, less experienced video game players had reduced sleep quality after the violent game session than more experienced players (Ivarsson, Anderson, Åkerstedt, & Lindblad, 2009). This suggests perhaps players can become acclimatised to playing prior to sleep, and therefore protected from the potential adverse effects of video games before bedtime. An additional explanation of this relationship may stem from the frequently used self-reported measures of sleep-related variables, such as onset latency or duration. With video game content potentially stimulating heightened cognitive or psychological arousal, this can skew individuals' perceptions of sleep-related outcomes, demonstrating discrepancies between participant reported sleep onset latency and duration, and actigraphy-defined measures (Tang & Harvey, 2004). Actigraphy is a non-invasive, unobtrusive method of recording movement and estimating sleep parameters, usually through a device worn on the wrist (Martin & Hakim, 2011).

Explanatory confounds

The inconclusive nature of these relationships presents the need to disentangle the confounds which may be influencing factors. For instance, in the longitudinal imputed analyses there was sex differences in risk-based decision making. In accordance with previous research (Charness & Gneezy, 2012), males tended to make riskier financial decisions, while females were more financially risk adverse. The current results demonstrate that in cross-sectional imputed analyses socioeconomic status is associated with decision-making (Dilworth-Bart, 2012; Noble, McCandliss, & Farah, 2007). Lawson, Hook, and Farah (2018) conducted a meta-analysis into the SES disparities in executive functions. The evidence supported the presence of SES inequalities in executive functions including: working memory, attention shifting, inhibition, composite variables of two or more, and other (e.g. planning). The reported effect sizes of the included studies suggested that SES inequalities range between small and medium in size. Across the included studies, working memory and inhibition were the most commonly examined EFs, each having twelve articles measure them. Reported effect sizes ranged between -0.04 and 0.47 and the synthesised effect size in those articles with meaningful SES variability was r = 0.22. This is suggestive of a small to medium relationship between SES inequalities and executive functions. However, this meta-analysis focused on young children rather than adolescents, and primarily focused on executive functions as a composite construct, rather than clarifying whether any specific aspects were disproportionately impacted by SES inequalities.

In the current study, substance use was negatively associated with sleep quality (Kwon *et al.*, 2019), suggesting increased alcohol use, smoking and illegal drugs (cannabis and others) was related to reduced sleep quality. This supports research by Fadhel (2020) who found that college student's quality of sleep decreased consistently as substance use increased. Evidence demonstrates that substance use impacts a broad variety of sleep quality domains (Kwon *et al.*, 2019); primarily reported is sleep duration, but also effects sleep regularity, timing, and efficiency. This relationship may also be bidirectional (Mike, Shaw, Forbes, Sitnick, & Hasler, 2016). Therefore, even potential explanatory factors may influence the inconclusive nature of the relationships between different screen uses, decision making, and sleep. The continued and comprehensive inclusion of confounds, and individuals' contextual factors is required in future research to understand the influence of these factors on executive function and sleep-related outcomes.

3.5.2 The influence of bias

It is important to note that no evidence of associations was found in the imputed findings. This is noteworthy as the imputed sample and analyses have increased reliability compared to the complete case data. The use of multiple imputation techniques in an attempt to reduce attrition bias and boost sample size increased the power of analyses. Therefore, the lack of associations within the imputed analyses is a more reliable estimate of the lack of relationships between leisure focused screen use, decision making and sleep quality in adolescents. The difference between the complete case sample and the imputed sample was that the complete cases analyses were a much smaller sample size and likely to be biased as a result of selective attrition. Although the imputed analysis is likely to account for and correct this as it was designed to do so, it is possible it did not do so adequately enough to overcome the bias entirely. The outcome variables of decision making and sleep quality at both ages were not imputed. When these measures were taken, attrition had already occurred from the original nationally representative sample at the start of the cohort study; decision making and sleep quality measures at age 14 in Sweep 6 had a smaller sample (n = 3908) compared to the number of participants who started that data collection sweep (n = 10,782), and who started the MCS at birth (n = ~19,000). Therefore, the imputed sample may still be affected by attrition bias. Despite multiple imputation being the preferred method of addressing missing values in data, model checks, which determine how the desired analyses may be affected by the current models, are not yet standard practice (Hayati Rezvan, Lee, & Simpson, 2015). Although the imputed data was compared alongside the complete case data, and the original Sweep 7 data (see Table 4), additional statistical simulation checks were not conducted (Nguyen, Carlin, & Lee, 2017).

3.5.3 Limitations

While this chapter contributes to the conversation and understanding of different types of screen uses and their associations, or lack thereof, with decision making and sleep, there are also a number of limitations. The three types of screen use were self-reported, and measured the time spent on these activities, raising the problematic issue of 'screen time' (general introduction), which was not understood as the conceptual issue it is today when the Sweep 6 data was collected in 2014/15. Although, a strength of this study is that the three categories were kept separate throughout, rather than being encumbered by the pitfalls of a composite 'screen time' measure. The three screen-based activities used are strictly leisure activities. Social networking and connection, active video game-play, and passively watching TV, DVDs or videos represent three distinct categories of screen use. However, this does not account for different screen-based pursuits during adolescence, such as educational assignments and homework. Additionally, despite its proven importance in adolescent academic attainment (Best, Miller, & Naglieri, 2011), only one aspect of executive function, decision making, was measured during the multiple Sweeps of data collection. Although there is measurement data in the MCS on participant's cognition, this primarily focuses on arithmetic ability rather than the specialised skills that cumulate under the umbrella term of executive functions. I therefore purposefully chose not to use the cognition measures. In future cohorts, additional measures of executive function should be included; for instance, working memory (Ahmed, Tang, Waters, & Davis-Kean, 2019).

If this study was to be improved upon, ideal measures would include participants' affordance-based uses of screen-based devices (e.g., social, entertainment, information, or educational), perhaps specifying video game platform and genre, and TV content. Previous research has demonstrated the content of screen-based device use to be the most important factor for young children (Huber *et al.*, 2018); therefore, similar claims may be true for adolescents too. In addition to measuring decision making, wider aspects of executive functions should be measured; such as working memory, inhibition, and attention. Tasks can be gamified (e.g., Balloon Analogue Risk Task and Self-Ordered Pointing Task) to aid engagement of child, adolescent, and young adult participants over the course of the cohort study. This would allow for more nuanced examinations of the potential associations of specific screen uses on specific aspects of executive functions. Accelerometers were used in the MCS to measure physical activity at age 7; however, despite the advancements in field, similar device technology has unfortunately not been harnessed for other objective physiological measurement. This would ideally be utilised in future data collection design and sweeps of cohort data to provide actigraphy or similar consumer-grade objective measures of sleep-related outcomes beyond self-report.

Although multiple imputation was used to boost the sample size and account for missing data attrition bias, this may not have adequately been achieved. Complete case data and imputed samples had less ethnic representation of the United Kingdom compared to the original MCS sample, and even the Imputed samples were considerably smaller than the original age 14 and 17 datasets. This smaller sample size may have drastically reduced the statistical power and rendered these findings unsuitable to be generalised across the population of young people in the United Kingdom. Using G*Power, I conducted post hoc power calculations to estimate the achieved power. The longitudinal analysis (n = 1929) of the three types of screen use (age 14) and decision-making (age 17) in the imputed sample (b = 0.05, α = 0.05) achieved 0.9 power. However, the logistic regressions estimating sleep quality (age 14: n = 3224, age 17: n = 1929), and the complete case cross-sectional (n = 834) and longitudinal (n = 576) analyses were underpowered ($\leq$30%). Therefore, despite the suggestion of a small association between various leisure screen uses and decision-making, and between video gaming and sleep at age 17, these results may have been a product of Type 1 error whereby, by chance, a false positive result for evidence of an association is found. This is particularly more common in small sample sizes, such as the ones in this study, as they lack the statistical power required for these analyses and may falsely inflate the effect size (Shreffler & Huecker, 2020).

3.5.4 Conclusions

In conclusion, according to the imputed analysis with reduced risk of bias, time spent on social media, playing video games, and watching TV, DVDs or videos was not associated with decision-making quality at age 14, nor risk or patience preferences in decision-making at age 17. Additionally, time spent on social media, playing video games, and watching TV, DVDs or videos was not associated with sleep quality at age 14 nor age 17. In the complete case analysis, there was weak evidence for a positive association between each of the three screen uses and decision making at age 14, and weak evidence of a negative association between playing video games and sleep quality at age 17. Although efforts were made to reduce the bias in samples, it is possible the current sample remained subject to attrition bias; therefore, the present findings should be considered cautiously. However, this presents evidence that time spent engaging in social media, video games, and watching TV has negligible, if any, relationship to decision making and sleep quality. To the best of my knowledge, this is the first study to investigate potential longitudinal associations of social media use, video gaming, and watching TV, DVDs, or videos using the Millennium Cohort Study. Going forward, research needs appropriately powered, rigorous experimental designs to determine the nature of these relationships more conclusively. Measures should also further specify the type of screen engagement participants partake in to increase the nuance in investigating the associations between screen-based technology, executive functioning, and sleep quality.

Chapter 4: Investigating the relationship between smartphone use, executive function, and sleep quality

4.1 Abstract

Introduction:

Executive functions are important cognitive processes for goal attainment and controlling automatic responses. Achieving sufficient sleep is an important aspect of mental and physical well-being. However, both are thought to be impacted by smartphone use. The aim of the current study was to overcome previous methodological issues and examine the relationships between smartphone use behaviours, executive functioning, and sleep quality.

Method:

A total of 217 participants completed the Smartphone Addiction Scale (SAS), two measures of sleep quality (Sleep Quality Scale (SQS) and the Pittsburgh Sleep Quality Index (PSQI)), and a short battery of behavioural tasks measuring attention (Sustained Attention Response Task), working memory (Self-Ordered Pointing Task), decision-making (5-item Delay-Discounting), and inhibition (Stop-Signal Task). Three confounding variables were also controlled for: physical activity time, mental ill-health (Generalised Anxiety Disorder (GAD-2) and Public Health Questionnaire (PHQ-2)), and quality of life (Kemp's Quality of Life score).

Results:

Hierarchical regression analyses found that increased SAS scores were associated with poorer sleep quality in both the SQS (b = .33, p <.001, 95% CI = 0.19 to 0.47) and the PSQI (b = .05, p = .04, 95% CI = 0.00 to 0.10). No associations were found between SAS scores and executive functions.

Discussion:

This may suggest smartphones are not a concerning influence on our cognitive processes, but caution is advised around sleep. It is suggested that future attempts to replicate this study should employ further objective measures of smartphone use behaviour and sleep quality.

4.2 Introduction

The previous chapter detailed the need for greater specificity and objectivity in executive function measurements and screen uses for these relationships to be more closely examined. To address this need, a study with objective behavioural measures was conducted, which focused on smartphone use as the most pervasive device.

Smartphones have become such a pervasive and ingrained aspect of our lives. The exponential growth of smartphone adoption is likely nearing a plateau (Lee & Calugar-Pop, 2019), but this is likely to be close to ubiquitous ownership. With consistent new developments in smartphone technology, and in the absence of any other technological contenders to compare, saturation is likely to remain stable (Haba, Hassan, & Dastane, 2017; Mao *et al.*, 2020; Zheng & Chen, 2020).

However, with new technology comes fear of unknown effects. Many technological advancements from the past century, including the increases in household radio ownership, have been met with fear over the unknown impacts on children and young people (Dennis, 1998; Furedi, 2015). These concerns are reoccurring, or cyclic, as the latest technology to cause such panic is smartphones and social media (Orben, 2020a). The most recent claim is that smartphones are damaging our attention spans (Hari, 2022), rather than perhaps redirecting our attention elsewhere. The concerns about the effects of smartphones have populated news stories since their debut by Apple in 2007 (Murphy, 2008). However, claims about their effects are often inflated and misrepresent the research findings (Etchells, 2017). Two critical behavioural outcomes have received a lot of media attention: sleep and executive functioning, however empirical evidence remains inconclusive.

4.2.1 Smartphones and Sleep

Sleep is an important protective factor against mental and physical ill-health, including impaired immune response (Besedovsky, Lange, & Born, 2012), weight gain (Patel & Hu, 2008), and mental illness (Zhai, Zhang, & Zhang, 2015) such as depressive symptoms and self-harm (Patalay & Gage, 2019). Evidence suggests smartphones may cause sleep disruptions. When used in proximity to bedtime, smartphones have a detrimental impact on all sleep domains, resulting in poor sleep quality, longer sleep latency, increased sleep disturbance and insomnia, and more daytime dysfunction and fatigue (Exelmans & Van den Bulck, 2016). There are a number of possible mechanisms of this association. It may be due to the exposure to blue light emitted from smartphones, which suppresses melatonin secretion and delays sleep onset (Chellappa *et al.*, 2013; Wood, Rea, Plitnick, & Figueiro, 2013), or smartphone use may directly displace sleep. Another possible explanation is that smartphones can be used for activities and affordances that are psychologically and physiologically stimulating, so may increase cognitive activity and arousal prior to bedtime (Cain & Gradisar, 2010).

Although "screen time" is a common method of quantifying exposure to devices, it is an intrinsically poor and reductionist measure; which fails to account for the diversity of technology and screen uses, and users' individual context (Orben *et al.*, 2018). For smartphones in particular, an alternative method has been the development and use of an abundance of quantative, self-report scales measuring 'problematic' or 'excessive' mobile device use (Bianchi & Phillips, 2005; Billieux, Van der Linden, & Rochat, 2008; Kwon *et al.*, 2013; Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013; Yildirim & Correia, 2015). These scales are often phrased to be related to smartphone 'addiction', and attempt to capture, conceptualise, and predict smartphone use behaviours, but do not represent clinical diagnostic tools. As there is evidence from these scales that smartphone use may be associated with reduced sleep quality (Haripriya *et al.*, 2019), they are often not causal associations. One possible mechanism to explain this relationship is sleep displacement. Mobile phone use is conceptualised as an unstructured leisure activity and is more likely to produce a time displacement, or distortion, effect (Hysing *et al.*, 2015; Kubiszewski, Fontaine, Rusch, & Hazouard, 2014; Lin *et al.*, 2015; Van den Bulck, 2004). Therefore, smartphone use in proximity to bedtime cannot be attributed to sleep-related behaviours with any causality using these currently common methods.

4.2.2 Smartphones and Executive Function

The higher level cognitive processes know as Executive functions (EF) into a framework of Unity / Diversity (Miyake & Friedman, 2012), which accounts for shifting, updating, and common EFs. The original component of inhibition has been found to be subsumed by working memory (Tiego *et al.*, 2018). However, Tiego *et al.* (2018) examined 11-12 year old children, focusing on a narrow age range to avoid developmental changes impacting their results. Given that adolescence is a crucial time for cognitive development and the maturation of neural pathways (Luna, Marek, Larsen, Tervo-Clemmens, & Chahal, 2015), it is possible that these outcomes may change over the developmental course (Lee, Bull, & Ho, 2013). Therefore, these findings would need to be replicated in older adolescent and adult populations.

Deficits in executive function were demonstrated by Ward *et al.* (2017) who posited the 'Brain Drain' hypothesis. They suggested that the mere presence of one's smartphone, even when not consciously attending to it, occupies finite cognitive resources and thereby leaves less available for other tasks. Participants were divided into three conditions of phone location: (1.) on the desk beside them, (2.) in their pocket or bag, or (3.) in another room. Findings demonstrated a significant effect of phone location salience on cognitive capacity, with those in the other room condition performing better on the EF tasks than those in the desk condition (Ward *et al.*, 2017).

However, a recent study by Pardo and Minda (2021) aimed to replicate the work of Ward *et al.* (2017). Using the same phone location conditions as the original study, they hypothesised that performance on an attention demanding task would decrease as proximity to phone location increased, as was found by the original study. Two behavioural tasks were used in both studies; the Automated Operation Span (OSpan) Task (Unsworth, Heitz, Schrock, & Engle, 2005), which measures the attentional control component of working memory, and a cue-dependent Go/NoGo Task

(Bezdjian, Baker, Lozano, & Raine, 2009), which measures sustained attention. However, the original findings were not replicated; there was no difference between phone location conditions on OSpan task performance. Ward *et al.* (2017) originally claimed the 'brain drain' effect was due to the challenging nature of the OSpan Task, however the average performance scores between the original study and the replication suggest that participants in the Pardo and Minda (2021) replication did not find the OSpan task as challenging. Therefore, perhaps the 'brain drain' effect of smartphone presence did not occur without the challenge of a difficult task dividing the available attentional resources. Additionally, the omnipresence of smartphones in our daily lives may have changed between 2017 and 2021 as the affordance and capabilities offered by smartphones increased, along with our reliance on the devices themselves for these capabilities. Therefore, although the original task and the replication used current undergraduate students as participants, the 2021 undergraduates may have an increased ability to 'tune out' or control their attention to ignore the presence of their smartphone regardless of the salience of its location. They would have been younger at the introduction of smartphones and have perhaps acclimatised to their presence to refine their attentional control and reduce the potential for their cognitive resources to be drained.

The effect of smartphone location was also studied by Hartanto and Yang (2016), who randomly assigned participants into either a separation or non-separation (control) condition. In the separation condition, phones were kept safe by the researcher for the duration of the experiment, whereas in the control condition phones were placed on silent and retained by participants. Participants completed the Smartphone Addiction Scale (SAS) and EF measures of task-switching (colour-shape switching task), inhibition (Stroop Task), and working memory (rotation-span task), as well as measures of fluid intelligence, anxiety, and state emotion. Mediated by the anxiety induced from the separation, smartphone separation impaired performance in task shifting, inhibition, and working memory. SAS scores also significantly increased Stroop task reaction time, suggesting smartphone addiction traits may amplify the detrimental effect on interference control.

Contrary to this, previous narrative reviews of the literature have found varying evidence for the associations between smartphone use and EFs (Liebherr, Schubert, Antons, Montag, & Brand, 2020; Wilmer *et al.*, 2017). Wilmer *et al.* (2017) focused on three facets of EF: attention, memory, and delay of gratification. Overall, the niche content of their review suggested smartphones were detrimental to executive functioning. However, a more recent systematic review examined the associations between smartphone use and inhibition, decision-making, and problem solving (Warsaw *et al.*, 2021). The available research had a low evidential value, suffering from poor experimental design and low power, and concluded that the evidence is inconclusive. Going forward, the literature needs increased rigor and objective methodology.

This study aimed to overcome these issues and empirically examine the relationships between smartphone use, executive functioning, and sleep quality. Four executive functions were focused on: attention, inhibition, working memory, and decision-making. These were chosen in accordance with core knowledge on EFs (Diamond, 2013; Miyake & Friedman, 2012) and based upon the existing literature in the field (Chapter One). I hypothesised that increased smartphone use would be negatively associated with all four measures of executive function (attention, inhibition, working memory, and decision-making). I also predicted that increased smartphone use would be negatively associated with sleep quality.

4.3 Method

4.3.1 Participants

The experiment was crowdsourced online through *Prolific,* an international research participation platform with tens of thousands of participants to enable and expedite the recruitment of niche and representative samples. Compared to other online research platforms, *Prolific* benefits from increased participant naivety and reliability of data (Peer, Brandimarte, Samat, & Acquisti, 2017). Participants also demonstrated reduced dishonest behaviours and lower dropout rates (Peer *et al.*, 2017). For the purposes of this study, participant access was restricted to UK recruitment.

Initially 237 individuals accessed the online study. After data cleaning, a total of 217 participants completed the study; the remainder 20 individuals withdrew before completion. The sample consisted of 109 females (50.2%) and 108 males (49.8%) with an age range of 18 to 30 years (*M* = 24.55, *SD* = 3.64). To be included participants had to be aged between 18 to 35 years old, fluent in English, own a smartphone, and have an internet connection and computer or laptop access. Exclusion criteria included a diagnosis of a psychiatric disorder or sleep disorder. The study was approved by the University of Liverpool's Health and Life Sciences Research Ethics Committee. Participants volunteered to take part in the study and were informed of the study's objectives before providing consent.

An *a priori* power calculation was conducted using G*Power. This was calculated with an effect size of $R^2 = 0.15$, alpha rate of 0.05, power of 80%, and six predictors; age, smartphone use, anxiety, depression, physical activity and quality of life. A sample size of 146 participants was estimated. To account for attrition and the potential for careless responding in crowdsourced data (Jones *et al.*, 2022), this was rounded up to a target sample size of 180 participants.

4.3.2 Materials

The experiment comprised of a series of questionnaires, followed by a short battery of tasks designed to measure distinct executive functions: attention, inhibition, decision-making, and working memory.

4.3.2.1 Questionnaire measures

Smartphone Addiction Scale – short version (SAS-SV)

The SAS-SV (Kwon *et al.*, 2013) is a 10-item self-reported questionnaire measured on a 6-point Likert scale from *'strongly disagree'* to *'strongly agree'.* It measures six factors: daily-life disturbance, positive anticipation, withdrawal, cyberspace-oriented relationship, overuse, and tolerance. Example items include '*Feeling impatient and fretful when not holding my smartphone*', and '*Missing planned work due to smartphone use*'. This was used as a measure of smartphone use behaviours. In the current sample, the Cronbach's Alpha = 0.83, which indicates good internal reliability. Higher scores on the SAS indicate increased reliance on smartphones, however the scale was not developed nor used as a clinical diagnostic instrument.

Pittsburgh Sleep Quality Index (PSQI) – short form

The short version of the Pittsburgh Sleep Quality Index (PSQI) (Buysse, Reynolds III, Monk, Berman, & Kupfer, 1989; Famodu *et al.*, 2018) is a 13-item self-report questionnaire measured through open ended questions and 4-point Likert scales. It measures five factors: duration, latency, efficiency, disturbances, and daytime dysfunction. Example open-ended items include: '*What time have you usually gone to bed?*' and '*How many hours of actual sleep did you get at night?*' Respondents are asked to indicate how often in the past month they had trouble sleeping due to a series of sleep behaviours; including '*cannot get to sleep within 30 minutes*' and '*have bad dreams*'. The Likert scale ranges from 0 = '*not during the past month*' and 3 = '*three or more times a week*'. They are also asked '*how much of a problem it has been to keep up enough enthusiasm to get things* *done?*', where 0 = '*no problem at all*' and 3 = '*a very big problem*'. In the current sample the Cronbach's Alpha = 0.66. Scores range between 0 to 21, with higher scores on the PSQI indicate reduced sleep quality.

Sleep Quality Scale (SQS)

The Sleep Quality Scale (SQS) (Yi, Shin, & Shin, 2006) is a 28-item self-reported questionnaire which is comprised of six factors: daytime dysfunction, restoration after sleep, difficulty in falling asleep, difficulty in getting up, satisfaction with sleep, and difficulty in maintaining sleep. Respondents must indicate how frequently they experience certain sleep behaviours, rated on a 4-point Likert scale, with 1 = '*few*' and 4 = '*almost always*'. Items include: '*difficulty in concentrating due to poor sleep*', '*increase of forgetfulness due to poor sleep*', and '*satisfaction with sleep*'. In the current sample, the Cronbach's Alpha = 0.86, which indicates good internal reliability. Possible scores range from 0 to 84, with higher scores indicating a lower sleep quality.

Generalised Anxiety Disorder (GAD-2)

The Generalised Anxiety Disorder (GAD-2) (Kroenke, Spitzer, Williams, Monahan, & Löwe, 2007) is a short 2-item screening tool to measure the prevalence of anxiety disorders. Respondents were asked to indicate how often they have experienced the following in the last two weeks; '*feeling nervous, anxious or on edge*' and '*not being able to stop or control worrying*'. This is measured on a 4-point Likert scale, with 0 = '*not at all*' and 3 = '*nearly every day*'. The Cronbach's Alpha = 0.87, which indicates good internal reliability. Scores range between 0 to 6, with higher scores indicating increased anxiety.

Public Health Questionnaire (PHQ-2)

The Public Health Questionnaire (PHQ-2) (Kroenke, Spitzer, & Williams, 2003) is a short 2-item self-report screening tool, which provides an initial indication of depressive symptoms.

Respondents were asked to indicate how often they have experienced the following in the last two weeks; '*little interest or pleasure in doing things*' and '*feeling down, depressed or hopeless*'. This is measured on a 4-point Likert scale, with 0 = '*not at all*' and 3 = '*nearly every day*'. The Cronbach's Alpha = 0.80, which indicates good internal reliability. Scores range between 0 to 6, with a score of 3 or greater indicating the increased likelihood of major depressive disorder.

Physical Activity

Participants were asked to report the number of days a week they did moderate to vigorous physical activity, and for how many minutes on average. Moderate to vigorous was defined as any physical activity that makes you get warmer, breathe harder and makes your heartbeat faster. This question was worded in accordance with previous research in this thesis.

Kemp's Single Item Quality of Life Scale

Kemp's Quality of Life Scale (QoL) (Siebens, Tsukerman, Adkins, Kahan, & Kemp, 2015) is a single item, self-defined subjective questionnaire measure. Respondents are instructed to take account of everything in their life and 'rate your overall Quality of Life' on a 7-point scale: 1 = '*life is very distressing*', 4 = '*life is so-so*', and 7 = '*life is great*'. This scale allows quality of life to be indicated through two extremes, low (and negative) to high (and positive), but also allows for a midpoint to convey that the absence of a negative quality of life does not imply a positive quality of life.

Attention Check

To ensure participants were reading the questions carefully before answering, a simple attention check question was used. Participants were asked to answer, '*Which planet are you currently on?'.* They were given a drop-down menu of four options (e.g., Mercury, Saturn, Earth, or Mars) to choose from. All participants who completed the experiment answered correctly.

4.3.2.2 Behavioural tasks

Attention

The Sustained Attention Response Task (SART) was used to measure attention. Participants were presented with a fixation point, followed by a single digit in the middle of the screen in varying font sizes (see Figure 3). They were required to press the spacebar to respond to non-target stimuli (e.g. digits 0-9) but had to withhold their response when presented with the target digit (e.g. 3). Each of the 9 digits were randomly presented 25 times for a total of 225 trials. The digits were presented for 250 milliseconds (ms) before being replaced with a mask of a cross inside a circle, which was presented for 900ms. Participants had to respond as quickly and accurately as possible. The main dependent variables were the mean reaction time latency (in ms) of valid and correct Go trials, and the absolute number of commission errors in NoGo trials.

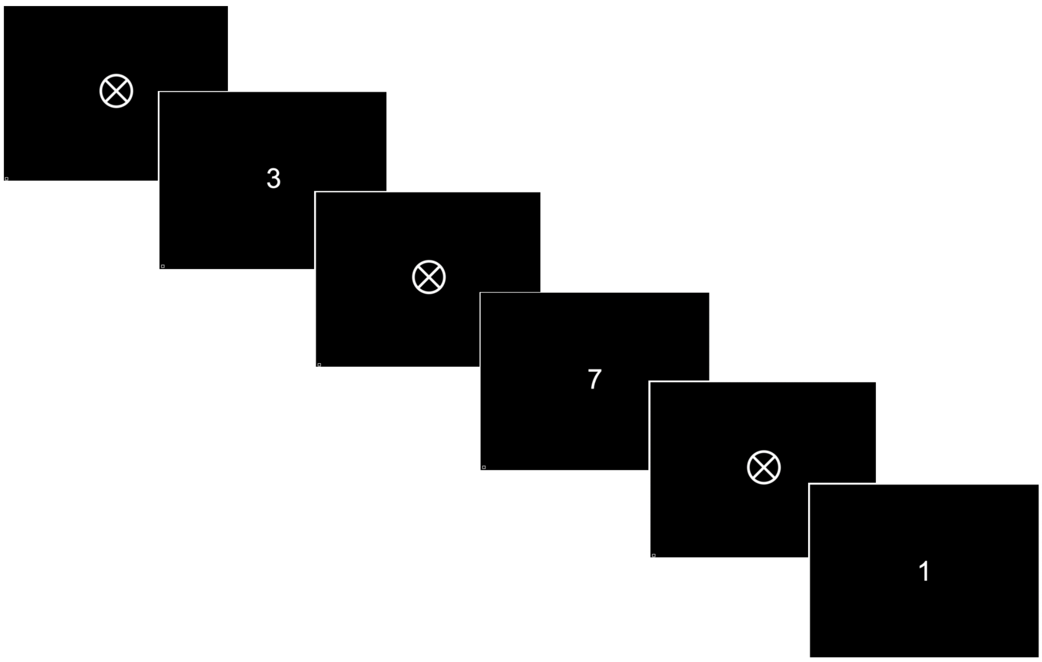

Figure 3: Example trials of the Sustained Attention Response Task.

Inhibition

Inhibition was measured using a Stop-Signal Task (Verbruggen *et al.*, 2019). Participants were presented with a fixation point followed by an arrow stimulus. They had to respond by pressing a key to denote whether the arrow was pointing either left or right. On one third of trials, a stop signal was presented. This was indicated by a red circle around the arrow stimuli to indicate that participants should withhold their response, and was presented at a variable time delay, or Stop Signal Delay (SSD) (see Figure 4). The SSD was initially set at 250ms and adjusted up or down by 50ms incrementally depending on performance. The delay increases if a response is successfully withheld upon the presentation of the stop signal. The delay decreases if the response to the previous stop signal response was unsuccessful. The stimulus onset asynchrony between the start of each trial was 2000ms. The task consisted of one practice block, and three test blocks with a total of 216 trials. The dependent variable for this is calculated using the recommended integration method to estimate the stop signal reaction time (SSRT) in ms; the time required to stop the initiated go process (Verbruggen & Logan, 2008). Higher reaction time was indicative of reduced inhibition ability.

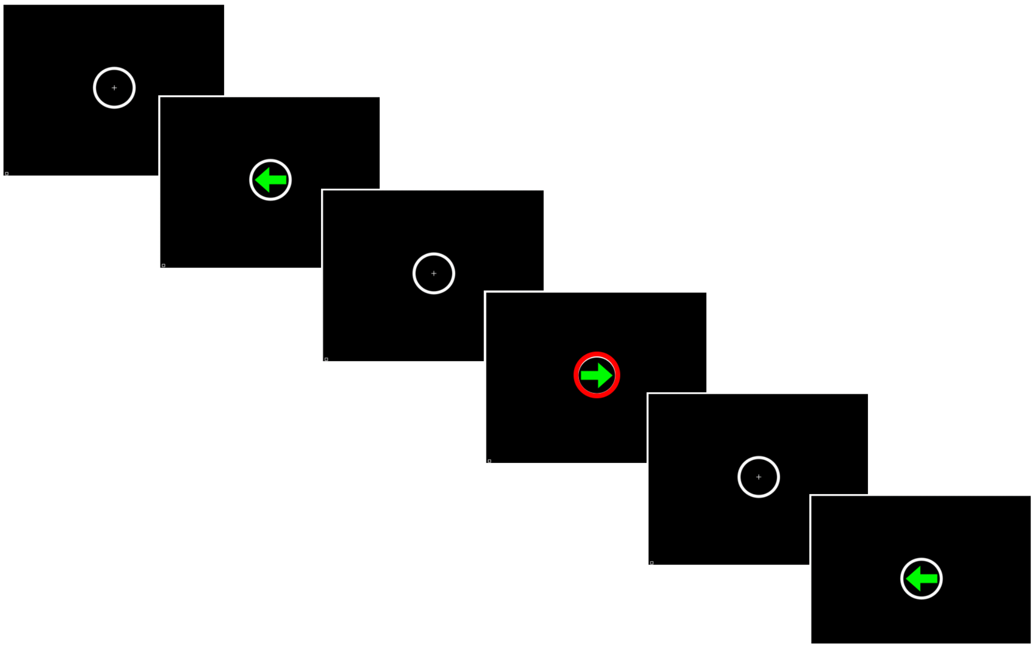

Figure 4: Example trials of the Stop Signal Task.

Decision Making

A 5-item Delay-Discounting Task was used to measure decision-making (Koffarnus & Bickel, 2014). Participants were presented with five trials and asked to choose between receiving a smaller amount of money immediately, or a larger amount after a variable time delay (e.g. in one month). The main DV was the k-value, which represents the discount rate inverse to the number of days a delay is tolerated to receive a higher payoff. The higher the *k* (discount rate), the less a participant was willing to wait for the delayed higher reward and the more they preferred the lesser, immediate reward.

Working Memory

The Self-Ordered Pointing Task was used to measure working memory. Participants were presented with a matrix of images of objects and responded by clicking a different picture on each trial, without clicking on the same image twice. After selecting an image, the objects were re-arranged for the next trial. Participants completed eight-item and ten-item image matrices. The main dependent variable was the total number of errors made. A higher number of errors, or pictures clicked more than once, indicated reduced working memory capacity.

4.3.3 Procedure

Participants signed up to the experiment through *Prolific*. They were presented with a participant information sheet and provided informed consent prior to taking part. The questionnaire section was completed first, followed by the four executive function tasks which measured attention, working memory, delayed gratification, and inhibition. These tasks were presented in a randomised order for each participant. The study took approximately 30 minutes to complete and participants were reimbursed for their time, in line with the *Prolific* fair payment policy (~£5 per hour).

4.3.4 Statistical Analysis

Data was analysed using IBM SPSS 27. Descriptive statistics were calculated for initial data exploration before inferential tests were conducted. Regression analyses were used to predict sleep quality from smartphone use, and executive functioning (attention, inhibition, working memory and decision-making) from smartphone use. All 217 participants were included in the analyses predicting sleep quality, attention, working memory, and decision-making. Stop Signal Task data cleaning included excluding participants who returned negative SSRT, which indicate anticipatory responses occurred before the stimulus was presented. According to the integration method of SST data cleaning (Verbruggen *et al.*, 2019), these results should be excluded from analyses, resulting in a sample size of 176 for this analysis. Our pre-registered analytic strategy can be seen in detail here https://osf.io/z6xj5. All regression analyses followed the same structure for entering variables. At the first step, Smartphone Addiction Scale (SAS) scores were added to comprise an unadjusted model. At the second step, physical activity time, Quality of Life (QoL) score, and Mental Health (MH) score were added to comprise a fully adjusted model.

4.4 Results

4.4.1 Demographics

A total of 217 participants completed the experiment (49.8% male) with a mean age of 24.55 and an average of 37.34 minutes of moderate to vigorous physical activity per week. The majority were White British (77%) and employed full time (47.5%) (see Table 13).

Initial examination of the data demonstrated that age and gender were not associated with either of the sleep quality outcomes, SQS scores (age: β = -.06, p = .39, gender: β = -.09, p = .19), or PSQI (age: β = -.09, p = .20, gender: β = .02, p = .77). Nor were they associated with the executive function outcomes, SART (age: β = -.10, p = .14, gender: β = -.03, p = .72), SOPT (age: β = -.05, p = .46, gender: β = -.06, p = .40), Delay discounting k rate (age: β = .07, p = .29, gender: β = -.07, p = .34), SSRT (age: β = .01, p = .89, gender: β = -.04, p = .70). Therefore, age and gender as covariates were not included within the analyses. The two measures of sleep quality, the SQS and the PSQI, demonstrated a moderate correlation, r = 0.61, p <.001.

Table 13: Percentage or Mean, standard deviation, and range of participant demographics, predictor, and outcome variables.

Variables			% or Mean (SD) and [range]
Demographic	Gender		
		Male	49.8%
		Female	50.2%
	Ethnicity		
		White British	77%
		Asian British	12.4%
		Mixed	4.1%
		Black, African, or Caribbean British	3.7%
		White Irish	1.4%
		Other	1.4%
	Employment		
		Employed, full time	47.5%
		Employed, part time	18.4%

	Self employed	7.4%
	Unemployed	26.7%
Covariates	Age	24.55 (3.64) [18, 30]
	Mental ill-health	3.54 (2.94) [0, 12]
	Physical Activity time (mins)	37.34 (33.07) [0, 240]
	Kemp's Quality of Life	4.81 (.98) [2, 7]
Predictor	Smartphone Addiction Scores (SAS)	31.74 (8.70) [10, 52]
Outcomes	Sleep Quality Scale (SQS)	28.07 (11.06) [0, 78]
	Pittsburgh Sleep Quality Index (PSQI)	5.99 (3.57) [0, 18]
	Delay Discount *k* rate	.15 (1.16) [0, 78]
	Sustained Attention Response Task NoGo commission errors	10.65 (5.60) [0, 25]
	Self-Ordered Pointing Task total errors	2.53 (3.08) [0, 16]
	Stop-Signal reaction time *	201.74 (87.70) [0, 490.23]

*Reduced sample size = 176

4.4.2 Sleep Quality

A linear regression analysis was conducted to predict Sleep Quality Scale (SQS) scores from SAS scores. The first step was an unadjusted model and added SAS scores. This model was significant (F (1, 215) = 36.72, p <.001, adjusted R^2 = .14). The second step added the variables of physical activity time, mental ill health, and perceived Quality of Life scores to comprise a fully adjusted model, and was significant, F (4, 212) = 31.11, p = <.001, adjusted R^2 = .36. Both mental ill health, and SAS scores were significantly positively associated with higher SQS scores (see Table 14). Neither physical activity time nor Quality of Life scores were associated with SQS scores.

Table 14: Regression analysis predicting Sleep Quality Scale (SQS) scores, including unstandardized regression coefficients, P Values and Confidence Intervals.

Model	Variables	*B*	Sig.	95% Confidence Intervals	
				Lower	Upper
1	SAS scores	.38	<.001	.33	.64
2	SAS scores	.26	<.001	.19	.47
	Physical activity	-.06	.31	-.06	.02
	Mental ill health	.51	<.001	1.44	2.39
	Quality of Life	.08	.23	-.54	2.22

PSQI scores were also predicted from SAS scores using a hierarchical regression. SAS scores were added at the first step. This yielded a significant model, F (1, 216) = 13.01, p <.001, adjusted R^2 = .05. SAS scores were weakly positively associated with PSQI scores, b = .24, p <.001, 95% CI: 0.04 to 0.15, adjusted R^2 = .05.

The second step also yielded a significant model, F (4, 212) = 16.35, p = <.001, adjusted R^2 = .22. SAS scores remained weakly positively associated with higher PSQI scores, b = .13, p = .04, 95%

CI: 0.00 to 0.10. Neither physical activity time (b = -.02, *p* = .81, 95% CI: -.02 to .01), nor Quality of Life scores (*b* = -.03, *p* = .68, 95% CI: -.59 to .39) were associated with PSQI scores.

4.4.3 Working Memory

The association between working memory and smartphone use was examined by predicting SOPT total errors from SAS scores. This model was a poor fit to the data, *F* (4, 211) = .98, *SE* = 3.08, *p* = .42, adjusted R^2 = <.01, suggesting there was no association between working memory and smartphone use.

4.4.4 Decision Making

The association between decision making and smartphone use was examined by predicting the delay discounting *k* rate from SAS scores. This model was a poor fit to the data, *F* (4, 212) = .40, *SE* = 1.16. *p* = .81, adjusted R^2 = -.001, and demonstrates support for the null hypothesis, that there was no association between decision making and smartphone use.

4.4.5 Attention

The association between attention and smartphone use was examined by predicting number of SART NoGo commission errors from SAS scores. This model was a poor fit to the data, *F* (4, 212) = .92, *SE* = 5.61. *p* = .46, adjusted R^2 = -.002, suggesting there was no effect of smartphone use on attention.

4.4.6 Inhibition

Variables were entered into the model in the same order as previous analyses. This yielded a non-significant model at the first step, *F* (1, 174) = .67, *SE* = 87.79, *p* = .42, adjusted R^2 = -.002.

The second step yielded a significant model, F (4, 171) = 3.06, SE = 85.71, p = .02, adjusted R^2 = .05. Kemp's Quality of Life score was positively associated with SSRT, b = .19, p = .02, 95% CI: 2.49 to 31.91. No further associations were found.

4.5 Discussion

The present study aimed to empirically examine the relationships between smartphone use behaviours, executive functioning, and sleep quality, while attempting to overcome some of the methodological issues presented in the existing literature. These issues include a reliance on self-reported measured of executive functions, increased risk of bias, and poor quality of evidence (Warsaw *et al.*, 2021). It was hypothesised that increased smartphone use would be negatively associated with all four measures of executive function (attention, inhibition, working memory, and decision-making), and that increased smartphone use would be negatively associated with sleep quality. A UK sample of 217 young adult participants was recruited with an almost equal gender split (49.8% male) and scored on their smartphone use, sleep quality, and a short battery of executive function tasks.

Contrary to predictions, smartphone use was not associated with any of the four executive functions, suggesting that mobile phones use behaviours were not associated with these developed and practiced cognitive processes. Instead, this suggests smartphones may be a neutral presence in our pockets and palms without impacting our attention spans, decision making process, inhibitory control, nor memory. These results are in accordance with Johannes, Veling, Verwijmeren, and Buijzen (2019), who examined participants' permanent alertness, or vigilance, towards their smartphone. It was predicted that it would interfere with their capacity to inhibit predominant responses on a concurrent stop-signal task. Although smartphone visibility and notification delivery invoked smartphone vigilance, there was no effect on response inhibition. Similarly, the presence of smartphones do not drain or effect cognitive resources, specifically working memory (Pardo & Minda, 2021).

Findings did support the second hypothesis, demonstrating a negative association between smartphone use behaviours and sleep quality. This was consistent across two independent measures of sleep quality; the Sleep Quality Scale, and the Pittsburgh Sleep Quality Index. Although both yielded significant models, the smartphone use behaviour scores accounted for a small amount of the variance (2-6%). In both instances, mental ill health scores explained more of the variance in the models (22-31%), suggesting that symptomology of anxiety and depression is better associated with reduced sleep quality (Fang *et al.*, 2019; Hertenstein *et al.*, 2019; Patalay & Gage, 2019). However, these findings should be interpreted with caution as they are associations not causal relationships. The relationship is likely to be complex and include interplay between more variables than have been examined in the current study.

The findings of the present study conflict with the existing literature; smartphone use has demonstrated associations with deficits in various aspects of executive function (Fortes *et al.*, 2019; Ralph *et al.*, 2014; Stothart, Mitchum, & Yehnert, 2015; Tang *et al.*, 2017; Thornton, Faires, Robbins, & Rollins, 2014; Wilmer *et al.*, 2017). Marty-Dugas *et al.* (2018) concluded that absent-minded smartphone use was associated with everyday lapses in attention. However, their results were based entirely on self-reported questionnaire measures of both smartphone use and inattention, and therefore must be interpreted with caution. Self-reported questionnaires, while useful for measuring some concepts, can lead to biased reporting as participants can over- or underestimate their behaviour, either consciously or unconsciously (Lee *et al.*, 2021; Lin *et al.*, 2015).

The research in this area is fraught with similar methodological issues. Previous systematic reviews have rated the quality of evidence presented by the literature as satisfactory or poor (Sohn, Rees, Wildridge, Kalk, & Carter, 2019; Warsaw *et al.*, 2021). As well as a reliance on self-reported measures, some studies do not control for confounding variables, and often lack comparable groups. However, perhaps it is difficult as, particularly in developed countries, smartphones have almost completely saturated the population (Lee & Calugar-Pop, 2019). This blurs the line between being able to quantify 'normal' and 'excessive' use from one another, and, coupled with efforts to move away from "screen time", is perhaps why measures of 'addiction' have grown in popularity.

The present study has limitations. Smartphone use was measured by a commonly used self-report questionnaire, the SAS, which quantifies potentially problematic excessive smartphone use behaviours. However, this does not allow for any nuanced information into the specific services and affordances people use their phones for. Although the questionnaire was not used as a diagnostic tool or to divide participants, due to the prevalence of smartphones in our lives it is difficult to separate 'normal' and 'pathological' or 'excessive' use from one another. Data collection occurred in May 2021, immediately following a period of national lockdown measures due to the Covid-19 pandemic. During this time smartphone use may have been atypical due to nationwide lockdowns (Sebire, 2020; Serra, Scalzo, Giuffrè, Ferrara, & Corsello, 2021). Research has found increased smartphone use during this time to attenuate the negative impacts of physical distancing measures and foster social connection and well-being (David & Roberts, 2021). Therefore, the current data may only be representative of this unique period of time.

Future research should base smartphone use measures on different quantitative parameters, such as use frequency and specific applications or affordances used. Since the uses of smartphones are so varied, it logically follows the assumption that any effects they may have, be it positive, negative, or neutral, differ based on the affordances and applications being utilised. For example, spending an hour watching comedic videos is likely to have differing effects than an hour spent researching for an assignment. The literature has gone some way to examine this when it comes to the effects of social media (Alonzo *et al.*, 2021; Quinn, 2018; Shensa, Sidani, Dew, Escobar-Viera, & Primack, 2018); Buchanan, Aknin, Lotun, and Sandstrom (2021) found that brief exposure to reading Twitter posts about Covid-related news reduced positive affect, whereas posts about Covid-related acts of kindness did not have the same effect, suggestive that not all social media exposure is detrimental. However, the wide variety of affordances offered by smartphones deserve continued empirical interest.

In conclusion, this experiment used subjective and objective measures to examine whether smartphone use was associated with sleep quality and executive functions. Participants self-reported their smartphone use behaviours using the SAS, and their sleep quality using the SQS and PSQI. Four short game-like tasks were used to objectively measure attention (SART), working memory (SOPT), decision making (5-item delay discounting task), and inhibition (SSRT). SAS scores were moderately associated with poor sleep quality, but not with any measure of executive function. This may suggest smartphones are not a concerning influence on our cognitive processes, but caution is advised around bedtime. In the future, this should be replicated using objective measures of smartphone use behaviour and sleep quality to reduce the bias of self-reported measures and increase the validity to real world applications.

Chapter 5: Understanding mobile phone use, sleep quality and acceptable monitoring methods from the participant's perspective: A focus group study

5.1 Abstract

Introduction:

The impact of mobile devices and smartphone technology on executive function and sleep outcomes respectively are topics of recent widespread debate, however these areas of literature are reliant on retrospective self-report and correlational data. This study aimed to further understand the practicalities of mobile phone usage from the user's perspective, and gain opinions of the acceptability of monitoring applications and wearable technology to objectively measure participant's sleep quality and other sleep-related outcomes in an ecologically valid way.

Method:

Two focus groups were conducted online, in an informal chat-room style. A total of 14 participants (6 males, 8 females), between 18 to 40 years old, took part and answered a series of open questions and prompts to facilitate discussion. Transcripts were analysed using Thematic Analysis, and four main themes were identified from the data; 'Functional uses of technology'; 'Attachment'; 'Distraction and disruption'; and 'Connection', which contained two sub-themes of 'Social connection' and 'Inability to disconnect'.

Results:

Using monitoring applications and wearable technology linked to their smartphones was seen as an acceptable measurement method for the majority of participants. Participant accounts reflected the broad functionality of smartphones for work, navigation, and fitness, and discussed the

benefits and detriments of the connectivity possibilities. Participants also recounted feeling attached to their phones, and their phones being sources of distraction, with time distorting effects.

Discussion:

In the future, these findings may go towards the design of an experiment using objective measures of smartphone use behaviours and sleep quality, and help reduce the reliance on self-reported measures.

5.2 Introduction

While the previous chapter utilised behavioural measures of four executive functions, increased objectivity is needed to measure smartphone use behaviours and sleep quality in ecologically valid ways. Although there is the potential of utilising existing technological advances for these purposes, their use would need to be acceptable to participants. To explore this, I conducted informal focus groups with proxy young adult participants, to inform the design of future experimental designs.

Excessive use of mobile devices has been found to be negatively associated with sleep outcomes, including: duration, quality, rise time, and next-day sleepiness (Exelmans & Van den Bulck, 2016; Hale & Guan, 2015; Heo *et al.*, 2017). Subsequently, sleep deprivation may lead to reduced executive functioning, with a decline in performance demonstrated in inhibition, task switching, memory, and decision making (Aidman *et al.*, 2019; Skurvydas *et al.*, 2020). Research into habitual smartphone use in young people found that increased habitual use was moderately associated with reduced everyday memory, and strongly associated with reduced sleep quality (Li, Fu, Fu, & Zhong, 2021). An additional moderated effect analysis demonstrated that pre-bedtime exposure to smartphone use strengthened the detrimental effect of habitual smartphone use on sleep quality, therefore higher pre-bedtime use was significantly associated with worse sleep quality (Li *et al.*, 2021). However, this was conducted on school aged individuals. Further investigation into the effect of habitual smartphone use on memory and sleep quality is needed in adult populations.

The research literature around smartphone use behaviours is reliant on retrospective self-reported and correlational data (Haripriya *et al.*, 2019; Ralph *et al.*, 2014). Self-reported data, especially around the use of smartphones and mobile devices, can be subject to participants over or underestimating their behaviours (Lee *et al.*, 2017; Lee *et al.*, 2021), perhaps based on the perceived desirability in the context of each study. Additionally, correlational findings can be interpreted as causation (Conn, 2017). This frequently happens in online articles, but can slip pass the peer-review process into journals without due diligence, which often fuels the sensationalist claims about the impact of smartphones, particularly on children and young people (Sarsenbayeva *et al.*, 2020;

Twenge, 2017). Objective investigations of these relationships are now necessary to provide clarity, enable evidence-based inferences, and provide the foundations for public understanding and policy change.

The most acceptable research measure of sleep has been polysomnography (PSG), which can only be conducted within laboratory conditions. This procedure is considered the gold standard for diagnosing sleep-related problems, and uses a variety of techniques such as EEG, ECG and pulse oximetry to evaluate causes of sleep disturbances (Rundo & Downey III, 2019). However, the laboratory based conditions of this measure makes it inconvenient, expensive and time consuming (Williams *et al.*, 2018).

A more recent and practical example of technological advancement for objective data collection for sleep quality data is wearable technology. Wearable technologies, also known simply as 'wearables', are hands-free, electronic devices that are usually worn as accessories, including smart bands, watches and even rings. These devices allow users to track and monitor their daily physical activity, health and sleep data using heart rate monitors and accelerometers or actigraphy (Düking, Hotho, Holmberg, Fuss, & Sperlich, 2016; Halson, 2014). *Fitbit* released their first wrist-worn device in 2012 (Vailshery, 2021) and gained substantial popularity quickly, with reported users increasing from 6.7 million in 2014, to 29.6 million in 2019 (Fitbit, 2020). According to recent insights, popularity is expected to continue, with projections of 280 million units being shipped globally by 2024 (Arkenberg *et al.*, 2021).

Compared to laboratory-based PSG, actigraphy in wearables have been found to be relatively reliable and valid for more ecologically valid monitoring of sleep-related outcomes (Marino *et al.*, 2013; Niel *et al.*, 2020; Quante *et al.*, 2018; Williams *et al.*, 2018), including efficiency, latency, and duration. For the majority, it has an approximate accuracy rate of 80% (Marino *et al.*, 2013), although there was some variation in the measurement of total sleep time and wakefulness after sleep onset (Marino *et al.*, 2013; Niel *et al.*, 2020; Williams *et al.*, 2018). However, given that the more recent paper (Niel *et al.*, 2020) used the same actigraphy device as the older paper (Marino *et* *al.*, 2013) the validity of actigraphy compared to laboratory-based PSG should be interpreted with caution.

The most popular consumer-grade wearable is the Apple Watch, which has sold over 30 million and holds a 30% market share (Wooden, 2022). Roomkham, Hittle, Lovell, and Perrin (2018) compared the reliability of sleep monitoring in Apple Watch compared to a clinically validated alternative, the Philips Actiwatch Spectrum Pro. Participants wore each device on their non-dominant hand for two consecutive days. The total sleeping time from both wearable devices was highly correlated (r = .99), and the Apple Watch had high overall accuracy and sensitivity (97.3% and 99.1%) (Roomkham *et al.*, 2018). Therefore, of the available consumer-grade devices, the Apple Watch may be considered a good measure of sleep for free-living, longitudinal research, and their users ideal participants. However, little is known about individual's acceptability of these measures as a tool for tracking sleep outcomes for research. In order to safeguard the possibility of using wearables as the new gold standard for reliable and objective measurement technique in future research, it is important to gain insights and understanding of how willing participants may be to either share their data, or to be provided with wearable technology for the purposes of study participation.

Therefore, the aims of the focus groups were to: (1.) further understand the practicalities of smartphone usage from the user's perspective; and (2.) gain insights into the acceptability and feasibility of monitoring applications and wearable technology to objectively measure participants' smartphone use behaviours, sleep quality, and other sleep-related outcomes in an ecologically valid way. A discussion schedule was used to initiate discourse on participant's experiences of, and their relationship with, their smartphones. Information was gathered on opinions of suitable methods for measuring natural mobile phone usage in a convenient and acceptable manner, and the potential pitfalls of measuring mobile phone use in an ecologically valid way. In order to discuss wearable technology for sleep, participants were asked their opinion of wearables, for example, using FitBit, Apple Watches or similar fitness and sleep tracker style wrist-worn wearable technology devices.

5.2.1 Justification

Several epistemological perspectives were considered for conducting this research, most notably pragmatism and constructivism. Pragmatism is orientated around the real world and contextualises knowledge to practical situations, such as the various ways people may use their mobile devices based upon desired outcomes (e.g., using video call functions to keep in touch with long-distance family). Alternatively, constructivism centres on attempting to understand how individuals engage and draw meaning from the world based on their history and social practices. This allows for subjective meanings which vary depending on perspective.

Different types of qualitative research methods can include written diary accounts, interviews, documents, case studies, ethnography, and focus groups. Two main methods of data collection were considered to undertake this research; interviews and focus groups. One-to-one interviews are used to gain an individual's views, experiences, belief, and motivations on the topic in question. Semi-structured interviews employ a schedule of questions to help direct the topic of discussion, while remaining flexible enough to explore an individual's topics which may be raised through this line of questioning. Structured interviews ask questions verbatim to a pre-arranged schedule without flexibility, and unstructured interviews can confuse both the researcher and participant by asking an open question across an entire topic without focus. Interviews are often used for more sensitive subject matters, to allow the researcher to create a safe space for the participant to answer and discuss their perspective.

Focus groups harness group dynamics to allow open discussion whilst being guided by a moderator. This enables inter-group discussion of ideas, opinions, and experiences, including agreement and opposing views, to be drawn out as part of a rich data collection experience. If conducting more than one focus groups, participants are often divided into small groups based on shared or similar (homogenous) characteristics, such as age or other variables of interest, whilst retaining diversity amongst other characteristics, (e.g. ethnicity) (Krueger, 2014). Through this, it is hoped that a comfortable group dynamic is achieved to enable a variety of perspectives to be gained. Due to these benefits, focus groups were the preferred qualitative research method to gain an understanding of participant's experiences and attitudes in relation to their smartphone use.

5.3 Method

To further understand these concepts, an exploratory qualitative approach was used, underpinned by a constructivist epistemology. Constructivism takes the view of reality being subjective and constructed through individual human experience (Chandra & Shang, 2017; Peters, Pressey, Vanharanta, & Johnston, 2013; Ramoglou & Tsang, 2016). It enables qualitative methods to be used to explore and discover new concepts and generate theories.

5.3.1 Ethics and consent

Ethical approval for this study was given by the Health and Life Sciences Research Ethics Committee of the University of Liverpool (Ref 5617). Participants were provided with an information sheet detailing the process of the study and what would be required from them if they chose to take part. Once any questions were answered to their satisfaction, participants returned an electronic consent form to the researcher prior to the focus group taking place.

5.3.2 Participants and recruitment

The study was advertised through social media, with a recruitment poster and additional information and contact details in posts shared and re-shared on Twitter and Facebook (see Appendix A). Interested individuals contacted the researcher for the opportunity to ask any questions and were provided with the link to a short screening questionnaire. Through this, volunteer and snowball sampling were used to recruit forty-nine participants to complete a short screening questionnaire to determine whether they met the inclusion criteria. The criteria to be considered for inclusion was being a healthy adult, between 18 and 40 years, currently being a smartphone owner, and having some interest in learning more about and discussing their usage habits. This age range was chosen for two main reasons; firstly, it is in accordance with the research presented in prior chapters of the thesis; and secondly, as recent demographics demonstrate that young to middle-aged adults are more likely to have already adopted or considering owning wearables (Trajectory, 2021). Therefore, for the acceptability and feasibility of using monitoring applications and wearables as objective data measures in future research to be tested, similar populations to those likely to be recruited should be used to act as a proxy for future participants. Although there are health-related applications for older adults, for example cardiac monitoring (Duncker *et al.*, 2021) and fall detection (Bet, Castro, & Ponti, 2019), there is less acceptance and adoption of this technology in those age groups (Farivar, Abouzahra, & Ghasemaghaei, 2020; Li, Ma, Chan, & Man, 2019).

One participant of the screening questionnaire reported having no interest in understanding their own smartphone use behaviours and was therefore not considered for taking part in the focus groups. Ten individuals who completed the screening questionnaire expressed the wish not to be audio and video recording during the discussions. A total of 14 participants (6 males, 8 females) were selected from those that completed the screening questionnaire. They were divided into two focus groups, each comprised of seven participants, based on similarities in the screening questionnaire, such as age range and degree of interest in smartphones. These groupings by similarities are reported to foster group cohesion and encourage open discussion in a non-judgemental environment (Gill, Stewart, Treasure, & Chadwick, 2008; Stewart & Shamdasani, 2014).

5.3.3 Procedure

The focus groups took place between July and August 2020 and were conducted in an informal, chat-room style using the 'chat' function on Microsoft Teams. The decision to conduct the discussions virtually was three-fold: one, due to the outbreak of the Covid-19 global pandemic in March 2020, and the subsequent government and departmental social distancing and lockdown restrictions (UK Government, 2020a); two, the enforced restrictions and use of video conferencing during work-from-home orders were found to induce anxiety (Gullo & Walker, 2021; Kwong *et al.*, 2020). Finally, the chat-room style enabled the sample of individuals not to be reduced by those who did not consent to recorded sessions and produced immediate transcripts without the risk of misinterpretation. Therefore, the more informal approach to the discussions was employed.

A discussion schedule was devised based on the information that was predicted to need to be known to develop an experimental study using objective measures of sleep quality and smartphone use behaviours. The study aimed to gain insights into the practicalities of mobile phone usage from the user's perspective, experiences, and attitudes around smartphones. This included throughout the Covid-19 pandemic, as an important contextual factor during the time of data collection. Opinions were gathered on suitable methods for measuring natural mobile phone usage and sleep-related outcomes in a convenient and acceptable manner, and the potential pitfalls of measuring mobile phone use in an ecologically valid way. The use of focus groups encouraged group discussion and the exchange of experiences and thoughts between participants.

Participants were provided with information sheets and consent forms, which they returned with electronic signatures prior to joining the focus group call. Each participant received an email invitation to join the Microsoft Teams call with their microphones muted and video turned off. The moderator (myself) was the only person with their video and microphone turned on, to act as a stable anchor point and facilitate the discussion. The session was opened by the moderator with a short welcome and housekeeping guidelines for how the session would be conducted and general chat-room etiquette. Participants provided their answers, replied to one another's discussion points, and answered prompts using the chat function built into Microsoft Teams. This had the benefit of focus groups transcriptions being complete at the end of the session and easily obtained from the chat window. Each of the two focus groups lasted for approximately one hour, with each of the core questions from the discussion schedule being allocated approximately ten minutes.

5.3.4 Discussion Schedule

The discussion schedule was comprised through an iterative trial and error process. The aim of these questions was to understand what needed to be known from potential participants to develop a study using objective measures. Initially, an extensive list of required information needed to be garnered from participants was written and was subsequently condensed so that two succinct questions did not cover the same topic. I then consulted with my postgraduate peers in my department to test how questions were phrased, to elicit open-ended responses. Questions were reworded where necessary before the discussion schedule was piloted on a group of colleagues who were familiar with the aims of the research and had qualitative expertise. This process allowed me to determine which questions were successful in facilitating the discussions, and which questions needed additional clarity for participants to help gain the insights into the mobile phone user's perspective. A total of six core questions and five additional prompts and questions of interest were finalised (see Figure 5). The questions were chosen and structured to be relatively broad and unspecified at the beginning to ease participants into the discussion, before narrowing down to focus on the opinions and insights needed. When considering their answers, participants were asked to focus the capabilities of smartphones as a device, rather than on the progression of the hardware handset itself.

Questions:

Focus on what smartphones do for you, rather than the hardware etc.

- What is your relationship with your phone like?
    - Tell me about your attachment to your phone.
- What good things can smartphones enable?
- What are the bad things / pitfalls of smartphones?
- Tell me about your own smartphone use?
    - How has your smartphone use changed due to the COVID-19 pandemic and social distancing measures?
    - How would you feel about tracking your use e.g. using an app?
- What do you think of wearable technology (e.g. FitBit)?
    - Would it be acceptable to wear it, including having the researchers have access to your data, to participate in a study?
    - What would be an acceptable length of time to wear one?
- How would you feel about using wearable tech to record your sleep quality for a research study?

Figure 5: Discussion schedule questions

5.3.5 Analysis

Two analysis methodologies were taken under consideration when approaching the concept of an appropriate analysis for the current study; Interpretative Phenomenological Analysis (IPA) (Smith, Flowers, & Larkin, 2009; Smith & Shinebourne, 2012) and Thematic Analysis (Braun & Clarke, 2006, 2021a). IPA is an interpretative approach, which aims to examine individual's personal lived experiences as they try to make sense of them (Alase, 2017). This level of detail into individual's experiences made it an important approach to consider, as it had potential to produce insights into individual opinion and experiences of smartphones and wearable technology. However, IPA is suited to complex, sensitive, and often ambiguous phenomena (e.g. pain, which is personally specific and difficult to articulate) (Smith & Osborn, 2015). Given that smartphones are ubiquitous with daily life nowadays, and that the aims of the research did not entail overly sensitive subject matter, IPA was disregarded.

Although often misinterpreted in the literature as being simplistic or as a part of other more popular methodologies, Thematic Analysis is a method in its own right, which can be applied across a wide range of epistemologies and research questions. It is a method of identifying, analysing, organising, describing, and reporting themes to provide a rich, detailed data set (Braun & Clarke, 2006). It is highly flexible and does not require prior technical knowledge, making it highly applicable and accessible (Nowell, Norris, White, & Moules, 2017). It has been noted as a useful method for examining participants' differing perspectives and highlighting similarities between them (Braun & Clarke, 2006; Brooks, McCluskey, Turley, & King, 2015).

The transcripts were analysed using Thematic Analysis and taking a semantic, inductive approach. I followed the procedure set out by Braun and Clarke (2006), including: familiarisation with the data, generation of initial codes, searching for themes, reviewing themes, and defining and naming themes. Although this procedure is relatively linear, it was also iterative and involved the continuous review of codes and themes to ensure they reflected the data as accurately as possible (see Figure 6). The semantic approach entails examining the actual content of the data at the explicit level, without looking for underlying meaning, whereas an interpretative, latent approach accounts for the subtext and assumptions underlying the data (Boyatzis, 1998). An inductive, or 'bottom-up', approach ensures the thematic analysis is data-driven. It involves allowing the data to determine the themes that are produced without the influence of existing preconceptions, to ensure an honest reflection of participant's opinions (Braun & Clarke, 2006, 2021a; Patton, 1990). This is in contrast to a theoretical approach, which is driven by an existing research question or theoretical underpinnings (Braun & Clarke, 2006). A semantic, inductive approach to Thematic Analysis was considered the most appropriate method to gain honest reflections of the participant's perspective and attitudes towards smartphone and sleep related behaviour monitoring.

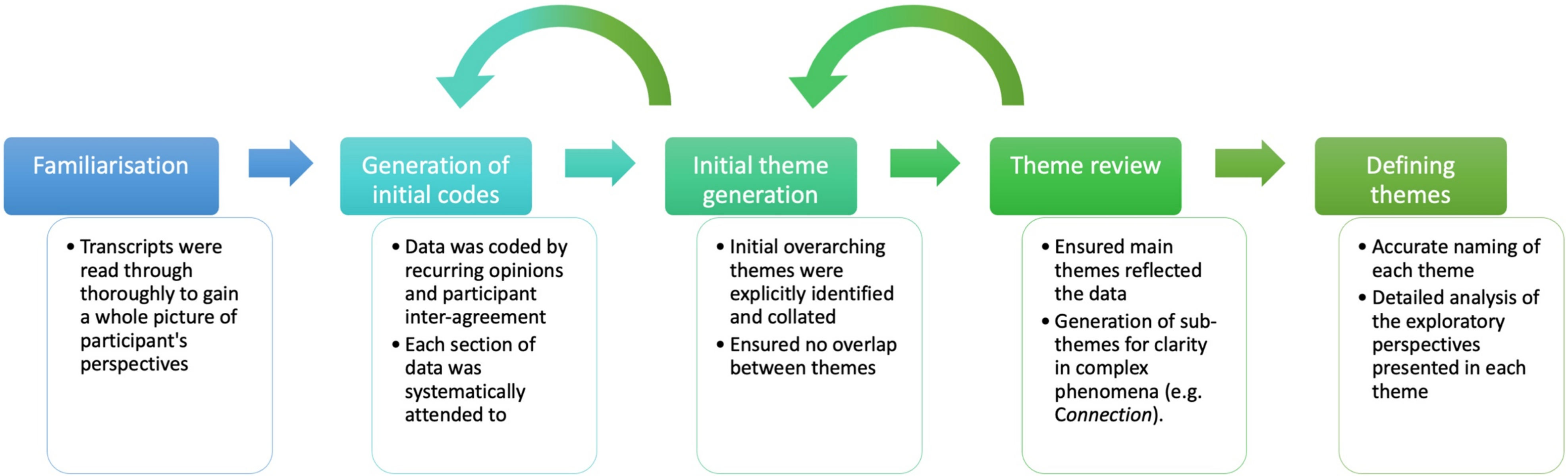

Figure 6: Flow diagram reflecting the iterative Thematic Analysis process.

5.4 Results

Two focus groups took place with a total of 14 participants, who also completed the short demographics portion of the screening questionnaire (see Table 15). All participants rated themselves as somewhat or very interested in understanding their smartphone behaviours *(How interested are you in understanding more about your own smartphone usage patterns?)* on a 5-point Likert scale (1 = not interested, 5 = very interested).

Table 15: Focus Group participant descriptives and demographics in percentages of the sample.

Demographics		*N*
Sex	Male	6
	Female	8
Age	18 – 24	4
	25 – 34	8
	35 – 40	2
Ethnicity	White British	11
	Asian British	2
	Other	1
Employment	Employed (full)	10
	Employed (part)	1
	Unemployed	1
	Student	2
Smartphone brand	iPhone	9
	Samsung	2
	Huawei	1
	One Plus	1
	Xiaomi	1

Four main themes were identified from the data; ‘Functional uses’; ‘Attachment’; ‘Distraction and disruption’; and ‘Connection’, with two sub-themes of ‘Social connection’ and ‘Inability to disconnect (see Figure 7).

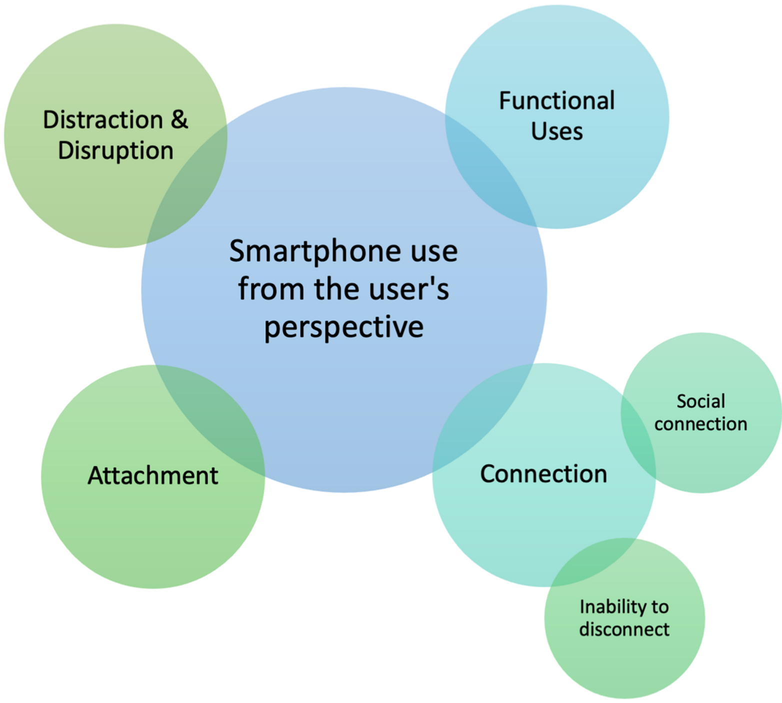

Figure 7: Diagram of the four core themes and two sub-themes presented by the data.

5.4.1 Functional uses

This theme encapsulates the versatile and useful properties smartphones and device technology have, either by internal systems or third-party downloadable content. Reflecting on the uses of their smartphones, participants found them to be invaluable and handy tools for a multitude of uses, including for example, convenience at work and information access; navigation and transport; entertainment; and news.

FG1P2: My phone is the only way to get on my server for work, No phone no work.

FG1P1: My phone helps me within my work life, if I need to research something quickly or fly emails to different people.

FG2P12: I could go to a meeting with just my phone and I'd feel confident that I'd be able to access most things that I would need whereas maybe 5-10 years ago I would have needed various documents etc.

FG1P3: Not getting lost in unfamiliar places, researching new information at the touch of a button.

Participants differed in which functionalities they valued most, with some preferring to regard their phone with a utilitarian approach, noting its usefulness in the workplace or for practical purposes (e.g., navigation) most. Whereas other participants enjoyed the ease of use for shopping, entertainment, and documenting their lives.

FG1P7: I can use my phone to pay for things and check my bank account regularly. I can use it as an alarm, for online shopping its quicker and easier on the apps and to access the internet quickly if I need to. Having access to maps in case I am ever unsure where I am or how to get somewhere. Always having a camera with me so I can photograph and video without having to carry a big camera with me.

FG2P13: I will take my phone literally everywhere with me – especially on outings, at work, everywhere and will always make sure it is almost fully charged… I use it to keep up to date with what's going on in the world, will read the news of the day / check out what's happening in the twitter-verse.

Wearable technology, such as FitBits and Smart Watches, were viewed favourably by the majority of participants. The utility of these was seen as an asset for the more fitness minded participants, allowing activity tracking but also health-related monitoring such heart rate and sleep.

FG1P4: I totally agree with them and especially because I'm quite a sporty person and there the best way to monitor heart rate etc.

FG2P9: Great for tracking fitness, sleeping etc. Apple watch are good I've had mine over 2 years now.

FG2P14: I wear a Fitbit every day for personal use anyway and I love it! I love counting my steps on it and especially the sleep tracking and stuff and measuring my heart rate especially if I've gone on like a hike or something I like to see the GPS map from it where I've been and the stats of my exercise!

Two participants tended to use their capacity of their wearable technology as an extension of their smartphone; enabling them to be able to receive and respond to messages or even engage in meditation like breathing conveniently from their wrist-worn device.

> *FG1P1: I adore my Samsung smart watch… Mine is a great asset at work, if I'm busy working on a report or dealing with customers, if I have employees from other stores messaging me, I can quickly check my watch to determine if the message is urgent or not.*

> *FG2P10: I own an Apple watch and enjoy that I can sync to phone. I like being able to track exercise and monitor heartrate (when I actually exercise), as well as the obvious of being able to receive messages (if phone in range). I like the 'Breathe' reminder, it pops up a couple of times a day and encourages deep breathing for a minute.*

However, there was also the acknowledgment of more worrisome aspects of wearable technology. The concern was raised that tracking your habits intensely could lead to excessive goal-checking behaviours and perhaps an expectation in yourself to achieve a certain goal daily.

> *FG2P11: I think having a piece of wearable tech can be good if you really want to work on something like fitness. But it can also become dangerous 'overtracking' your daily habits.*

FG2P12: Yeah definitely tracking everything you're eating and the exercise you're doing, I have friends who can't not do a certain amount of steps now etc.

Thirteen of the fourteen participants who took part were agreeable to the possibility of smartphone use monitoring and using fitness tracking devices to participate in research studies. Some were already invested users of wearable technology and reflected on recognising the usefulness of this information to answer pertinent questions, in both a personally applicable and a societal research context.

FG2P13: This is one aspect of smartphone use which does affect me personally as my quality of sleep is relatively poor and I believe there is a strong link between the two. I would be happy to participate in a study which may demonstrate this at a larger scale… I would be very interested to find out these results as I would like to make a few changes in my own life in relation to this.

FG2P14: I literally only ever take my Fitbit off when I shower or when I charge it so I'd be happy to wear one all day and night… Would be happy to share the data for research purposes.

FG2P12: I think it would be interesting to see your habits so would wear it for a study.

FG1P1: I already do wear mine which tracks my sleep, steps and heart rate so that would be fine for me. [Usage monitoring] might be quite helpful to concentrate if you pin point the apps you over use compare to other apps

FG1P5: I wouldn't mind that I would be interested in this and being part of a study would make me stick to it… I feel this would be a way to really open my eyes to usage. No hiding!

FG1P4: I wouldn't mind tracking my phone use on an app as I'd like to see how much I use my phone on a weekly, monthly basis.

FG2P10: Totally happy to have usage tracked, I think it would be interesting to see patterns of usage and what gets used the most – most likely social media for myself, I quite like getting the weekly notification off Apple (especially when it says my usage has gone down).

5.4.2 Connectivity

A main theme of connectivity was drawn from the data, with all participants reflecting on how smartphones have enabled seamless instantaneous communication. However, this ease of communication was recognised to have drawbacks as well as benefits. Therefore, this was conceptualised into two sub-themes: 'social connection' and 'inability to disconnect'.

5.4.2.1 Social connection

This sub-theme encompasses the communication and social connectivity that smartphones enable. This aspect of smartphones was important to all participants for maintaining relationships with friends and family regardless of geography. This had been especially crucial throughout the period of social isolation during Lockdown between April and June 2020 (UK Government, 2020a).

FG2P8: It's really important to me for keeping in touch with people… Speaking to friends & family from wherever you are.

FG2P14: Communication like with long distance friends, facetime is great, especially in current circumstances.

FG2P9: Would say I used facetime and whatsapp video messenger alot more to keep in contact with family and friends.

Participants did not let physical distancing requirements harm their social interactions during the Covid-19 pandemic, leading to the adoption of new and existing applications and features. This is in accordance with the Uses and Gratifications Theory (Katz & Blumler, 1974), mapping onto the 'personal relationships' motivation of media use.

FG2P13: Have communicated more with friends who are all in similar situations and my smartphone has allowed for staying in touch to be so much easier. Development of new apps during this time such as zoom / houseparty has meant we've adopted ways of communication we hadn't really used before.

5.4.2.2 Inability to disconnect

The second sub-theme within the 'connection' was the notion of not wanting to be connected. Participants identified that smartphones essentially made them always reachable, either for social or work reasons, and blurred the lines between work and leisure time. They reflected that this was exhausting and left them unable to disconnect from the digital technological sphere. This was true for participants who had been working from home during the pandemic, with the demand of their work increasing and expectations of longer working hours from management.

FG1P3: Unable to disconnect, therefore an expectation for people to work/respond in leisure time.

FG1P5: Agree that standard working hours are becoming much looser. Constantly being emailed and Whatsapped… Our work has increased massively during covid so even though we have physically been in work the expectation to move at speed and work at home after hours is there.

FG1P1: I agree with about the expectation of constantly being at the beck and call, if someone doesn't response within a certain time period it's almost like you can't comprehend that they could be doing anything other than being on their phone.

FG2P12: Becoming disconnected to the "real world" especially with social media.

FG2P13: Being "available" 24/7 – can become draining.

FG2P8: It's very easy for me to get sucked into using my phone all the time especially because the nature of my work AND my hobbies are so online related.

This inability to disconnect from everything, especially during the height of the Covid-19 pandemic, was noted to impact upon people's mental health too. Participants reported increased anxiety and detriment to their mental state.

FG2P13: At the start of the pandemic I used it a lot to keep up to date with government guidance / information on how things are going in the rest of the world and also monitoring potential new information about COVID itself (that became quite anxiety-inducing) constant updates on death tolls and personal stories also became quite detrimental to my own mental health and the availability of all this information so easily may have had an impact.

FG2P14: I also found myself getting more and more anxious when on my phone generally especially twitter like with seeing fake news about Covid, and also just daily updates that just couldn't be escaped.

5.4.3 Attachment

Participants recognised and reflected on being attached to their smartphone, both physically and emotionally. One participant referred to their phone as a 'third hand' and 'an extension' of themselves, suggestive of a reliance on it to function.

FG1P1: My phone is practically like a third hand. Definitely an extension of myself, personally I feel as if I wouldn't be a full person without my phone, which is sad to say.

FG1P3: Very dependent on it - tend to carry it everywhere and feel strange if I don't have it.

FG1P2: It's in my pocket when leaving the house; I wouldn't say it's part of my personality as such but it's a valued asset.

FG2P12: I would say I am very attached to my phone, it essentially holds my life in it!

Participants went on to elaborate further of their relationship with their phone, emphasising their reliance on it for across different aspects of their life. One participant described their reliance on it for utilitarian purposes but that they were emotionally attached, suggesting a deeper connection beyond smartphones usefulness.

FG2P12: It's my way of connecting to anything I need whether it's to speak to people socially, to use for work, to buy things, to keep up to date with what's happening with the world, my to-do lists etc.

FG2P8: I do my banking, communications, some socialising, I'm very emotional attached I think haha.

FG2P11: I view it as a handy tool for a number of things: from work, to socializing, to relaxation.

5.4.4 Distraction and disruption

This theme captures participants' experiences of smartphones being a distraction in their lives and disrupting other activities. Using their smartphones seemed to displace other activities, and create time distortion effects, with more time than you think passing during smartphone use. This was also perceived to be wasted time.

FG1P5: My main concern at the moment is lack of concentration on other tasks that can creep in… I may not fully concentrate on a TV programme because I pick the phone back up… that mindless scrolling! What a waste.

FG1P4: You can sit on them for hours and not even realise well I can! Scrolling through social media is just too easy.

FG1P1: App's such as TikTok or Instagram tend to make me fall down a rabbit hole of scrolling, and without realising it an hour or two could pass.

FG2P14: It's so easy to just spend empty hours staring at a phone screen achieving absolutely nothing.

Participants also commented on the disruption of social comparison. They reflected that endless instantaneous access to social media presents distorted views of other's lives, and the potential of negative consequences which can arise when drawing these perceived comparisons to yourself.

FG2P10: Easy to fall into comparing yourself with others when browsing social media, especially Facebook and Instagram.

FG2P13: Instant and constant access to social media – can lead to comparisons between own life and others (potentially detrimental to mental health).

FG2P14: Yes I think it's so easy to like fall into the trap of comparison to others particularly on Instagram and stuff and I think generally this has a lot of negative impact.

FG2P12: Can lead you to feel bad about yourself and your life and what you perceive others to be achieving that you aren't… seeing everyone post about the happy times in their lives so you get a distorted view.

5.5 Discussion

The aims of the present study were two-fold; first, to further understand the practicalities of mobile phone usage from the user's perspective; and secondly, to gain insights into the acceptability of monitoring applications and wearable technology to objectively measure participants' smartphone use behaviours, sleep quality, and other sleep-related outcomes in an ecologically valid way. Four main themes were identified from the data; 'Functional use'; 'Connection', with two sub-themes of 'Social connection' and 'Inability to disconnect; 'Attachment'; and 'Distraction and disruption'.

Participants reported that their smartphones were more than devices to make calls or send text messages, which led to the positive and negative impacts of smartphones being discussed. Mobile devices were seen as handy tools, useful for everything from document access at work, to navigation and entertainment. The myriad of communication and social connectivity possibilities, especially video calls, were important methods of keeping in touch. One participant even phrased their smartphone as being 'an extension' of themselves. This idea of your smartphone being part of your sense of self supports previous qualitative research by Harkin and Kuss (2021); their participants reported that the features and applications enabled by using smartphones allowed ordinary daily experiences to become stimulating and educating. Participants in the current study reflected these opinions, harnessing the functional features of their phones to capture memories, purchase items, and keep up-to-date with the news.

Given the global impacts of the Covid-19 pandemic, it was important to understand how smartphone use and attitudes were affected by it. Current participants reported experiencing increased anxiety from exposure to endless social media newsfeed content about the Covid-19 pandemic. The emotional consequences of exposure to Covid-related news on Twitter has been found to immediately reduce positive affect and optimism (Buchanan *et al.*, 2021). On the other hand, the current findings also highlighted the importance of smartphones for keeping in touch with loved ones and friends, throughout the Covid-19 lockdown measures and prior to the pandemic. Video calls were most notably mentioned as methods of contacting family and friends and maintaining these relationships over long distance. This evidence suggests support for the Stimulation Hypothesis, which posits that online communication may enhance existing relationships and, therefore, one's wellbeing through mediating variables of time spent with friends, and the quality of these friendships (Valkenburg & Peter, 2007).

However, smartphones also brought the expectation to always be available, which was draining and detrimental to well-being. Participants reported that smartphones increased the expectation that people are available outside of their working hours, leading to an inability to disconnect from their work. This is supported by Büchler, ter Hoeven, and van Zoonen (2020), who demonstrated that constant connectivity and the inability to disengage from work was negatively related to employee well-being.

The present participants reported feeling physically or emotionally attached to their smartphones, using them as a connection to anything they needed. One participant shared that they carried it with them everywhere and distinctly noticed when it was absent, while another claimed their phone was a 'valued asset'. These attitudes towards their smartphones supports previous qualitative research by Fullwood, Quinn, Kaye, and Redding (2017), in which participants attributed anthropomorphic qualities to their phones, attributing it to having a virtual friend in their pocket. This notion seemed to increase user's attachments to their smartphones.

Wearable technology was viewed favourably by all participants in the present study. Those that already owned wearables used them to view messages, monitor their heart rate and sleep statistics in addition to the fitness-related benefits. All but one participant agreed that being asked to use and share data from monitoring applications and wearable technology for research purposes would be acceptable. These perceptions of wearable technology reported by participants are in accordance with previous research; the majority of consumers aged between 18 to 39 years tend to either already own a wearable device or would like to own one in the future, outweighing those who outright reject the developing technology (~20%) (Trajectory, 2021).

Expense is cited as the barrier to consumers owning wearables (Trajectory, 2021), which may lead to future participant samples consisting of existing wearables users being biased. While participants with the disposable income to spend on health-related technology may be overrepresented, this could be overcome by supplying the technology to participants for measurements and intervention purposes, provided the research itself is supported by appropriate funding. However, in regard to public health, it is also possible that the affordability barrier to wearable technology may exacerbate health inequalities (Babones, 2008; Trajectory, 2021; Weiss *et al.*, 2018; Yao *et al.*, 2022), with only those who can afford the technology having access to a wealth of personalised health data and insights at their fingertips. Given that the relationship between sleep and executive function may be bi-directional (Hua *et al.*, 2021), being given the opportunity to understand these health-related behaviours through using wearable technology may lead to better sleep quality and executive functioning in those with the disposable income to do so. However, by making wearables somewhat affordable, this may be mitigated by lower income individuals prioritising these insights for themselves. Previous research has found that those of a lower socioeconomic status spend more time using screens compared to their wealthier counterparts (Carson *et al.*, 2010; Männikkö *et al.*, 2020). This may suggest that they prioritise digital technology ownership (e.g., smartphones), perhaps for its versatility in functional and entertainment capacities; therefore, if wearable technology was marketed similarly, perhaps these health inequalities could be reduced.

Current participants' agreement to the idea of using wearable technology to participate in research may act as a proxy for future participants, enabling future research to make use of wearables as objective measures of sleep-related outcomes and other health-related parameters. Indeed, these future studies may go beyond the concept of wrist-worn Smartwatches and health trackers (e.g., Apple Watch). Research by Mehrabadi *et al.* (2020) has compared an 'Oura' Smart Ring and the Samsung Smartwatch to medical-grade actigraphy. The parameters of both wearables were significantly correlated with the actigraphy, however mean differences between the Smartwatch and the actigraphy were considerably higher than the ring, suggesting that the more discreetly worn device outperformed the wrist-worn wearable (Mehrabadi *et al.*, 2020). The Smart Ring may be the more advanced consumer-grade wearable in the current market, but it remains to be seen whether they are adopted as highly as devices like the Apple Watch, which offer the additional visual features of your network connected smartphone in a smaller wrist-worn device.

The advancing landscape of wearable technology may be useful for objective measurements of health-related data in future research, either by recruiting existing users or through supplying the technology to participants for measurements and intervention purposes. However, given the expense often cited as the barrier to consumers owning wearables (Trajectory, 2021), samples consisting of existing users may be biased. It is also possible that these barriers to wearable technology may exacerbate health inequalities (Trajectory, 2021), with only those who can afford the technology having access to a wealth of personalised health data and insights at their fingertips.

The broad spectrum of uses and functions that smartphones enable means there is no set format for their use, which consequentially makes usage habits personal. This was true for the current participants too, who reported that their smartphones were used for everything from storage to navigation, work, and hobby-related activities. This is in accordance with the Uses and Gratifications (U&G) Theory (Katz & Blumler, 1974), which argues that media consumption choices are personalised to fulfil individual's needs. Although this theory dates from prior to the internet, it remains as relevant for mass communication in modern computer-mediated communication as it is for newspapers, radio, and television (Lin, 1996; Ruggiero, 2000; Vezzoli, Zogmaister, & Coen, 2021). As well as specific functional needs, this theory may extend to needs related to self-presentation; participants in a qualitative study by Harkin and Kuss (2021) fulfilled this through smartphone 'hygiene'; through the selection of background images and cleaning out irrelevant and retaining personally pertinent apps.

Limitations of the present study include that it was cross-sectional and contained a single wave of data collections, the small group settings of the online focus groups may have created the potential for socially desirable answers. The informal chat room style focus groups did not allow for the nuance from intonation, pauses, facial expressions collected when using the intended and usual audio or visual recordings. The small number of participants in this study makes it unlikely that data saturation was reached. However, data saturation, the point at which no new themes are generated from the data (informational redundancy), is not a goal of thematic analysis (Braun & Clarke, 2021b; Guest, Bunce, & Johnson, 2006); it is neither useful nor theoretically coherent. Instead, the relevance of the collected data, or informational power, may be a better method of conceptualising sample size (Braun & Clarke, 2021b). In addition to this, the focus groups were conducted amid the height of a global pandemic which changed the way people used their mobile phones and other screen-based technology (Sañudo, Fennell, & Sánchez-Oliver, 2020); therefore, the findings may only be relevant in the context of the Covid-19 lockdown and physical distancing measures.

5.5.1 Implications and conclusions

The present study demonstrates the potential for objective measures of smartphone use and sleep related outcomes in future research. Participants were open to having their smartphone use behaviours monitored (i.e., which applications they are using and duration of use), a feature which is now built into smartphone operating systems. Importantly, participants agreed that being asked to use wearable technology to measure their sleep related outcomes was acceptable. This acceptance may be used in proxy of participant acceptance for a similar, young adult sample in future research designs.

Although these findings were not able to be implemented into an experiment design during the current doctoral research, future experimental studies should capitalise on the available technology to objectively measure smartphone use behaviours, sleep quality, and other sleep-related outcomes (e.g., duration and latency).

Chapter 6: General Discussion

The overall aim of this thesis was to examine the associations between digital technology use and executive functions, and digital technology use and sleep in populations of adolescents and young adults. It was hypothesised that (H1) digital technology use would be associated with executive functioning, and (H2) digital technology use would be negatively associated with sleep quality. Specifically, I aimed to address the question of how exposure to mobile, digital technologies is associated with executive functioning and sleep using a mixed methods approach. Combining quantitative and qualitative approaches has the benefit of delivering stronger, more granular findings around conceptually uncertain topics such as digital technology (UK Government, 2020b). Chapter-specific discussions and interpretations of findings can be found in the relevant empirical chapters. This general discussion presents executive summaries of the studies and reflections on the key findings taken together. The implications of my thesis are discussed, and suggestions are given for the future directions of this research, which were beyond the scope of this thesis.

Overall, the current studies present evidence which both supports and refutes the hypotheses. The primary research studies in Chapters Three and Four refuted H1, finding no associations between digital technology and executive functions. The screen media use of neither the adolescent population of the imputed sample of the MCS study (Chapter Three) nor the young adult population of the prospective online study (Chapter Four) was related to their executive functioning. These two studies utilised different methodologies and samples and controlled for similar confounds including physical activity and mental health. Yet both point to there being no relation between digital technology use and EF. Conversely, the systematic review forming Chapter Two found evidence which supported H1, that digital technology was associated with EF. Inhibition and decision-making were negatively associated, and working memory was positively associated with smartphone use. The variation in these findings may be explained by the confounding variables that were controlled for; the studies contained within the systematic review were at risk for methodological bias, with some not reporting any adjustments to account for confounds (Warsaw *et al.*, 2021). Therefore, a strength of this thesis is the confound adjustments tailored into each study; Chapter Three controlled for pre-birth and childhood factors such as ethnicity, SES, physical activity, emotional difficulties, and substance use; Chapter Four controlled for physical activity, mental ill-health, and perceived quality of life. The absence of these adjustments may make the relationships found in the systematic review studies false and perhaps due to confounding factors.

The second hypothesis (H2) predicted that digital technology would be negatively associated with sleep quality. While Chapter Three found no evidence in the imputed sample of adolescents of screen use being associated with sleep quality, Chapter Four supported H2 by demonstrating small negative associations between smartphone use behaviours and sleep quality in young adults. Potential explanations may be dependent on the age of the populations, or perhaps on the temporal aspects of the studies themselves. The MCS study included both cross-sectional (short-term) and longitudinal (long-term) data, while the online study with a young adult sample was more focused on short-term impacts of smartphone use behaviours. This suggests digital technology use may have short-term implications for negative associations with sleep quality. However, the evidence should be interpreted with caution as specific temporal evidence or manipulations were outside the scope of this research and not used.

In Chapter Two, I systematically reviewed the existing peer-reviewed literature to explore whether exposure to mobile technology was associated with executive functioning in healthy young adults, aged 18 to 35 years. This was the preliminary piece of work to scope out what has been done in the field so far and highlighted gaps in methodological rigor and inconclusive findings. Increased smartphone use was negatively associated with inhibition, decision making, working memory, and delayed gratification (Chen *et al.*, 2016; Fortes *et al.*, 2020; Fortes *et al.*, 2019; Frost *et al.*, 2019; He *et al.*, 2020; Tang *et al.*, 2017). Video gaming was associated with working memory and inhibition (Fortes *et al.*, 2020; Huang *et al.*, 2017), but not with multitasking (Donohue *et al.*, 2012). However quality assessments determined that the evidence base was of poor quality and subject to high risk of bias; the articles demonstrated imprecise reporting of results and an over-reliance of self-reported questionnaires to quantify behaviour, which correlate poorly with objective behavioural measures (Buchanan, 2016). This indicated that associations between smartphones or video games and executive function could not be conclusively determined from the existing body of evidence.

I attempted to address the methodological issues highlighted by findings of Chapter Two by examining the associations between digital technology and executive functioning, and digital technology and sleep quality, through two studies; an observational epidemiological study and a prospective empirical study. Chapter Three used the Millennium Cohort Study to determine whether screen use at age 14, in 3 discrete categories (time spent on social media, video gaming, and passively watching content on TV, DVDs and videos) was associated with executive function (decision making), and sleep at age 14 and 17. In an effort to reduce the impact of attrition bias on the sample, I used multiple imputation to estimate missing values. Compared to the complete case analyses (CCA), the increased sample size and narrower confidence intervals across the imputed analyses suggest that they were the more reliable estimate than the CCA. The increased sample size of the imputed analysis also ensured it was appropriately powered to examine the longitudinal relationship between screen use and age 17 decision-making (n = 1929). In the imputed analysis, there was no evidence for any associations between screen media uses, decision-making, or sleep quality at age 14 (n = 3224) or age 17 (n = 1929).

In Chapter Four, participants were crowdsourced online through *Prolific,* and completed questionnaire measures of smartphone use (SAS) behaviours and sleep quality (SQS & PSQI). Gamified behavioural tasks were used to objectively measure four executive functions (attention, inhibition, working memory, and decision-making). The Smartphone Addiction Scale (SAS) is one of many measurement scales that have been developed and administrated to quantify excessive smartphone use behaviours without constituting a clinical diagnosis. Although the concept of 'smartphone addiction' is unlikely, with the content accessed through smartphones and the internet being of greater important in behavioural addictions, the Smartphone Addiction Scale (SAS) was utilised as it is a validated and frequently used scale within the field, which does not rely on the concept of 'screen time' to quantify smartphone use. Self-reported estimates of smartphone use may not be related to actual use, as neither duration nor number of interactions were related to participants scores on the Mobile Phone Problem Use Scale (MPPUS) (Andrews *et al.*, 2015). In the future, the development and administration of measurement tools which focus on smartphone uses and functionality, or affordances, and the purpose or gratification from this use, should be developed as a priority to be used in collaboration with to corroborate objective monitoring measurements.

There was no evidence of association between digital technology use and decision making in either study (Chapters Three and Four), and no evidence for associations between smartphone use behaviours and working memory, sustained attention, or inhibition (Chapter Four). While the MCS study had three discrete categories of screen uses (social media, video gaming, and watching TV, DVDs, or videos), Chapter Four specifically focused on smartphone use, which was measured using a non-clinical measure of smartphone addiction (SAS) to quantify participant's smartphone use behaviours. This was chosen to be focused on as the exposure to digital technology, as smartphones are the primary screen-based device ubiquitously used by most of the population. Almost every adult, and a large proportion of adolescents, use a smartphone for communication, information, and leisure functionality. Taken together, this suggests that neither smartphone use, and through this social media as the primary way social media is accessed, playing video games, nor watching TV is likely to be associated with the four primary executive functions I focused on. However, the available MCS data only had collected measures of decision making; therefore, longitudinal examinations of attention, memory, and inhibition are necessary to increase certainty in the lack of associations. It is also important to note that Chapter Three examined a UK adolescent population, whereas Chapter Four examined a UK young adult population. These findings are in accordance with previous research, which found no relationship between smartphones and inhibition (Johannes *et al.*, 2019), or smartphones and working memory or sustained attention (Pardo & Minda, 2021). Therefore, smartphones may be a neutral presence in our pockets and palms without impacting our attention spans, decision making process, inhibitory control, nor memory. It is worthwhile to mention that research on adolescent social media use lacks diversity, and particularly over represents the global northern hemisphere (Ghai, Fassi, Awadh, & Orben, 2021). Increased sample diversity across research in all regions is crucial to further our understanding of how social media and other digital technology use may impact young people.

Chapter Four also demonstrated evidence of a negative association between smartphone use behaviours and sleep quality, which was consistent across both Sleep Quality Scale, and the Pittsburgh Sleep Quality Index. However, mental ill health scores explained more of the variance in the models. In accordance with previous research, this suggests that symptomology of anxiety and depression is better associated with reduced sleep quality (Fang *et al.*, 2019; Hertenstein *et al.*, 2019; Patalay & Gage, 2019). While there is weak evidence of small associations between smartphone use behaviours and reduced sleep quality, it is important to remember that these were cross-sectional analyses on self-reported questionnaire data. This limits the degree to which it can be claimed to be true, and must be interpreted with caution so as to not overstep the extent of the analyses. Future work could explore the potential for indirect associations between smartphone use and sleep via mental ill health, such as whether negative smartphone use experiences (e.g., cyber bullying) increase mental ill health.

In Chapter Five, I explored the acceptability and feasibility of using digital technologies to increase the objectivity of future measurement methods. The aims of the focus groups were twofold: (1.) to further understand the practicalities of smartphone usage from the user's perspective; and (2.) gain insights into the acceptability and feasibility of using smartphone use monitoring applications and wearable technology to objectively measure participant's sleep quality and other sleep-related outcomes in an ecologically valid way. The transcripts were analysed using a semantic, inductive approach to Thematic Analysis (Braun & Clarke, 2006, 2021a). Mobile devices were seen as handy tools and extensions of participants' selves; providing useful functionality even while being the focus of physical and emotional attachment. The array of communication and social connectivity possibilities, especially video calls, were cited as important methods of keeping in touch with friends and family, particularly throughout the Covid-19 pandemic and periods of national lockdown measures (UK Government, 2020a). Wearable technology was viewed favourably and the use of these devices and data was deemed acceptable by the majority of participants. These perceptions of wearable technology are in accordance with current research on similar demographics; the vast majority of consumers aged between 18 to 39 years tend to either already own a wearable device or would like to own one in the future (81%), outweighing those who outright reject the developing technology (19%) (Trajectory, 2021). This agreement to the idea of using wearable technology for research participation, either through existing user's or by providing the devices to willing participants, may act as a proxy for future participants. Through this, future research would be able to make use of wearables as objective measures of sleep-related outcomes and other health-related parameters. Given that interest and demand for these products will ensure their continued development, new and upcoming wearables may provide increased reliability and validity in comparison to medical grade actigraphy. More recently, the discreetly-worn 'Oura' Smart Ring outperformed the Samsung Smartwatch Mehrabadi *et al.* (2020), making it perhaps the more advanced consumer-grade wearable in the current market, but it remains to be seen whether they are adopted as highly as devices like the Apple Watch, which offer the additional visual features of your network connected smartphone in a smaller wrist-worn device.

6.1 Implications

Taken together, the findings presented within this thesis demonstrate that any relationship between digital technology, in particular smartphones and video games, and executive functions may be so small it is negligible on an individual level (Funder & Ozer, 2019). However, this body of work was also heavily impacted by extraneous factors out of my control; namely the MCS data collection and the impact of the Covid-19 pandemic upon my experimental plans. Therefore, the evidence presented throughout this thesis adds incremental evidence to the lack of associations, but should be interpreted with some caution. Psychological science has a history of focusing on significance values, whereas effect sizes and confidence intervals are more informative values denoting the magnitude of the relationship. Although the empirical findings of this body of work are primarily non-significant, particularly in relation to digital technology and executive functions, that is not to say there is no interpretation of the effect size. The effect sizes were very small, as indicated by revised benchmark guidelines (Funder & Ozer, 2019). This indicates that digital technology is perhaps only very weakly associated with executive functions (Fortes *et al.*, 2020; Fortes *et al.*, 2019; Frost *et al.*, 2019; Hartanto & Yang, 2016; Liebherr *et al.*, 2020; Marty-Dugas *et al.*, 2018; Thornton *et al.*, 2014; Ward *et al.*, 2017; Wilmer *et al.*, 2017). However, these are observed effect sizes, based on the achieved samples in Chapters Three and Four, which are likely to be biased. Given the scale of digital technology, how multiple aspects of it are used daily by almost the whole population, it may be possible for generalised effect sizes to be larger than the observed effect sizes (Anvari *et al.*, 2022), supporting the potential for small relationships between digital technology and executive function found previously in the literature. On the other hand, the ubiquity and prevalence of digital technology perhaps means we have become habituated to it as exposure has increased (Anvari *et al.*, 2022). Therefore, the generalised effect sizes may be even smaller than the observed in this body of work. Increased population representation is needed to produce findings with increased generalisability to further investigate these relationships. Extensive and large-scale reviews have calculated average effects sizes for social psychological literature and found an average effect size of r = .19 to .21; suggesting that effect sizes of .10, .20, and .30 could be considered as small, typical, and relatively large (Gignac & Szodorai, 2016; Richard, Bond Jr, & Stokes-Zoota, 2003). By comparison, the effect sizes presented within this thesis may be more accurate as anecdotal evidence.

The current findings reduce the need for concern around the use of screen-based devices and 'screen time'. This is perhaps most notable in relation to children and adolescents; providing evidence opposing the notion that screen-based device use and digital technology is detrimental to their cognitive development. While there is strict policing and regulations of mobile devices in school environments (Department for Education, 2022; Mason, 2022), I have investigated and presented evidence which indicates that they may have less baring on executive functions, and therefore related academic performance, than first thought. It stands to reason, based on executive functions being closely related to academic performance (Ahmed *et al.*, 2019; Best *et al.*, 2011), that it should not have an effect on their school performance. Digital technology has the capacity to be an excellent tool for learning and education, providing a platform through which children and young people can access information and develop skills, as well as being more accessible for those who require different functions or with special educational needs (Buzio, Chiesa, & Toppan, 2017). Therefore, it should be harnessed to provide educational content, given that the content itself is what is vital when it comes to children and young people's engagement with screen-based devices (Huber *et al.*, 2018). This should go some way to reducing parental and public concern as to the effects of digital technology and 'screen time', and hopefully encourage parents to engage with their child's preferred content. Smartphones and video games may provide sources of connection, meaning, adaptive coping, and entertainment to young people (Carras *et al.*, 2018; Lai & Fung, 2020); demonising this will likely do more harm to the wellbeing of young people than digital technology itself is.

Regarding sleep, the use of digital technology in proximity to bedtime should be considered at the individual level and perhaps approached with caution, particularly towards smartphones as the primary device on nightstands. While they are ubiquitous in modern life for education, information, and leisure activities, the use of digital technology and screen-based devices in the lead up to bedtime deserves continued empirical attention. Although causal associations cannot be concluded as temporal aspects were not measured, as it was outside the scope of this thesis, the mechanism most likely underlying this is the exposure to blue light. If essential or required to be used, Night Shift mode may be activated on devices if available to adjust the spectral light exposure to an orange hue, paired with lowered screen brightness (Nagare *et al.*, 2019).

Although it is important not to overstate my findings and the strength of evidence presented in this thesis, these findings should be applied to inform evidence-based guidelines and decisions by policymakers and other stakeholders. However, this is not to say we should dismiss digital technology and screen-based devices as harmless. Extensive use may still pose a public health concern. A recent review and meta-analysis summarised the use of competitive electronic sport (eSport) video gaming on health and lifestyle outcomes (Chan *et al.*, 2022). Findings demonstrated associations with poor lifestyle outcomes across domains of physical activity, nutrition, and sleep; including increased sedentary behaviour and sleep deprivations, and decreased physical activity, sleep quality and duration, and poorer diet (Chan *et al.*, 2022). The specific content individuals are accessing through digital technology and devices may affect their executive functioning; for instance, impaired decision making in gambling contexts (James *et al.*, 2019; Meshi, Elizarova, Bender, & Verdejo-Garcia, 2019). Recently, Meshi *et al.* (2019) empirically examined the associations between excessive social networking sites and value-based decision making using the Iowa Gambling Task. Results demonstrated a negative relationship between SNS and decisions on the IGT; however, this was correlational evidence that was only demonstrated from the final block of 20 trials. This may suggest that the effect of impaired, riskier decisions may be a result of fatigue rather than of social networking sites, as cognitive fatigue has been associated with greater variability in economic decision-making (Mullette-Gillman, Leong, & Kurnianingsih, 2015). The findings of associations between digital technology and impaired sleep quality may impact the mental and physical health of adolescents and young people (Clark *et al.*, 2015; Scott, Webb, Martyn-St James, Rowse, & Weich, 2021).

The current findings and implications should be carefully worded for accurate and accessible dissemination. Press releases of scientific findings have previously been found to inadvertently overstate correlational findings, which preclude causal relationships (Sumner *et al.*, 2014). Therefore, while the mass media articles communicating the impacts of digital technology may be accurately reporting the details of press releases, the scientific interpretation of results may be overstating findings. The subsequent inaccurate overstating of findings may be an accidental result of attempts to be clear and impactful, or the routine focus on significance levels in psychological science rather than the magnitude of the relationship means that even professional researchers may misunderstand the implications of their own findings (Funder & Ozer, 2019). After Sumner *et al.* (2014) disseminated their assessment of these over-statements, subsequent press releases were compared to the equivalent time period in the prior year. Over-statements of correlational findings in press releases decreased from 28% to 13% after publication (Bratton *et al.*, 2020); although, overstatements in news articles remained. However, this was also based on correlation evidence, and therefore should be interpreted with caution.

Overall, these studies presented in this thesis provide fundamental groundwork in terms of advancing the reliable evidence base of this area of research. The use of mixed methods provided the opportunity to comprehensively and robustly study associations between digital technology, executive function, and sleep. This was done so within the limits of digital technology being conceptually unclear, characterised either by a strong focus on ‘screen time’, or measurement scales of smartphone or internet ‘addiction’ (Harris *et al.*, 2020; Kaye *et al.*, 2020). The combination of quantitative and qualitative methods can help combat the limitations of their separate use; combined, they can add nuance and granularity to findings (Doyle *et al.*, 2009) providing the best of both insights into phenomena.

A strength of this thesis is its contribution to and use of open science, through open access data and pre-registered studies. The last decade has seen an increased appreciation for reproducibility in psychological science (Nosek *et al.*, 2022), which refers to making knowledge and data transparent and replicable. This increases the integrity of results and deters dishonest practices, such as p-hacking (running multiple analyses until a p-value is significant) and HARKing (hypothesising after results are known) (Allen & Mehler, 2019). I have strived to ensure the work in this thesis meets these transparent practices through using freely available data and ensuring pre-registrations, data, transcripts, and quantitative code is available through the Open Science Framework. The only exception to this is the work in Chapter Five using focus groups, as by definition of qualitative and exploratory research, my Thematic Analysis is explicitly not replicable. The specific themes are generated by my individual interpretative engagement with the data. Transparency is important for honest reporting of work, but replication does not equate to trustworthiness in qualitative research (Pratt, Kaplan, & Whittington, 2020). The process of quantitative open science, and the practice of replicating studies to test their validity and implications, is vital for the advancement of knowledge, particularly in the field of understanding digital technology as an area which has frequently had to start from scratch (Orben, 2020a).

6.2 Reflections

The studies presented in this thesis cover a broad spectrum of methodologies, from quantitative primary and secondary data analysis to qualitative focus groups. Undertaking these studies, from conception and design through to analysis, has provided the opportunity to broaden my knowledge and obtain practical experience in methods and analyses I only knew in theory. This has been an often challenging but overall enjoyable learning curve. The use of mixed methods is a particular strength of this work, and has enabled an in depth examination of these relationships and corroborated findings for increased validity (Doyle *et al.*, 2009). Additionally, the inclusion of the focus groups study illustrates the quantitative approaches with greater insight, as well as providing the foundations for the ongoing exploration of the study of digital technology, executive functions, and sleep. A further strength of this thesis is the commitment to open access science as it features pre-registered studies, either on PROSPERO or the Open Science Framework, and the use of freely available data.

The secondary data analysis of the MCS presented the steepest learning curve as, by comparison to my previous research experiences, epidemiology was a new branch of science to conduct. The freely available data for this study through the MCS presented its own frustrating challenges and, in an ideal world, would have some crucial additions to the screen use and decision-making measures available. Although, on the whole, the screen uses are kept as separate entities, they are primarily leisure-based activities. This does not account for different screen-based pursuits during adolescence, such as educational assignments and homework. Ideal measures would include participants' affordance-based uses of screen-based devices (e.g., social, entertainment, information, or educational), perhaps specifying video game platform and genre, and TV content. Additionally, despite its proven importance in adolescent academic attainment (Best *et al.*, 2011), only one aspect of executive function, decision making, was measured. Future cohort studies should plan to include additional objective measures of these important mental processes in an engaging, perhaps gamified, manner.

The onset of the Covid-19 pandemic greatly impacted my original study designs for Chapters 3 and 4. Amid national lockdown measures and institutional closures, it was essential that I converted my participant-led face-to-face studies to be entirely online using crowdsourcing platform, *Prolific,* and Microsoft Team chat functions. Initial conception and design of these two studies was that the outcomes of the focus groups (Chapter Five) would lead to the participant-led co-creation of the empirical study (Chapter Four). The focus groups were largely the same in terms of discussion schedule questions as initially planned, but originally these would have been conducted in person. Face-to-face focus groups may have allowed for increased group cohesion between the participants, and perhaps a larger sample with increased ethnic diversity. In turn, this perhaps would have led to more in-depth discussions of the practicalities of smartphone use and naturalistic methods of measuring smartphone use behaviours and using wearable technology for sleep and other health-related outcome measurements. Through these findings and the participant-led co-creation, naturalistic, objective measures of smartphone behaviours through monitoring applications or operating systems would have been used in the experiment reported in Chapter Four. Whilst I did objectively measure four aspects of executive function (working memory, sustained attention, inhibition, and decision-making) using gamified tasks, participants' agreement for the use of wearable technology would have enabled objective measurement of sleep and other health-related outcome data (e.g., physical activity) if the pandemic had not occurred. These original plans would have resulted in studies of increased methodological rigor and accuracy that this field needs.

Finally, a limitation of this thesis is that each outcome was examined independently. Given that executive functioning and sleep quality are both intrinsically linked health behaviours (Aidman *et al.*, 2019; Wilckens *et al.*, 2014), more complex analysis models could have been used to further examine the relationships. For example, the empirical study in chapter four could have benefitted from conducting an analysis modelling the mediating impact of sleep quality on the association between smartphone use behaviours and EF. If this research is to be taken further, and the potential of wearable technology for objective measurement is to be utilised, then analysis models of increased complexity should be employed to model the interlinked nature of digital technology, EF, and sleep.

6.3 Future Directions

Going forward, participants' agreement for the use of wearable technology and data sharing of sleep habits and smartphone use monitoring applications or software should be capitalised upon. This would not only enable our understanding of how affordances offered by digital technologies, and smartphones in particular, are used, but also enable increased objectivity in the measurement of constructs. Given the controversy surrounding smartphone addictions existence (Chapter One), smartphone use measures should be based on different quantitative criteria than the Smartphone Addiction Scale (SAS) used in Chapter Four. Criteria could include use frequency, and specific applications or gratifications gleaned. Since the uses of smartphones are so varied, it logically follows the assumption that any effects they may have, be it positive, negative, or neutral, differ based on the affordances and applications being utilised. For example, spending an hour watching comedic videos is likely to have different effects than an hour spent researching for an assignment. Having some measure of what people are using their smartphones for will allow us to begin to unpick the specific effects different uses has on outcomes.

The increased scientific rigor found in more recent studies, as noted in Chapter Two, must be maintained and advanced if there is to be any aspiration to continue the movement towards high-quality psychological science. Both of these suggestions should be applied towards replicating and improving upon the online study I conducted in Chapter Four, which would enable objective measures of smartphone use behaviours and sleep-related data in addition to the behavioural measures of executive functioning, as I had originally hoped to do prior to the outbreak of the Covid-19 pandemic. Given the interconnected relationship between executive functioning and sleep, future research could examine whether sleep mediates the relationship between digital technologies and executive function, which may provide insight into how they are associated. This would expand our understanding of the impacts of digital technology use further, which can truly only be achieved through high quality, longitudinal experimental designs using robust objective measures.

From a broader context, the field needs to move away from ‘screen time’ as the most popular measure, particularly when it is retrospectively self-reported. Understanding technology use from an affordance-based perspective, why and for what purpose, is not only more interesting psychologically, but also conceptually more appropriate. To address this, behavioural measurement and observation should be objective, or corroborated objectively as a minimum. Furthermore, examining the purpose and reasoning behind technology use is appropriate to the use of mixed methods research as I did here, which enables individuals’ insights into their uses and gratifications from technology to be recorded as in depth, qualitative data as well as empirical. The combination of these techniques provides a unique and rich investigation into the uses and effects of digital technology. The resulting research will inform public debate and hopefully inform robust evidence-based practice and policy.

6.4 Conclusions

The area of digital technology and understanding the relationships it may have with aspects of cognition and health-related behaviours is still a relatively new research topic. One which has become heavily populated with research within a short span of time as research and public interest, and the need for understanding, has increased. However, as evidenced in Chapter Two, the influx of research to address the gap in the literature was of poor quality, often bias, and unlikely to demonstrate true effects of the nature of the relationships. The overall aim of this thesis was to examine the extent to which digital technology was associated with executive function and sleep quality in adolescent and young adult populations. Throughout, I have taken initial steps to improve the body of literature and evidence using secondary data analysis and epidemiology to conduct large-scale, longitudinal examination, a well-designed experiment, and detailed focus groups to gain users' attitudes and opinions. While the Covid-19 pandemic impacted my original plans, and lessened the extent to which I could conduct the studies in an objective and methodologically sound manner, I have instead laid crucial groundwork for the continuation of these studies. The experiment I conducted online should be replicated with improvements to the measurements of smartphone use behaviours (affordances and purpose) and sleep quality, with the benefit of the knowledge that young adults who own wearable technology may be likely to accept sharing their data to participate. Ultimately, this collection of work demonstrates inconclusive evidence that digital technology including smartphones and video games were unlikely to be meaningfully associated with the attention, working memory, inhibition, or decision-making aspects of executive functioning in UK adolescents or young adults. There was evidence of a small association between digital technology (smartphones and video games) and reduced sleep quality, suggesting that caution should be taken in proximity to bedtime. Going forward, longitudinal experiments using comprehensive, objective measures of all constructs are now needed to further our knowledge and enable stronger conclusions.

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