Digital use and adolescent mental well-being: A study on social inequalities, digital maturity, and interventions

A thesis submitted in fulfilment of the requirements for the degree of PhD,

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Declaration of authorship

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Declaration of co-authorship

This signed declaration describes the contribution of the candidate and the co-author(s) to each of the studies included in this thesis to identify the candidate's independent contribution to each work.

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Title of dissertation: Digital use and adolescent mental well-being: A study on social inequalities, digital maturity, and interventions

Study 1: Problematic social media use and adolescent mental well-being: The role of socioeconomic inequalities in cross-national perspective

Şeyma Çelik is the first author of this paper. This paper was co-authored by Prof. Pablo Gracia. Şeyma Çelik conducted the literature review, developed the theoretical framework, conducted analyses, and wrote the initial manuscript draft of this paper. Prof Pablo Gracia provided advice and feedback on the theoretical framework and analyses, and contributed to the writing and editing of further drafts of the manuscript.

Study 2: Digital user profiles and adolescent mental well-being: The role of digital maturity

Şeyma Çelik is the first author of this paper. This paper was co-authored by Prof. Pablo Gracia and Dr Giampiero Tarantino. Şeyma Çelik conducted the literature review, developed the theoretical framework, collected the data, conducted analyses, and wrote the initial draft of this paper. Prof Pablo Gracia provided advice and feedback on the theoretical framework and analyses, and contributed to the writing and editing further drafts of the paper. Dr Giampiero Tarantino assisted with data collection, provided feedback on the theoretical framework, and advised on subsequent drafts of the manuscript.

Study 3: The impact of school-based interventions targeting adolescent digital use and mental well-being: A systematic review and meta-analysis

Şeyma Çelik is the first author of this paper. This paper was co-authored by Dr Giampiero Tarantino, Prof. Pablo Gracia, and Paula Gonzàlez Vila. Şeyma Çelik conducted the literature review, developed the theoretical framework, conducted the main analyses, and wrote the initial draft of the paper. Dr Giampiero Tarantino advised on the theoretical framework, and supervised the development of the literature screening and data analysis strategy, interpretation of the results, and edited further drafts of the paper. Prof Pablo Gracia provided advice and feedback on the theoretical framework and on the writing and editing of further drafts of the manuscript. Paula Gonzàlez Vila assisted in literature screening ad quality assessments, data extraction, and editing of further drafts of the paper.

Study 4: Does digital detox reduce adolescents' problematic phone use and improve affective well-being? A controlled field experiment with experience sampling method

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Statement by the co-authors:

I hereby confirm that the doctoral candidate's described contribution to the work where I am listed as co-author is correct, and I consent to including the work in the named dissertation.

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Summary

The research examining the relationship between digital use and adolescent mental well-being boomed exponentially in the last decade. Despite important empirical progress, existing literature presents gaps in several directions. First, to date, there is a lack of micro–macro perspectives that jointly test how individual socioeconomic status and broader inequality contexts moderate the link between digital use and well-being. Previous studies tend to isolate either individual or family mechanisms from country-level patterns; few studies integrate them to identify where risks concentrate and why. Second, the mechanisms in this relationship are often explored with a single concept or a few concepts at a time. Yet, a holistic approach to underlying mechanisms that are rooted in theoretical reasoning remains underused to explain why some user profiles fare better than others. Third, intervention designs that can apply to wider audiences at once need further attention and evidence to pronounce their effectiveness. Finally, interventions that centre on individuals' agency tend to be investigated in (young) adults, with mixed findings on digital behaviours and adolescent mental health. Although schools are key developmental settings, rigorous evaluations targeting adolescents' digital practices and well-being remain limited and fragmented. This thesis tackles each of these gaps in the literature and examines the relationship between digital use and adolescent mental well-being with four complementary studies that span cross-national, person-centred, and intervention approaches.

Study 1 uses data from the Health Behaviour in School-aged Children study to explore the interplay between Problematic Social Media Use (PSMU) and socioeconomic inequalities in relation to positive and negative mental well-being outcomes. Results show that PSMU is linked to higher psychological complaints and lower life satisfaction,

with stronger relationships among adolescents from lower Socioeconomic Status (SES). These inequalities are consistent across countries, but are strongest in countries with medium-inequality levels. This study demonstrates persistent socioeconomic inequalities in the relationship between problematic digital use and mental well-being, with the partial role of larger socioeconomic contexts in this association.

Study 2 investigates the distinct types of digital user profiles and whether adolescents with each type would differ in their mental well-being. Furthermore, this study explores the role of digital maturity, self-determined and competent technology use, as an explanatory mechanism. Adopting a Generalised Latent Class Analysis approach on primary data collected from Irish adolescents, the results indicate three digital user profiles: Light, Reserved, and Outgoing. Both Reserved and Outgoing users reported poorer mental well-being than Light users, but lower digital maturity fully explains the disadvantage of Outgoing users. Overall, this study emphasises the nuanced variations in how adolescents engage with digital devices, and how their outcomes (digital maturity and mental well-being) might differ accordingly. underscoring the importance of self-determined and competent technology use.

Study 3 aims to examine whether school-based interventions could be an effective strategy to address the excessive and problematic digital use and negative mental well-being outcomes. This study conducts a pre-registered systematic review and meta-analysis, showing that school-based interventions can reduce screen time, depressive symptoms, anxiety, as well as life satisfaction and psychological difficulties. However, evidence for effects on problematic digital use is more limited. This study affirms the critical role of school settings that can be utilised to improve adolescents' digital use habits as well as alleviate their mental health problems.

Study 4 tests the effectiveness of a digital detox intervention using a controlled field experiment design with an experience sampling method to capture the momentary associations. Specifically, this study examines whether doing a week of digital detox (i.e., setting a daily time off from phones) could reduce adolescents' (problematic) phone use and improve their affective well-being in the short term, and whether individuals' adherence to the protocol and subjective experience of the digital detox intervention could moderate the effectiveness of the intervention. The results indicate no overall change after the intervention week, with the exception that adolescents in the intervention group improved in coping with their problematic use symptoms; perhaps being informed about potential harms of excessive phone use helped the intervention group to recontextualise their problematic phone use tendencies. Additionally, adolescents who did shorter digital detox sessions reduced their phone use after the digital detox, suggesting that shorter, more feasible detox sessions could be more successful in changing phone use habits.

Together, this thesis indicates that (i) SES inequalities shape the well-being risks of PSMU, (ii) digital maturity is a key mediator of the association between digital user profiles and mental well-being, and (iii) school interventions hold potential –under certain conditions– in mitigating problematic digital use and supporting adolescent well-being.

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Love you all!

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Chapter 1: Introduction

1.1 Motivation and Objectives

Over the last decades, adolescent' time spent on digital technologies has increased dramatically (Ofcom, 2024). Scholars have indicated that digital technologies can strongly shape adolescent daily socialization, learning, and emotions in multiple different directions. For instance, social media can both bolster relatedness, self-expression, and information access (Valkenburg & Peter, 2009; Boyd & Hargittai, 2013; Livingstone et al., 2018; Odgers & Jensen, 2020), and expose young people to risks including cyberbullying, harmful comparisons, and compulsive patterns of use (Van Rooij et al., 2010; Livingstone et al., 2018). Scholars increasingly focused on the negative aspects and potential harms of digital use in adolescent mental well-being. While the strength and sometimes direction of "screen time" associations have been found to be small or mixed, researchers identified that the context, use patterns, and subjective experiences can be more crucial determinants of adolescent well-being outcomes (Przybylski & Weinstein, 2017; Odgers & Jensen, 2020; Valkenburg et al., 2022; Beyens et al., 2020).

One important strand of literature has focused on subjective experiences has shown that problematic digital use –a measure of addictive and risk-taking use– is linked to psychological distress, somatic complaints, eating disorders, and negative mood (Van Den Eijnden et al., 2018; Wong et al., 2020; Shannon et al., 2022; Elhai et al., 2017; Sohn et al., 2019). Additionally, research on the 'second' and 'third' digital divides has suggested that beyond access, disparities in skills, uses, and outcomes advantage adolescents from higher Socioeconomic Status (SES) (van Deursen & van Dijk, 2019; Van Dijk, 2006; Büchi & Hargittai, 2022). In fact, recent studies indicate that higher-SES adolescents often receive more academic and socio-emotional benefits from digital media than the low-SES (Bohnert & Gracia, 2021; Bohnert & Gracia, 2023; Loh et al., 2025). This literature motivates an integrated account of how social inequalities, which have been largely studied in sociological research on intergenerational inequalities (Bernardi & Gil-Hernández, 2021; Breen & Muller, 2020; Bukodi & Goldthorpe, 2024; Torche, 2014), intersect with distinct digital practices in shaping adolescent well-being.

Additionally, scholarship adopting person-centric approaches has focused on distinct profiles of young people who engage with digital devices and mediums in diverse ways. Researchers have argued that the risks and benefits associated with different activities, such as gaming, browsing, and posting contents online, may lead to different mental well-being outcomes. On the one hand, active engagement with others through digital platforms (e.g., meeting new people online) could effectively support social well-being. On the other hand, exposure to online contents with little active participation may lead to excessive social comparisons and reduced mental well-being (Angelini et al., 2024; Verduyn et al., 2022; Yang et al., 2021). Critically, research suggests that adolescents rarely adopt a singular digital use style (Trifiro & Gerson, 2019). This motivates a close examination of the mechanisms under which different adolescent digital user profiles relate to various well-being outcomes.

Finally, research on school-level interventions has aimed to address the potential negative consequences of digital use, such as excessive and problematic use, as well as their harms on mental well-being. Studies imply that school-based interventions can be effective tools to foster students' behaviours related to positive health outcomes, such as reducing sedentary habits and promoting active lifestyles (Demetriou & Höner 2012; Kriemler et al., 2011; Owen et al., 2017), motivating healthy eating habits (Medeiros et al., 2022; Van Cauwenberghe et al., 2010) and benefiting health outcomes (Cilar et al., 2020; Paulus et al., 2016). Yet, the literature has provided limited evidence on the effectiveness of school-based interventions targeting adolescents in term of (i) producing balanced and healthy digital use habits and (ii) improving mental well-being outcomes. In relation to this literature on digital interventions, research on digital detox programmes –a quite novel approach to improve individuals' self-efficacy and well-being within digital contexts (Radtke et al., 2022)– has largely concentrated on adults and moreover has yielded inconclusive findings.

In short, this thesis has identified three major gaps that can be summarised as follows. First, research has yet to adopt a through micro–macro perspective that examines how family SES and broader inequality contexts shape the relationship between PSMU and well-being. This means that previous studies have been largely restricted to single countries, thus missing the importance of the macro-level contexts. Second, concepts related to digital autonomy, particularly those rooted in Self-Determination Theory on needs for youth autonomy, competence, and relatedness (Ryan & Deci, 2000), remain poorly understood when examining its application to understand the relationship between adolescent digital user profiles and mental well-being outcomes. Third, school-based intervention evidence in relation to digital use and mental well-being is limited, fragmented, and disproportionately centred on adults. Although schools constitute crucial developmental contexts, few school-based interventions have been systematically tested for their effectiveness in fostering healthier digital practices and well-being, and specifically in the context of digital detox practices.

The present thesis seeks to address the abovementioned gaps by integrating cross-national, mechanism-focused, and intervention-oriented approaches. Combining individual and contextual inequalities in a unified micro–macro framework, focusing on mechanisms linked to digital autonomy, and addressing the role of school-based interventions to motivate adolescents' healthier digital habits and mental well-being, this thesis provides an innovative contribution to existing knowledge on how adolescent digital media use shapes mental well-being outcomes.

This doctoral thesis pursues three main objectives: (1) to examine how socioeconomic inequalities at the family and country levels moderate the association between problematic social media use and adolescent mental well-being; (2) to identify distinct digital user profiles and analyse their associations with mental well-being, while assessing whether digital autonomy and self-efficacy mediates the relationship between adolescent user profiles and well-being outcomes; and (3) to evaluate the effectiveness of school-based digital interventions, including digital detox, in reducing problematic digital use and improving adolescents' mental well-being.

1.2 Digital Use and Mental Well-Being in Adolescence

Digital technologies are essential to adolescents' contemporary lives, and bring to young people both opportunities (e.g., networks and educational tools) and risks (e.g., cyberbullying and online addiction) (Holmarsdottir et al., 2024; Livingstone & Helsper, 2010; Ólafsson et al., 2013; Van Rooij et al., 2010; Schoon et al., 2024). Previous studies have examined the association between digital use and adolescent mental well-being, and generally found that excessive digital use tend to impair mental well-being (Bohnert & Gracia, 2021; Keles et al., 2020; Walsh et al., 2020). Notably, the context and conditions of how adolescents engage with digital devices matter strongly (Beyens et al., 2020). Although individual factors such as digital literacy, autonomy, and social skills are central in shaping adolescents' online experiences (De Coninck et al., 2023; Horwood & Anglim, 2019; Lamash et al., 2024), the mechanisms linking digital use to adolescent mental well-being outcomes are still not clearly understood. This dissertation aims at contributing to this ambitious research agenda.

1.2.1 Turbulences of Mental Well-being During Adolescence

Adolescence is a unique developmental period involving many biological as well as social changes (Blakemore & Mills, 2014). It is a particularly critical life-course stage where identity formation escalates and social dynamics and comparisons become critical for self-evaluation Harter, 2012; Sebastian et al., 2008; & Van der Aar et al., 2018). Moreover, how young people interacts with their social environments can be a strong predictor of their mental well-being. For instance, online social comparisons with peers that are in a higher position in the social hierarchy could lead to more negative self-evaluation and poorer mental well-being, (McComb et al., 2023), particularly in the most hierarchical and unequal societies (Cheung & Lucas, 2016; Nesi & Prinstein, 2015; Wilkinson & Pickett, 2009). Due to the increased risk factors related to the inherent nature of adolescence, it is often acknowledged that adolescence is a turbulent age period for mental well-being outcomes (Blakemore & Mills, 2014). With this in mind, researchers called attention for the potential role of digital devices in harming adolescents' mental well-being outcomes (Busch & McCarthy, 2021; Kurniasanti et al., 2019; Pellegrino et al., 2022), implying that adolescence is key to identify the elements of digital use behaviours that pose risks for individuals' mental well-being.

This dissertation focuses specifically on adolescent mental well-being outcomes. Previous studies have adopted an objective conception of well-being that specifies positive well-being as healthy, congruent and vital functioning, rather than mere subjective experiences and perceptions of happiness (Castellacci and Tveito 2018). In this thesis, mental well-being is broadly defined as having positive feelings and psychological functioning, as well as not suffering from any negative mental health problems (Ryan & Deci, 2001). This indicates some related dimensions of well-being that should be treated as complementary, but also as separate constructs.

1.2.2 Digital Use as an Encompassing Term

The term digital use is utilised in different contexts throughout the thesis. However, it is important to note that digital use is a flexible term that has different implications depending on how it is defined. Adolescent digital use has been defined and measured differently across studies. More broadly, digital use refers to using any mobile devices (phones, tablets, computers, etc.) in any context or activity (social media, gaming, online shopping, etc.) and with any subjective experiences while (not) using mobile devices (problematic use) (Scott et al., 2024; Verduyn et al., 2022). The diverse purposes for which adolescents use digital devices are likely to lead to different mental well-being outcomes. For example, fostering social support online was found to be associated with lower social anxiety (Best et al., 2014), but various forms of online gaming were found to be linked to aggression and depressive mood (Holtz & Appel, 2011). Therefore, this thesis aims to use the most appropriate definitions of digital use that are more suitable to answer the key research question of each study.

1.2.2.1 The Limitations in the Screen Time Literature

Screen time is one of the most common measures used by researchers. It could refer to the duration (e.g., the total screen time in hours per day) or the frequency of use (e.g., how often a mobile device is used in a week). Additionally, screen time can relate to either device- or context-specific use (e.g., social media use, computer use), or total combined use (Browne et al., 2021; Vandewater & Lee, 2009). An advantage of screen time is that time could be an easily comparable unit, which makes it particularly useful in cross-national studies. Moreover, it could also be seen as a proxy of risk use, as more screen time is associated with lower self-control (Twenge & Campbell, 2018), lack of parental mediation (Chen & Jingyuan, 2019), or being exposed to harmful contents online (Livingstone et al., 2017).

On average, the association between screen time and mental well-being has been found to be relatively small (Odgers & Jensen, 2020; Przybylski & Weinstein, 2017; Valkenburg et al., 2022). But relying solely on screen time can be limited to see the full picture. For instance, time alone could not illustrate the diverse types of digital use such as gaming, social media, communication, including adolescents' subjective experiences while using digital devices or more complex digital use styles, such as multitasking (i.e., using multiple devices at the same time or while focusing on other tasks). In addition, the high prevalence of digital devices today means usage is more fragmented throughout the day as opposed to a dedicated digital use duration, which can make it challenging for individuals to accurately estimate their screen time (Verbeij et al., 2021). Contemporary researchers aim to tackle this issue by using screen tracking methodologies, but this approach remains a niche solution rather than a widely applied methodology.

1.2.2.2 (Problematic) Social Media Use

A great portion of digital use literature pays specific attention to social media. Adolescents use social media is highly prevalent among adolescents today, involving a wide range of digital interactions (e.g., socialising, gaming, sharing content, learning activities) across increasingly diverse and complex online platforms (e.g., TikTok, Instagram, YouTube, WhatsApp) (Scott et al., 2024; Verduyn et al., 2022). It is important to consider that each platform algorithms that are designed to increase engagements, and may lead to addiction-like feelings and behaviours. Because addiction can be seen as a pathological disorder and be too intense to define the social media users' negative experiences (Carbonell & Panova, 2017), some scholars coined the term *Problematic Social Media Use* (PSMU) to describe addictive and risk-taking social media behaviours such as wanting to use social media more, failing to limit social media use, or escaping from negative feelings through social media use (Van Den Eijnden et al., 2016).

One advantage of PSMU concept is that it aims to capture more universal experiences involving social media use, rather than specific contexts of a social media platform. For instance, the popularity of social media platforms as well as the features they provide change frequently and from country to country, making it challenging to assess the long-term implications on adolescents' problematic use tendencies. However, the feelings of escapism, withdrawal, or being preoccupied with social media in general could be more widely applicable to a broad range of adolescents (Van Den Eijnden et al., 2016). Moreover, access to social media tends to be relatively easier than access to various mobile devices for disadvantaged youth, as many social media platforms such as Instagram and TikTok are free to open an account, and they can be used from any digital device with Internet access. In this thesis, PSMU is used to examine the socioeconomic inequalities and cross-country variations in the relationship between adolescents' digital use and their mental well-being.

1.2.2.3 The Types of Users

Previously, some researchers have attempted to disentangle the various forms of digital use such as the types of activities (e.g., gaming, chatting, scrolling) or the specific contexts of online media use (e.g., social media platforms, educational contents) (Browne et al., 2021; Winstone et al., 2022). Scholars have argued that the adolescents' types of digital use may lead to either positive or negative outcomes. For instance, 'active' digital use behaviours (e.g., posting content or chatting others) may support social connectedness and improve mental well-being, while 'passive' digital use (e.g., browsing) may lead to social comparisons and reduced mental well-being (Angelini et al., 2024; Verduyn et al., 2022; Yang et al., 2021). Although this dual framework could enlighten some of the user patterns and their outcomes, it may not capture how individuals can engage in various forms of digital use concurrently rather than in isolation

(Trifiro & Gerson, 2019). For instance, adolescents may want to seek new connections which may exacerbate adolescents' social well-being problems, but also try to maintain close friendships online which may help their mental well-being (Verduyn et al., 2022; Yang et al., 2021). To capture more complex user types, one study on early adolescents identified four user profiles (broadcasters, high communicators, moderate communicators, minimal) (Winstone et al., 2022), and another study found three distinct profiles (passive public, passive private, and active private) (Beyens et al., 2024). However, to date, there has been no global classification that can demonstrate the diverse patterns of young people' digital use types.

1.2.2.4 Smartphone Use

Smartphones are a common option for adolescents of getting a digital device, and serve utilitarian purposes such as communication, listening to music or navigation, with constant accessibility to the digitalised world. Also, mobile phones tend to be more private than communal. For instance, a laptop or a gaming device could be shared within family. By contrast, each member of a family would get their personalised phone to carry with them. Taken together, investigating adolescents' relationship with their phones crucial to understand whether engaging with phones on a regular basis could impact their mental well-being.

To explore the potential harms on adolescents' mental well-being, researchers increasingly focused on the addictive natures of smartphones (Busch & McCarthy, 2021). For example, who excessively use their smartphones may show signs of feelings of dependency on smartphones for mood regulation, compulsion to use smartphones by losing sense of control when using smartphones, or by exceeding the intended usage duration, and being mentally preoccupied with the phone when being out of range (Foerstel et al., 2015; Panova & Carbonell, 2018). These negative experiences can be disruptive for adolescents' daily lives and can be detrimental to their mental well-being (Burnell et al., 2024; Elhai et al., 2017; Mei et al., 2018; Sohn et al., 2019). Although some scholars are apprehensive about defining smartphone addiction as a stand-alone mental health disorder (Busch & McCarthy, 2021; Elhai et al., 2017; Panova & Carbonell, 2018), there is growing concerns on problematic use patterns that can undermine mental well-being outcomes and adolescents' daily functioning.

1.3 Socioeconomic Inequalities Approach

Although the world trends illustrate a rapid digitalization process, there are differences in how the process of digitalization occur within and between countries. The digital divides framework argues that the socioeconomic inequalities shape these differences manifest in young people from different socioeconomic backgrounds (Helsper, 2021; Ragnedda, 2018; Vartanova & Gladkova, 2019). When referring to digital divides, scholars have stressed the importance of studying not only SES gaps in accessing different types of digital tools (1st digital divide), but also regarding how adolescents from different SES backgrounds engage with digital devices and what skills they get from them (2nd digital divide) and the outcomes they obtain from their digital engagement (3rd digital divide). The issues in the first level digital divides are still persistent and requires attention (van Deursen & van Dijk 2019). However, in highly developed countries such as member states of the EU and countries in North America, trends in digital divides indicate a shift towards second level digital divides (inequalities in skills and experiences) (Poushter, 2016; Ragnedda & Muschert, 2013; Vartanova & Gladkova, 2019). Even in the highly developed and wealthier countries, the socioeconomic inequalities exist at school and individual level in the digital skills, digital literacy, and non-academic screen time (Livingstone et al., 2011; van Deursen & van Dijk 2019; Robinson et al., 2015).

Diffusion theory argues that these divides stem from the pacing of the distribution of the most advance technological and digital resources within a country, e.g., access to most advance devices, high speed Internet, the education programmes or technical support for learning appropriate digital literacy skills in which high-SES groups take advantage of these resources earlier and easier compared to low-SES groups (Rogers et al., 2014). The diffusion theory suggests an overall slower digital adoption and lower internet use rates in more unequal countries, which could lead to more salient disparities in adolescents' access and use of digital resources, as well as in digital skills (Fuchs, 2009; Zhang, 2013). This may amplify potential unequal harms of adolescents' digital use for their mental well-being. For instance, research suggest that lower SES adolescents tend to spend more time using digital devices for non-academic purposes compared to higher SES adolescents who are more likely to use digital resources to advance their academic outcomes (Bohnert & Gracia, 2021; Ma, 2021). Moreover, lower SES adolescents tend to have more negative online experiences more compared to their high-SES peers (Livingstone et al., 2018), and are more likely to have psychological problems associated with their digital use (Allen & Wella, 2015).

Previous cross-national literature also shows that adolescents' digital use is associated with mental well-being, although there are variations in the strength of the association depending on the well-being outcome examined (Kardefelt-Winther et al., 2020; Boear at al., 2020; Orben & Przybylski, 2019). For instance, a recent study on cyberbullying behaviour among adolescents showed that the association between risky social media use is associated with both perpetuation and victimisation of cyberbullying behaviour tendencies, but results are not consistent across countries for different victimisation outcomes (Craig et al., 2020). Another study found that risky social media use is a consistent risk factor for mental and social well-being across countries, but excessive social media use is only a risk factor when the average social media use within the country is low (Boer et al., 2020). Yet, neither of these comprehensive cross-national studies examined socioeconomic differences in the strength of the association between digital engagement and mental well-being.

The media and communication literature has indicated that adolescents' digital contexts differ quite sharply across countries (Smahel et al., 2020; Livingstone et al., 2011). For instance, while the percentage of adolescents who have daily access to the internet is similar in Italy, Spain, and Malta (approximately 80%), the average hours spent online changes from around seven to eight to just below ten respectively (Smahel et al., 2020). Country-level socioeconomic factors are also found to be related to digital divides across adolescents from different countries. One study found that adolescents from lower-SES in countries with higher income inequality engage with social media in a more harmful ways, compared to higher-SES adolescents, regardless of the national wealth (Lenzi et.al., 2021). However, the role of country-level socioeconomic indicators on the third level digital divide (outcomes) has not been investigated in detail. Although there is consistent evidence that country-level socioeconomic factors (partly) explain the variation in mental health inequalities in adolescents across countries (e.g., Hammami et al., 2022; Levin et al., 2011; Elgar et al., 2015), there is a lack of literature on whether similar effects are also prominent in the third level digital divides across countries. Chapter 2 (Study 1) examines digital divides in adolescents' mental well-being across SES groups, specifically how much of its variation is due to family-level socioeconomic factors, and how much of it can be explained by country-level indicators.

1.4 Digital Maturity as a Novel Mechanism

The fragmented literature on adolescents' digital use limits a wholistic understanding of how young people engage with mobile devises and online mediums. In this context, the

DIGYMATEX research project aimed to address this issue and coined a new term named digital maturity (Laaber et al., 2022). The conceptualisation of digital maturity was built upon *Self-Determination Theory* (SDT) (Ryan & Deci, 2020). According to SDT, satisfaction of psychological needs for autonomy, competence, and relatedness are essential for mental well-being and psychological growth. Digital use can be both beneficial or harmful in this process, depending on how satisfy or thwart their needs through digital engagement (Parent, 2023; Peters et al., 2018; West et al., 2024). For instance, adolescent online social interactions have been understood to support social capital (Domahidi, 2018; Shankleman et al., 2021; West et al., 2024). Similarly, digital autonomy and competence can support mental well-being (Vissenberg et al., 2022; Reinecke et al., 2014).

Digital maturity research aims to adapt these fundamental concepts to capture the unique conditions of the digital spaces. Autonomy is defined by the adolescents' agency in choosing the types of mobile devices and online activities. Competence is defined in the context of digital literacy, risk awareness, and problem-solving skills. Finally, relatedness is defined by the impulse and emotion regulations in digital contexts, respect towards others, and digital citizenship. However, to date, it is unclear whether higher digital maturity could explain the association between digital use and adolescents' mental well-being outcomes.

Theoretically, digital maturity can improve adolescents' mental well-being by fostering their psychological need satisfaction through helping them to perceive digital devices as tools to achieve personal goals (Laaber et al., 2024; Van de Casteele et al., 2024). This implies that differences in adolescent digital maturity could explain why certain online users show poorer mental well-being than others. A recent study found an inverse relationship between screen time and digital maturity, such that adolescents with high screen time tend to be more prone to use their digital devices in ways that impair their digital maturity (Siddiqui & Valogianni, 2022). However, research has not yet provided an examination of whether digital maturity mediates the association between distinct digital user profiles and adolescent well-being. Chapter 3 (Study 2) addresses this gap by examining the role of digital maturity in mediating the relationship between adolescents' digital user profile and mental well-being.

1.5 Intervention Research

Parents, scholars, and policymakers alike consider addictive or compulsive media use as one of the most extreme outcomes of adolescent risky behaviours (e.g, Davis, 2001; van Rooj et al., 2010; Kurniasanti et al., 2019). Scholars increasingly highlight the addictive natures of smartphones, internet, and social media (Busch & McCarthy, 2021; Kurniasanti et al., 2019; Pellegrino et al., 2022). However, some scholars caution against using the term addiction and define these negative experiences as problematic media use (Busch & McCarthy, 2021; Elhai et al., 2017; Panova & Carbonell, 2018). Nevertheless, the growing concerns on adolescents' digital well-being indicates a need for digital intervention strategies for those who are more at-risk. The second half of this thesis aims to explore potential intervention strategies to address adolescents' (problematic) digital use and their potential impact on negative mental well-being outcomes. First, the existing evidence specifically in the context of school-based interventions is investigated. Second, a digital detox field study is conducted.

1.5.1 School-based Interventions

A wide range of policies and guidelines to protect young people from the harmful effects of risky digital use have been developed across countries and health organisations. Such policies and guidelines include recommendations for limiting screen time for children and teens and promoting offline activities, as well family protection software programs that prevents children to access risky contents online (O'Neill, 2013; Oh et al., 2022; Mac Cárthaigh, 2020). The common strategy of these programmes is to involve parents or schools, as the main agents to facilitate or conduct the intervention process. Although family-based interventions seem to be preferable among younger children (Marsh et al., 2014), school-based intervention designs could be a more ideal strategy for adolescent populations (Dekkers & Luman, 2023). First, existing facilities and the staff already trained in youth development could reduce the cost of the intervention programmes, and help to reach a wider audience in a more efficient way. Second, schools can offer more consistent schedule and standardised routine to administer the designed interventions which could be more challenging in individual and family-based designs. It is also possible to integrate planned interventions into the education structure and have a more holistic approach within schools, which could improve the effectiveness of the intervention design (Busch et al., 2013). Because health and lifestyle behaviours are more susceptible to peer influence during adolescence compared to other development periods (Giletta et al., 2021; Mollborn & Lawrence, 2018), delivering interventions in school contexts can add a relatedness element to boost peer support, and ultimately contribute to changing social norms and creating a more positive context for adolescents' digital use and mental well-being.

Several systematic reviews and meta-analyses suggest that school-based interventions are effective in changing students behaviours in relation to several health indicators including substance use (Hennessy & Tanner-Smith, 2015; Paulus et al., 2016), risk of obesity (Jacob et al., 2021), sedentary behaviours and physical activity (Demetriou & Höner 2012; Kriemler et al., 2011; Owen et al., 2017), healthy eating habits (Medeiros et al., 2022; Van Cauwenberghe et al., 2010), sleep quality (Chung et al., 2017), and mental health problems (Cilar et al., 2020; Paulus et al., 2016). However, whether school-based interventions are effective in changing adolescents' digital use is yet to be explored. This thesis contributes to examine school-based intervention programmes to assess their effectiveness in targeting adolescents' digital use and mental well-being.

Across studies on digital use interventions, the evidence on the importance of context is inconsistent. Although one systematic review on interventions on digital use outcomes in Korea concluded that application-based interventions are more favourable to therapy-based interventions (Mac Cárthaigh, 2020), another systematic review found that interventions that are mainly delivered through nondigital education programs were more successful in reducing screen time than digital interventions (Oh et al., 2022). Studies focussing on the addictive nature of digital use highlighted that group-based treatments have promise, however, more research to prove their effectiveness is needed (Yeun & Han, 2016; Ayub et al., 2023). Several studies testing the effectiveness of school interventions to reduce screen time had a focus on physical health rather than mental health outcomes. Thus, studies investigating school-based physical activity interventions typically operationalised "screen time" as a proxy of sedentary-behaviour, often using sedentary time and screen time constructs interchangeably (e.g. Guo et al., 2025; McMihan et al., 2017; Rodrigo-Sanjoaquín et al., 2025). Moreover, the existing studies omit mental health outcomes from their reviews. To date, only one study reviewed the school-based interventions in the context of screen-based sedentary behaviours and mental health outcomes (Lai et al., 2025), although their methodology lacked a comprehensive literature screening for mental well-being indicators, which resulted in limited studies to be analysed for conclusive evidence.

Overall, previous studies provide limited evidence on the extent of effectiveness of school-based interventions on digital use specifically. This motivates our focus on reviewing and quantifying, using a multidimensional approach, the separate effects of school-based interventions on both specific digital use outcomes (e.g., screen time, problematic social media use), as well as specific types of mental well-being outcomes (e.g., anxiety, depressive symptoms, life satisfaction, psychological difficulties). In Chapter 4 (Study 3), the existing evidence on how school-level interventions can foster healthy forms of adolescent digital use and mental well-being is examined by means of a systematic review and meta-analysis.

1.5.2 Digital Detox

The notion of practicing "digital detox" as a solution to excessive digital use has become highly popular both in pop culture as well as in research field (Nassen et al., 2023; Radtke et al., 2022; Schmuck, 2020; Syvertsen & Enli, 2019; Ugur & Koc; 2015). The perspectives on what digital detox should entail varies; the general definition is refraining from using electronic devices (e.g., smartphones) in pre-defined ways (e.g., cutting smartphone use during school hours and sleep hours, reducing total phone use, reduce social media consumption) and for a time period (one day, several hours, weeks) (Radke et al., 2021). Typically, the main purposes of digital detox are to reduce screen time or social media use, replacing time spent online with offline activities that may be ignored due to intense digital use, and improve mental well-being (Nassen et al., 2023; Radtke et al., 2021).

Digital detox could be a great strategy to apply a SDT framework-based intervention targeting adolescents' digital use habits. According to SDT, a successful mechanism for behavioural change should target individuals' intrinsic motivations through supporting their autonomy, competence, and relatedness needs (Ryan & Deci, 2017). Moreover, theories on identity development also emphasise that intervention strategies on adolescents' digital use should be based on adolescents' self-control and autonomy, and foster adolescents' sense of agency on their behaviours (Granic et al., 2020; Maniccia, 2011). Digital detox can offer this mechanism by helping young people to autonomously set their own offline time duration and type that is also suitable to their competence levels (Brockmeier et al., 2025). Additionally, it could be a friendly challenge if there is a collective medium to practice digital detox (Ko et al., 2016). Using the specific apps allowing for all these customisations could also help adolescents to monitor their progress and help them to stay consistent until they comfortable with the new habit (Villalobos-Zúñiga & Cherubini, 2020).

Although research in this area has boomed in recent years, the main focus of the digital detox research was on adults, or young adult population, with a notable lack of evidence on adolescent age groups. Studies on older participants found that generally, short and intense forms of abstinence could have unwanted effects of increased craving, loneliness, or fear of missing out (Radke et al., 2022; Przybylski et al., 2021; Vally & D'Souza, 2019; Wilcockson et al., 2019). Other adult studies with a wide range of approaches found mixed results, from positive (e.g., Alanzi et al., 2024), to negative (e.g., Lambert et al., 2022), and sometimes no significant results (Lemahieu et al., 2025). The inconsistent evidence, combined with the lack of attention to adolescence as key life-course stage in shaping individuals' digital habits and well-being trajectories, warrants a further investigation on whether digital detox could be an effective strategy to help adolescents to reduce their digital use and cope with the negative well-being consequences of their digital use. Chapter 5 (Study 4) aims to fill this gap in the literature by conducting a field experiment in the context of secondary schools in Ireland.

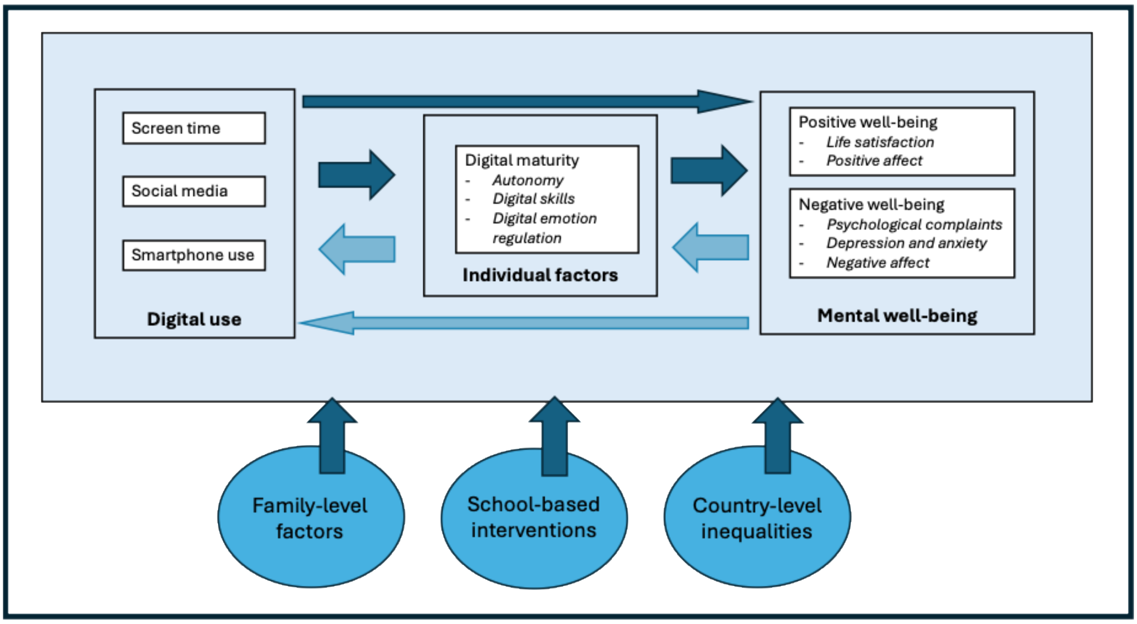
1.6 Conceptual Framework of the Thesis

This thesis develops a conceptual framework linking adolescents' digital use to mental well-being through individual competencies and broader social contexts. As illustrated in

Figure 1.1, digital use is explored through three central behavioural dimensions: screen time, social media use, and smartphone use. These forms of digital use capture different but interrelated ways through personal differences in which adolescents interact with digital environments in their daily lives. Rather than assuming a direct and uniform relationship between digital engagement and well-being, the framework emphasises the importance of intermediary mechanisms (i.e., digital maturity) that shape how digital experiences translate into psychological outcomes. These processes are also situated within broader contexts that shape adolescents' digital experiences. At the micro level, family-level resources such as socioeconomic status and parental support may influence both digital practices and the mental well-being outcomes. At the institutional level, school-based interventions can play an important role in promoting healthier digital behaviours through structured programmes or habit re-forming strategies. Finally, at the macro level, country-level inequalities shape the broader disparities in digital skills, opportunities, and outcomes. By integrating these individual, institutional, and societal dimensions, the framework adopts a micro–macro perspective that highlights how structural inequalities intersect with adolescents' digital practices to shape mental well-being.

It is important to note that the relationships between adolescents' digital use, digital maturity, and mental well-being may be bidirectional, which is acknowledged in Figure 1.1**.** While this thesis primarily conceptualises digital use and digital maturity as factors shaping adolescent mental well-being, albeit limited research suggests that the reverse relationship may also occur (e.g., Flannery et al., 2023; Laaber et al., 2024; Orben et al., 2022). Although these reciprocal dynamics are not plausible, examining them falls beyond the scope of the present thesis. The empirical analyses therefore focus on the pathways through which digital practices and digital maturity relate to adolescent well-being outcomes, while acknowledging that these relationships may operate in multiple directions over time. Taken together, this conceptual model emphasises that the relationship between digital use and adolescent well-being is not uniformed but is mediated by individual competencies and embedded within broader social contexts. By integrating perspectives on digital practices, digital maturity, social inequalities, and intervention approaches, the framework provides a comprehensive basis for examining how adolescents' digital lives relate to their mental well-being.

Figure 1.1 Theoretical framework of the thesis



1.7 Data and Methodology

This thesis utilized a variety of methodologies and datasets. Each method has unique advantages suitable to the corresponding main research questions of the four studies within the thesis. This section is structured as follows. First, the datasets used in each of the four studies of the thesis are presented. Second, the empirical strategy of each empirical chapter is presented. Finally, ethical considerations and data management issues for the whole thesis are addressed.

1.7.1 Secondary Cross-national Data

Study 1 used a cross-national secondary data from Health Behaviour in School-aged Children (HBSC; Inchley et al., 2020) 2017/2018 survey. The HBSC collects nationally representative cross-sectional self-report data from early adolescents aged 11-to-15 across over 40 countries, although the final sample consisted of 35 countries, due to missing information on macro-level variables for some of the countries. The latest publicly available dataset included measures such as adolescents' screen time, PSMU, psychological complaints, and life satisfaction. HBSC measures individual level SES with family affluence scale (FAS; Torsheim et al., 2016) which allows for a comparable assessment of socioeconomic markers within and between countries. In addition, study 1 drew data from the Works Bank database for macro level variables: income inequalities (Gini index; World Bank, 2022a), countries' national wealth (gross-domestic product per capita; GDP; World Bank, 2023a), educational expenditure (World Bank, 2022b), and internet use prevalence (World Bank, 2023b). Data for the year of 2018, or the latest available year was used for each of these measures.

1.7.2 Primary Observational Data

Study 2 used a primary dataset collected from adolescents at secondary schools through online surveys during April-June 2023. The sampling strategy combined convenience and purposive sampling. First, all secondary schools in counties Dublin, Meath, Kildare, and Wicklow were invited to participate in this project. Due to the limitations with transport, schools located in farther counties could not be invited. Five schools representing different socioeconomic and geographical areas agreed to participate (four in Dublin County, one in Wicklow). Based on Pobal HP Deprivation Index (Haase, 2016), two of the participating schools were located in socioeconomically disadvantaged areas, two were from an average socioeconomic level area, and one from and affluent area. The research team conducted the survey to students in those schools during a scheduled visit. To maximise our sample size, the online survey was sent to every other secondary school across Ireland with the request to share the link with their students' parents. In total, 413 participants aged between 12 to 18 agreed to be in the study and at least on parent or guardian gave written consent prior to answering the survey. Although online surveys had parents to fill out demographic information in detail, some of the parents in the participating five schools only returned the consent form, and opt out to not fill out parental survey.

This primary data collection was integrated within the DIGYMATEX project funded by the European Commission H2020 within the call 'DT-TRANSFORMATIONS-07-2019 - The impact of technological transformations on children and youth.' The main goal of the DIGYMATEX project was to create and test a new scale named Digital Maturity Inventory (DIMI; Laaber et al., 2023). The DIMI consists of 32 items that measure digital maturity across 10 dimensions that broadly captures aspects of digital autonomy, risk awareness, and respect towards others in online contexts. Adolescents' digital maturity was measured using DIMI at this study as well. In addition, other digital use indicators (mobile device use intensity, purposes of mobile media use, and types of SNS use) were measured. For outcome mental well-being measure, The World Health Organisation - Five Well-Being Index (WHO-5) was used. This scale has been widely used in the literature (Cosma et al., 2022; Topp et al., 2015) to measure participants' subjective psychological well-being in a concise way.

1.7.3 Secondary Synthesised Data

The dataset of study 3 consisted of synthesized data from peer-reviewed articles selected through a screening process. Six electronic databases (Web of Science, PubMed, PsycINFO, CINAHL, EMBASE, and ERIC) were searched in October 2023, and a second round of database search was conducted in February 2025. The inclusion criteria comprised of: (1) studies on adolescents between the ages of 12-18 or secondary school students; (2) school-based interventions targeting adolescents' digital use and mental well-being, where the exposure or training program was delivered within the school settings; (3) studies that use at least one indicator of digital use (e.g., screen time, smartphone use, social media use, problematic internet use) and at least one indicator of mental well-being (e.g., depressive symptoms, anxiety, life satisfaction, quality of life) as outcome. Considering the limited number of studies conducted in this research area, articles that employed different designs, such as randomised controlled trials (RCTs), non-randomised trials, or pre- and post- designs, were included. The initial search yielded 1284 articles and after the screening stages, a total of 17 studies were included in the systematic review, of which 11 provided data for the meta-analyses. The data were extracted for the outcomes screen time, problematic digital use, anxiety, depression, life satisfaction and flourishing, and psychological distress (as a subscale of Strengths and Difficulties Scale). The contents of the included studies were used as qualitative data for the systematic review.

1.7.4 Primary Intensive Longitudinal and Experiment Data

Study 4 produce a primary intensive longitudinal dataset, spanning over three weeks, to structure the data with an Experience Sampling Method design (ESM, Csikszentmihalyi & Larson, 1983). Since the goal of study 4 was to test the effectiveness of a digital detox intervention, the study used a clustered nonrandomised controlled trial (cNRCT). The participants for this study were recruited via the same secondary schools who agreed to participate in data collection in Study 2, therefore the sampling strategy for the schools were also the same for Study 4. These schools were allocated to either the control (N = 2) or the experiment group (N = 3) prior to data collection phase, although the school staff and students of the intervention group were informed only when the intervention week started. First, schools were allocated into two groups with the considerations of the demographic areas and sample sizes within schools. The completely random allocation was not possible due constraints regarding sample size variations across schools and uneven school number with an imbalance of socioeconomic backgrounds. Then, the two groups were assigned to each treatment condition with the group with larger sample size to be the intervention group to achieve higher statistical power. The control group included one school from disadvantaged area and one average area. The intervention group included one school from disadvantaged area, one from average area, and one from affluent area.

One class was randomly selected from each of the 6 school grades (students from 12 to 18 years old), which were then invited to participate in our study. A total of 252 students provided parental consent and participated in the study. After the initial assessment survey that was conducted in schools, which was also a part of the dataset for study 2, participants were instructed to answer 1-minute questionnaires (beeps) that were sent to their phones four random times a day excluding school and sleep times. To make sure the responses were truly measured at random times, and to prevent accumulation of unanswered questionnaires on participants' phones, the beeps were set to expire after 10 minutes. This data collection schedule lasted one full week before the intervention week (pre-assessment), and one week after the intervention week (post-assessment). Additionally, participants in the intervention group were asked to log their digital detox session during the intervention week while the participants in the control group were asked to repeat the same schedule with before. All participant schools and families received an educational voucher as an acknowledgement of participation from the research team.

The concepts measured at each beep included: positive and negative momentary affect, recent phone use, and problematic phone use indicators (momentary withdrawal, momentary perceived loss of control). A modified and shortened version of the Positive and Negative Affect Scale (PANAS; Watson et al., 1988) for momentary affect, and withdrawal and loss of control subscales from the Mobile Phone Problem Use Scale - 10 (MPPUS-10; Foerster et al., 2015) for momentary problematic phone use indicators were used. Further, during intervention week, participants reported the duration of their digital detox sessions, planned activities, and how easy they found their digital detox session.

1.7.5 Data Analysis Strategies

This thesis uses a multi-method design to answer each research question. Study 1 and Study 4 used linear mixed effect modelling. Study 2 employed generalised latent class analysis and mediation modelling. Study 3 conducted qualitative narrative synthesis for results from articles not suitable for the inclusion in the meta-analytic synthesis, and arm-based random-effects meta-analyses for the suitable articles for quantitative research, synthesising arm-level outcomes using the percentage change. Analyses for Study 1 and Study 2 were performed using Stata 18, and analyses for Study 3 and Study 4 were performed using R Studio.

In Study 1, individuals were nested within countries with random intercepts for countries and random slopes for PSMU. Using a stepwise approach, models with individual level interaction between PSMU and SES, cross-level interactions between PSMU and income inequalities, and the three-way interaction between PSMU, SES and income inequality were examined. Further, a three-level model design where individuals nested within schools and schools nested within countries were tested. A school level affluence inequality variable created using the same Gini index formula with the income inequality variable, and the cross-level interactions, were also conducted.

In Study 2, the digital use indicators (*intensity*, *type*, and *purpose*) consisted of 12 variables in total were used to perform Generalised Latent Class Analyses (GLCA). Based on a three-step approach (Bolck et al., 2004), the 3-class model was determined to be the best fit for the dataset. Then, a Mediation Model was used to assess whether adolescents belonging to each of these three digital user profiles had different mental well-being outcomes, and whether these differences could be explained by their digital maturity. Additional analyses were conducted to examine heterogeneity by gender and community-level SES differences in the mediation model.

As for Study 3, risk of bias assessments and assessment of the overall quality of the evidence base were performed before conducting the analysis. For the arm-based random-effects meta-analyses, studies with control groups contributed with both arms, and single-arm studies (pre- and post-intervention without control) contributed with the intervention arm only. A treatment indicator in meta-regression estimated the intervention effect while accounting for between-study heterogeneity evaluated using the I^2, which measure the extent to which the results of studies are consistent. For all the meta-analyses, the percentage changes from baseline to post-intervention were calculated for the control and the intervention groups. The magnitudes of the percentage changes in the outcomes of interest were evaluated using Cohen's *d* thresholds (Cohen, 1988). A precision-of-estimate approach was used to interpret the results rather than relying on the *p* value to interpretate the level of evidence for substantial and trivial magnitude in a more nuanced way. Further, sensitivity analyses to test whether results differed depending on the selection of the 0.5 correlation coefficient and Egger tests to check for potential publication bias (Egger et al., 1997) were conducted.

Finally, in Study 4 beeps were nested within individuals, with random intercepts for individuals and random slope for time. To control for the probable inertia of the time variant variables, all analyses were conducted with constraining errors in adjacent beeps by an autocorrelation structure (AR1) using package *lme4* (Bates et al., 2022). First, a cross-level interaction of time and experiment group was examined to test the group differences at pre- and post- assessments. Second, three-way interactions of phone use variables, time, and group were assessed to test if the intervention impacted the association between phone use and emotional outcomes. Third, and finally, analyses on the intervention group subsample were conducted to explore whether differences in digital detox practices (days of compliance, duration of sessions, and perceived easiness) moderated the fluctuations in the outcomes at pre- and post-assessments.

1.7.6 Ethical Considerations and Data Management

The HBSC survey and macro-level data used in Study 1, and the synthesised data obtained from published articles used in Study 3 were publicly available and completely anonymous. The methodology for Study 2 and Study 4 received ethical approval prior to data collection process from the Faculty of Arts, Humanities and Social Sciences. Because the age group of the sample was minors, active consent from parents and adolescents were obtained before participants filled out the online surveys. Participating schools and parents of the students received a voucher for compensation of their time and effort. The datasets were anonymized as soon as possible once the data collection period ended. Any identifying information of the participants were separated from rest of the datasets, and stored in a safe cloud, only shared among the research team. The anonymized data were stored in another cloud space, shared among the research team and the partner teams in DIGYMATEX. No sensitive information was collected in any of these studies.

1.8 Structure of the Thesis

The goal of the Chapter 1 was to introduce the core concepts and frameworks used in this thesis. The following four chapters are structured to present four empirical studies with distinct research questions. Chapter 2 (Study 1) examines socioeconomic inequalities in the relationship between PSMU and mental well-being of adolescents at the individual and country levels by applying a multi-level modelling approach to a cross-national dataset. Chapter 3 (Study 2) uses a primary data to categorise distinct digital user profiles with GLMA method, and explore whether the differences in their digital maturity levels could explain their differences in mental well-being outcomes with a mediation analysis. Chapter 4 (Study 3) conducts a systematic review and meta-analysis to examine effectiveness of school-based interventions targeting adolescents' digital use and mental well-being. Chapter 5 (Study 4) designs a digital detox strategy and tests its effectiveness using a field experiment design with cNRCT methodology. Chapter 6 sums up the core findings, discusses the implications, limitations, overall contribution of the thesis to the literature on adolescents' digital use and mental well-being, and avenues for future research in light of these findings.

Chapter 2: Study 1 - Problematic Social Media Use and Adolescent Mental Well-Being: The Role of Socioeconomic Inequalities in Cross-National Perspective

The peer reviewed and edited version of this chapter is published in ***Information, Communication and Society*** *with open access:*

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Abstract

How social inequalities shape the relationship between social media use and adolescent well-being is unclear. Using a novel micro-macro approach, this study examines how family socioeconomic status (SES) and country-level income inequalities moderate the influence of risk-induced social media use on adolescent mental well-being. We conduct mixed-effect multilevel models with data across 35 countries from the *Health Behaviour of School Aged Children* (HBSC) study (N ~ 145,000), benefiting from high-quality cross-country measures of Problematic Social Media Use (PSMU) –i.e., risk-related social media use–, Psychological Complaints, and Life Satisfaction. Results indicate that: (i) PSMU is associated with higher Psychological Complaints and lower Life Satisfaction, but effects are stronger for low-SES adolescents than for high-SES adolescents; (ii) the relationship between adolescent PSMU and poorer mental well-being is larger in medium–inequality countries than in both low– and high–inequality countries; and (iii) SES gaps in the association between PSMU and adolescent well-being are generally stable regardless of school–level and country–level inequalities. Overall, this study indicates that low-SES adolescents are more harmed by risk-related social media than high-SES adolescents, but higher country-level inequalities do not worsen the negative association between risk-related social media use and adolescent well-being.

Keywords: Adolescent mental well-being; Socioeconomic inequalities; Problematic social media use; Cross-national research

2.1 Introduction

In recent years, adolescent social media use has increased dramatically (Livingstone et al., 2018; Odgers and Jensen, 2020), a transformation that has coexisted with strong inequalities by family socioeconomic status (SES) shaping individuals' opportunities and well-being (Bernardi & Gil-Hernández, 2021; Breen & Muller, 2020; Bukodi & Goldthorpe, 2024; Elgar et al., 2017; Hamammi et al., 2024; Hertel & Groh-Samberg, 2019; Jackson, 2015; Torche, 2014). Although social media can help adolescents to boost their sense of belonging, life goals, and connectivity, it can also carry negative consequences, including cyberbullying, unrealistic body standards or gaming addiction (Boyd & Hargittai, 2013; Livingstone et al., 2018; Odgers & Jensen, 2020; Valkenburg & Peter, 2009). Previous studies found that *Problematic Social Media Use* (PSMU), a concept that captures addictive and risk-taking social media behaviours, is associated with higher adolescent psychological distress, somatic symptoms, eating disorders or negative mood (Shannon et al., 2022; Van Den Eijnden et al., 2018; Van Rooij et al., 2010; Wong et al., 2020). Despite increasing evidence on how engaging with social media affects adolescent well-being, how socioeconomic inequalities shape the relationship between social media use and adolescent well-being is not well understood.

Scholars have argued that *digital divides* are important societal mechanisms that contribute to explain SES inequalities in adolescent outcomes in our increasingly digitalised world. While research has stressed that SES inequalities in digital access persist, and even so in high-income industrialised countries, research approaching socio-digital inequalities has increasingly focused on the relationship between digital skills or use (2nd level divide) and outcomes (3rd level divide) (Van Deursen & van Dijk, 2019; Van Dijk, 2006; Büchi & Hargittai, 2022). Following this conceptual framework, recent research has found that high-SES adolescents, compared to low-SES adolescents, benefit comparatively more from their use of digital devices in their academic and socio-emotional outcomes (Bohnert & Gracia, 2023; Loh et al, 2025). Further, a recent cross-national study showed that adolescent PSMU differs across diverse inequality contexts (Lenzi et al., 2022). Yet, whether social inequalities operating at various societal levels, e.g., individual, family, community, country, influence how social media use links to adolescent well-being is unknown. The present study contributed to tackling this important gap in the social media, adolescence and well-being literatures.

This study adopts a micro-macro framework to investigate the moderating role of socioeconomic inequalities in the relationship between adolescent social media use and mental well-being. We argue that, while PSMU is linked to lower adolescent mental well-being, this association is moderated by socioeconomic inequalities playing at the family and country level. At the *individual level*, the negative association between PSMU and mental well-being should be larger for low-SES adolescents than for their high-SES peers. This expectation reflects the disadvantages low-SES teens regarding accessing to resources of minimising harm-related social media practices, such as protective social, physical, educational, and digital resources that high-SES teens tend to access more easily (Helsper, 2021; Robinson et al., 2015; van Deursen & van Dijk, 2019; Ma, 2021; Mollborn et al., 2022; Notten et al., 2009). At the *country level*, macro-level inequalities may lead to stronger associations between adolescent PSMU and lower mental well-being. This expectation would reflect that the diffusion of technological tools and resources is slower and more segmented in more unequal socioeconomic contexts (Hilbert, 2016; Fuchs, 2009; Zhang, 2013), while country-level income inequalities lead to mechanisms of social comparison and status anxiety that harm adolescents (Pickett & Wilkinson, 2007; Wilkinson & Pickett, 2009) in ways that may apply to social media settings too. Finally, SES gaps in the association between PSMU and mental well-being could be dependent on the societal levels of socioeconomic inequalities.

We specifically examine three research questions, namely: (1) How does the association between adolescent PSMU and mental well-being differ by SES?; (2) How does the association between adolescents' PSMU and their mental well-being vary across countries with different levels of socioeconomic inequalities?; and (3) How do SES gaps in the association between adolescent PSMU and mental well-being operate across different contextual socioeconomic inequalities? We answer this questions with a multilevel design, using high-quality data from a large sample of adolescents across 35 countries, which contains rich harmonised measures of Problematic Social Media Use (PSMU), as well as widely validated cross-country measures of mental well-being. We conceptualise mental well-being as a multidimensional construct encompassing both cognitive evaluations and emotional health, focusing on two complementary definitions of mental well-being, namely life satisfaction, defined as a global cognitive appraisal of one's overall life circumstances, and psychological complaints, conceptualised as recurrent feelings of low, irritable, or nervous and sleeping problems (Inchley et al., 2020).

Overall, our study is, to our knowledge, the first in providing micro-macro level evidence on how individual- and country-level socioeconomic inequalities moderate the association between PSMU and adolescent mental well-being. In doing so, the present study advances the literature on adolescent well-being, social media and social inequalities by adopting novel cross-national approach within these research fields.

2.2 Background

2.2.1 The Role of SES in Adolescent Social Media Use and Mental Well-Being

Previous research has consistently shown that high-SES children and adolescents report lower mental well-being problems (e.g., decreased levels of anxiety, lower depressive symptoms, fewer behavioural problems) than their low-SES counterparts (Bodovski & Farkas, 2008; Loft & Waldfogel, 2020; Pietropoli & Gracia, 2025; Reiss, 2013). Scholars highlight the contrasts in the family contexts; while high-SES parents can allocate more time, invest in their children's development financially, and provide more human capital overall, low-SES parents tend to lack these opportunities due to higher financial stress and economic uncertainties (Kalil & Ryan, 2020; Li & Chzen, 2024). As digital technologies penetrate in everyday family life, the question of how digital media use links to SES gaps in adolescent well-being has naturally become more pressing. From a *digital divides* approach, existing inequalities operating within "offline" settings are intertwined with inequalities that occur within "online" worlds. This implies that lower-SES families may lack the necessary resources to minimise the potential risks associated with harmful forms of social media engagement. By contrast, high-SES families would be more advantaged, for example by applying parental strategies to help adolescents in coping with potential risky media behaviours or negative online experiences (Büchi & Hargittai, 2022; Hargittai & Hinnant, 2008; Van Dijk, 2006).

Studies on digital divides in youth consistently that high-SES adolescents access protective social, physical, educational, and online resources to cope with potentially harmful online experiences, whereas low-SES adolescents often lack family resources to ensure a protective support in digital settings (Helsper, 2021; Robinson et al., 2015; van

Deursen & van Dijk, 2019). Adolescents from more privileged SES groups were found to be more prone to receive social and technical support and supervision through their families or schools (Ma, 2021; Mollborn et al., 2022). By contrast, low-SES adolescents often miss consistent online support from their social and family environment while engaging with screens (Gracia & Garcia-Roman, 2018). Other studies found that high-SES adolescents use their digital devices for educational purposes more frequently, while lower-SES adolescents spend more time navigating social media platforms without digital protection (Lenzi et al., 2022; Ma, 2021; Notten et al., 2009). Some studies found that high-SES adolescents are disproportionately protected and advantaged when it comes to socioemotional and academic outcomes from spending time in digital activities (Bohnert & Gracia, 2023; Gracia et al., 2023; Loh et al, 2025).

In addition, social media may also expose adolescents to lifestyles, opportunities, and consumption patterns beyond their immediate socioeconomic context. While offline interactions are often limited to neighbourhood and school-based proximity, social media platforms allow adolescents to encounter content from celebrities, influencers, and peers whose lifestyles may reflect substantially different socioeconomic resources (Lou & Kim, 2019). Platform features such as algorithm-based recommendations, favouring towards visual posts, and publicly available popularity metrics may further prioritise aspirational content, thereby increasing the visibility of status markers and luxurious lifestyles. These forms of exposure may increase the salience of upward social comparisons, which may be unevenly distributed across socioeconomic groups (Cheung & Lucas, 2016; Wirtz et al., 2020). Differences in social networks, engagement patterns, and available digital guidance may lead lower-SES adolescents to encounter a greater share of aspirational or comparison-inducing content, while having fewer resources to contextualise or manage these experiences. While existing research has not investigated how PSMU is associated with SES inequalities in adolescent well-being outcomes, based on previous theories and research findings, it can be hypothesised that lower-SES adolescents are more at risk of their PSMU than higher-SES adolescents.

Hypothesis 1: *The expected negative association between PSMU and mental well-being is stronger for lower-SES adolescents than for higher-SES adolescents.*

2.2.2 The Moderating Role of Country-Level Inequalities

Although digitalisation is a global trend, adolescent social media prevalence varies across countries (Livingstone et al., 2011; Smahel et al., 2020). For instance, while the percentage of adolescents with daily access to the internet is similar in Italy, Spain, and Malta (approximately 80%), adolescent average time spent online per day differs by more than hour across these same countries (Smahel et al., 2020). One study found that the strength of the association between PSMU and lower adolescent well-being differs across countries (Boer et al. 2020). Another cross-national study found macro-level inequalities to be associated with higher adolescent PSMU (Lenzi et al., 2022). However, how country-level socioeconomic factors moderate the association between social media use and adolescent well-being is unclear.

Previous literature has elaborated two main mechanisms to explain how country-level socioeconomic inequalities may moderate the association between social media use and adolescent well-being. First, country-level income inequalities may result in digital inequalities that negatively affect adolescent well-being (Hilbert, 2016; Helsper, 2021). According to diffusion theory (Rogers et al., 2014), the advancement of technological tools and digital resources in a country follows a gradual process by which high-SES groups take advantage in obtaining, and benefiting from, ICT resources. Studies found that more unequal countries present slower digital adoption and access rates than more equal countries (Fuchs, 2009; Zhang, 2013). Therefore, more unequal countries may have adolescents with fewer digital resources and ICT skills, which may result in less effective strategies against the risks of adolescent PSMU when macro-level income inequalities are more prevalent.

Second, adolescents' online social comparisons and status anxiety may be particularly salient in more unequal countries, thus leading to stronger associations between PSMU and adolescent well-being as country-level inequalities grow. Adolescence is a life stage in which social comparisons become critical for self-evaluation and identity formation, and these patterns are particularly prevalent in the most hierarchical and unequal societies (Harter, 2012; Sebastian et al., 2008; & Van der Aar et al., 2018; Wilkinson & Pickett, 2009). Similar processes could apply to online mediums, as for example adolescents frequently compare their lives in social media in relation to people who have higher socioeconomic privileges than them (Cheung & Lucas, 2016; Nesi & Prinstein, 2015). Following previous literature, mechanisms of online social comparisons and digital anxieties toward peers may be particularly salient in highly unequal countries.

Hypothesis 2: *The association between PSMU and lower mental well-being is stronger in countries with higher income inequality than in more economically equal countries.*

2.2.3 Intersecting SES and Country-Level Inequalities

Family-level and country-level inequalities may interact in explaining the association between PSMU and adolescent mental well-being. However, this relationship remains unexplored. We propose two alternative hypotheses to answer this question. One perspective suggests that family SES gaps in the association between adolescent PSMU and mental well-being are stronger as country-level income inequality increases. The slow diffusion of digital resources in more unequal countries may further hit low-SES adolescents, as they struggle particularly to access structural support systems like digital literacy programmes and mental health services in unequal contexts (Fuchs, 2009; Zhang, 2013). By contrast, high-SES adolescents in high-inequality countries could get access to such buffering resources. This heterogeneity may be less likely to manifest in more equal contexts. Additionally, the starker social status distinctions of more unequal contexts could induce low-SES adolescents to even more intense feelings of deprivation from better life standards and even lower self-esteem in social media settings, thus lowering their mental well-being, compared to low-SES adolescents from more equal societies (Harter, 2012; Sebastian et al., 2008; Cheung & Lucas, 2016).

Hypothesis 3a: *SES gaps in the association between PSMU and adolescent mental well-being are stronger in countries with higher income inequalities than in countries with lower income inequalities.*

An alternative approach suggests that family SES gaps in the association between PSMU and mental well-being are stable across countries with different levels of inequalities. The role of macro-level inequalities could be relatively trivial if we consider that mechanisms connecting PSMU to mental well-being operate at the interpersonal level, for example through processes related to family support, digital skills or social comparisons (Mollborn et al., 2022; Nesi & Prinstein, 2015; Livingstone et al., 2018). Moreover, it could be argued that the global prevalence of contemporary social media platforms leads adolescents from equivalent social classes, even if they live in countries with different socioeconomic inequalities, to be exposed to relatively similar digital contents and online risks.

Hypothesis 3b: *SES gaps in the association between PSMU and adolescent well-being are stable across different country-level inequality contexts.*

2.3 Methods

2.3.1 Sample

The data used in this study is obtained from the *Health Behaviour in School-aged Children* (HBSC) study conducted in 2017-2018 (Inchley et al., 2020). HBSC is a school-based survey that collects data from adolescents aged 11, 13 and 15 years old through a cluster sampling approach in each country included in the study ($n = 46$) every four years. All participating countries use a representative sampling for their respective school-aged adolescents and follow a standard protocol, ensuring that the data collection takes place during the same school year and using the same methodology. Countries that omitted data on any of the study variables ($n = 4$: Bulgaria, Macedonia, Slovakia, Switzerland) and countries with missing data on our country-level variables ($n = 7$: Azerbaijan, Croatia, France, Greece, Greenland, Russia, Türkiye) were excluded from the sample. We then had to exclude participants who reported that the questions related to social media use did not apply to them, indicating not using social media at the time of the survey ($N = 8{,}151$). Finally, we excluded individual observations containing missing data on our outcome variables ($N = 4{,}085$ for missing psychological complaints, $N = 2{,}149$ for missing life satisfaction), key explanatory measures ($N = 16{,}407$ for missing PSMU, $N = 3{,}589$ for missing SES) and control variables ($N = 5{,}975$ for missing control variables).

The study final sample included a total of 144,934 adolescents across 35 countries ($M_{age} = 13.62$, 52.6% girls). Attrition analyses showed no statistically significant differences between excluded and non-excluded cases in social media use. However, excluded participants were significantly younger ($t(183{,}909) = 64.080$, $p < 0.001$), more likely to be male ($\chi^2(1, N = 185{,}290) = 933.663, p < 0.001$) and from low-SES background ($\chi^2(2, N = 176{,}181) = 341.187, p < 0.001$). The percentages of excluded participants per countries are reported in the Appendix (Table A2.1).

2.3.2 Individual-Level Measures

Psychological Complaints. The psychological subscale of the HBSC-symptom checklist, which has four items: (1) feeling low, (2) irritability/bad temper, (3) feeling nervous, and (4) sleeping difficulties (Gariepy et al., 2016) was used. Each item had a 5-point response scale measuring how often during the past 6 months the complaint was experienced (0 = rarely or never, 1 = about every month, 2 = about every week, 3 = more than once a week, 4 = about every day). A mean score was computed for participants who answered at least three of the four subscale items; higher scores indicated more problems (range, 0–4). The checklist had good internal consistency in all survey years ($\alpha = 0.78$) and had convergent validity with emotional well-being (Gariepy et al., 2016).

Life Satisfaction. The Cantril Ladder, an 11-point ladder on how participants feel about their life, was used. The bottom step of the ladder represented the worst possible life, coded as 0, and the top of the ladder represented the best possible life, coded as 10. The Cantril Ladder has shown high reliability among adolescents (Levin, & Currie, 2014).

PSMU. The Social Media Disorder Scale (Boer et al., 2022; Van den Eijnden et al., 2016) was used. PSMU contains nine items: (1) regularly failing to think of anything else but social media, (2) regularly feeling dissatisfied because wanting to spend more time on social media, (3) often feeling bad when not being able to use social media, (4) failing to spend less time on social media, (5) neglecting other activities (e.g. hobbies, sport) because wanting to use social media, (6) regularly having arguments with others because of social media use, (7) regularly lying to parents or friends about the time spent on social media, (8) often using social media to escape from negative feelings, and (9) having serious conflict with parents or siblings because of social media use. Each item had a dichotomous (1 = yes; 0 = no) response scale capturing whether participants experienced each of the item over the last year. A sum score was computed for participants who answered at least six of the nine items; higher scores indicated more problematic social media use (range: 0–9). The scale showed good validity and reliability across countries (α = 0.89) (Boer et al., 2022).

SES. The Family Affluence Scale (FAS) (Currie et al., 2008), which contains six items on material wealth indicators from participants' families: (1) number of cars, vans, or trucks, (2) having (child's) own bedroom, (3) number of computers, (4) dishwasher ownership, (5) number of bathrooms, (6) number of holidays abroad, was used. A sum score was computed for participants who answered all the questions, the total score ranged from 0-to-13. Three SES categories were created within each country using the total FAS score; the lowest 33% of the participants were coded as low-SES, highest 33% of the participants were coded as high-SES, and the rest of the participants were coded as middle-SES. The FAS is a widely used validated SES indicator in large-scale surveys like HBSC, ensuring cross-national comparability (Currie et al., 2008). Previous analyses have demonstrated that FAS is a proxy of inequalities beyond wealth, showing strong correlations with parental education, occupational status or cultural capital (Torsheim et al., 2016).

Control variables. Considering that adolescent mental well-being covaries with *Age* and *Gender*, we controlled for these two variables in our analyses. Age was measured in years and months, and gender was coded following the original binary question from the HBSC data, with 0 = boys and 1 = girls. We also controlled for Frequent social media use (FSMU) to eliminate potential confounding effects. FSMU was measured by a four items scale adapted from the EU Kids Online Survey (Mascheroni & Ólafsson, 2014), asking participants the frequency of online contact through social media with (1) close friends, (2) friends from a larger friend group, (3) friends that they met through the Internet, and (4) other people such as parents, siblings, or classmates. Each item had a 4-point response scale (0 = never/almost never, 1 = every week, 2 = daily, 3 = several times daily, 4 = almost all the time), as well as a "do not know/does not apply" option. The "do not know/does not apply" responses were recoded as missing values. A mean score was computed for participants who answered at least three of the four subscale items; higher scores indicated more frequent social media use (range: 0–4).

2.3.3 Country-Level Measures

The country-level data were obtained from the World Bank for the year 2018. Income Inequality was measured by the Gini index scores of the countries (World Bank, 2022a). Gini index theoretically ranges from 0 (perfect equality of individuals) to 100 (perfect inequality of individuals). Using Gini index scores, we created a three-level categorical variable, with one-third of the countries at each level. Country-level variables were categorised into tertiles for three main reasons. First, using tertiles facilitates substantive interpretability by allowing us to compare adolescents living in relatively low, medium, and high socioeconomic contexts, which aligns with our theoretical focus on cross-national stratification rather than marginal linear effects (Firebaugh, 2008). Second, categorisation reduces sensitivity to extreme values and influential cases, which is particularly relevant given the relatively small number of countries and the heterogeneous distributions of macro-level indicators (Bryan & Jenkins, 2016). Third, tertiles ensure comparability across countries by placing them on a common relative scale. This approach is effective when country-level variables differ markedly in range and dispersion.

We used three country-level control variables that were identified in previous research as potential confounders of country-level income inequality (Cruz-Jesus et al., 2017; Nordrum and Gracia, 2024; Van Deursen & Van Dijk, 2019; Boer et al., 2020). We controlled for: (i) National Income: measured by countries' gross domestic product (GDP) per capita in thousands of billions of international dollars (World Bank, 2023a); (ii) Educational Expenditure: measured as the percentage of governments' expenditure on secondary education (World Bank, 2022b); and (iii) Internet Use Prevalence: measured as the percentage of individuals using the Internet regularly in each country (World Bank, 2023b). As with the inequality measures, we created a three-level categorical variable for each country-level control variable, with one-third of countries being at each category (low, medium, high).

2.3.4 Analytical Strategy

We adopted a mixed-effect multilevel regression modelling approach, where adolescents were clustered within countries. We followed the same steps for psychological complaints and for life satisfaction separately. We first added the control variables (age, gender, and FSMU), SES (low-SES as the reference group), and fixed and random effects of PSMU (Model 1a and Model 1b). Individual-level continuous variables were group mean centred. We interpreted cross-country variations of the random effects using the 95% prediction interval. Second, we added the interactions effects of PSMU with SES (Model 2a and Model 2b). Third, we added the cross-level interactions of PSMU with country-level measures (Model 3a and Model 3b). Next, we added a cross-level interaction between SES and Gini variables and three-way interactions between SES, Gini, and PSMU variables (Model 4a and Model 4b). To evaluate the overall statistical significance of the moderating variables, we used χ^2 tests. Finally, as additional analyses, we further examined the role of socioeconomic inequalities at the school level.

We conducted multiple analyses to assess the quality and robustness of our empirical models. First, to account for differences in population size and sampling, we replicated (not shown) the analyses with international weights and conducted sensitivity tests excluding the countries with largest samples. Second, we replicated the analyses with only OECD countries to test whether results persist with a sample of countries that have relatively similar economies. Third, we tested for potential multicollinearity among both individual- and country-level predictors. Finally, we repeated the analyses using a log-transformed PSMU variable to check whether the results are independent of the skewness of the distribution.

2.4 Results

2.4.1 Descriptive Results

Table 2.1 shows the means and percentages of the study variables per country. The average score of PSMU was below 3 in all countries, with Malta being the highest (2.98) and Iceland the lowest (1.27). Italy had the highest mean of psychological problems (1.75), and Canada had the lowest mean of life satisfaction (7.27), whereas Kazakhstan had the lowest mean of psychological problems (0.80) and the highest mean of life satisfaction (8.56). The income inequality scores ranged between 25 to 39. Israel had the highest levels of income inequality (38.6), followed by Russia (37.5), whereas Slovenia (24.6), Republic of Moldova (25.7) and Czech Republic (25) had the lowest income inequality levels.

2.4.2 Individual-Level Associations and Interactions

Table 2.2 (supplemented by Table A2.2 in the appendix) shows the multilevel results for psychological complaints and life satisfaction, which are also presented graphically in

Figure 2.1. Overall, there were disproportionately high psychological complaints and low life satisfaction among girls, older adolescents, and lower-SES adolescents. Results of Model 1a demonstrated that PSMU had a statistically significant positive association with psychological complaints (See also Figure 2.1, Panel A). The association with psychological complaints was consistently positive across countries, although the strength of the association varied from borderline small to borderline moderate (95% PI: [0.190/0.383]). PSMU had statistically significant association with life satisfaction (Model 1b). The association with life satisfaction was consistently negative across countries, and it ranged from small to moderate (95% PI: [-0.506/-0.181]).

Model 2a and 2b show the associations of PSMU with the outcome variables across SES groups. In Model 2a, there was a statistically significant SES gradient in the association between PSMU and psychological complaints ($\chi^2(2, N = 144{,}934) = 7.06$, $p = 0.029$), with weaker associations for high-SES adolescents compared to low-SES adolescents (B = -0.006 (SE = 0.003); $p = 0.029$). However, the association was not statistically significantly different between mid-SES and low-SES adolescents ($p = 0.802$). In Model 2b, we found a statistically significant SES gradient in the association between life satisfaction and PSMU ($\chi^2(2, N = 144{,}934) = 16.74$, $p < 0.001$) such that the association was weaker in high-SES (B = 0.021 (SE = 0.005); $p < 0.001$) and middle-SES adolescents (B = 0.013 (SE = 0.005); $p = 0.013$), compared to low-SES adolescents. However, the differences between high-SES and mid-SES adolescents were not statistically significant ($p = 0.133$). Marginal effects of SES on the outcome variables are illustrated in the Appendix (Figure A2.2).

2.4.3 Cross-Level Interactions

In Table 2.2, we see that the cross-country variance in the association between PSMU and adolescent mental well-being outcomes by the country-level variables explained is

28% for psychological complaints and 47% for life satisfaction, as observed in the PSMU slopes for psychological complaints (0.0006026-0.0004333)/0.0006026 =0.281) and life satisfaction (0.0017707-0.0009468)/0.0017707 = 0.465).

In terms of cross-level interactions, Model 3a illustrated mixed results (see Table 2.2 and Figure 2.1, Panel B). Gini levels moderated the association between PSMU and psychological complaints ($\chi^2(2, N = 144{,}934) = 6.14, p = 0.046$). Interaction terms indicate that, relative to low-Gini countries (reference group), the association between PSMU and psychological complaints was stronger in mid-Gini countries (B = 0.020, SE = 0.010, $p = 0.035$), while differences between high-Gini and low-Gini countries were not statistically significant ($p = 0.691$). GDP levels moderated the positive association between PSMU and psychological complaints ($\chi^2(2, N = 144{,}934) = 6.57, p = 0.037$). Specifically, relative to low-GDP countries, the association between PSMU and higher psychological complaints was attenuated in high-GDP countries (B = −0.048, SE = 0.021, $p = 0.025$), indicating that adolescents in wealthier contexts experience smaller increases in psychological complaints linked to PSMU, compared to adolescents in less wealthy countries. Educational expenditure ($\chi^2(2, N = 144{,}934) = 2.88, p = 0.237$) and IUP ($\chi^2(2, N = 144{,}934) = 4.12, p = 0.127$) did not moderate the association between PSMU and psychological complaints, although there was a statistically significant differences between high-IUP to low-IUP countries (B = 0.042, SE = 0.021, $p = 0.042$).

Model 3b indicated that Gini levels moderated the cross-country variations in the negative association between adolescent PSMU and life satisfaction ($\chi^2(2, N = 144{,}934) = 7.90, p = 0.019$), with stronger effects for mid-Gini countries than for low-Gini countries (B = −0.039 (SE = 0.014); $p = 0.007$), and no statistically significant differences between low-Gini and high-Gini countries ($p = 0.712$). While GDP ($p = 0.460$) and educational expenditure ($p = 0.437$) did not moderate the association between adolescent PSMU and life satisfaction, IUP levels did moderate the association ($\chi^2(2, N = 144{,}934) = 8.91$, $p = 0.012$). The negative association was stronger in high-IUP (B = −0.092, SE = 0.031, $p = 0.003$) and mid-IUP countries (B = −0.067, SE = 0.029, $p = 0.019$) than in low-IUP countries. Marginal effects of SES on the outcome variables are illustrated in the Appendix (Figure A2.2).

Finally, the results of Model 4a and 4b showed opposing results (Figure 2.1, Panel C). For psychological complaints, the three-way interaction was statistically significant ($\chi^2(4, N = 144{,}934) = 13.97$, $p = 0.007$), but not for life satisfaction ($\chi^2(4, N = 144{,}934) = 2.72$, $p = 0.606$). The results of Model 4a and 4b are presented in the Appendix (Table A2.3 and Figure A2.3).

2.4.5. Sensitivity Analyses and Robustness Check

The results of the sensitivity analyses remained stable across specifications, indicating that our conclusions are not driven by disproportionate sample sizes across countries or the participation to the HBSC survey. The results of the analyses including only OECD are reported at Tables A2.4 and A2.5. The test for multicollinearity showed that at the individual level, pairwise correlations across gender, age, family social media use, socioeconomic status, and problematic social media use were generally low in magnitude ($|r| < 0.20$), indicating that collinearity is unlikely to bias model estimates. At the country level, we examined both the continuous and categorical (tertile) versions of GDP per capita, Internet use prevalence, and educational expenditure. Belsley's condition index values (6.6 for continuous predictors; 9.0 for categorical tertiles) were well below the conventional threshold of 30, providing no evidence of any problematic level of collinearity.

Because the main predictor variable PSMU had a positively skewed distribution, a robustness check was conducted by repeating the analyses with a group-mean centred log-transformed PSMU variable using the formula: log(1 + PSMU). The log-transformed PSMU coefficients of these analyses are reported in the Table A2.6. The results remained largely stable across all analyses, indicating that the results were not driven by the skewed distribution of PSMU.

2.4.6 Additional Analyses: School-Level Effects

We additionally tested the role of school-level socioeconomic inequalities in the associations between PSMU and adolescent mental well-being outcomes (see Table A2.7, Table A2.8, and Table A2.9 in the Appendix). Schools are one of the main mediums for adolescents to socialise with peers, and therefore school-level socioeconomic contexts may reflect distinct social comparisons in offline and online mediums that are not necessarily captured at the macro level (Lenzi et al., 2022). We applied a three-level random coefficient multilevel model with individuals nested within schools and schools nested within countries, using a stepwise approach. Using the participants' FAS scores, we created two school-level variables approximating schools' socioeconomic contexts. To measure school-level affluence, we used an aggregated FAS score of the individuals nested within schools. To analyse school-level inequality, we computed the Gini index score of each school, using the *fastgini* command in Stata 18. We created three categories within each country for both indicators, where one-third of schools were categorised as low, mid, or high level.

Across schools, the association between adolescent PSMU and psychological complaints was consistently positive (beta = 0.291; 95% PI: [0.143/0.439]), and the one between adolescent PSMU and life satisfaction consistently negative (beta = -0.345; 95% PI: [-0.666/-0.024]). While SES gradients in the PSMU and psychological complaints relationship ($\chi^2(2, N = 138{,}335) = 9.12$, $p = 0.010$) and in the PSMU and life satisfaction relationship ($\chi^2(2, N = 138{,}335) = 18.62$, $p < 0.001$) persisted across schools, school-level inequalities were not associated with neither adolescent psychological complaints nor life satisfaction. Finally, the results of three-way interactions between PSMU, school inequality and SES (not shown) indicated that higher school inequality levels did not increase the family SES inequalities in the association between PSMU and adolescent mental well-being.

2.5 Discussion

This study has examined the role of socioeconomic inequalities in how adolescents' social media use shapes their mental well-being outcomes at both the micro and macro level. Our study brings important findings to the intersecting literatures on adolescent well-being, social media and social stratification.

First, at the *individual level*, our study shows that higher PSMU is consistently linked to more frequent psychological complaints and to lower life satisfaction scores, while indicating clear inequalities by family SES in such associations. We found that the association between higher PSMU and lower mental well-being is stronger for adolescents from low-SES backgrounds, compared to their peers from high-SES backgrounds, in line with *Hypothesis 1*. These results add to recent sociological research on social and digital divides in adolescent outcomes (Bohnert & Gracia, 2023; Loh et al., 2025) by revealing how high-SES families can mobilise their resources –e.g., family support, digital parenting strategies, digital skills– as buffers to mitigate risky social media behaviours, whereas the low-SES are more harmed by risk-related social media situations. Although such SES gaps were observed for the two outcomes of mental well-being that we examined, SES gradients were stronger for life satisfaction than for psychological complaints. This finding underscores the importance of examining measures with distinct implications for adolescent well-being and health in digital contexts, an issue that future social stratification and digital divides research on adolescent well-being should further address.

Second, at the *country level*, we found mixed results that only partially support *Hypothesis 2*. We found that adolescents from low–inequality countries are more protected from higher PSMU in their psychological complaints and life satisfaction than adolescents in mid–income inequality countries. More equal countries may provide stronger support systems and educational opportunities to gain beneficial ICT skills and digital literacy, as well as youth mental health resources preventing potential social media harms (Fuchs, 2009; Zhang, 2013; Helsper, 2021). The relatively unequal context of mid–inequality countries may lead to stronger comparisons of material socioeconomic indicators on social media, which could exacerbate the potential risks of higher PSMU (Cheung & Lucas, 2016; Nesi & Prinstein, 2015). However, we found no differences between low-inequality and high-inequality countries in these interactions, contradicting the notion that adolescents' mental well-being is more vulnerable to the risks of higher PSMU in more unequal countries (Hilbert, 2016; Pickett & Wilkinson, 2007; Wilkinson & Pickett, 2009). One explanation for this counterintuitive finding could be that adolescents in high-inequality contexts are conscious of the prominent disparities in their country, and therefore could be better equipped to address such systemic issues online (e.g., through solidarity with peers from a similar social status) (Stornaiuolo & Thomas, 2017; Xenos et al., 2014). Additionally, high-inequality countries often present high levels of geographical segregation, where high- and low-income groups are more prone to interact with people from their same social class (Reardon and Bischoff, 2011; Wilkinson & Pickett, 2009). This segregation may contribute to reduce potential mechanisms of social comparison and status anxiety in high-inequality countries if adolescents are particularly likely to socialise with peers from their own socioeconomic background. As a result, in high-inequality countries, adolescents may face fewer chances of displaying status-based comparisons in online mediums with peers from another social class background. Future studies should address these potential explanatory mechanisms linking macro-level socioeconomic contexts to adolescents' social media experience and their mental well-being.

Third, family SES played a similar role in the association between PSMU and adolescent mental well-being across countries with different levels of inequalities, thus rejecting *Hypothesis 3a* and confirming *Hypothesis 3b.* Previous literature highlights how digital skills, social support, and social comparisons act as the most prominent explanations for negative outcomes derived from PSMU, highlighting that these mechanisms operate at the micro level (Mollborn et al., 2022; Nesi & Prinstein, 2015; Livingstone et al., 2018). This finding suggests that micro-level processes of inequality in everyday family life, compared to broader macro-level structural inequalities, are particularly powerful in explaining socio-digital mechanisms shaping the links between adolescent social media use and well-being.

Fourth, additional school-level analyses addressed if mechanisms of SES inequalities operated at a lower level than countries, as peer comparisons in proximity (such as school settings) can be a strong contributor to adolescent mental well-being (Harter, 2012; Lenzi et al., 2022; Nesi & Prinstein, 2015, & Van der Aar et al., 2018). Results showed that school-level inequalities do not moderate the association between PSMU and adolescent well-being. This finding confirms, once again, that inequalities at the family level are more important than macro-level contextual inequalities, at least in relation to how risk-related social media use negatively influences adolescent mental well-being.

Finally, we found other macro-level socioeconomic factors to be consistently important in explaining the relationship between PSMU and adolescent mental well-being, namely country-level wealth. Our analyses showed that adolescents in wealthier countries are more protected from higher PSMU in their mental well-being than adolescents in less wealthy countries. Because households in wealthier countries have higher disposable income, parents in high-income countries could afford higher quality digital devices, better internet services, and mental health support to prevent the harmful effects of adolescent risk-related online time (Hilbert, 2010; Van Dijk, 2020). These findings may also reflect that wealthier countries have access to educational resources to help young people to get digital skills training and support from schools and teachers; instead, poorer countries present more financial challenges to access such digital and educational resources (Ma et al., 2019). Future research should more extensively investigate these income-related macro-level mechanisms.

Our study has policy implications that need to be highlighted. At the *family level*, because PSMU can be a sign of addiction-like digital use behaviours (Van Den Eijnden et al., 2016; Van Rooij et al., 2010), implementing early digital interventions and prevention programmes targeted to reduce PSMU could help adolescents in dealing positively with social media and improve their well-being. These programmes should particularly address low-SES families, as adolescents in these vulnerable homes are most harmed by risky and addictive social media habits. At the *country level*, special focus should be given to countries with moderate levels of income inequality and lower levels of national income, the ones where risk and addictive related social media use seems most harmful to adolescent mental well-being. For example, policies aiming to diffuse digital resources more rapidly across families and adolescents and educational programmes on digital literacy and risk awareness may help adolescents to get protective resources against risky online interactions, particularly in families and countries with scarcer resources. In addition, integrating digital well-being education into school curricula and community programmes could provide adolescents with the skills to critically navigate online environments regardless of their family background. Policymakers should also consider that reducing broader socioeconomic inequalities may indirectly protect adolescents from the harms of problematic social media use among low-SES adolescents.

This study is not without limitations. First, our study cannot account for bidirectionality (e.g., lower mental well-being leads to higher PSMU) which a recurrent problem in social media research (Johnson & Knobloch-Westerwick, 2014). Although previous single-country longitudinal studies suggest that PSMU predicts mental well-being outcomes (Boer et al., 2021; Alonzo et al., 2021), unfortunately there are currently no longitudinal surveys to apply a multi-level cross-national designs that conclusively grasp causal relationships. Second, it could be argued that the construct of PSMU is a proximal indicator of mental well-being of adolescents, and that measuring these two constructs concurrently could create potential biases in our models. However, whereas mental well-being encapsulates broader emotional and psychological states via life satisfaction and psychological complaints (Gariepy et al., 2016; Levin, & Currie, 2014), PSMU measurement used in this study was derived from behavioural addiction frameworks and captures subjective complaints and consequences in relation to social media use in particular, such as loss of control, preoccupation, withdrawal, or disruption of daily activities (Van den Eijnden et al., 2016).

Third, while our study included additional analyses on schools, which in many respects are proxies of neighbourhood segregation and meso-level inequalities, future research should specifically address the role of socioeconomic inequalities related to meso-levels factors. Finally, our study did not examine the specific underlying mechanisms through which PSMU relates to adolescent well-being across different SES groups. Future research should investigate these pathways, with particular attention to the mediating role of digital skills, which is a key mechanism developed within the digital divide literature.

In conclusion, this study contributes to the growing body of sociological research on PSMU and adolescent mental well-being, using an innovative framework within this literature that links micro to macro level mechanisms. Our analyses provide new understandings of the complex interplay of family SES and broader structural inequalities. Higher PSMU is consistently associated with greater psychological complaints and lower life satisfaction across countries. Yet, we show that lower-SES adolescents are at greatest risk than high-SES adolescents. Moreover, our study indicates an interesting nonlinear pattern of country-level inequalities moderating these associations: mid-inequality countries pose the greatest harms of adolescent risk-related social media use. The similar effects observed for low-inequality and high-inequality countries require further exploration to disentangle how country-level socioeconomic structures shape adolescents' well-being related to their social media engagement. Overall, this forwards the literature by adding new conceptual and empirical tools to understand how socio-digital inequalities shape adolescents' risk-related online experiences and well-being across national contexts. Future research will benefit from our study to address the societal determinants of adolescents' social media behaviours and well-being outcomes in contemporary societies.

2.6 Tables and Figures

Table 2.1 Means and percentages of individual and country level measures

Country	*N*	Individual level							Country level			
		Girl	Age	FAS	FSMU	PSMU	PC	LS	GDP	EE	IUP	Gini
Albania	1,300	57 %	13.62	6.26	2.06	2.60	1.14	8.17	13.5	21.56	65.4	30.1
Armenia	3,039	54 %	13.72	4.22	1.81	1.48	1.15	8.34	13.55	46.87	68.25	34.4
Austria	3,552	53 %	13.38	9.29	2.02	1.68	1.21	7.70	56.96	39.63	87.48	30.8
Belgium (F)	3,540	52 %	13.48	9.31	1.75	1.85	1.25	7.79	52.54	42.13	88.65	27.2
Belgium (W)	4,249	52 %	13.47	8.52	2.06	2.13	1.50	7.51	52.54	42.13	88.65	27.2
Canada	8,225	54 %	13.85	8.94	1.95	1.67	1.33	7.28	49.99	26.4	94.64	33.3
Czech Rep.	9,608	51 %	13.51	8.11	1.49	1.55	1.41	7.77	41.14	29.01	80.69	25
Denmark	2,628	53 %	13.43	9.64	2.03	1.42	1.22	7.69	57.48	40	97.32	28.2
England	2,651	48 %	13.50	9.08	1.82	1.85	1.50	7.45	47.57	37.84	90.69	35.1
Estonia	4,257	51 %	13.86	8.21	1.96	1.73	1.43	7.72	36.25	25.2	89.36	30.3
Georgia	3,333	53 %	13.53	5.28	1.76	1.53	1.16	7.96	14.59	29.04	62.72	36.4
Germany	3,560	55 %	13.62	9.40	1.77	1.74	1.17	7.65	55.24	41.26	87.04	31.7
Hungary	3,346	54 %	13.60	7.32	1.81	1.78	1.43	7.58	31.91	40.2	76.07	29.6
Iceland	5,888	52 %	13.74	9.25	1.97	1.27	1.35	7.61	57.21	27.27	99.01	26.1
Ireland Republic	3,012	50 %	13.53	9.28	1.92	2.44	1.31	7.50	84.56	35.55	87	30.6
Israel	4,434	56 %	13.75	8.58	2.08	1.43	1.62	7.88	39.91	30.78	83.73	38.6
Italy	3,692	53 %	13.74	7.87	2.07	2.46	1.75	7.58	43.04	42.74	74.39	35.2
Kazakhstan	3,306	52 %	13.36	4.18	1.72	1.29	0.80	8.56	26.15	68.56	78.9	27.8

Latvia	3,684	52 %	13.58	7.28	1.54	1.81	1.45	7.37	30.88	33.4	83.58	35.1
Lithuania	3,422	51 %	13.77	6.98	1.95	1.81	1.28	7.90	36.38	38.63	79.72	35.7
Luxembourg	3,102	52 %	13.69	10.16	1.95	2.05	1.49	7.66	116.97	40.71	97.06	35.4
Malta	2,170	54 %	13.43	8.67	1.97	2.98	1.58	7.32	45.56	37.54	81.66	28.7
Moldova Republic	4,336	52 %	13.59	9.01	1.85	1.47	1.13	7.75	57.83	40.49	91.89	28.1
Netherlands	2,377	52 %	13.14	9.93	1.95	1.88	1.18	7.90	69.81	28.58	96.49	27.6
Norway	4,534	52 %	13.71	7.80	2.11	2.00	1.52	7.45	32.03	31.31	77.54	30.2
Poland	5,079	54 %	13.38	8.18	2.09	1.57	1.19	7.77	34.93	42.61	74.66	33.5
Portugal	3,860	52 %	13.66	5.15	1.97	2.23	1.18	8.25	12.66	36	76.12	25.7
Romania	3,891	52 %	13.25	6.31	2.09	2.65	1.38	8.34	29.57	39.09	70.68	35.8
Scotland	4,251	54 %	13.56	9.03	2.04	2.00	1.33	7.63	47.57	37.84	90.69	35.1
Serbia	3,075	53 %	14.18	7.37	1.94	1.77	1.13	8.19	17.72	22.89	73.36	35
Slovenia	4,720	51 %	13.70	9.43	1.72	1.47	1.24	7.94	38.96	34.51	79.75	24.6
Spain	3,689	52 %	13.75	8.59	2.05	2.62	0.98	8.05	40.7	37.32	86.11	34.7
Sweden	3,275	52 %	13.76	9.45	2.10	1.66	1.64	7.43	53.52	27.39	89.25	30
Ukraine	5,161	55 %	13.57	5.72	1.83	1.88	1.41	7.66	12.63	30.73	62.55	26.1
Wales	10,688	52 %	13.71	9.31	1.85	2.21	1.37	7.60	47.57	37.84	90.69	35.1
Total	144,934	53 %	13.63	8.14	1.90	1.87	1.35	7.70	41.53	31.7	36.09	82.91

Note. Data for country-level indicators were obtained from the year 2018, or the latest available year prior to 2018. FAS: Family Affluence Scale; FSMU: Frequent social media use; PSMU: Problematic social media use; PC: Psychological complaints; LS: Life satisfaction; GDP: Gross domestic product. Educ. Exp.: Educational expenditure. IUP: Internet use prevalence. Belgium (F) includes Flanders and Belgium (W) includes Wallonia

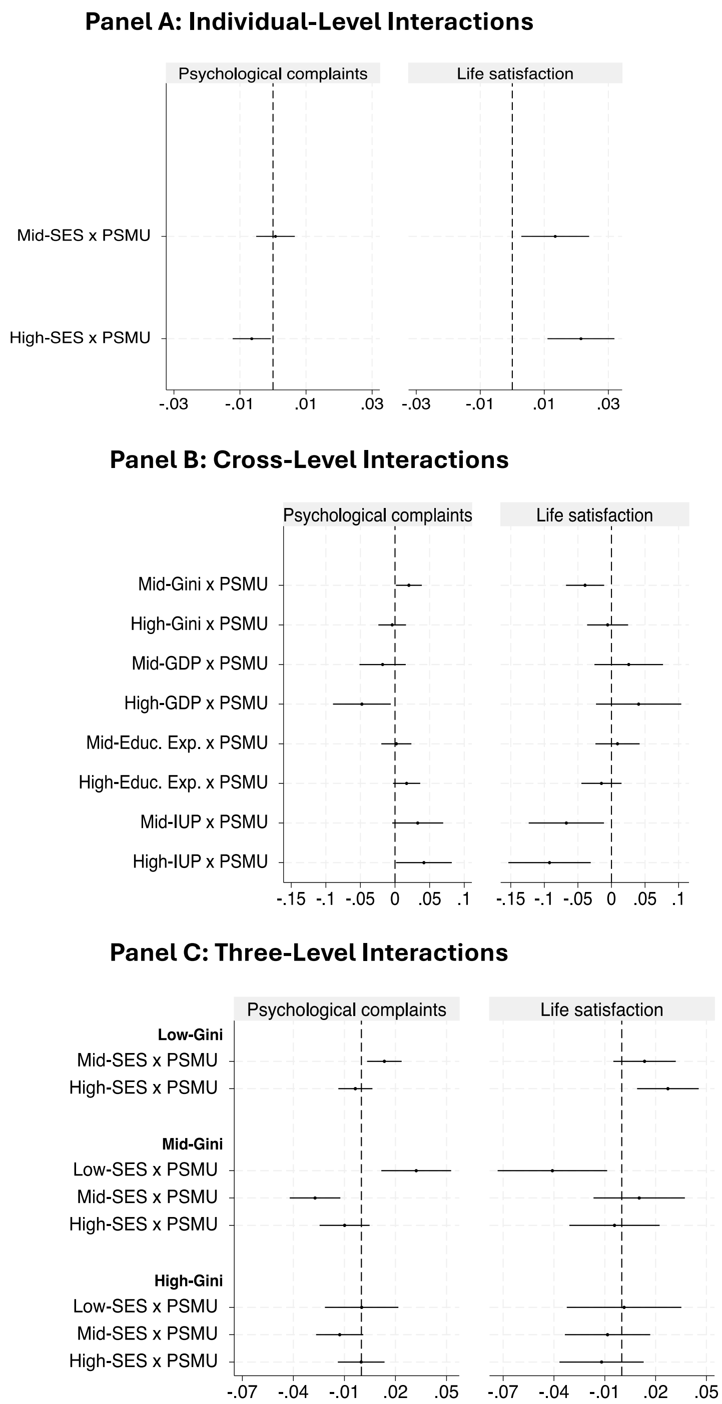
Table 2.2 Mixed-effect multilevel models on psychological complaints and life satisfaction

	Psychological complaints			Life satisfaction		
	Model 1a: Random effect	Model 2a: Ind. level interaction	Model 3a: Cross-level interactions	Model 1b: Random effect	Model 2b: Ind. level interaction	Model 3b: Cross-level interactions
	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Fixed effects						
Intercept	1.179*** (0.033)	1.179*** (0.033)	1.094*** (0.080)	7.626*** (0.053)	7.626*** (0.053)	7.924*** (0.114)
Low-SES						
Mid-SES	-0.035*** (0.006)	-0.035*** (0.006)	-0.035*** (0.006)	0.136*** (0.005)	0.136*** (0.005)	0.136*** (0.005)
High-SES	-0.053*** (0.006)	-0.053*** (0.006)	-0.053*** (0.006)	0.291*** (0.011)	0.290*** (0.011)	0.290*** (0.011)
Problematic Social Media Use (PSMU)	0.139*** (0.004)	0.141*** (0.005)	0.128*** (0.010)	-0.167*** (0.008)	-0.179*** (0.008)	-0.132*** (0.016)
Ind. level interaction						
PSMU x Low-SES						
PSMU x Mid-SES		0.001 (0.003)	0.001 (0.003)		0.013* (0.005)	0.013* (0.005)
PSMU x High-SES		-0.006* (0.003)	-0.006* (0.003)		0.021*** (0.005)	0.021*** (0.005)
Cross-level interactions						
PSMU x Low-GDP						
PSMU x Mid-GDP			-0.018 (0.017)			0.026 (0.026)
PSMU x High-GDP			-0.048* (0.021)			0.040 (0.032)
PSMU x Low-Educ. Expenditure						
PSMU x Mid-Educ. Expenditure			0.002 (0.011)			0.009 (0.017)
PSMU x High-Educ. Expenditure			0.017 (0.010)			-0.015 (0.015)
PSMU x Low-Internet Use Prevalence						

PSMU x Mid- Internet Use Prevalence			0.033			-0.067*
			(0.019)			(0.029)
PSMU x High-Internet Use Prevalence			0.042*			-0.092**
			(0.021)			(0.031)
PSMU x Low-Gini						
PSMU x Mid-Gini			0.020*			-0.039**
			(0.010)			(0.014)
PSMU x High-Gini			-0.004			-0.006
			(0.010)			(0.016)
Random parameters						
Residual variance PSMU	0.001***	0.001***	0.000***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance at country level	0.037***	0.037***	0.030***	0.094***	0.093***	0.060***
	(0.009)	(0.009)	(0.007)	(0.023)	(0.023)	(0.015)
Variance at ind. level	0.909***	0.909***	0.909***	2.991***	2.991***	2.991***
	(0.003)	(0.003)	(0.003)	(0.011)	(0.011)	(0.011)
PSMU 95% PI (std.)	[0.190/0.383]			[-0.506/-0.181]		
Model statistics						
Free Parameters	10	12	28	10	12	28
AIC	397739	**397735**	397749	570368	570356	**570354**
BIC	**397838**	397854	398026	**570467**	570474	570630

Note. $N_{\text{individuals}}$ = 144,934, $N_{\text{countries}}$ = 35. Individual level controls include age, gender, Frequent social media use. Fixed effects of country-level indicators are added in Table A2.2. Explained cross-country variance in Problematic Social Media Use (PSMU) slopes: (0.0006026-0.0004333)/0.0006026 =0.281 for psychological complaints, and (0.0017707-0.0009468)/0.0017707 = 0.465 for life satisfaction. SES: Socioeconomic Status. GDP: Gross domestic product. AIC: Akaike information criterion. BIC: Bayesian information criterion. Lowest AIC and BIC for each outcome are shown in bold. *p<0.05, **p<0.01, ***p<0.001

Figure 2.1 Interaction coefficients for psychological complaints and life satisfaction (95% CI)



Note. $N_{\text{individuals}}$ = 144,934, $N_{\text{countries}}$ = 35. Panel A: Model 2a and Model 2b; Panel B: Model 3a and Model 3b; Panel C: Model 4a and Model 4b. For brevity, only the interaction coefficients are illustrated. SES: Socioeconomic Status. PSMU: Problematic Social Media Use. GDP: Gross domestic product. Educ. Exp.: Educational expenditure. IUP: Internet use prevalence.

2.7 Appendix

Table A2.1 Excluded cases per country

Country	Excluded Cases (%)	Total *N*
Albania	26.35	1,765
Armenia	35.57	4,717
Austria	13.97	4,129
Belgium (Flemish)	18.30	4,333
Belgium (Wallonia)	23.83	5,578
Canada	36.49	12,950
Czech Republic	16.91	11,564
Denmark	17.38	3,181
England	21.96	3,397
Estonia	9.90	4,725
Georgia	21.43	4,242
Germany	18.10	4,347
Hungary	11.69	3,789
Iceland	15.84	6,996
Ireland	21.42	3,833
Israel	42.51	7,712
Italy	10.91	4,144
Kazakhstan	32.09	4,868
Latvia	16.50	4,412
Lithuania	9.88	3,797
Luxembourg	23.78	4,070
Malta	15.76	2,576
Netherlands	7.71	4,698
Norway	23.98	3,127
Poland	13.21	5,224
Portugal	17.09	6,126
Republic of Moldova	17.63	4,686
Romania	14.80	4,567
Scotland	15.34	5,021
Serbia	21.82	3,933
Slovenia	16.71	5,667
Spain	14.61	4,320
Sweden	21.74	4,185
Ukraine	22.51	6,660
Wales	32.99	15,951
Total	21.78	185,290

Table A2.2 Fixed effects of country-level predictors on intercepts for psychological complaints and life satisfaction

	Psychological complaints		Life satisfaction	
	Model 3a: Cross-level interactions	Model 4a: 3-way interactions	Model 3b: Cross-level interactions	Model 4b: 3-way interactions
Fixed effects (country-level)	B (SE)	B (SE)	B (SE)	B (SE)
Low-GDP (reference)				
Mid-GDP	0.231 (0.133)	0.231 (0.133)	–0.070 (0.190)	–0.070 (0.190)
High-GDP	0.178 (0.166)	0.178 (0.166)	–0.107 (0.237)	–0.107 (0.237)
Low-Educ. Expenditure (reference)				
Mid-Educ. Expenditure	–0.069 (0.087)	–0.069 (0.087)	0.010 (0.124)	0.010 (0.124)
High-Educ. Expenditure	–0.084 (0.077)	–0.084 (0.077)	0.048 (0.663)	0.048 (0.663)
Low-Internet Use Prevalence (reference)				
Mid- Internet Use Prevalence	–0.076 (0.147)	–0.076 (0.147)	–0.067* (0.029)	–0.067* (0.029)
High-Internet Use Prevalence	–0.080 (0.161)	–0.080 (0.161)	–0.092** (0.031)	–0.092** (0.031)
Low-Gini (reference)				
Mid-Gini	0.068 (0.074)	0.078 (0.074)	–0.192 (0.106)	–0.257* (0.107)
High-Gini	0.093 (0.079)	0.109 (0.080)	–0.047 (0.113)	–0.128 (0.114)

Note. $N_{\text{individuals}}$ = 144,934, $N_{\text{countries}}$ = 35. Analyses present the Fixed effects of country-level predictors on intercepts for psychological complaints and life satisfaction that are not presented in the comparable models in Table 2.2. *p<0.05, **p<0.01, ***p<0.001.

Table A2.3 Three-way cross-level interaction coefficients on psychological complaints and life satisfaction

	Psychological complaints	Life satisfaction
	Model 4a: 3-way interactions	Model 4b: 3-way interactions
	B (SE)	B (SE)
Fixed effects		
Intercept	1.086*** (0.080)	7.971*** (0.114)
Problematic Social Media Use (PSMU)	0.123*** (0.011)	-0.134*** (0.016)
Cross-level interactions		
PSMU x Low-SES x Low-Gini (ref)		
PSMU x Mid-SES x Low-Gini	0.014** (0.005)	0.013 (0.009)
PSMU x High-SES x Low-Gini	–0.004 (0.005)	0.027** (0.009)
PSMU x Low -SES x Mid-Gini	0.032** (0.010)	–0.041* (0.016)
PSMU x Mid-SES x Mid-Gini	–0.027*** (0.008)	0.010 (0.014)
PSMU x High-SES x Mid-Gini	–0.010 (0.007)	–0.004 (0.014)
PSMU x Low-SES x High-Gini	0.000 (0.011)	0.001 (0.017)
PSMU x Mid-SES x High-Gini	–0.013† (0.007)	–0.008 (0.013)
PSMU x High-SES x High-Gini	–0.000 (0.007)	–0.012 (0.013)
Random parameters		
Residual variance PSMU	0.000*** (0.000)	0.001*** (0.000)
Variance at country level	0.030*** (0.007)	0.060*** (0.015)
Variance at ind. level	0.909*** (0.003)	2.990*** (0.011)
Model statistics		
Free Parameters	36	36
AIC	397742.9	570354
BIC	398098.7	570630

Note. $N_{\text{individuals}}$ = 144,934, $N_{\text{countries}}$ = 35. Analyses present the three-way cross-level interaction coefficients for psychological complaints and life satisfaction that are not presented in the comparable models in Table 2.2. †*p*<0.10, **p*<0.05, ***p*<0.01, ****p*<0.001.

Table A2.4 Mixed-effect multilevel models on psychological complaints and life satisfaction (OECD countries)

	Psychological complaints			Life satisfaction		
	Model 1a: Random effect	Model 2a: Ind. level interaction	Model 3a: Cross-level interactions	Model 1b: Random effect	Model 2b: Ind. level interaction	Model 3b: Cross-level interactions
	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Fixed effects						
Intercept	1.221*** (0.033)	1.221*** (0.033)	1.277*** (0.067)	7.538*** (0.036)	7.539*** (0.036)	7.663*** (0.76)
Low-SES						
Mid-SES	-0.042*** (0.007)	-0.041*** (0.007)	-0.035*** (0.006)	0.285*** (0.012)	0.284*** (0.012)	0.284*** (0.012)
High-SES	-0.072*** (0.007)	-0.072*** (0.007)	-0.053*** (0.006)	0.518*** (0.012)	0.517*** (0.012)	0.518*** (0.011)
Problematic Social Media Use (PSMU)	0.141*** (0.005)	0.144*** (0.005)	0.128*** (0.010)	-0.181*** (0.007)	-0.193*** (0.008)	-0.179*** (0.016)
Ind. level interaction						
PSMU x Low-SES						
PSMU x Mid-SES		0.000 (0.003)	0.001 (0.003)		0.013* (0.005)	0.013* (0.006)
PSMU x High-SES		-0.009** (0.003)	-0.009** (0.003)		0.025*** (0.006)	0.025*** (0.006)
Cross-level interactions						
PSMU x Low-GDP						
PSMU x Mid-GDP			-0.022 (0.013)			0.003 (0.019)
PSMU x High-GDP			-0.027 (0.015)			-0.003 (0.023)
PSMU x Low-Educ. Expenditure						
PSMU x Mid-Educ. Expenditure			0.011 (0.012)			-0.013 (0.017)
PSMU x High-Educ. Expenditure			0.013 (0.011)			0.005 (0.016)
PSMU x Low-Internet Use Prevalence						

PSMU x Mid- Internet Use Prevalence			-0.005			-0.013
			(0.013)			(0.017)
PSMU x High-Internet Use Prevalence			0.005			0.005
			(0.015)			(0.016)
PSMU x Low-Gini						
PSMU x Mid-Gini			0.021†			-0.037*
			(0.010)			(0.016)
PSMU x High-Gini			-0.002			0.003
			(0.012)			(0.018)
Random parameters						
Residual variance PSMU	0.001***	0.001***	0.000***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance at country level	0.028***	0.028***	0.017***	0.033***	0.033***	0.021***
	(0.008)	(0.007)	(0.005)	(0.009)	(0.009)	(0.006)
Variance at ind. level	0.898***	0.898***	0.898***	2.995***	2.995***	2.995***
	(0.004)	(0.008)	(0.004)	(0.012)	(0.012)	(0.012)
PSMU 95% PI (std.)	[0.206/0.370]			[-0.492/-0.247]		
Model statistics						
Free Parameters	10	12	28	10	12	28
AIC	330434.1	**330428.7**	330435.2	476155.1	**476141.3**	476153.9
BIC	**330531.1**	330545.2	330706.9	**476252.1**	476257.8	476425.6

Note. $N_{individuals}$ = 120,960, $N_{countries}$ = 27. Individual level controls include age, gender, Frequent social media use. Fixed effects of country-level indicators are added in Table A2. Explained cross-country variance in Problematic Social Media Use (PSMU) slopes: (0.0006277-0.0003962)/0.0006277 =0.369 for psychological complaints, and (0.001166-0.0008108)/0.001166 = 0.305 for life satisfaction. SES: Socioeconomic Status. GDP: Gross domestic product. AIC: Akaike information criterion. BIC: Bayesian information criterion. Lowest AIC and BIC for each outcome are shown in bold. †*p*<0.1 **p*<0.05, ***p*<0.01, ****p*<0.001

Table A2.5 Three-way cross-level interaction coefficients on psychological complaints and life satisfaction (OECD Countries)

	Psychological complaints	Life satisfaction
	Model 4a: 3-way interactions	Model 4b: 3-way interactions
	B (SE)	B (SE)
Fixed effects		
Intercept	1.262*** (0.067)	7.707*** (0.077)
Problematic Social Media Use (PSMU)	0.139*** (0.011)	-0.179*** (0.017)
Cross-level interactions		
PSMU x Low-SES x Low-Gini (ref)		
PSMU x Mid-SES x Low-Gini	0.015** (0.006)	0.007 (0.010)
PSMU x High-SES x Low-Gini	–0.005 (0.006)	0.029** (0.010)
PSMU x Low -SES x Mid-Gini	0.034** (0.012)	–0.040* (0.018)
PSMU x Mid-SES x Mid-Gini	–0.029*** (0.008)	0.016 (0.015)
PSMU x High-SES x Mid-Gini	–0.009 (0.008)	–0.006 (0.015)
PSMU x Low-SES x High-Gini	0.004 (0.013)	0.005 (0.020)
PSMU x Mid-SES x High-Gini	–0.017* (0.008)	0.002 (0.014)
PSMU x High-SES x High-Gini	–0.002 (0.008)	–0.006 (0.014)
Random parameters		
Residual variance PSMU	0.000*** (0.000)	0.001*** (0.000)
Variance at country level	0.017*** (0.004)	0.060*** (0.015)
Variance at ind. level	0.897*** (0.004)	2.990*** (0.011)
Model statistics		
Free Parameters	36	36
AIC	330423.2	476141
BIC	330772.5	476490.4

Note. $N_{individuals}$ = 120,960, $N_{countries}$ = 27. Analyses present the three-way cross-level interaction coefficients for psychological complaints and life satisfaction that are not presented in the comparable models in Table 2. **p*<0.05, ***p*<0.01, ****p*<0.001.

Table A2.6 Coefficients of log-transformed PSMU variable at each model

	Psychological complaints	Life satisfaction
	B (SE)	B (SE)
Model 1: Random effect		
Problematic Social Media Use (PSMU)	0.425*** (0.012)	-0.507*** (0.020)
Model 2: Ind. level interaction		
PSMU	0.434*** (0.013)	-0.549*** (0.022)
PSMU x Low-SES (ref)		
PSMU x Mid-SES	-0.003 (0.009)	0.050** (0.016)
PSMU x High-SES	-0.023** (0.009)	0.073*** (0.016)
Model 3: Cross-level interactions		
PSMU	0.401*** (0.028)	-0.423*** (0.043)
PSMU x Low-GDP (ref)		
PSMU x Mid-GDP	-0.028 (0.046)	0.050 (0.070)
PSMU x High-GDP	-0.104† (0.058)	0.066 (0.087)
PSMU x Low-Educ. Expenditure (ref)		
PSMU x Mid-Educ. Expenditure	0.027 (0.030)	0.005 (0.045)
PSMU x High-Educ. Expenditure	0.028 (0.027)	-0.006 (0.041)
PSMU x Low-Internet Use Prevalence (ref)		
PSMU x Mid- Internet Use Prevalence	0.059 (0.051)	-0.156 (0.077)
PSMU x High-Internet Use Prevalence	0.088 (0.056)	-0.220 (0.084)
PSMU x Low-Gini (ref)		
PSMU x Mid-Gini	0.051* (0.026)	-0.111** (0.039)
PSMU x High-Gini	-0.014 (0.028)	-0.018 (0.042)
Model 4: 3-way interactions		
PSMU	0.388*** (0.029)	-0.426*** (0.045)
PSMU x Low-SES x Low-Gini (ref)		
PSMU x Mid-SES x Low-Gini	0.029† (0.015)	0.046† (0.027)
PSMU x High-SES x Low-Gini	–0.016 (0.015)	0.085** (0.027)
PSMU x Low -SES x Mid-Gini	0.085** (0.029)	–0.119* (0.045)
PSMU x Mid-SES x Mid-Gini	–0.074** (0.022)	0.036 (0.040)
PSMU x High-SES x Mid-Gini	–0.029 (0.022)	–0.008 (0.040)
PSMU x Low-SES x High-Gini	-0.007 (0.030)	0.000 (0.048)
PSMU x Mid-SES x High-Gini	–0.028 (0.021)	-0.022 (0.038)
PSMU x High-SES x High-Gini	0.004 (0.021)	–0.028 (0.038)

Note. $N_{\text{individuals}}$ = 144,934, $N_{\text{countries}}$ = 35. For brevity, only PSMU coefficients are reported. †*p*<0.10, **p*<0.05, ***p*<0.01, ****p*<0.001.

Table A2.7 Three-level random coefficient multilevel model on psychological complaints and life satisfaction

	Psychological complaints			Life satisfaction		
	Model 1a: Random effect	Model 2a: Ind. level interaction	Model 3a: Cross-level interactions	Model 1b: Random effect	Model 2b: Ind. level interaction	Model 3b: Cross-level interactions
	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)	B (SE)
Fixed effects						
Intercept	1.189***	1.188***	1.075***	7.615***	7.615***	7.921***
	(0.033)	(0.033)	(0.080)	(-0.053)	(-0.053)	(-0.115)
Low-SES						
Mid-SES	-0.042***	-0.041***	-0.047***	0.297***	0.297***	0.299***
	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(-0.012)
High-SES	-0.069***	-0.069***	-0.081***	0.530***	0.530***	0.534***
	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(-0.012)
PSMU	0.141***	0.145***	0.133***	-0.168***	-0.180***	-0.132***
	(0.004)	(0.005)	(0.010)	(0.053)	(0.008)	(0.017)
Ind. level interaction						
PSMU x Low-SES						
PSMU x Mid-SES		-0.001	-0.002		0.014*	0.015**
		(0.003)	(0.006)		(0.006)	(0.006)
PSMU x High-SES		-0.008*	-0.010**		0.024***	0.028***
		(0.003)	(0.003)		(0.006)	(0.006)
Cross-level interactions						
PSMU x Low-School Affluence						
PSMU x Mid- School Affluence			-0.001			-0.007
			(0.004)			(0.007)
PSMU x High- School Affluence			-0.006			-0.018*
			(0.004)			(0.008)
PSMU x Low- School Gini						
PSMU x Mid- School Gini			0.002			-0.009
			(0.004)			(0.007)
PSMU x High- School Gini			-0.004			0.004
			(0.004)			(0.008)
Random parameters						
Residual variance PSMU (country level)	0.001***	0.001***	0.000***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Residual variance PSMU (school level)	0.001***	0.001***	0.001***	0.006***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Variance at country level	0.037***	0.037***	0.029***	0.093***	0.092***	0.059***
	(0.009)	(0.009)	(0.007)	(0.023)	(0.023)	(0.015)
Variance at school level	0.024***	0.024***	0.023***	0.072***	0.072***	0.072***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
Variance at ind. level	0.883***	0.883***	0.883***	2.886***	2.886***	2.886***
	(0.003)	(0.003)	(0.003)	(0.011)	(0.011)	(0.011)
PSMU 95% PI (std.) country	[0.202/0.380]			[-0.506/-0.184]		
PSMU 95% PI (std.) school	[0.143/0.439]			[-0.666/-0.024]		
Model statistics						
Free Parameters	12	14	38	12	14	38
AIC	378746.6	**378741.5**	378680.3	542709.8	542694.2	**542693.8**
BIC	**378864.6**	378878.2	379054.1	**542827.9**	542832.9	543067.6

Note. $N_{individuals}$ = 138,335, $N_{schools}$ = 4,365, $N_{countries}$ = 35. The individual level control variables (age, gender, Frequent social media use), fixed effects of school-level indicators, and fixed effects and cross-level interactions of country-level variables (Gross domestic product per capita, educational expenditure, Internet use prevalence, Gini) are omitted from the table (see Table A2.8). To maximise statistical robustness in the modelling, schools with less than 10 students (N_{school} = 1,182, $N_{individual}$ = 6,599) were not included in these analyses. SES: Socioeconomic Status. PSMU: Problematic Social Media Use. Sch.: School. AIC: Akaike information criterion. BIC: Bayesian information criterion. Explained cross-country variance in PSMU slope: (0.0005402-0.0003967)/0.0005402 = 0.266 for psychological complaints and (0.0005402-0.0003967)/0.0005402 = 0.266 for life satisfaction. Explained cross-school variance in PSMU: (0.0012669-0.0012641)/0.0012669 = 0.002 for psychological complaints and (0.0012669-0.0012641)/0.0012669 = 0.002 for life satisfaction. Lowest AIC and BIC for each outcome are shown in bold. *p<0.05, **p<0.01, ***p<0.001.

Table A2.8 Fixed effects of school- and country-level predictors on the intercepts and cross-level interactions of country-level variables for psychological complaints and life satisfaction

	Psychological complaints		Life satisfaction	
	Model 3a: Cross-level interactions	Model 4a: 3-way interactions	Model 3b: Cross-level interactions	Model 4b: 3-way interactions
	B (SE)	B (SE)	B (SE)	B (SE)
Fixed effects (school-level)				
Low-School Affluence (reference)				
Mid-School Affluence	0.228** (0.009)	0.228** (0.009)	–0.026 (0.017)	–0.026 (0.017)
High-School Affluence	0.082*** (0.011)	0.082*** (0.011)	–0.017 (0.019)	–0.016 (0.019)
Low-School Gini (reference)				
Mid-School Gini	0.002 (0.009)	0.009 (0.014)	0.006 (0.167)	0.003 (0.025)
High- Sch. Gini	-0.000 (0.010)	-0.003 (0.014)	0.011 (0.119)	0.002 (0.026)
Fixed effects (country-level)				
Low-GDP (reference)				
Mid-GDP	0.243 (0.132)	0.243 (0.132)	-0.077 (0.190)	-0.077 (0.190)
High-GDP	0.196 (0.165)	0.196 (0.165)	-0.129 (0.237)	-0.129 (0.237)
Low-Educ. Expenditure (reference)				
Mid-Educ. Expenditure	–0.069 (0.086)	–0.069 (0.086)	0.017 (0.123)	0.017 (0.123)
High-Educ. Expenditure	–0.083 (0.077)	–0.083 (0.077)	0.055 (0.111)	0.055 (0.111)
Low-Internet Use Prevalence (reference)				
Mid- Internet Use Prevalence	–0.090 (0.146)	–0.090 (0.146)	–0.236 (0.209)	–0.236 (0.209)
High-Internet Use Prevalence	–0.093 (0.159)	–0.093 (0.159)	–0.285 (0.229)	–0.285 (0.229)
Low-Gini (reference)				
Mid-Gini	0.066 (0.074)	0.066 (0.074)	-0.203 (0.074)	-0.203 (0.074)
High-Gini	0.089 (0.079)	0.089 (0.079)	-0.063 (0.113)	-0.063 (0.113)
Cross-level interactions (country-level)				
PSMU x Low-GDP				
PSMU x Mid-GDP	-0.020 (0.017)	-0.020 (0.017)	0.027 (0.026)	0.027 (0.026)

PSMU x High-GDP	-0.045* (0.021)	-0.045* (0.021)	0.037 (0.032)	0.037 (0.032)
PSMU x Low-Educ. Expenditure				
PSMU x Mid-Educ. Expenditure	-0.000 (0.011)	-0.001 (0.011)	0.012 (0.017)	0.013 (0.017)
PSMU x High-Educ. Expenditure	0.015 (0.010)	0.015 (0.010)	-0.010 (0.015)	-0.011 (0.015)
PSMU x Low-Internet Use Prevalence				
PSMU x Mid- Internet Use Prevalence	0.033 (0.018)	0.033 (0.018)	–0.066* (0.028)	–0.066* (0.028)
PSMU x High-Internet Use Prevalence	0.041* (0.020)	0.041* (0.020)	–0.093** (0.031)	–0.093** (0.031)
PSMU x Low-Gini				
PSMU x Mid-Gini	0.018 (0.009)	0.018 (0.009)	-0.034* (0.015)	-0.034* (0.015)
PSMU x High-Gini	-0.005 (0.010)	-0.005 (0.010)	-0.002 (0.016)	-0.002 (0.016)

Note. $N_{\text{individuals}}$ = 138,335, N_{schools} = 4,365, $N_{\text{countries}}$ = 35. Fixed effects of school-level indicators, and fixed effects and cross-level interactions of country-level variables (Gross domestic product per capita, educational expenditure, Internet use prevalence, Gini) that were not added in Table A3. To maximise statistical robustness in the modelling, schools with less than 10 students (N_{school} = 1,182, $N_{\text{individual}}$ = 6,599) were not included in these analyses. *p<0.05, **p<0.01, ***p<0.001.

Table A2.9 Three-way cross-level interaction coefficients on psychological complaints and life satisfaction

	Psychological complaints	Life satisfaction
	Model 4a: 3-way interactions	Model 4b: 3-way interactions
	B (SE)	B (SE)
Fixed effects		
Intercept	1.074*** (0.080)	7.925*** (0.114)
Problematic Social Media Use (PSMU)	0.137*** (0.011)	-0.142*** (0.018)
Cross-level interactions		
PSMU x Low-SES x Low- School Gini (ref)		
PSMU x Mid-SES x Low- School Gini	–0.009 (0.006)	0.034** (0.011)
PSMU x High-SES x Low- School Gini	–0.011† (0.006)	0.036** (0.011)
PSMU x Low-SES x Mid- School Gini	–0.003 (0.006)	0.008 (0.012)
PSMU x Mid-SES x Mid- School Gini	0.011 (0.008)	–0.032* (0.014)
PSMU x High-SES x Mid- School Gini	0.004 (0.008)	–0.015 (0.014)
PSMU x Low-SES x High- School Gini	–0.007 (0.006)	0.013 (0.012)
PSMU x Mid-SES x High- School Gini	0.010 (0.008)	–0.020 (0.014)
PSMU x High-SES x High- School Gini	–0.002 (0.008)	–0.006 (0.014)
Random parameters		
Residual variance PSMU (country level)	0.000*** (0.000)	0.001*** (0.000)
Residual variance PSMU (school level)	0.001*** (0.000)	0.006*** (0.001)
Variance at country level	0.029*** (0.007)	0.059*** (0.015)
Variance at school level	0.022*** (0.001)	0.072*** (0.004)
Variance at ind. level	0.883*** (0.003)	2.886*** (0.011)
Model statistics		
Free Parameters	46	46
AIC	378689.0	542699.8
BIC	379141.5	543152.3

Note. $N_{\text{individuals}}$ = 138,335, N_{schools} = 4,365, $N_{\text{countries}}$ = 35. Three-way interactions following from the models presented in Table A3. To maximise statistical robustness in the modelling, schools with less than 10 students (N_{school} = 1,182, $N_{\text{individual}}$ = 6,599) were not included in these analyses. †p<0.10, *p<0.05, **p<0.01, ***p<0.001.

Figure A2.1 Marginal effects of SES

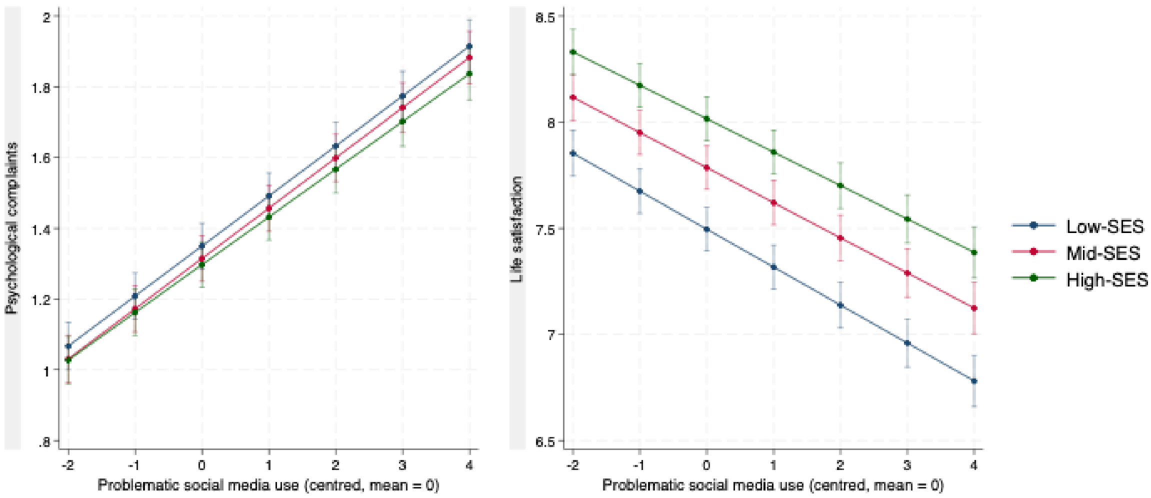
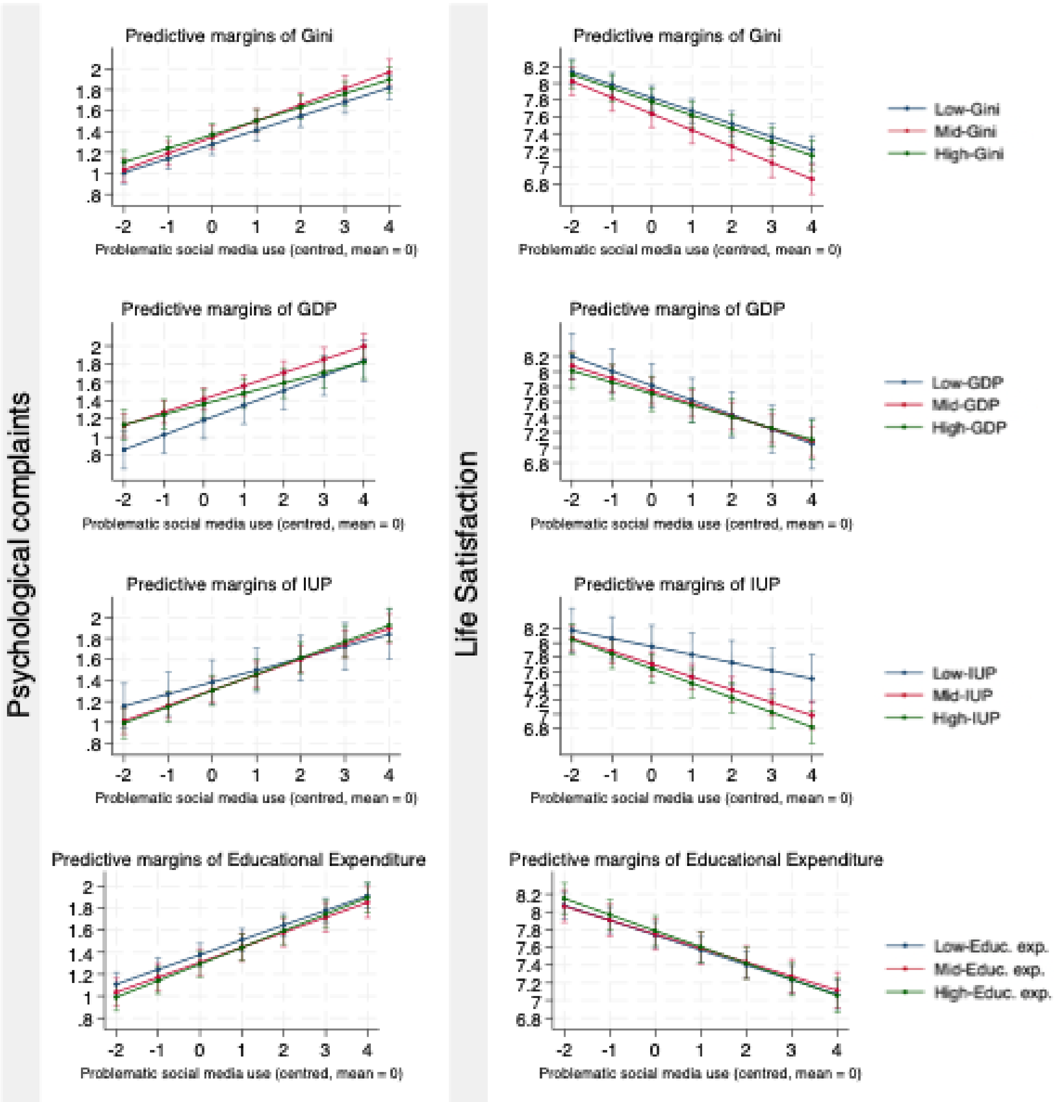
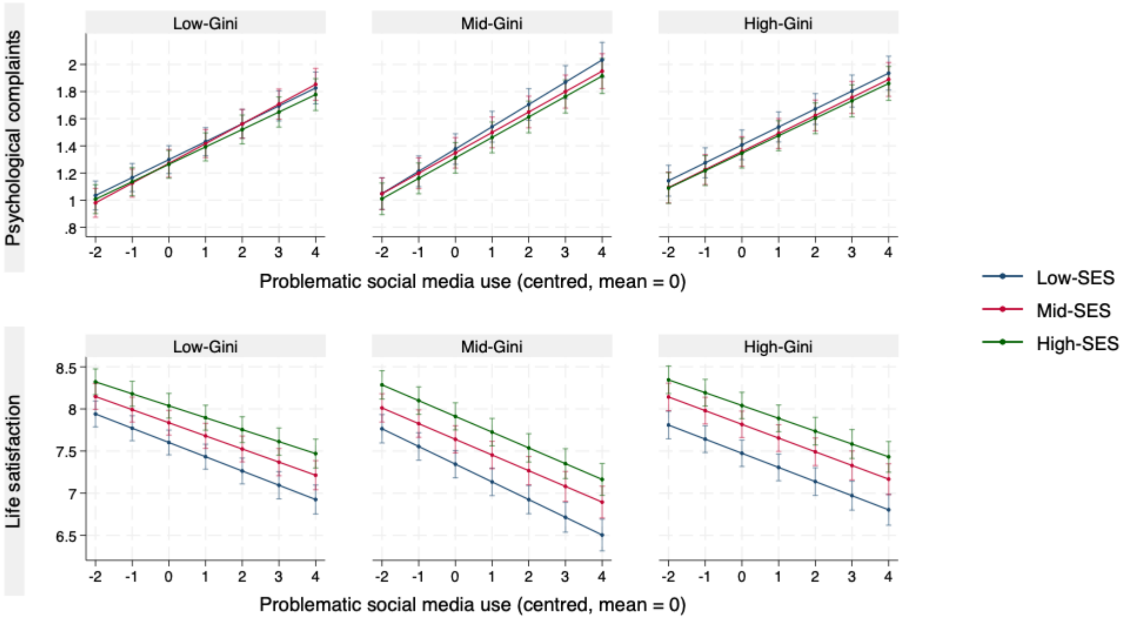


Figure A2.2 Marginal effects of country-level indicators



Note. $N_{\text{individuals}}$ = 144,934, $N_{\text{countries}}$ = 35. 95% Confidence Intervals. GDP: Gross domestic product. Educ. Exp.: Educational expenditure. IUP: Internet use prevalence.

Figure A2.3 Marginal effects of SES in low- mid- and high-Gini countries



Note. $N_{\text{individuals}}$ = 144,934, $N_{\text{countries}}$ = 35. 95% Confidence Intervals. GDP: Gross domestic product. Educ. Exp.: Educational expenditure. IUP: Internet use prevalence.

Chapter 3: Study 2 - Digital User Profiles and Adolescent Mental Well-Being: The Role of Digital Maturity

An edited version of this chapter is under review at ***Cyberpsychology, Behavior, and Social Networking*** *as of April 2026.*

Abstract

This study examines how different digital user profiles link to adolescents' mental well-being, and proposes a novel focus on digital maturity –i.e., the self-determined use of digital technologies to support psychological growth– to explain this relationship. We applied Generalised Latent Class Analysis (GLCA) and Mediation Analysis to a sample of 349 adolescents in Ireland (M_{age} = 15.44, 52.10% girls). Results identified three classes of digital users, including (i) '*Light'* users (i.e., low-intensity users, mainly restricted to communication activities), (ii) '*Reserved'* users (i.e., medium-intensity users who focus on private communication and passive forms of media entertainment), and (iii) '*Outgoing'* users (i.e., high-intensity users who have a highly active and public-oriented online profile). Both '*Outgoing'* and '*Reserved*' users showed lower levels of mental well-being than '*Light*' users. Yet, while the reduced mental well-being of '*Outgoing'* users was fully mediated by their lower digital maturity, compared to '*Light*' users, digital maturity did not mediate the well-being disadvantage of '*Reserved'* users relative to *'Light'* users. Overall, this study indicates that distinct digital user typologies capture important differences in adolescent mental well-being, while suggesting that lower digital maturity contributes to explain the lower mental well-being of adolescents with risk-related digital profiles.

Key words: Adolescent well-being; Digital maturity; Digital technology use; Online activities; Social media

3.1 Introduction

Digital technologies are essential to adolescents' contemporary lives, and bring both opportunities (e.g., networks and educational tools) and risks (e.g., cyberbullying and online addiction) (Holmarsdottir et al., 2024; Livingstone & Helsper, 2010; Ólafsson et al., 2013; Van Rooij et al., 2010; Schoon et al., 2024). While studies found that high levels of digital use relate to lower mental well-being (Bohnert & Gracia, 2021; Keles et al., 2020; Walsh et al., 2020), the context and conditions of digital use matter strongly (Beyens et al., 2020). Previous research indicated that individual factors such as digital literacy, autonomy, and social skills are central in shaping adolescents' online experiences (De Coninck et al., 2023; Horwood & Anglim, 2019; Lamash et al., 2024). Yet, the mechanisms linking digital use to adolescent mental well-being outcomes are still not clearly understood.

The present study examines how different digital user profiles shape adolescents' mental well-being, and proposes a novel focus on digital maturity –i.e., self-determined use of digital technologies to support psychological growth– to explain this relationship. Digital maturity is a new, empirically validated concept that captures three dimensions of digital technology, namely (i) digital/online autonomy, (ii) problem-solving digital skills, and (iii) online social and citizenship interactions (Laaber et al., 2023). While digital maturity is expected to support youth psychological growth and mental well-being, its role in mediating how different profiles of digital users are associated with adolescent well-being remains unknown. Our study closes this important gap in the literatures on adolescence, digital media and well-being by analysing Irish primary data and combining a generalised latent class analysis (GLCA) with a mediation analysis modelling strategy.

3.1.1 Digital User Profiles and Adolescents' Mental Well-being

Digital use is highly prevalent among adolescents today, involving a wide range of digital interactions (e.g., socialising, gaming, sharing content, learning activities) across increasingly diverse and complex online platforms (e.g., TikTok, Instagram, YouTube, WhatsApp) (Scott et al., 2024; Verduyn et al., 2022). On average, the association between screen time and mental well-being has been found to be relatively small (Odgers & Jensen, 2020; Przybylski & Weinstein, 2017; Valkenburg et al., 2022). However, adolescents utilize digital devices for diverse purposes that are likely to lead to different mental well-being outcomes. For example, fostering social support online was found to be associated with lower social anxiety (Best et al., 2014), but various forms of online gaming were found to be linked to aggression and depressive mood (Holtz & Appel, 2011).

A growing body of literature has examined how adolescent time spent on different social media platforms links to dissimilar mental well-being outcomes. While earlier studies focused particularly on Facebook use (Marino et al., 2018; Valenzuela et al., 2009), each digital platform offers somewhat unique opportunities for engagement, social interaction and peer support, as well as specific risks linked to social comparisons, cyberbullying or fear of missing out (Craig et al., 2020; Masciantonio et al., 2021; Steele et al., 2020). For example, Instagram was found to pose a greater risk for young people's body image compared to Facebook, as Instagram promotes more visual engagement and comparisons (Engeln et al., 2020; Kleemans et al., 2018). Another study on adolescents found that Instagram, TikTok, and YouTube were linked to more depressive symptoms, whereas Twitter (for boys), Snapchat, and Facebook had no significant association with mental well-being (Gentzler et al., 2023). Overall, different types of social media seem to have dissimilar implications for adolescents' emotional regulation, life satisfaction and global mental well-being.

Scholars have argued that 'active' digital use behaviours (e.g., posting content or chatting others) may support social connectedness and improve mental well-being, while 'passive' digital use (e.g., browsing) may lead to social comparisons and reduced mental well-being (Angelini et al., 2024; Verduyn et al., 2022; Yang et al., 2021). However, this dual framework may not adequately illustrate digital use patterns as individuals can engage in various forms of digital use concurrently rather than in isolation (Trifiro & Gerson, 2019). For instance, adolescents may want to seek new connections which may exacerbate adolescents' social well-being problems, but also try to maintain close friendships online which may help their mental well-being (Verduyn et al., 2022; Yang et al., 2021). Focusing on distinct patterns of digital user profiles could help to disentangle this issue, but this literature remains inconclusive. One study on early adolescents identified four user profiles (broadcasters, high communicators, moderate communicators, minimal), showing that broadcasters (i.e., high communication engagement and actively sharing online content) had lowest mental well-being (Winstone et al., 2022). However, another study found no clear association between different types of digital users (passive public, passive private, and active private) and adolescents' mental well-being (Beyens et al., 2024). Additionally, the mechanisms linking young people's online engagement styles with mental well-being outcomes are unclear.

Our study contributes to the adolescence, digital media and well-being literatures through examining whether distinct digital user profiles link to variations in mental well-being, addressing specifically the role of digital maturity as a novel mediating factor. Rather than studying single digital behaviours in isolation (e.g., time spent on gaming, browsing, or social networking), our study focuses on different profiles of adolescents' digital users to capture whether combinations of digital practices shape adolescents' digital experiences. We do so by adopting a novel person-centred approach that encapsulates coherent forms of digital use that could correlate to different well-being outcomes.

3.1.2 The Role of Digital Maturity

The study of the relationship between adolescent digital use and mental well-being can be understood through the lens of Ryan and Deci's (2017) seminal work on Self-Determination Theory (SDT). SDT emphasises relatedness, autonomy, and competence as essential for psychological growth and well-being, capturing whether digital use is beneficial or harmful for mental well-being, depending on whether such psychological needs are fulfilled (Parent, 2023; Peters et al., 2018; West et al., 2024). Using this approach, adolescent online social interactions have been understood as mechanisms for relatedness purposes and social capital (Domahidi, 2018; Shankleman et al., 2021; West et al., 2024) and digital autonomy/competence as enablers of mental well-being (Vissenberg et al., 2022; Reinecke et al., 2014). However, the SDT framework lacks a specific application to digital contexts, which motivates new conceptual frameworks addressing digital autonomy, online relatedness, and ICT competence.

Digital maturity encapsulates adolescents' complex digital use behaviour through mechanisms that are unique to online settings, including: (i) autonomy in digital use and in online mediums, (ii) problem-solving skills regarding digital contexts, and (iii) online positive and negative social interactions including aspects of digital citizenship (Laaber et al., 2023). This holistic framework suggests that the benefits and risks associated with digital use are not uniform, but conditional on how adolescents engage with digital devices. For example, digital maturity could be improved by learning relevant digital skills to navigate the digital world, gaining agency to avoid harmful online content, and fostering digital relatedness through social media (Arenas & Yazdi, 2022). By contrast, one recent study with Austrian, Danish, and Spanish data found weak associations between adolescents' self-reported active digital use and their levels of digital maturity (Koch et al., 2024b).

Theoretically, digital maturity can improve adolescents' mental well-being by fostering their psychological need satisfaction (Laaber et al., 2024; Van de Casteele et al., 2024) through helping them to perceive digital devices as tools to achieve personal and academic goals (Laaber et al., 2024). This implies that differences in adolescent digital maturity could explain why certain online users show poorer mental well-being than others. Yet, to date, research has not provided an empirical examination of whether digital maturity mediates the association between distinct digital user profiles and adolescent mental well-being outcomes.

3.1.3 The Present Study

This study examines how different profiles of adolescents' digital users relate to variations in mental well-being, and it further examines whether digital maturity mediates this relationship. We investigate two main questions: (1) How do different digital user profiles relate to adolescent mental well-being?; and (2) What role does digital maturity play in mediating the association between digital profile users and adolescent mental well-being?

Our study identifies different digital users by using a latent typology approach that accounts for rich combinations of variations in digital use. We do so by considering differences in *intensity* (i.e., how often adolescents use digital devices), *type* of digital network (e.g., communication vs interactive), and *purpose* of usage (e.g., meeting friends, getting in touch with new people, sharing content publicly). This multidimensional approach to digital user profiles is novel in capturing important variations in adolescent well-being. For example, some young people use digital media sporadically and mainly for maintaining close ties with friends, and this may indicate low overexposure and more protected forms of digital use (Best et al., 2014; Domahidi, 2018). By contrast, users relying on entertainment and private community platforms may point to more inward-facing forms of digital engagement, while still involving exposure to comparison, exclusion, or fear of missing out (Burnell et al., 2019; Winstone et al., 2023). Additionally, high-intensity and outward-looking adolescents in their digital activity who actively seek information, share content, and connect with broader publics may open opportunities for self-expression and social capital (Yang et al., 2021), but at the cost of exposing adolescents to online scrutiny, conflict, and pressures of constant connectivity (Livingstone et al., 2021; Gomez et al., 2022). Our study incorporates these nuances of digital user profiles to capture (i) whether complex overlapping categories of digital user profiles are associated with adolescent mental well-being and (ii) whether digital maturity mediates the relationship between digital user profiles and adolescent mental well-being outcomes.

Building on SDT (Ryan & Deci, 2017) and previous literature, we develop two hypotheses. First, we hypothesise that digital user profiles differ in their mental well-being, and concretely that adolescents with lower-intensity and socially focused online styles report better mental well-being than adolescents with higher-intensity, outward-facing and entertainment-driven profiles (*Hypothesis 1*). Second, we hypothesise that digital maturity mediates the relationship between digital user profiles and adolescent mental well-being. Specifically, adolescents with high-intensity and outward-facing profiles may be subject to lower levels of digital maturity, which in turn may reduce their capacity to regulate and sustain beneficial online interactions to their well-being, compared to adolescents with better balanced and risk-averse digital profiles (*Hypothesis 2*).

3.2 Methods

3.2.1 Participants

The study got approval from the Ethics Committee of the Faculty of Humanities, Arts and Social Sciences from Trinity College Dublin. After ethics approval, a sample of 413 adolescents between the ages of 12 and 18 was recruited through contacting secondary schools in Ireland to participate in a cross-sectional online survey to take place during April-June 2023. The sampling strategy combined convenience and purposive sampling. First, we approached Principals from secondary schools representing all socioeconomic and geographical areas across Dublin and the surrounding Irish counties around the Dublin County. Five schools representing different socioeconomic and geographical areas agreed to participate. Based on standard socioeconomic indicators (Haase, 2016), two schools were located in socioeconomically disadvantaged areas, two were from an average socioeconomic level area, and one from and affluent area. We conducted the survey to students in those schools during a scheduled visit. We asked remaining schools and every other school across Ireland to share the link for the online survey with their students to maximise participation in the study. All participants in the study and at least on parent or guardian gave written consent prior to answering the survey.

We excluded a few participants from the original sample. First, adolescents who did not own a mobile device or had no social media account (n = 21) had to be excluded from the study, as they constituted a group that could not provide comparable information on digital measures. Second, some participants did not answer the mental well-being and digital maturity items (n = 28). These cases were excluded through listwise deletion, following guidelines that missing outcome data cannot be validly imputed or estimated with maximum likelihood methods, particularly when no reliable proxies are available in the data (Allison, 2009). Third, adolescents who reported their gender as non-binary (n = 8) lacked statistical power to be added into the regression models, and therefore were excluded from the sample. Finally, a small remaining number of cases had missing data on other demographic variables (age, immigration background) (N = 7). These observations represented ~1% of the sample and were excluded through listwise deletion, which has been shown not to produce biased estimates when the proportion of missing data is very low (McNeish, 2017). The final sample consisted of a total of 349 adolescents.

3.2.2 Measures

Mental Well-being. The World Health Organisation - Five Well-Being Index (WHO-5) was employed to measure adolescents' mental well-being. This scale has been widely used in the literature (Cosma et al., 2022; Topp et al., 2015) to measure participants' subjective psychological well-being by asking them the extent to which they feel cheerful, active, rested, relaxed, and interested in life on a 5-point scale (1 = *very rarely/never* to 5 = *very often/always*; Cronbach's α = 0.873). We calculated the mean score of the five items to create an overall mental well-being score; higher values represented better mental well-being.

Digital User Profiles. The variable of digital user profiles was based on latent classes that were created by considering three sources of variables: *intensity*, *type*, and *purpose*. *Intensity* came from a self-reported measure of daily amount of digital device use with three intensity usage groups within the sample (1 = low-intensity, 2 = moderate-intensity, 3 = high-intensity). *Type* was measured by asking participants to report which of the social networking sites (SNS) they use: communication SNS (WhatsApp, Telegram, Signal), classic SNS (Facebook, Twitter), interactive SNS (Instagram, TikTok, Snapchat), video-heavy SNS (YouTube), and private community SNS (Discord). *Purpose* categories were measured by asking participants to report their reasons for using mobile devices: socialising with friends ("To stay in touch with what friends are doing", "Because all my friends do"); socialising with others online ("To meet new people", "To talk or write with others"); sharing content online ("To share photos or videos with others", "To share my opinion"); entertainment/passive use ("To fill spare time", "To find funny and entertaining content"); seeking information ("To stay up to date with news and current events", "To research new products to buy"); and gaming ("To play games").

Digital Maturity. The Digital Maturity Inventory (DIMI) (Christensen et al. 2025; Laaber et al., 2023) was used to measure adolescents' digital maturity. The DIMI consists of 32 items that measure digital maturity across 10 dimensions (e.g., "I choose the content I want to see" for autonomy within digital contexts dimension; "I make sure to be careful" for digital risk awareness; "I care about the feelings of others" for respect towards others in digital contexts). The questions were prompted with *"When using a mobile device…"* and all items were measured on a 5-point scale (1 = *very rarely / never* to 5 = *very often / always*; the scale was modified as 1 = *not at all* to 5 = *completely* for digital literacy dimension; Cronbach's $\alpha = 0.849$). This scale is validated to be used as a continuous measure. We calculated the final digital maturity score according to Laaber et al. (2023); higher values represented better digital maturity. Table A1 in the Appendix provides detailed information about the DIMI measure.

Controls. We controlled for age, gender, immigration background, and school neighbourhood area. Age, gender, and immigrant status were self-reported measures from participants. Participants' school neighbourhood area was identified according to the

Pobal HP Deprivation Index 2016 (Haase, 2016), representing three distinct groups reflecting different Socioeconomic Status (SES): disadvantaged, average, and affluent.

3.2.3 Analytical Strategy

We employed GLCA to identify dominant classes of digital users within our dataset. We tested model solutions with an increasing number of classes, and used model fit indices and comparisons to identify the optimal number of classes. Bayesian information criterion (BIC), sample-size adjusted BIC, consistent Akaike information criterion (CAIC), and approximate weight of evidence criterion (AWE), were considered for model fit criteria, with lower values indicating better fit. We also considered Bayes factor (BF) in which above 3 is desirable (Wagenmakers, 2007), and average latent class posterior probability (ALCPP) in which above 0.80 is an acceptable fit (Weller et al., 2020). We additionally used Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (VLMR-LRT) to confirm our decision (Nylund-Gibson & Choi, 2018). Following Masyn (2013), on top of the mentioned criteria of model selection, we reported entropy. We adopted a three-step approach (Bolck et al., 2004): (i) we established the number of classes that suits the best for our dataset; (ii) we created a latent class variable assigning individuals to the groups by their highest probability; and (iii) we then examined the latent classes as predictors of mental well-being and digital maturity.

We subsequently conducted Mediation Analysis using a stepwise approach. First, we examined the associations between the identified digital user latent classes and mental well-being, and the association between the digital user latent classes and digital maturity in separate models. Second, we added the digital user latent classes and digital maturity as predictors of mental well-being in the same model. Finally, we added a path between the digital use latent classes and digital maturity and investigated the mediation of digital maturity. Goodness of the mediation model was assessed using fit indices (CFI, TLI, RMSEA, SRMR) with recommended thresholds (Hu & Bentler, 1999) and the R^2 of each endogenous variable. We carried out all analyses in Stata 18.

3.3 Results

Table 3.1 shows the means and percentages of each variable used in our study. Girls represented 53.01% of the sample, and 34.38% of the sample was from a disadvantaged geographical area. The majority of participants were native Irish, with 17.48% being from an immigrant background. The most common purposes of mobile device use were entertainment (87.11%) and socialising with friends (93.70%). Communication SNS was the most common type of mobile device use (92.26%), closely followed by Interactive SNS (91.98%). The least common type of mobile device use was Private community SNS (Discord) (37.25%). Table A2 illustrates inter-item covariances of all the variables used in the analyses.

3.3.1 Generalised Latent Class Analysis

Table 3.2 presents the GLCA results for one-, two-, three-, and four-class model results. The four-class model needed three constraints to be stable, and a five-class model was still unstable after five constraints. The majority of relevant model fit criteria (SABIC, CAIC, and AWE) supported a three-class model. Lowest value of ALCPP scores of two- and three-class model were above 0.80, showing high model fit levels. Additional BF analyses (not shown) indicated the best support for three-class model. Altogether, we favoured the lower scores of SABIC, CAIC, and AWE, with the support of ALCPP, to conclude that the three-class model was the optimal empirical choice. We then allocated each participant to the class in which they had the highest probability of being a part of.

Figure 3.1 presents the marginal probabilities of digital use predictors across the three classes. We identified the first class as *Light Users* (34.67% of the sample). *Light*

Users had low usage intensity and used mobile devices for mainly communication purposes. They were also the least likely to use mobile devices for socialising with others and for gaming, and also the least likely to use classic SNS, video-based SNS and private community SNS. We defined the second class as *Reserved Users* (23.78% of the sample). *Reserved Users* showed moderate level of usage intensity. Additionally, their usage purpose combined communication, entertainment, and gaming reasons, while they were the most likely to have private community SNS and adopt video-heavy SNS. Finally, we labelled the third class as *Outgoing Users* (41.55% of the sample). Participants in the *Outgoing Users* class had high usage intensity. This group showed a lower range of SNS types than *Reserved Users*, and also the highest probabilities of seeking information, sharing content, and meeting people online.

Table 3.3 presents the demographic distributions of the latent classes. Multinomial logistic regression analyses (see Table A3.3) showed that there were no statistically significant age, immigration, and neighbourhood area differences across classes. Girls were the least likely to be in the *Reserved Users* class compared to *Light Users* (OR = 2.353, p = 0.004) and *Outgoing Users* (OR = 3.491, p < 0.001) classes.

3.3.2 Mediation Analysis

We started by examining the latent classes as predictors of digital maturity and mental well-being (Table 3.4). Model 1a showed that *Outgoing Users* had statistically significantly lower digital maturity than *Light Users* (b = -11.320, p = 0.012, β = -0.31), while *Reserved Users* did not differ statistically from *Light Users* in their digital maturity (b = -6.173, p = 0.227, β = -0.17). Model 1b showed that both *Reserved Users* (b = -0.317, p = 0.003, β = -0.40) and *Outgoing Users* (b = -0.228, p = 0.010, β = -0.30) had lower mental well-being compared to *Light Users,* with statistically significant differences observed for both groups. When digital maturity was added to Model 1b as a predictor of mental well-being (Model 2), the difference in mental well-being was no longer statistically significant between *Outgoing Users* and *Light Users* (b = -0.150, p = 0.077, β = -0.20). By contrast, the statistically significant difference between *Reserved Users* and *Light Users* in mental well-being persisted (b = -0.275, p = 0.007, β = -0.35). SES participants with higher digital maturity had higher mental well-being than participants with lower digital maturity (b = 0.007, p < 0.001, β = 0.35).

The final mediation model is depicted in Model 3, and Figure 3.2 illustrates the explored pathways and standardised coefficients of this final model. The model fit indicators suggested that the model has acceptable to good fit (RMSEA = 0.082; CFI = 0.971; TLI = 0.798; SRMR = 0.027). The overall R^2 was 0.109, meaning that only 11% of the variance was explained across all endogenous variables in the model. The results indicated that for *Outgoing Users*, digital maturity negatively contributed to their mental well-being compared to *Light Users* (b = -0.077, p = 0.022, β = -0.10). The direct path from *Outgoing Users* to mental well-being was not statistically significant (b = -0.155, p = 0.067, β = -0.20) in Model 3. This suggests that the lower mental well-being of *Outgoing Users* is fully explained by their lower digital maturity levels. By contrast, for *Reserved Users,* digital maturity did not contribute to explain variations in mental well-being, with no statistically significant associations (b = -0.060, p = .111, β = -.08). The combined effects of direct and indirect paths showed statistically significant differences from *Light Users* for both *Reserved Users* (b = -0.331, p = 0.002, β = -0.42) and *Outgoing Users* (b = -0.232, p = 0.009, β = -0.31).

3.3.3 Additional Analyses: Heterogeneity by Gender and Socioeconomic Group

As additional analyses, we investigated the role of two important variables in the context of adolescent digital use and well-being: gender and SES (e.g., Bohnert & Gracia, 2023; Gracia et al., 2023; Laaber et al., 2023; Koch et al., 2024a; Ren et al., 2022). First, we ran Model 3 to study gender differences (Figure 3.3). The multi-group model had a significantly better fit ($\chi^2(8) = 534.01$, $p < 0.001$), revealing gender differences in the data. Subsequently, we constrained each path to be equal to test the null hypothesis (no path estimates differed across boys and girls), and next unconstrained each path one at a time to allow variances across boys and girls. Based on the Wald $\chi2$ test, we found gender differences in the paths between *Reserved Users* and mental well-being (Wald $\chi2(1) = 5.208$, $p = 0.022$), *Outgoing Users* and mental well-being (Wald $\chi2(1) = 9.469$, $p = 0.002$) and digital maturity and mental well-being (Wald $\chi2(1) = 30.683$, $p < 0.001$). Among boys, both *Reserved Users* ($b = -0.330$, $p = 0.011$, $\beta = -0.43$) and *Outgoing Users* ($b = -0.237$, $p = 0.073$, $\beta = -0.33$) had lower mental well-being compared to *Light Users*, although the difference was only marginally significant for *Outgoing Users*. Among girls, neither *Reserved Users* ($b = -0.212$, $p = 0.195$, $\beta = -0.25$) and *Outgoing Users* ($b = -0.010$, $p = 0.378$, $\beta = -0.12$) differed statistically in their mental well-being, compared to *Light Users.* The association between digital maturity and mental well-being was significantly positive for both boys ($b = 0.0067$, $p < 0.001$, $\beta = 0.34$) and girls ($b = 0.0071$, $p < 0.001$, $\beta = 0.37$), but marginally stronger for girls than boys. Second, we ran Model 3 with multi-group analysis to asses SES variations (disadvantaged area vs. average area vs. affluent area). The unconstrained multi-group model did not have a significantly better fit than the single group model ($\chi^2(20) = 23.51$, $p = 0.264$). This implies that the observed mediation models in our data did not differ by SES groups. Analyses (not shown) did not reveal any relevant SES difference in the data.

3.4 Discussion

This study has added to the adolescence, digital media and well-being literatures by examining the relationship between digital user profiles and adolescent mental well-being, and by further investigating how digital maturity –i.e., a novel concept indicating the self-determined use of digital technologies to foster psychological growth– mediates this relationship. To do so, we applied Generalised Latent Class Analysis (GLCA) and Mediation Analysis to a newly collected survey from adolescents in Ireland which contain high-quality multidimensional measures of digital use, digital maturity, and mental well-being.

The main results of the study can be summarised at four main levels. First, we identified three distinct types of digital user profiles based on their intensity, type and purpose of digital use that add to the literature on adolescent digital media use: *Light Users*, *Reserved Users*, and *Outgoing Users*. *Light Users* scored low on the most digital use indicators and engaged only with communication-related SNS. *Reserved Users* had a more complicated pattern, with the most diversity of SNS use, and being the most prone to engage with private community SNS and video-heavy SNS. Finally, *Outgoing Users* had the highest range of active purpose of digital use indicators, including information seeking, socialising others, and sharing content, although having less diverse SNS use than *Reserved Users*. Our study complements a recent study on early adolescents in the UK, which identified four latent classes of social media use: high communicators, moderate communicators, broadcasters and minimal users (Winstone et al., 2022). Interestingly, our study did not find a group with minimal use report, which may reflect the high prevalence of socially-oriented platforms such as Snapchat and Instagram within Irish secondary schools (Everri & Park, 2018).

Second, adolescent user profiles were associated with variations in mental well-being, which confirmed our initial expectations (Hypothesis 1). *Light Users* reported higher mental well-being than both *Reserved Users* and *Outgoing Users.* These results indicate that low-intense and moderate communication-oriented users, just like *Light Users*, are protected from adverse well-being conditions (e.g., Holtz & Appel, 2011; Best et al. 2014). Additionally, these findings add to emerging literature on content sharing (Winstone et al., 2022), showing how online profiles based on active content sharing (e.g., persistent social media posting) and excessive online communication (e.g., continuous online texting) are prone to psychological harm. Considering that *Outgoing Users* were the most actively engaged in social media through publicly sharing content and opinions online, their digital behaviours may indicate over reliance on other people's social validation (Naeemi & Tamam, 2017). Moreover, high-intensity mobile device use could lead *Outgoing Users* to more negative online experiences linked to psychological harm, such as online conflicts and social comparisons (Livingstone et al., 2021; Gomez et al., 2022). As for *Reserved Users*, being exposed to online content without actively participating may trigger a feeling of fear of missing out (FOMO), which could harm their life satisfaction and emotional well-being (Burnell et al., 2019). Also, low offline social support among more discrete and less social digital users (Winstone et al., 2023; O'Day & Heimberg, 2021) may further explain the lower mental well-being of *Reserved Users*.

Third, our analyses revealed that higher digital maturity is associated with better mental well-being. As digital maturity reflects adolescents' agency and autonomy to use digital devices in self-determined ways (Laaber et al., 2024), this finding confirms that digitally mature adolescents are well equipped to support their basic psychological needs through a healthy and productive approach to online engagement. Digital autonomy could help adolescents to avoid over-reliance on digital experiences for need satisfaction. Higher digital maturity and digital autonomy may also help adolescents balance their online and offline lives, which could help them to maintain in-person social connectedness while reducing the risks of negative social engagements online (Koch et al., 2024b). Moreover, adolescents with higher digital competence may not only be better at avoiding digital risks. They may also be more skilled to seek mental health resources provided by digital mediums to support their psychological development (Pretorius et al., 2019). Overall, this finding confirms that digital maturity acts as a protective factor in adolescents' mental well-being.

Fourth, we found that digital maturity contributes to explain differences in mental well-being between digital user profiles, just as hypothesised (*Hypothesis 2*). The lower digital maturity of *Outgoing Users* fully mediated the poorer mental well-being of this group of adolescents, but digital maturity did not mediate the mental well-being disadvantage of *Reserved Users* relative to *Light Users*. These findings suggest that *Light Users* manage digital devices responsibly in ways that help maintaining close friendships, due to their digital skills, autonomy, and meaningful online connections linked to digital maturity (West et al., 2024). By contrast, *Outgoing Users* are not only the user group with lowest digital maturity levels, but their low digital maturity plays an important role in explaining their poorer mental well-being. This finding suggests how lacking digital self-efficacy drives psychological disadvantages for risk-oriented digital users (Valkenburg et al., 2022).

Our study has some important policy implications. Our findings indicate that promoting digital maturity among adolescents could be a key enabler to foster mental well-being, as adolescents who have higher levels of digital maturity tend to have better mental well-being outcomes, potentially due to acquiring all the necessary tools to be able to navigate existing online risks. Yet, policies targeting digital maturity may not work equally for all adolescents. *Outgoing Users* may benefit from interventions that target developing digital autonomy and emotion regulations in digital contexts, which could help them to cope with the negative social interactions online. However, the observed vulnerability of *Reserved Users*, even after accounting for digital maturity, suggests that a different strategy, perhaps one targeting their potential underlying social anxiety and low self-esteem, could promote beneficial social engagements in online contexts for this group of adolescents.

This study has some limitations that should be mentioned. First, when interpreting the association between adolescent digital behaviours and mental well-being, the possibility of bidirectional relationship should be considered. For example, adolescents with existing depressive symptoms may engage in riskier forms of digital consumption (Valkenburg et al., 2022) and adolescents with higher digital maturity may use digital devices in more beneficial ways (Laaber et al., 2024). Unfortunately, our data do not allow us to identify reverse causality. Second, some relevant confounding factors were not included in this study, particularly personality traits or parental support, which are relevant to adolescent digital maturity and mental well-being (Koch et al., 2024a; Clark, 2011). As parental mediation is an important mechanism driving the interplay between adolescent digital behaviours and mental well-being (Koch et al., 2024a; Üstündağ-Alkan et al., 2021), future studies should address the role of parents' digital maturity in shaping adolescent well-being within digital contexts. Finally, although the present study examined digital maturity as a mediator between digital user profiles and mental well-being, alternative conceptualizations are also possible. For instance, digital maturity may also function as a moderator, such that the association between different digital user profiles and well-being varies depending on adolescents' digital maturity levels. Because the present study was guided by theoretical perspectives that position digital maturity as a mechanism shaped by digital engagement and leading to positive well-being outcomes (Christensen et al., 2025; Laaber et al., 2024), a mediation design was prioritized in this study. Future research, particularly using longitudinal or experimental designs, could further examine whether digital maturity also plays a moderating role or whether more complex models better capture these relationships. Nevertheless, our study offers important insights to better understand how digital user profiles shape adolescents' mental well-being in the current digitalised society.

3.5 Conclusion

This study is the first to examine how digital maturity mediates the relationship between adolescents' digital user profiles and their mental well-being. We show that digital maturity mediates the lower mental well-being observed for adolescents defined as *Outgoing Users* –i.e., high-intensity and active–public oriented–, but it does not explain the poorer mental well-being of *Reserved Users* –medium-intensity users with private communication and passive-entertainment focus–, compared to *Light Users* –low-intensity users, mainly restricted to communication activities–. Our findings emphasize the importance of fostering digital skills, autonomy, and connectedness to support mental well-being among risk-induced adolescents with the most active and outgoing digital media behaviours. Altogether, the present study will serve as a guide for future research addressing the causal pathways between digital use, digital maturity, and mental well-being to further understand how adolescents' digital use links to their well-being outcomes.

3.6 Tables and Figures

Table 3.1 Summary statistics. Means (M) and standard deviations (SD)

Variable	Percent
Age (*M* (SD))	15.16 (1.56)
Girls (%)	53.01
Native Irish (%)	82.52
School neighbourhood (%)	
Disadvantaged area	34.38
Average area	43.55
Affluent area	22.06
Mental well-being (*M* (SD))	3.22 (0.77)
Digital maturity (*M* (SD))	366.57 (39.57)
Mobile device use predictors - Purposes	
Entertainment (%)	87.11
Information seeking (%)	61.32
Socialising friends (%)	93.70
Socialising others (%)	60.74
Sharing content (%)	54.15
Gaming (%)	32.38
Mobile device use predictors - Types	
Communication SNS (%)	92.26
Traditional SNS (%)	41.26
Interactive SNS (%)	91.98
Video-based SNS (%)	81.95
Private community SNS (%)	37.25
Mobile device use predictor - Intensity (%)	
Low	32.95
Moderate	34.10
High	32.95

Note. *N* = 349. SNS: Social Networking Sites.

Table 3.2 Model fit evaluation information

Model	LL	df	BIC	SABIC	CAIC	AWE	BF	Entropy	ALCPP	VLMR-LRT
1-Class	-2351.038	13	4778.192	4718.387	4751.676	4758.676	0.001	-	-	-
2-Class	-2242.872	27	**4643.830**	4518.367	4584.943	4598.943	2.732	**0.939**	**0.877**	**<0.001**
3-Class	-2211.937	41	4663.932	**4472.808**	**4569.130**	**4589.630**	2.638	0.646	**0.820**	**<0.001**
4-Class	**-2189.433**	55	4683.330	4533.930	4763.750	5056.103	-	0.701	0.791	**<0.001**

Note. *N* = 349. The model became unstable with the 5-class model. Bold text indicates model met fit criteria.
LL = log-likelihood; BIC = Bayesian information criterion; SABIC = sample-size adjusted BIC; CAIC = consistent Akaike information criterion; AWE = approximate weight of evidence criterion; BF = Bayes factor; ALCPP = average latent class posterior probability; VLMR-LRT = Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test.

Table 3.3 Means and percentages of demographic variables across clusters

Variable	Light Users	Reserved Users	Outgoing Users
Class Size (%)	34.67	23.78	41.55
Age (M)	15.28	15.05	15.11
Girls (%)	57.02	30.12	62.76
Native Irish (%)	85.12	85.54	78.62
School neighbourhood (%)			
Disadvantaged area	31.40	33.73	37.24
Average area	45.45	45.78	40.69
Affluent area	23.14	20.48	22.07

Note. $N = 349$.

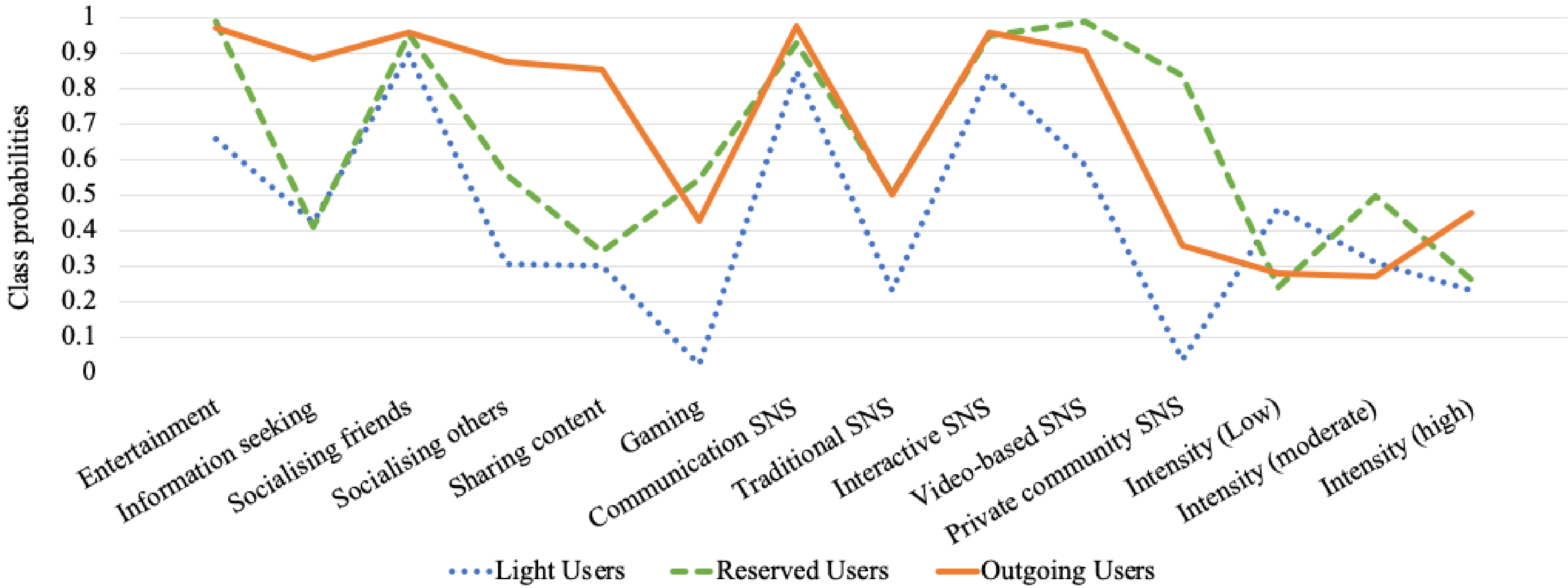
Table 3.4 Unstandardised model results. Mediation analysis

Antecedent	Consequent					
	Digital maturity			Mental well-being		
	Estimate	SE	95% CI	Estimate	SE	95% CI
Model 1a						
Light Users (ref)						
Reserved Users	-6.173	5.653	[-17.254, 4.907]			
Outgoing Users	-11.320*	4.805	[-20.737, -1.902]			
Constant	359.300***	22.104	[315.976, 402.624]			
Residual variance	1502.194					
R^2	0.038					
Model 1b						
Light Users (ref)						
Reserved Users				-0.317**	0.107	[-0.527, -0.107]
Outgoing Users				-0.228*	0.091	[-0.406, -0.049]
Constant				4.421***	0.419	[3.600, 5.242]
Residual variance				0.539		
R^2				0.097		
Model 2						
Light Users (ref)						
Reserved Users				-0.275**	0.100	[-0.471, -0.079]
Outgoing Users				-0.150	0.086	[-0.318, 0.017]
Digital Maturity				0.007***	0.001	[0.005 ,0.009]
Constant				1.962	0.518	[0.948, 2.977]
Residual variance				0.469		
R^2				0.215		
Model 3						
Direct effects						
Light Users (ref)						
Reserved Users	-8.564	5.588	[-19.516, 2.387]	-0.271**	0.101	[-0.468, -0.073]
Outgoing Users	-11.049*	4.827	[-20.510, -1.587]	-0.155	0.086	[-0.324, 0.013]
Digital Maturity				0.007***	0.001	[0.005, 0.009]
Constant	373.196***	3.564	[366.210, 380.181]	1.455***	0.368	[0.735, 2.176]
Indirect effects						

Light Users (ref)				
Reserved Users		-0.06	0.040	[-0.138, 0.018]
Outgoing Users		-0.077*	0.035	[-0.146, -0.008]
Direct + Indirect effects				
Light Users (ref)				
Reserved Users		-0.331**	0.108	[-0.542, -0.119]
Outgoing Users		-0.232*	0.091	[-0.412, -0.053]
Residual variance	1537.050	0.477		
R^2	0.015	0.216		

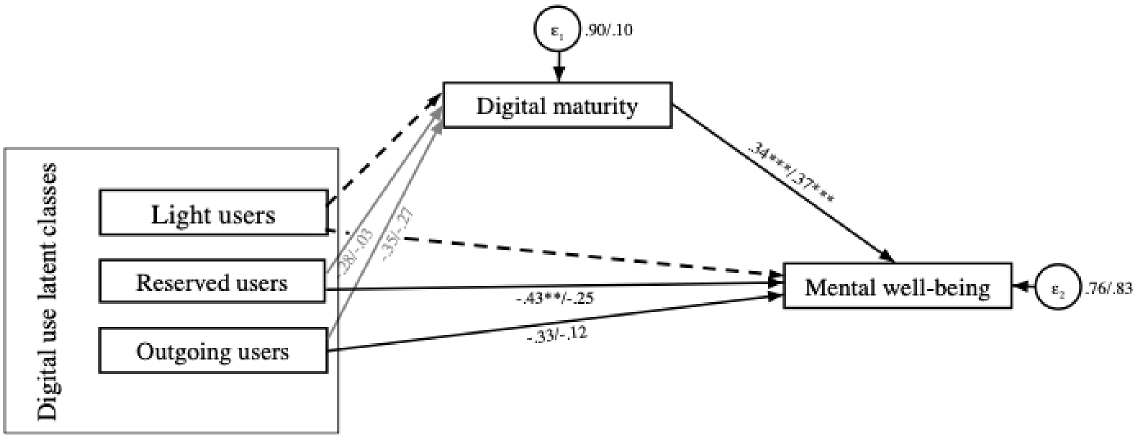
Note. N = 349. Analyses in Models 1a, 1b, and 2 has control variables: age, gender, neighbourhood SES, immigration background. Gender (on digital maturity), age, school neighbourhood, and immigration background were removed from the analyses in the Model 3 due to non-significant associations.
*p < .05, **p < .01, ***p < .001.

Figure 3.1 Probability of mobile device use predictors for each digital user class



Note. N = 349. SNS: Social Networking Sites. Because digital use intensity is an ordinal variable, the probabilities of all three levels are shown.

Figure 3.2 Standardised coefficients of multi-group mediation model, gender differences



Note. N = 349 (N_{boys} = 164, N_{girls} = 185). Light users as reference category, represented with dashed arrows. Results reported as boys/girls. Gray paths do not significantly differ between boys and girls. *p < .05, **p < .01, ***p < .001.

3.7 Appendix

Table A3.1 Digital Maturity Index (DIMI) items (Laaber et al., 2023)

Dimension	Item *"When using a mobile device…"*	Scale
Digital Literacy	I know how to change the privacy settings (for example, deactivate cookies) I know how to adjust the privacy settings of social media sites (for example, Instagram, Snapchat, TikTok) I know how to store photos, documents or other files in the cloud (for example, Google Drive, iCloud) I know how to protect a device (for example, with a PIN, a fingerprint, facial recognition) I know how to figure out if a website can be trusted	Not at all true of me (1) –Not very true of me (2) – Neither true or untrue of me (3) – Mostly true of me (4) – Very true of me (5)
Individual Growth in Digital Contexts	I learn new things I learn something useful I learn new skills I can take on new challenges	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)
Autonomous Choice to Use Mobile Devices	I am online because otherwise I feel like I am missing out on something I am online because I feel like I have to be online all the time I have the feeling that it is controlling my life I immediately look at messages, even if I am busy doing other things	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)
Autonomy Within Digital Contexts	I choose the content I want to see I look for content that interests myself I do the things that I like I decide what I do	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)
Support-seeking Regarding Digital Problems	and I don't know what to do, I ask others for help and there is a technical problem, I ask others for help (for example, a friend, parent, sibling) I ask others for help when I have a problem and I have problems with others on the internet, I get help	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)
Regulation of Negative Emotions in Digital Contexts	and I become annoyed or upset online, I stay in a bad mood for a long time and I become annoyed or upset online, it takes me a long time to feel better and I become annoyed or upset online, there are only few things that can make me feel better	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very

Dimension	Item *"When using a mobile device…"*	Scale
		often / Always (5)
Regulation of Impulses in Digital Contexts	and somebody insults me, I try to get back at them and somebody criticizes me online or in a text, I immediately react without considering the consequences and a message makes me angry, I react too quickly and then later regret the way I responded people who make me angry had better watch out	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)
Respect Towards Others in Digital Contexts	I care about the feelings of others I watch my language when I disagree with someone, so that what I say doesn't come across as mean I make sure that pictures I post or send of other people will not insult them or get them into trouble I respect the opinions and knowledge of others	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)
Digital Citizenship	I use the internet to support campaigns for issues like environmental protection or to spread awareness for climate change I use it to stand up for things that really matter in the world I use it to improve life in my neighborhood, town or world I repost content about social issues or discrimination on the internet	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)
Digital Risk Awareness	I am very careful I make sure to be careful my own safety is very important to me I think about the fact that there are also dangers online	Very rarely / Never (1) – Rarely (2) – Sometimes (3) –Often (4) –Very often / Always (5)

Table A3.2 Inter-item covariance matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Mental well-being	0.599																	
2. Digital maturity	10.518	1565.780																
3. Age	-0.060	0.908	2.418															
4. Girls	-0.086	1.860	0.003	0.250														
5. Native Irish	0.035	0.250	-0.033	-0.016	0.145													
6. School area[a]	0.035	2.888	0.069	0.014	0.001	0.551												
7. Entertainment	-0.024	-0.492	-0.057	0.008	-0.008	0.019	0.113											
8. Information seeking	-0.031	-1.368	0.063	0.033	-0.007	0.015	0.033	0.238										
9. Socialising friends	0.008	0.015	0.012	0.005	-0.005	0.024	0.000	0.013	0.059									
10. Socialising others	-0.026	-1.651	-0.050	0.036	-0.029	-0.040	0.030	0.040	0.007	0.239								
11. Sharing content	-0.027	-0.239	0.035	0.045	-0.014	0.012	0.024	0.078	0.006	0.087	0.249							
12. Gaming	0.006	-0.579	-0.113	-0.028	-0.004	-0.015	0.039	0.016	0.015	0.056	0.031	0.220						
13. Communication SNS	-0.001	0.909	-0.010	0.012	0.001	0.019	0.016	0.019	0.004	0.016	0.013	0.005	0.072					
14. Traditional SNS	-0.050	-2.265	0.142	-0.004	-0.023	-0.052	0.013	0.031	-0.006	0.022	0.014	0.013	0.012	0.243				
15. Interactive SNS	-0.008	-0.997	0.018	0.011	0.006	0.016	0.010	0.018	0.015	0.014	0.009	0.009	0.002	0.016	0.074			
16. Video-based SNS	-0.046	-1.144	-0.012	-0.005	-0.009	-0.008	0.023	0.022	0.000	0.035	0.020	0.027	0.015	0.034	0.006	0.148		
17. Private comm. SNS	-0.038	-2.106	-0.080	-0.054	-0.001	-0.011	0.037	-0.008	0.003	0.026	0.005	0.077	0.012	0.050	0.007	0.056	0.234	
18. Device use intensity[b]	-0.095	-6.230	0.033	0.063	-0.032	-0.040	0.040	0.026	0.006	0.046	0.043	0.029	-0.003	0.043	0.017	0.040	0.009	0.661

Note. *N* = 349. SES: Socioeconomic Status. SNS: Social Networking Sites. Private comm. SNS: Private community SNS [a]Disadvantaged area is the reference caregory. [b]Low intensity is the reference category.

Table A3.3 Covariate logits and odds ratios for the demographic variables (3-class model)

	Reference class					
	Light Users		Reserved Users		Outgoing Users	
Class membership	Logit	OR	Logit	OR	Logit	OR
Age						
Light Users	-	-	0.120	1.127	0.050	1.051
Reserved Users	-0.120	0.887	-	-	-0.070	0.932
Outgoing Users	-0.050	0.952	0.070	1.073	-	-
Girls						
Light Users	-	-	0.856**	2.353	-0.394	0.674
Reserved Users	-0.856**	0.425	-	-	-1.250***	0.286
Outgoing Users	0.394	1.484	1.250***	3.491	-	-
Native Irish						
Light Users	-	-	-0.051	0.950	0.507	1.660
Reserved Users	0.051	1.053	-	-	0.558	1.748
Outgoing Users	-0.507	0.602	-0.558	0.572	-	-
School neighbourhood - Average						
Light Users	-	-	0.033	1.034	0.18	1.198
Reserved Users	-0.033	0.967	-	-	-0.116	1.158
Outgoing Users	-0.18	0.835	0.093	0.863	-	-
School neighbourhood - Affluent						
Light Users	-	-	-0.147	1.097	0.147	0.890
Reserved Users	-0.093	0.912	-	-	-0.209	0.812
Outgoing Users	-0.18	1.123	0.209	1.232	-	-

Note. N = 349. Each covariate is examined in a separate logistic regression model. Disadvantaged Area is the reference category for school neighbourhood variable.

Chapter 4: Study 3 - The impact of school-based interventions targeting adolescent digital use and mental well-being: a systematic review and meta-analysis

An edited version of this chapter under review at ***Adolescent Research Review*** *as of April 2026 (second round of revisions).*

Abstract

How effective school-level interventions in targeting adolescents' digital use and mental well-being are remains debated. This study conducted a pre-registered systematic review and meta-analysis (PRISMA; Cochrane) of school-based interventions among adolescents aged 12–18. Searches across Web of Science, PubMed, PsycINFO, CINAHL, EMBASE, and ERIC (October 2023; updated February 14, 2025) identified 17 eligible studies, with 11 contributing to meta-analyses. Designs included cluster RCTs, non-randomized trials, and pre–post studies. Analyses applied arm-based random-effects models reporting percentage change from baseline in digital-use and mental-health outcomes, with heterogeneity assessed via I^2 and sensitivity analyses varying pre–post correlations. Results show that school interventions are largely effective at reducing screen time relative to the control group, while evidence for problematic digital use is inconclusive. For mental well-being, interventions confer advantages for anxiety and depressive symptoms as well as life satisfaction and psychological difficulties, compared to the control group. Sensitivity analyses yield consistent patterns, whereas funnel tests suggested no strong publication bias, though small *k* warrants caution. Overall, this study indicates that school-level interventions reduce screen time and improve mental well-being indicators, while effects on problematic use remain mixed.

Keywords: adolescents, digital use, mental well-being, school-based interventions, systematic review, meta-analysis

4.1 Introduction

In today's highly digitalised world, online social media platforms have become more and more prevalent in adolescents' lives (Scott et al., 2024; Verduyn et al., 2022), offering a wide range of online activities (e.g., socialising, gaming, sharing content, learning activities) which could be both beneficial and harmful for youth well-being (Livingstone & Helsper, 2010; Ólafsson et al., 2013; Schoon et al., 2024; Van Rooij et al., 2010). For instance, while social media offers online communication and social support (Best, et al., 2014), it could also lead to negative social comparisons, fear of missing out, and exposure to harmful contents (Burnell et al., 2019; Livingstone et al., 2017; Fioravanti et al., 2021; McComb et al., 2023). Various policies and guidelines aiming to prevent the harmful effects of risky digital use were introduced, such as limiting screen time for children and teens, promoting offline activities, and protection software programs that prevent children to access risky contents online (O'Neill, 2013; Oh et al., 2022; Mac Cárthaigh, 2020). Many programmes have involved parents as the main agents to facilitate or conduct the intervention process (e.g., Feng et al., 2024; Lin et al., 2021), which is a highly suitable approach for younger children as parents are a more relevant actor in children's daily lives (Marsh et al., 2014; Selman & Dilworth-Bart, 2024).

In the context of adolescence, however, schools have been identified as crucial settings to foster adolescents' daily routines and socialisation patterns, which could make schools themselves a key agent in facilitating such interventions (Dekkers & Luman, 2023). Previous studies have shown that school-based interventions can be effective tools in improving students' behaviours in relation to sedentary and active lifestyle (Demetriou & Höner 2012; Kriemler et al., 2011; Owen et al., 2017), healthy eating habits (Medeiros et al., 2022; Van Cauwenberghe et al., 2010), and health outcomes (Cilar et al., 2020; Paulus et al., 2016). Yet, the literature has provided limited evidence on the effectiveness of school-based interventions in (i) producing healthier and more balanced digital use habits and (ii) improving mental well-being outcomes. To tackle this important gap, the present systematic review and meta-analysis aims to assess if school-based interventions are effective in promoting healthier forms of adolescents' digital use and mental well-being. Our study contributes to key policy and scientific debates regarding the extent to which school-based interventions can work in reducing the amount and harmful nature of adolescents' digital use and social media and improving their mental well-being.

4.1.1 Conceptualising Adolescent Digital Use

Adolescent digital use has been defined and measured differently across studies. Screen time is the most common measure used by researchers and refers to the duration, such as the total screen time in hours per day, and sometimes the frequency of use, such as how often a mobile device is used in a week , of time spent using digital devices. Screen time can relate to either device- or context-specific use (e.g., social media use, computer use) or total combined use (Browne et al., 2021; Vandewater & Lee, 2009). Some researchers have also attempted to disentangle various forms of digital use. These forms refer to the types of activities (e.g., gaming, chatting, scrolling) or the specific contexts of online media use, such as social media platforms or educational contents (Browne et al., 2021; Winstone et al., 2022). Subjective experiences with digital devices and mediums, such as problematic internet use, are also considered to be key elements of digital use behaviours (Almourad et al., 2020; Busch & McCarthy, 2021; Steele et al., 2020). The literature on problematic digital use is similarly diverse in its terminology and conceptual focus, with studies referring to constructs such as problematic internet use, social media addiction, smartphone addiction, or more broadly digital or screen addiction (Montag et al., 2019; Kuss & Griffiths, 2017; Panova & Carbonell, 2018). Despite these variations, these constructs generally aim to capture broader difficulties related to individuals' engagement with digital technologies, such as problematic behavioural patterns (e.g., losing control over use) or the negative consequences of use (e.g., disruptions to daily functioning) (Almourad et al., 2020). In our study, we account for the complexity of adolescents' digital use by considering both screen-based time and subjective experiences with problematic digital use.

4.1.2 Conceptualising Adolescent Mental Well-being

Although the term mental well-being is an encompassing concept, it can be summarised as having positive feelings and psychological functioning as well as not suffering from any negative mental health problems (Ryan & Deci, 2001). This brief definition suggests two broader dimensions that should be treated as related but separate constructs. In the mental health literature, positive mental well-being is often examined through concepts such as life satisfaction, positive affect, self-esteem, and connectedness (Bentley et al., 2019; Diener, 2000). By contrast, negative mental well-being is mainly understood as severity of mental illness indicators such as symptoms of anxiety and/or depression, psychological distress, negative affect, and poor emotion regulation (Collishaw, 2015). Each of these concepts could be measured in numerous ways, usually through self-report tools for adolescent age group. In addition to the global measurements capturing both dimensions such as Strengths and Difficulties questionnaire (SDQ; Goodman, 2001), positive and negative affect scale (PANAS; Watson et al., 1988), there are also measurements assessing one of two indicators of each dimensions such as WHO-5 well-being index (Topp et al., 2015) for positive mental well-being (see Black et al., 2023; Rose et al., 2017 for reviews) and Children's Depression Inventory (Kovacs, 1992), The screen for child anxiety related emotional disorders (SCARED; Birmaher et al., 1997). Using a multidimensional approach to mental well-being, this systematic review and meta-analysis aims to explore the effectiveness of school-based interventions focusing on both positive and negative dimensions of mental well-being, which provides a comprehensive and multidimensional understanding of adolescent mental well-being (Huppert & Whittington, 2003; Ryan & Deci, 2001).

4.1.3 Relationships between Adolescent Digital Use and Mental Well-being

Despite research documenting benefits of specific forms of digital use for adolescents' mental and social well-being (Haddock et al., 2022; Zhou & Cheng, 2022), factors associated with risky digital use, such as lack of safety and privacy in digital mediums and being exposed to cyberbullying, are considered to have harmful effects on adolescents' mental health outcomes (Gracia et al., 2023; Li et al., 2024; Livingstone et al., 2017). More commonly, excessive digital use has been shown to predict negative mental health outcomes in young people (Bohnert & Gracia, 2021; Paulich et al., 2021; Santos et al., 2023; Twenge & Campbell, 2018), although the strength of the association has been found to be rather small in a number of studies (Best et al., 2014; Odgers & Jensen, 2020; Valkenburg et al., 2022). The digital use literature has also highlighted growing concern about the harms associated with the addictive or compulsive use of social media, mobile devices, and online content as predictors of mental health problems (e.g., Cai et al., 2023; Kurniasanti et al., 2019; Sohn et al., 2019). This implies that digital use should not be regarded as inherently harmful, but rather the risk factors ought to be investigated in context of their negative associations with mental health outcomes. In our study, we add to previous literature by systematically and jointly studying the effectiveness of intervention programmes focusing on impacting both adolescent digital use (e.g., reducing smartphone use; improving problematic social media use) and mental well-being (e.g., increasing life satisfaction, reduced anxiety).

4.1.4 The Effectiveness of School-level Interventions on Digital Use and Well-being

Intervention designs that are implemented in school settings and utilise the advantages of schools could be desirable contexts for changing young people's, particularly adolescent populations', behavioural outcomes (Dekkers & Luman, 2023; Lopez-Fernandez & Kuss, 2020). Theoretically, considering that health and lifestyle behaviours are more susceptible to peer influence during adolescence compared to other development periods (Giletta et al., 2021; Mollborn & Lawrence, 2018), schools can act as a vital space to foster social support and change the norms involving digital use behaviours. Schools are also a key part of students' daily life, and interventions delivered to be in line with the school-related routines could enable young people to change daily habits according to the intervention programme (Ayub et al., 2023; Oh et al., 2022; Yeun & Han, 2016). From a more practical perspective, the availability of the school facilities and the staff already trained in youth development could reduce the cost of the intervention programmes, and help to reach a wider audience in a more efficient way (Greenberg & Abenavoli, 2017). Schools can also offer a more consistent schedule and a standardised routine to administer the designed interventions, which could be more challenging in individual and family-based designs. Integrating successful interventions into the education setting and having a more holistic approach within schools could improve the long-term effectiveness of such interventions (Busch et al., 2013).

School-based interventions promoting healthier digital use have adopted different strategies. For instance, one study from Australia used schools to give an interactive educational seminar to students, and supplemented the contents with eHealth messages, parental newsletters, and behavioural contract in order to reduce screen time and related outcomes including mental well-being (Babic et al., 2016). Another study from China used schools as a setting to conduct group-based therapy sessions to students at risk of Internet addiction in order to reduce their symptoms and mental health symptoms, which was also supplemented by parental and teacher training sessions (Du et al., 2010). However, across studies on digital use interventions, the evidence on the importance of context is inconsistent. Although one systematic review on interventions on digital use outcomes in Korea concluded that application-based interventions are more favourable to therapy-based interventions (Mac Cárthaigh, 2020), another systematic review found that interventions that are mainly delivered through nondigital education programs were more successful than digital interventions in reducing screen time (Oh et al., 2022). Studies focussing on the addictive nature of digital use highlighted that group-based treatments have promise and need more research to prove their effectiveness (Ayub et al., 2023; Yeun & Han, 2016).

Several studies testing the effectiveness of school interventions to reduce screen time had a focus on physical health rather than mental health outcomes. Thus, studies investigating school-based physical activity interventions typically operationalised "screen time" as a sedentary-behaviour proxy, combined with total sedentary time within the same construct. For example, one study (McMichan et al., 2018) synthesised classroom physical-activity trials where screen time was treated as one of several indicators constituting sedentary behaviour, without estimating effects separately. Another study (Rodrigo-Sanjoaquín et al., 2025) evaluated 24-hour movement interventions in which screen time was included under the broader sedentary-behaviour category alongside accelerometer-measured sitting and sleep outcomes, again without distinct coefficients. Likewise, one more study (Guo et al., 2025) pooled school-based behaviour-change interventions where screen time was classified as a subdomain of sedentary behaviour, however, the meta-analysis was conducted at the sedentary-behaviour level. These studies cannot capture the ways school programmes may directly reshape digital use (e.g., reducing recreational screen exposure or problematic patterns) nor does it prioritise mental-health endpoints beyond movement frameworks. In light of this limited literature, scholars have called for further empirical investigations of school-based treatments targeting adolescents' digital use and how these impact, not only their digital use, but also their well-being (Lopez-Fernandez & Kuss, 2020; Rodrigo-Sanjoaquín et al., 2025; Throuvala et al., 2019). This motivates our focus on reviewing and quantifying with a multidimensional approach the separate effects of school-based interventions on specific digital use outcomes (e.g., screen time, problematic social media use) as well as specific types of mental well-being outcomes (e.g., anxiety, depressive symptoms, life satisfaction, psychological difficulties).

4.1.5 The Present Study

There is an urgent need for understanding how schools could also be used to facilitate targeting adolescents' digital use and their mental well-being. The main goal of this systematic review and meta-analysis is to explore the effectiveness of school-based interventions targeting regulating adolescents' digital use behaviours and in improving adolescents' mental well-being. We investigate the existing studies that utilise schools for changing adolescents' digital use behaviour, such as screen time and problematic use, and positive and negative mental health improvements. Our primary research questions are:

1a. Are school-based interventions targeting adolescent digital use effective in reducing digital use and promoting healthier digital habits?

1b. Are school-based interventions targeting adolescent digital use effective in improving mental well-being?

Additionally, we also explore the types of school-based interventions that have been used to promote healthy digital use and mental well-being among adolescents. Our secondary research question is:

2. What mechanisms and frameworks are used in school-based interventions targeting digital use patterns and mental well-being?

4.2 Methods

This systematic review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) and the Cochrane Handbook for Systematic Reviews of Interventions (Higgins et al., 2024). The protocol for this systematic review and meta-analysis was registered both at PROSPERO (CRD420250648902) and the Open Science Framework (https://osf.io/28f7c/?view_only=1031f2d0d9bc4a96af98e553fe0793a2).

4.2.1 Search Strategy

Six electronic databases (Web of Science, PubMed, PsycINFO, CINAHL, EMBASE, and ERIC) were searched in October 2023, and a second round of database search was conducted on the 14th of February 2025. The PICO (Population, Intervention, Comparator, and Outcome) framework was used to inform the search strategy (Schardt et al., 2007). The search strategy was built around these five concepts and their synonyms: (1) adolescents; (2) smartphone; (3) mental health; (4) intervention; and (5) school-based. The full search strategy is reported in Table A4.1. All searches had English language restrictions and no publication date limit. Considering the limited number of studies conducted in this research area, we included articles that employed different designs, such randomised controlled trials (RCTs), non-randomised trials, or pre- and post- designs.

4.2.2 Eligibility Criteria

Our inclusion criteria comprised of: (1) studies on adolescents between the ages of 12-18 or secondary school students; (2) school-based interventions targeting adolescents' digital use and mental well-being, where the exposure or training program was delivered within the school settings; (3) studies that use at least one indicator of digital use (e.g., screen time, smartphone use, social media use, problematic internet use) and at least one indicator of mental well-being (e.g., depressive symptoms, anxiety, life satisfaction, quality of life) as outcome. Our exclusion criteria comprised: (1) studies conducted in any context other than secondary schools; (2) studies that employed a cross-sectional, cohort, or any qualitative research design; (3) studies that did not directly measure any indicator of digital use or mental health; and (4) studies that only measured physical well-being outcomes (e.g., sedentary behaviours, obesity, sleeping problems).

4.2.3 Screening Process

The title/abstract of the studies yielded by the database search were imported into Covidence software (Covidence, Melbourne, Australia), which automatically removed the duplicates. Two authors (SC and GT) independently screened the title and abstract of the included studies. The full text of the titles and abstracts that were deemed eligible for inclusion were then independently screened by two other authors (SE and PGV) in the full-text screening. Any discrepancies in any of these steps were discussed between the authors until an agreement was reached.

Further, we used a backwards citation chasing to screen all records referenced by any relevant systematic review found during the full-text screening process. For these systematic reviews, we screened the included studies for finding articles that were missed by the database searches.

4.2.4 Data Extraction

Two authors (SC and PGV) independently extracted the data from included studies. This data included descriptive information of the studies (authors, country, year of the publication), intervention characteristics (intervention design, theoretical framework, duration, data collection timepoints), sample characteristics (sample size in total and per intervention group, gender distribution, mean and standard deviation of age), and means and standard deviations for outcomes of interest. Such outcomes included mental health domains (such as anxiety and depressive symptoms), well-being indicators (such as life satisfaction and strengths and difficulties); and screen time indicators (such as, total time spent on screen) and attitudes on digital use (e.g., problematic social media use, addictive behaviours).

4.2.5 Risk of Bias Assessment and GRADE

Two extractors independently assessed the quality of the intervention studies following the Risk of Bias 2 (RoB2) for studies that used an RCT design and the Risk Of Bias In Non-randomized Studies of Interventions (ROBINS-I) for studies that employed a non-randomized design (Sterne et al., 2019). Next, two coders employed the GRADE approach to assess the overall quality of the evidence base (Guyatt et al., 2008). This tool assesses five domains: overall risk of bias, inconsistency, indirectness, imprecision, and publication bias. After grading each of the five domains as either "serious" (i.e., problematic) or "non-serious" (non-problematic) (Guyatt et al., 2008), the certainty of evidence was assessed starting from high certainty of evidence and downgrading it by as many levels as the number of serious grades in the domains. For example, if an outcome of interest had only one "serious" domain, the certain of evidence was downgraded by one, going from high to moderate. If an outcome of interest had two "serious" domains, the certain of evidence was downgraded by two, going from high to moderate, and from moderate to low. Any discrepancies in the data extraction process were discussed among the extractors.

4.2.6 Data Analysis Plan

4.2.6.1 Narrative Synthesis

Results from the articles that were not suitable for the inclusion in the meta-analytic synthesis, such as articles that did not report enough data to extract means and standard deviations, were summarised using a narrative approach. In these types of studies, we described the nature of the interventions and the findings of the paper.

4.2.6.2 Meta-Analysis

We performed six different meta-analyses, one for each of the outcomes of interest for which we had enough data, including (1) total hours per week of screen time, (2) problematic use, (3) anxiety, (4) depressive symptoms, (5) life satisfaction scores, and (6) strengths and difficulties – psychological difficulties scores. We conducted arm-based random-effects meta-analyses, synthesising arm-level outcomes using the percentage change. Comparative (RCTs and non-randomised control trials) studies contributed with both arms, and single-arm studies (pre- and post-intervention without control) contributed with the intervention arm only. A treatment indicator in meta-regression estimated the intervention effect while accounting for between-study heterogeneity evaluated using the I^2, which measure the extent to which the results of studies are consistent. Thresholds for the interpretation of I^2 followed the Cochrane Handbook for Systematic Review and Meta-Analysis recommendations: 0% to 40%, might not be important; 30% to 60%, may represent moderate heterogeneity; 50% to 90%, may represent substantial heterogeneity; 75% to 100%, considerable heterogeneity (Higgins et al., 2024). For all the meta-analyses, the percentage changes from baseline to post-intervention were calculated for the control and the intervention groups.

Following Hopkins and Rowlands (2024)'s recommendations for standardising differences in means in meta-analyses, we standardised the extracted data as follows. For the meta-analyses of questionnaire scores (problematic use, anxiety, depression, life satisfaction/flourishing, and SDQ), we rescaled all the means and standard deviations into a common scale, ranging from 0 to 100, and we calculated the mean difference (post-intervention minus pre-intervention) for the control and the intervention groups. This approach was deemed necessary to improve interpretability, considering that all the questionnaires used to collect such measures had different scale anchors (for example, scales from 0 to 40, or from 0 to 18).

For the meta-analyses regarding the screen time outcomes (hours/day), the percentage changes from baseline to post-intervention were calculated for the control and the intervention groups. Regarding the screen time measures (hours/day), considering that we could not assume the normal distribution of these measures with our data, we decided to log-transform the percentage changes prior to the analyses by using the following formula: $100 \times \log[1 + (\text{mean change/baseline value})]$. Further, we calculated the standard error of the log-transformed percentage change by log-transforming the division of the standard deviation change (Higgins et al., 2019) over the square root of the sample size. Therefore, the log-transformed percentage changes and the log-transformed standard errors for each of the outcomes of interest were meta-analysed using the R Studio package metafor (Viechtbauer & Cheung, 2010), and the random-effects solutions are expressed in log-transformed percentage. Back transformations were calculated using the following formula: $100 \times \text{exp}x/100 - 100$.

The magnitudes of the percentage changes in the outcomes of interest were evaluated using Cohen's *d* thresholds. We converted the percentage changes into equivalents of Cohen's thresholds for small (d = 0.2), moderate (0.5), and large (0.8) magnitudes (Cohen, 1988). We calculated each equivalent percentage change thresholds multiplying the relevant Cohen's *d* threshold value by the mean of observed baseline standard deviations for each study estimate included in the meta-analysis (Hopkins, 2009). Different thresholds resulted from the different outcomes, as the mean of the observed baseline standard deviation changed in base on the studies included. The resulting thresholds for small, moderate, and large effects for each of the outcomes of interest are reported in the supplementary material. Sampling uncertainty was expressed as 95% confidence interval (CI).

We decided to adopt the precision-of-estimate approach, rather than relying on the *p* value as a sole way to interpret the results. This approach offers a more nuanced interpretation of the level of evidence for substantial and trivial magnitudes using the entire range of the CI, and it is commonly used in meta-analyses of questionnaires scores (see Madigan et al., 2023). We interpret the magnitude of the effects by evaluating the lower and upper 95% CI and the area of the sampling distribution, which are aligned with the p-values. If the 95% CI limits crossed both substantial positive and substantial negative values (see thresholds in the supplementary material), the sampling uncertainty for the effect was considered inconclusive; otherwise, sampling uncertainty was deemed conclusive and interpreted based on how much area of sampling distribution fell into *positive substantial* and *trivial* magnitudes (Hopkins, 2022). Thresholds for interpreting sampling uncertainty and deciding whether an effect had weak, some, good, very good, or strong conclusive evidence are reported in Table A2.

4.2.6.3 Sensitivity Analyses and Publication Bias

To calculate the SD change from before to after the interventions, we needed the correlation of outcome of interest at each of the measurement points (Higgins et al., 2024). Because this data was not reported in the articles included in the analyses, we used a correlation value of 0.5. To test whether results differ depending on the selection of the correlation coefficient, we conducted sensitivity analyses using the values 0.2, and 0.8. Further, we performed Egger test for both the control and intervention arms using the standard errors as predictors to check for potential publication bias (Egger et al., 1997). Funnel plots for publication bias both for the intervention and control groups were further created.

4.3 Results

4.3.1 Study Selection and Characteristics

The results of the search strategy are displayed in Figure 1. The initial search yielded 1284 articles and after the screening stages, a total of 17 studies were included in the systematic review, of which 11 provided data for the meta-analyses. Notably, there were two articles produced from the same intervention design and dataset: one article reporting the digital use outcome (O'Dean et al., 2024) and one article reporting mental well-being outcomes (Smout et al., 2024.).

Table 4.1 presents the characteristics of the included studies. The majority of the articles were from Australia (Babic et al., 2016; Lubans et al., 2016; O'Dean et al., 2024; Smout et al., 2024; Wilksch et al., 2015). Two studies were conducted in South Korea (Choi et al., 2020; Kim et al., 2018) and one study was conducted in each of the following countries: Brazil (Barbosa Filho et al., 2019), China (Du et al., 2010), Finland (Aittasalo et al., 2019), Israel (Kor & Shoshani, 2023), Malaysia (Ke & Wong, 2018), Netherlands

(Busch et al., 2013), Peru (Sharma et al., 2018), Switzerland (Das-Friebel et al., 2019), Thailand (Manwong et al., 2018), and Türkiye (Bağatarhan & Siyez, 2022). Six studies used specific eligibility criteria for sampling participants; three studies only included participants that indicated problematic digital use (Bağatarhan & Siyez, 2022; Du et al., 2010; Kim et al., 2018), two studies included participants with high screen time (Babic et al., 2016; Lubans et al., 2016), and one study excluded participants with any mental health problems (Manwong et al., 2018).

Most studies adopted a clustered RCT design, with additional three studies having control groups that were not randomly assigned (Busch et al., 2013; Choi et al., 2020; Sharma et al., 2018), and two studies adopted a pre-post design (Ke & Wong, 2018; Kim et al., 2018). The length of the studies varied greatly, shortest studies were a month long (Das-Friebel et al., 2019; Kim et al., 2018) and the longest study spanned across three school years (Kor & Shoshani, 2023; Sharma et al., 2018).

Table 4.2 summarises the types of intervention designs that were tested in the included studies. All studies had in common that they targeted digital use and at least one dimension of mental well-being as either their primary or secondary outcomes, but studies interventions adopted different designs and approaches, showing an interesting diversity of interventions. Nine interventions developed training sessions or updated existing health education programmes to be delivered in schools (Aittasalo et al., 2019; Babic et al., 2016; Barbosa Filho et al., 2019; Busch et al., 2013; Kor & Shoshani, 2023; Lubans et al., 2016; Manwong et al., 2018; O'Dean et al., 2024; Sharma et al., 2018; Smout et al., 2024; Wilksch et al., 2015) and seven studies introduced group-based therapy sessions (Bağatarhan & Siyez, 2022; Choi et al., 2020; Das-Friebel et al., 2019; Du et al., 2010; Ke & Wong, 2018; Kim et al., 2018; Manwong et al., 2018; Sharma et al., 2018). Additionally, several studies included some form of parental education and/or teacher training (Babic et al., 2016; Bağatarhan & Siyez, 2022; Barbosa Filho et al., 2019; Das-Friebel et al., 2019; Du et al., 2010; Lubans et al., 2016; Sharma et al., 2018) components to the intervention designs. Two intervention designs also utilised online tools such as smartphone apps (Lubans et al., 2016; O'Dean et al., 2024; Smout et al., 2024) and e-messages (Babic et al., 2016). The most common theoretical frameworks across the studies were Cognitive-behavioural approach (Bağatarhan & Siyez, 2022; Du et al., 2010; Ke & Wong, 2018; Kim et al., 2018), Self-determination theory (Babic et al., 2016; Lubans et al., 2016; O'Dean et al., 2024; Smout et al., 2024), and positive psychology (Ke & Wong, 2018; Kor & Shoshani, 2023).

4.3.2 Narrative Synthesis of the Studies Excluded from the Meta-analysis

Six studies were excluded from the meta-analysis because they did not report adequate data to be meta-analysed. Three of them investigated a multi-component health education programme that targets multitudes of youth well-being factors. Busch et al., (2013) conducted a pilot study for their health education programme and compared the intervention group to a sample of another cohort from the same participating school. Even though pilot studies do not test efficacy, the results, reported as the median scores within each group, showed that the intervention group had higher mental well-being compared to the control cohort, and boys in the intervention group had lower computer screen time compared to the control cohort. Sharma et al. (2018) implemented a pre-post intervention design with a non-random control group to assess the effectiveness of a school-wide health programme which also involved health check-ups, psychological counselling to at risk students, and parent and teacher trainings. They found that students in the intervention schools had stable screen time and reduced depressive symptoms at post-measurement and students in the control schools had increased screen time and stable depressive symptoms at post-measurement. Barbosa Filho et al. (2019) used a socio-cognitive theory and socioecological theory in their approach and tested their health education programme in socioeconomically disadvantaged youth in Brazil. They observed a decrease in screen time in the intervention group, however, this was not significantly different compared to the control group. This study did not report on mental well-being outcomes, although the variables were reported to be measured in their research methodology publication (Barbosa Filho et al., 2019b).

The other three studies had a narrower focus in targeting various health predictors. Wilksch et al. (2015) investigated the effectiveness of three versions of a four weeklong educational program mainly targeting early adolescents' eating disorder and obesity risk factors, including screen time and depression. None of the intervention groups reported a significant decrease in screen time or depression compared to control group, with the exception that the boys in the intervention group that targets media internalisation, perceived pressure to be thin/muscular, weight concern had significantly lower depressive scores at the 12-month follow up measurement point compared to the control group. Das-Friebel et al. (2019) conducted a pilot clustered RCT to examine the effects on a psychoeducative seminar on sleep quality predictors, including electronic media use before sleep, and depressive symptoms. Their results showed a significant decrease in the electronic media use in the intervention group compared to the control group. However, they did not find a significant reduction in depressive symptoms. Finally, Aittasalo et al. (2019) used a health action process approach and developed three education lessons involving behavioural theory-driven content that aims to reduce sedentary behaviours including screen time. The lessons were delivered by the previously trained teachers. The intervention did not change the average screen time between the intervention and control groups. The secondary outcomes were the psychosocial indicators including intent and confidence in reducing screen time, which were also not significantly changed across the intervention and control groups.

4.3.3 Risk of Bias

Figures A4.1 and A4.2 show the results of the RoB2 assessment for the studies included in the meta-analyses. The majority of the studies had some concerns due to potential bias arising from the randomisation process (Aittasalo et al., 2019; Babic et al., 2016; Das-Friebel et al. 2019; Lubans et al., 2016; Manwong et al., 2018; Wilksch et al., 2015), and one study had high risk of bias in the randomisation process due to assigning participants across the two intervention conditions based on parental consent (Bağatarhan & Siyez, 2022). One study had high risk of bias due to selection of the reported results (Barbosa Filho et al., 2019) as they omitted mental well-being indicators that were reported in their methodology article from their study. Remaining of the studies yielded low risk of bias.

Figures A4.3 and A4.4 report the results of the ROBINS-I assessments assessment for the studies included in the meta-analyses. Three studies had moderate risk of bias; two studies had no information on the bias due to deviations from the intended interventions domain (Busch et al., 2013; Choi et al., 2020), and one study had moderate risk on the bias due to selection of participants domain (Sharma et al., 2018) because they did not differentiate students who did or did not have data on the pre- and post-assessments. Remaining of the studies yielded low risk of bias.

4.3.4 Meta-analysis

Screen Time (hours/day). Five studies reported data for screen time (Babic et al., 2016; Kor & Shoshani, 2023; Lubans et al., 2016; Manwong et al., 2018; O'Dean et al., 2024), resulting in 10 estimates. There was strong conclusive evidence against the intervention effect for the control groups ($\Delta = 9.1\%$; 95% CI: 2.6% to 15.5%; $p = 0.006$), which reported an average increment of screen time of 8.7% hours/day after the intervention (this value is logarithm back-transformed). There was weak conclusive evidence for the intervention effect for the intervention groups (Δ = -3.7%; 95% CI: –10.0% to 2.7%; $p = 0.259$), which indicated an average decrease of screen time of 3.6% hours/day after the intervention (this value is logarithm back-transformed). The difference between the groups at post-intervention indicated strong conclusive evidence for the intervention effect, with a logarithm back-transformed difference in screen time of 12% (Δ = -12.7%; 95% CI: –16.2% to -9.3%; $p < 0.001$), as presented in Table A4.4 and Figure 4.2. Heterogeneity was moderate (I2 = 40.4%).

Problematic Digital Use. Five studies reported data for problematic digital use (Internet, smartphones, and social media) (Choi et al., 2020; Du et al., 2010; Ke & Wong, 2018, Kim et al., 2018; Manwong et al., 2018), resulting in eight estimates. Although these studies use scales for measuring different aspects of problematic digital use, the analysed measurements are comparable in the ways they assess the problematic nature of adolescents' digital use since the questionnaires include a broader range of indicators of problematic digital use, such as withdrawal, obsession/loss of control, or negative impact on life. There was inconclusive evidence for changes for both the intervention (Δ = -6.2; 95% CI: –16.6 to 4.27; $p = 0.247$), the control groups (Δ = -4.7; 95% CI: –15.4 to 6.0; $p = 0.392$). However, the contrast between the groups provided weak conclusive evidence for the intervention effect in favour of the intervention group (Δ = -1.4; 95% CI: –5.4 to 2.5; $p = 0.468$), indicating that at post-intervention, the intervention group decreased ~1.4 points more compared to the control group. (Table A4.4 and Figure 4.3). Heterogeneity was substantial (I2 = 92.0%).

Anxiety. Seven studies were included in the meta-analysis assessing anxiety scores (Babic et al., 2016; Choi et al., 2020; Du et al., 2010; Ke & Wong, 2018; Kim et al., 2018; Kor & Shoshani, 2023; Smout et al., 2024), resulting in 15 estimates. Table A4.4 and Figure 4.4 display the changes in anxiety scores after the intervention. There was very good conclusive evidence for the intervention effect (Δ = -4.8; 95% CI: –9.1 to 0.6; p = 0.026), resulting in a reduction in anxiety scores in the intervention groups of ~5 points on a scale ranging from 0 to100. In contrast, the evidence of the change in the control groups was weak, but still conclusive (Δ = -3.2; 95% CI: –7.4 to 1.1; p = 0.145). The difference between the groups at post intervention resulted in strong conclusive evidence for the intervention effect, indicating a significant reduction in anxiety scores in the intervention group compared to the control group (Δ = -1.7 95% CI: -2.3% to -1.0; p < 0.001). Heterogeneity was substantial (I2 = 81.1%), indicating that approximately 81% of the observed variability in effect estimates across studies was attributable to true between-study differences rather than sampling error.

Depression. Five studies reported data for depression scores (Ke & Wong, 2018; Kim et al., 2018; Kor & Shoshani, 2023; Manwong et al., 2018; Smout et al., 2024), resulting in eight estimates. There was some conclusive evidence against the intervention effect in the control group (Δ = 1.1; 95% CI: –2.8 to 5.11; p = 0.575), resulting in an increment in the depression scores. There was weak conclusive evidence for the intervention effect in the intervention groups (Δ = -2.3; 95% CI: –6.2 to 1.7; p = 0.255), indicating a reduction of 2.3 points (on the scale 0 to 100) in the depression scores. As shown in Table A4.4 and Figure 4.5, the difference between the groups at post intervention showed strong conclusive evidence for the intervention effect (Δ = -3.4; 95% CI: –4.4 to -2.5; p < 0.001), indicating a significant difference of ~3.4 points in the depression scores between the groups. Heterogeneity was substantial (I2 = 85.7%), suggesting that most of the variability in effect sizes across studies reflects true differences between studies rather than random variation due to sampling error.

Life Satisfaction. Three studies reported data for life satisfaction scores (Babic et al., 2016; Kor & Shoshani, 2023; Lubans et al., 2016), resulting in six estimates. There was strong conclusive evidence against the intervention effect in the control group (Δ = -2.8; 95% CI: –4.9 to -0.7; p = 0.009), indicating a decline in the life satisfaction scores, and very good conclusive evidence for the intervention effect in the intervention group, which showed an increase in life satisfaction (Δ = 2.0; 95% CI: -0.1 to 4.0; p = 0.061). As illustrated in Table A4.4 and Figure 4.6, the meta-analysis revealed strong conclusive evidence for the intervention effect (Δ = 4.7; 95% CI: 3.3 to 6.2; $p < 0.001$), indicating a significant increment in life satisfaction scores in the intervention group compared to the control group. Heterogeneity was moderate (I^2 = 41.8%), suggesting that a meaningful proportion of the variability in effect estimates across studies reflects real between-study differences rather than sampling error, although random variation still accounts for a substantial share of the observed dispersion.

Strengths and Difficulties. Three studies reported data for SDQ – psychological difficulties scores (Babic et al., 2016; Choi et al., 2020; Du et al., 2010; Manwong et al., 2018), resulting in six estimates. There was some conclusive evidence for the intervention effect in the control groups (Δ = -0.5; 95% CI: -3.6 to 2.6; p = 0.764) and very good conclusive evidence for the intervention effect in the intervention groups (Δ = -3.0; 95% CI: -6.1 to 0.1; p =0.055). As illustrated in Table A4.4 and Figure 4.7, the meta-analysis revealed very good conclusive evidence (Δ = -2.6; 95% CI: -4.8 to -0.3; p = 0.024), indicating a significant reduction in SDQ scores in the intervention group compared to the control group. Heterogeneity was substantial (I^2 = 71.1%), indicating that a large proportion of the variability in effect estimates across studies is attributable to genuine between-study differences rather than sampling error, suggesting meaningful inconsistency in the observed effects.

4.3.5 Sensitivity Analyses and Publication Bias

Table A4.5 shows the results of the sensitivity analyses using correlation coefficients of 0.2, 0.5, and 0.8. Overall, the results are consistent with our main meta-analysis findings, which used the correlation value of 0.5. Table A4.6 shows the complete Egger test results for each of the outcomes of interest. Figure A4.5 illustrates the funnel plots for the screen time outcome. Test results indicate no evidence of funnel asymmetry in the control arm ($z = -0.74$, $p = 0.457$) and in the intervention arm ($z = -0.53$, $p = 0.594$), meaning there is no clear evidence of funnel asymmetry in these arm-specific analyses. Given only 5 arms per group and high heterogeneity (Control $I^2 = 83.75\%$; Intervention $I^2 = 61.69\%$), these findings should be interpreted cautiously. Figure A4.6 illustrates the funnel plots for the problematic use outcome. Test results were significant for the intervention arm (intervention: $z = -4.11$, $p < 0.001$), meaning there is evidence of funnel asymmetry in the intervention group. Figure A4.7 illustrates the funnel plots for the anxiety outcome. The test results showed no evidence of funnel asymmetry for the control arm ($k = 6$; $z = 0.08$, $p = 0.933$) and asymmetry for the intervention arm ($k = 9$; $z = -2.46$, $p = 0.014$). Figure A8 illustrates the funnel plots for the depressive symptoms. The test results were not significant for either arm (control: $z = 0.44$, $p = 0.658$; intervention: $z = -0.75$, $p = 0.453$), indicating no clear evidence of funnel asymmetry. However, given the small number of studies, these findings should be interpreted cautiously. Figure A4.9 illustrates the funnel plots for life satisfaction and flourishing outcomes. The test results were not significant for either arm (control: $z = 0.84$, $p = 0.400$; intervention: $z = -0.789$, $p = 0.430$). Heterogeneity is negligible in the intervention arm ($I^2 = 0\%$), but with only three studies per arm, these results should be interpreted cautiously. Figure A4.10 illustrates the funnel plots for the SDQ – psychological difficulties outcome. The test results showed no evidence of funnel asymmetry for the control arm ($z = 0.280$, $p = 0.780$) and asymmetry for the intervention arm ($z = -4.84$, $p < 0.001$). However, given that the number of studies is rather low across the analyses ($k = 3$), these results should also be interpreted cautiously.

4.3.6 Certainty of Evidence

We assessed the certainty of evidence using the GRADE approach. Notably, the certainty of evidence was not downgraded for screen time (hours/day) and life satisfaction; it was downgraded once and reported as moderate SDQ – psychological difficulties; twice and reported as low for depression; and thrice and reported as very low for screen time (problematic use) and anxiety. The overview of the reasons for downgrading the certainty of evidence for the outcomes of interest are reported in Table A4.7.

4.4 Discussion

This study has conducted a systematic review and meta-analysis to examine the effectiveness of school-based interventions targeting digital use on adolescents' digital use patterns (i.e., screen time, problematic use) and their mental well-being (i.e., depressive symptoms, anxiety, life satisfaction and flourishing, and psychological difficulties).

The results of our study can be summarised as follows. First, our findings indicate that school-based interventions are effective tools for changing adolescents' digital use patterns, specifically in reducing screen-based time. Results from the meta-analyses showed that, after the intervention, hours per day of screen time increased by 8.7% in the control groups and decreased by 3.6% in the intervention groups, showing a significant difference between the groups at post-intervention of 12% (back-transformed percentage change). Problematic digital use reduced by 6.2 points (on a scale from 0 to 100) in the intervention group and by 4.7 points in the control group. Even though these decreases were not significant within group, our analysis revealed weak statistically significant differences between the groups at post-intervention, with the intervention group decreasing ~1.4 points more than the control group. Our analyses addressing screen time separately critically contribute to previous literature on this topic, as most previous meta-analyses have investigated the effectiveness of school-based interventions on sedentary behaviours, wherein screen time is part of several components measured within an umbrella construct of sedentary time (Lai et al., 2025; Rodrigo-Sanjoaquín et al., 2025). Regarding problematic use, while our results lack enough statistical power to be conclusive, the results are in line with some research indicating that school-based interventions are effective tools in reducing problematic digital use (Ayub et al., 2023; Yeun & Han, 2016), albeit future studies that could include more observations and participants are needed. Overall, the finding that school-based interventions targeting digital use lead to reduced screen time supports previous scholarship suggesting that schools, with their highly structured daily routines and strong peer effects on changing norms, are effective spaces to change student behaviours within the context of interventions (Dekkers & Luman, 2023; Giletta et al., 2021; Lopez-Fernandez & Kuss, 2020).

Second, our study found conclusive evidence for the effectiveness of the school-based interventions in improving positive mental well-being and reducing negative mental well-being indicators, although evidence of improvements slightly varied in each well-being measure. For negative mental well-being measures, we found that in the intervention groups, the anxiety score declined by 4.8 points and the depression score declined by 2.3 points. In the control groups, anxiety scores decreased by 3.2 points, whereas depression scores increased by 1.1 points. Further, psychological difficulties were reduced by 3 points in the intervention groups, compared to a negligible reduction of 0.5 point in the control groups. This contrast was statistically significant and indicated that at post-intervention, the difference between the two groups was 2.6 point. In relation to the positive mental well-being, our findings showed that school-based interventions are helpful in improving life satisfaction, which increased by 2 points in the intervention groups, compared to a -2.8-point reduction in the control groups. While previous studies have indicated that school-based interventions can be effective in promoting young people's mental health outcomes (Cilar et al., 2020; Paulus et al., 2016), our study is, to our knowledge, the first meta-analysis to study how school-based interventions directed to change digital habits impact adolescent positive and negative well-being. Our findings globally indicate that, when adolescents are subject to school-based programmes intending to produce more balanced and healthier digital habits, they become less prone to psychological problems like depression and anxiety and more prone to improving their life satisfaction and flourishing. One reason for this could be that the interventions may be successfully targeting digital use, which could improve adolescents' digital maturity and, in turn, may help them to benefit from their digital use, rather than being harmed by it (Celik et al., 2025; Laaber et al., 2023). Future studies should address the reasons and potential mechanisms that explain why positive and negative well-being are subject to improvements when adolescents participate in school-based programmes oriented toward more balanced digital media engagement.

Third, results from our narrative synthesis showed a variety of mechanisms and frameworks used in the school-based intervention designs, which were more apparent in the approach to digital use in intervention designs. One common approach in the literature, particularly in universal multi-component interventions targeting several health-related risk factors, was to measure screen time as a proxy of sedentary behaviour, rather than focusing specifically on screen time as specific engagement with digital devices (e.g., Busch et al., 2013; Lubans et al., 2016; Sharma et al., 2018). Other studies narrowed their focus on problematic digital use, but many of them did not run high-quality RCTs (except for Du et al. 2010 and Manwong et al., 2018). This suggests a need for school-based interventions that target problematic digital use with more robust methodological designs. Various studies integrated digital device components into their designs, including smartphone apps (Lubans et al., 2016) and online messages (Babic et al., 2016). Although these tools could allow a more dynamic feature for the intervention designs, their effectiveness could differ based on participants' digital skills to navigate through them (Livingstone & Helsper, 2010), an area that deserves more attention in future research.

Overall, our study found a variation in the length and size of the interventions. Some studies had a small and relatively short design, and some studies invested in a long-term design covering the entire participating schools. For example, Kim et al. (2018) tested a one-month-long group-based therapy intervention on problematic digital use with only 17 students, while Busch et al. (2013) applied a health education program to 336 students that lasted three years. Also, there was not enough evidence to draw conclusions on when in time interventions were more effective, and whether and how the length of interventions matters to produce effective outcomes. Moreover, the studies also differed in design (cluster RCTs, non-randomised controlled trials, and single-arm pre-post studies), and participant selection, with some studies including universal school samples and others focusing on adolescents with excessive screen time or problematic digital use. These variations along with the differences in the operationalisation of the related but non-identical constructs likely contributed to the substantial heterogeneity observed in several of the meta-analyses, meaning that the high between-study variability in effect sizes reflected genuine differences across studies rather than random error alone.

However, this heterogeneity does not render the findings uninformative. Rather, it suggests that the pooled estimates should be interpreted as average effects across a diverse and still methodologically developing intervention literature. The use of random-effects models was appropriate for this purpose, as it accounts for variation in true effects across studies. Moreover, for several outcomes, the overall direction of effects was broadly consistent, with intervention groups showing more favourable post-intervention changes than control groups. The sensitivity analyses also showed that the results were robust to different assumptions regarding the pre-post correlation coefficients. Nevertheless, because the number of studies per outcome was limited, we could not conduct adequately powered moderator analyses to formally test sources of heterogeneity. Future research with a larger evidence base should examine whether intervention type, duration, target group, and outcome operationalisation explain variation in effectiveness.

This study had some limitations which warrant a careful interpretation of the meta-analyses' results. First, the small number of studies for some investigated outcomes reduced the power of the analysis, making it difficult to explore the true effect of interventions. To remedy this possible outcome, we adopted a conducted arm-based random-effects meta-analyses analysis strategy which allowed us to increase the sample size by including pre-post studies without a control group, which led to lower GRADE assessments for several of the outcomes. Second, in terms of study design, we observed that many of the studies applied multi-component interventions. While this approach could be beneficial to have a more comprehensive approach for improving mental well-being (Busch et al. 2013), it makes unclear how much of the intervention content is specifically focused on digital use. Third, mainly due to the lack of consensus in defining and operationalizing problematic use in the literature (Almourad et al., 2020), we encountered studies with a variety of problematic use measurements (e.g., internet overuse, phone addiction, social media addiction). Although pooling these studies with different contexts of digital engagement may partly constrain the precision of this measurement, our analysis on problematic digital use still offers an insight into the extent of the effectiveness of school-based interventions on negative experiences that apply to various forms of digital use. Fourth, due to the limited number of studies included in the meta-analysis, publication bias assessed through Egger's test and funnel plots could be underpowered, potentially reducing the ability to detect asymmetry and small-study effects. Accordingly, the absence of clear evidence of publication bias should not be interpreted as definitive evidence that publication bias is not present. Finally, our data did not have enough statistical power to separate between short- and long-term effects in the interventions. Future studies will hopefully be able to separate between short-, medium-, and longer-term effects of school-level interventions on digital habits, both in terms of digital use patterns and mental well-being.

Taken together, despite some limitations, our study provides strong policy implications for school-based interventions. Because of the great concerns about excessive screen time and addictive components of online activities and their impacts on adolescent mental well-being (Santos et al., 2023), our findings contribute to the search for a successful solution to address these issues. As schools are the fundamental learning and socialising setting for young people, interventions designed to be delivered through the education systems in group formats to improve digital habits seem to be effective in addressing adolescents' digital use problems as well as their mental well-being. We provide enough evidence to justify investigating alternative school-based interventions further to study the precise mechanisms by which these school-level interventions may be effective to improve adolescents' digital lives and well-being.

Finally, we recommend that future studies focus on preregistering theory-driven components and high-quality RCT designs. Doing so would ensure follow-up measurements for long-term results, as well as reporting evidence on implementation fidelity and cost-effectiveness. With these improvements, the effectiveness of school-based interventions in reducing adolescents' problematic digital use and improving positive mental well-being could be assessed more systematically.

Overall, this study provides some key findings for the broader frameworks of the thesis and motivates the digital detox intervention experiment in Chapter 5 to incorporate schools as an element of the intervention design. First, because a large portion of the studies used SDT framework (e.g., Babic et al., 2016; Lubens et al., 2016), the findings emphasise the importance of supporting individuals' basic psychological needs for autonomy, competence, and relatedness. Improvements in the screen time and positive and negative mental well-being outcomes observed in the intervention groups are consistent with SDT that environments supporting these psychological needs contribute to better mental well-being. Considering that digital maturity is a holistic concept tailored to capture these needs in online concepts (Laaber et al., 2023; Laaber et al., 2024), it is also crucial to foster digital maturity of young people in school contexts. Additionally, these results could be interpreted through digital divides literature. School-based programmes can reach adolescents across diverse socioeconomic backgrounds and by incorporating digital use interventions within educational content, these programmes may help reduce inequalities in adolescents' capacity to develop healthy digital habits and to protect their mental well-being. However, the heterogeneity in intervention designs and the limited evidence on problematic digital use highlight that future research should more explicitly consider how socioeconomic and contextual inequalities shape adolescents' engagement with interventions and their ability to benefit from them.

4.5 Conclusion

There are growing societal and scientific concerns regarding the potentially negative impacts of adolescents' excessive and problematic digital use on their well-being. Although schools can act as key contexts for implementing interventions targeting adolescents' digital behaviours and well-being, previous literature has provided limited evidence on whether school-based interventions are effective in helping adolescents to reduce their digital use and improve their mental well-being. To address this timely research question, our study employed an innovative arm-based random-effects meta-analytic approach to investigate the effectiveness of school-based interventions, combined with a narrative synthesis to summarise studies that were not suitable for inclusion in the meta-analysis. The findings of our study showed that school-based interventions are effective in reducing adolescents' screen use and, anxiety and depressive symptoms. These findings indicate that schools play a key role in adolescents' daily digital habits and mental well-being, implying that schools could be a critical context to promote behaviour change and mental health support among adolescents. Yet, the available interventions remain methodologically thin for problematic digital use and for bolstering positive well-being, with many multicomponent programs and short-term designs obscuring strong implications. Future research should investigate school-based interventions targeting problematic digital use and positive mental well-being specifically and using robust RCT designs that allow to effectively tackle adolescents' digital use.

4.6 Tables and Figures

Table 4.1 Characteristics of the included studies

Authors, year	Country	Design	*N*	Gender, n (%)	Mean age, years (SD)	Inclusion criteria
Aittasalo et al., 2019	Finland	Multimodal cluster RCT	1550	705F, 845M	13.9 (0.5)	All eighth graders from participating secondary schools
Babic et al., 2016	Australia	Cluster RCT	322	211F, 111M	14.4 (0.6)	Students who reported more than 2 hrs a day of screen-time
Bağatarhan and Siyez, 2022	Turkey	Multimodal cluster RCT	52	Not reported	15-16, no more information is given	Students at risk of internet addiction according to the Internet Addiction Scale
Barbosa Filho et al., 2019	Brasil	Cluster RCT	1085	526F, 559M	Ages 11-13: 574, Ages 14-18: 511	All students from participating secondary schools
Busch et al., 2013	Netherlands	Pre-post with control group	356	183 F, 173M	16, no more information is given	All students from participating schools
Choi et al., 2020	South Korea	Case-control study	49	41F, 8M	16, no more information is given	All sophomore students from participating schools
Das-Friebel et al., 2019	Switzerland	Cluster RCT	352	163F, 189M	15.09 (1.65)	All students from participating secondary schools
Du et al., 2010	China	Cluster RCT	56	11F, 45M	15.39 (1.69) Intervention 16.63 (1.23) Control	Students who meet Beard's diagnostic criteria for Internet addiction
Ke and Wong, 2018	Malaysia	Pre-post without control group	45	16F, 29M	15.69 (1.08)	Voluntary sampling, priority given to students with problematic internet use levels

Kim et al., 2018	South Korea	Pre-post without control group	17	10F, 7M	12-17, no more information is given	Students who met Young’s diagnostic criteria for problematic internet use
Kor and Shoshani, 2023	Israel	Cluster RCT	1670	809F, 861M	12.96 (2.01)	All students from participating secondary schools
Lubans et al., 2016	Australia	Cluster RCT	361	361M, all boys	12.7 (0.5)	All students from participating secondary schools
Manwong et al., 2018	Thailand	Cluster RCT	245	129F, 116M	13.30 (0.68)	All students from participating secondary schools except those with any diseases or physical or mental health problems
O'Dean et al., 2024 and Smout et al., 2024	Australia	Cluster RCT	6639	3280F, 3359M	12.7 (0.50)	All students from participating secondary schools who spoke English fluently
Sharma et al., 2018	Peru	Pre-post with control group	Pre: 587 Post: 1532	Pre: 310F, 277M Post: 895F, 623M	Ages 11-14: 661, Ages 15-20: 592 Not reported: 12	All students from participating secondary schools
Wilksch et al., 2015	Australia	Cluster RCT	1316	840F, 476M	13.21 (0.68)	All students from participating secondary schools

Note. RCT: Randomized controlled trial.

Table 4.2 Intervention characteristics of the included studies

Authors, year	Intervention Characteristics			Digital Use		Mental Health	
	Content	Framework	Duration	Variables	Type of measure	Variables	Type of measure
Aittasalo et al., 2019	Behavioural theory-driven content during three health education lessons.	Health Action Process Approach	4 weeks	Excessive screen time	Time (days)	Confidence in reducing screen time	Categorical levels
Babic et al., 2016	eHealth messaging (main), interactive seminar, a behavioural contract and parental newsletters	Self-determination theory	6 months	ASAQ	Time (minutes/ day)	SDQ - Difficulties subscale; KPDS; Flourishing Scale	mean score
Bağatarhan and Siyez, 2022	Cognitive-behavioural prevention program for participants. Psycho-education program for parents (group 1 only).	CBT	8 sessions	YIAT	mean score	OCS	mean score
Barbosa Filho et al., 2019	Health education for students and families and teacher training	Socio-cognitive theory; Socio-ecological theory	5 months	Screen time (TV and computer use/gaming)	Time (<2 hrs a day)	NA	NA
Busch et al., 2013	Health school policy and health education	Health promoting school approach	3 years	CIUS; Screen time: TV, computer, gaming	CIUS: mean score; ST: Time (hrs)	SDQ	mean score
Choi et al., 2020	20 minutes long meditation program sessions in the morning, two times a week	Mind subtraction meditation	12 weeks	Korean Smartphone Addiction Proneness Scale	mean score	Stress scale; Stress Coping (emotion focusing subscale)	mean score
Das-Friebel et al., 2019	25 minutes psychoeducative school-based intervention, parent information	NA	4 weeks	Bedtime electronic media use	frequency	General Depression Scale; SDQ - Hyperactivity/ Attention subscale	GDS: Frequency; SDQ: mean score
Du et al., 2010	School-based group CBT, psychoeducation for teachers, and parent training	CBT	8 sessions	Internet Overuse Self-Rating Scale	mean score	SDQ; Screen for Child Anxiety Related Emotional Disorders	mean score

Ke and Wong, 2018	Weekly CBT in a group format by registered school counsellors	Positive psychology; CBT	8 weeks	PIUQ	mean score	SIAS DASS	mean score
Kim et al., 2018	Group CBT, 2 sessions per week	CBT	1 month	IAS	mean score	CDI STAI	mean score
Kor and Shoshani, 2023	Training in self-awareness, addiction resistance, problem solving, emotion regulation, etc. Delivered by trained teachers.	Positive psychology; addiction prevention	2 years	Screen Time Scale: Daily screen use	Time (hrs /day)	GSI; Brief Multidimensional Students' Life Satisfaction Scale; PANAS-C	mean score
Lubans et al., 2016	Professional development for teachers, sport sessions, seminars, a smartphone app, and parental strategies for reducing screen time	Self-Determination Theory	20 weeks	Recreational screen time	Time (minutes/ day)	Flourishing Scale	mean score
Manwong et al., 2018	Group activity-based motivational enhancement therapy and health education	Group-based motivational enhancement therapy	8 weeks	Average duration of social media usage; SMAT.	Time (hrs /day); mean score	Center for Epidemiologic Studies-Depression Scale; SDQ	mean score
O'Dean et al., 2024 and Smout et al., 2024	6 health education online modules, internet-based feedback, optional teacher-facilitated activities and smartphone app.	Self-Determination Theory; Social cognition and Social influence	approx. 6 weeks	Screen Time: TV, device use	Time (hrs /day)	Patient Health Questionnaire; PROMIS Anxiety Pediatric; KPDS.	mean score
Sharma et al., 2018	Health education, check-ups, a canteen, counselling for high-risk students, mini-gyms, teacher training, parent workshops.	NA	18 months	Sedentary behaviours (TV, gaming, Internet)	Time (>2 hrs a day)	Psychological Distress	mean score
Wilksch et al., 2015	Two lessons per week. Three programs: Media Smart; Life Smart; Helping, Encouraging, Listening and Protecting Peers	NA	4 weeks	Screen Time (TV, DVD, Internet, computer, console)	Time (hrs /day); mean score	Child Depression Inventory – Short Form	Frequency

Note. Only variables of our interests are reported for brevity. CBT: Cognitive-behavioural therapy. NA: not reported in the article.
ASAQ: Adolescent Sedentary Activity Questionnaire. CIUS: Compulsive Internet Use Scale. IAS: Internet Addiction Scale. PIUQ: Problematic Internet Use Questionnaire. S-MAT: Social Media Addiction Test. YIAT: Young Internet Addiction Test.
CDI: Children's Depression Inventory. DASS: Depression Anxiety Stress Scale. GSI: Global Severity Index. KPDS: Kessler Psychological Distress Scale. OCS: Online Cognition Scale. SDQ: Strengths and Difficulties Questionnaire. SIAS: Social Interaction Anxiety Scale. STAI: State-Trait Anxiety Inventory. PANAS-C : Positive and Negative Affect Scale-Children

Figure 4.1 Prisma flow diagram

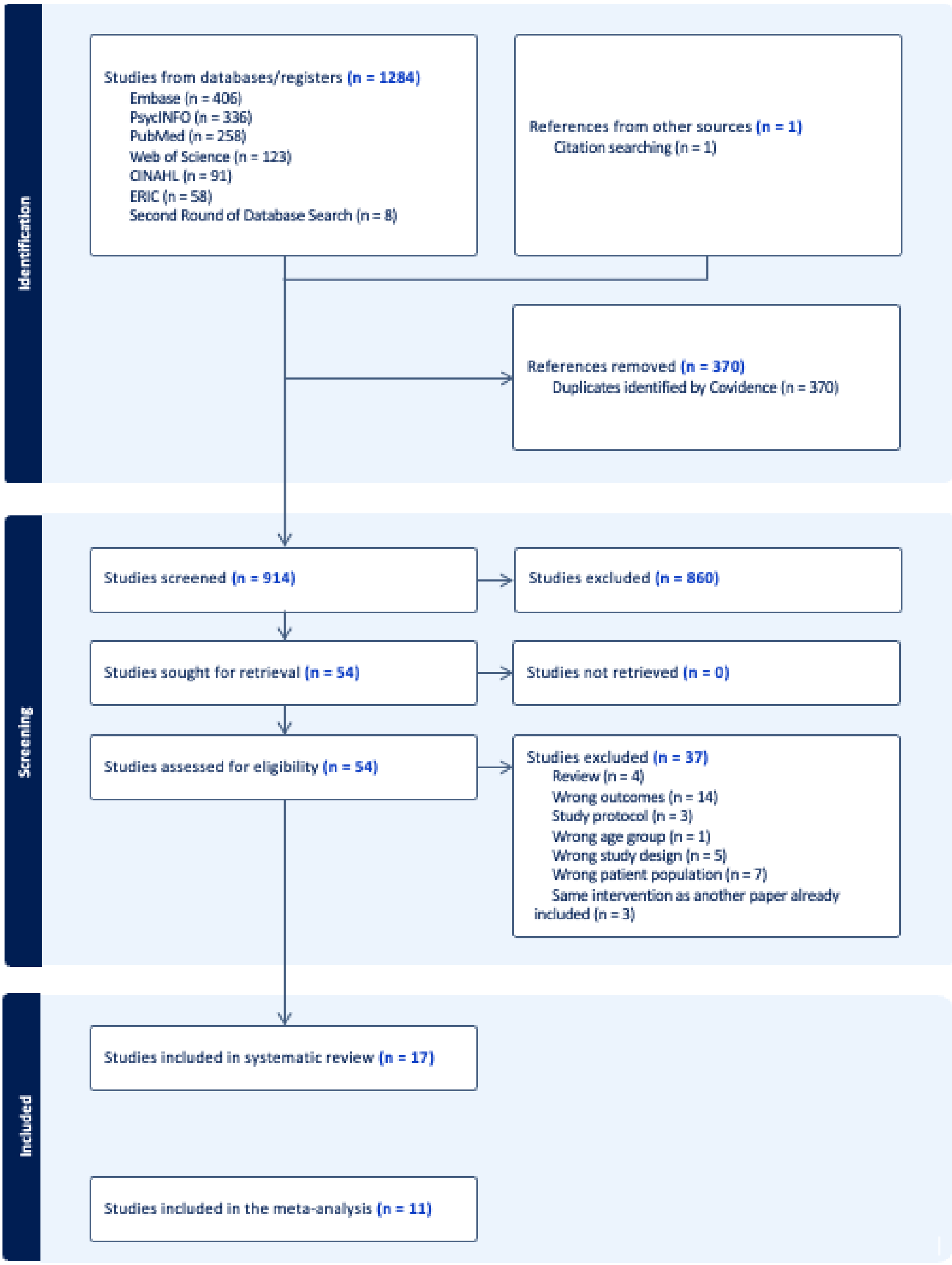
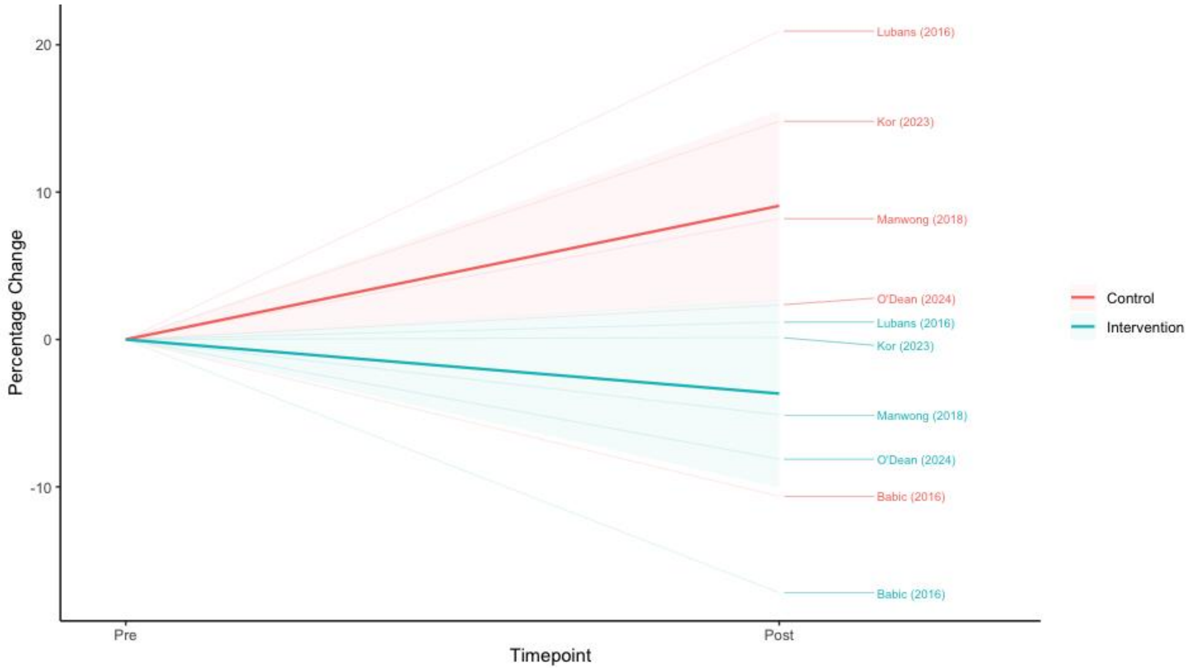
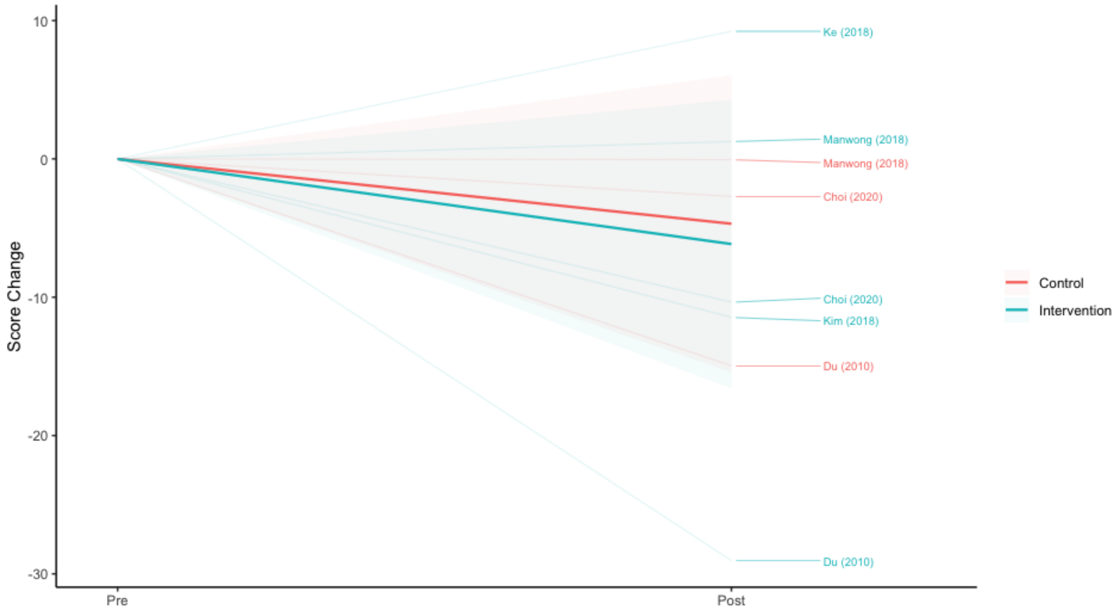


Figure 4.2 Percentage change in screen time from pre- to post- intervention: control vs. intervention



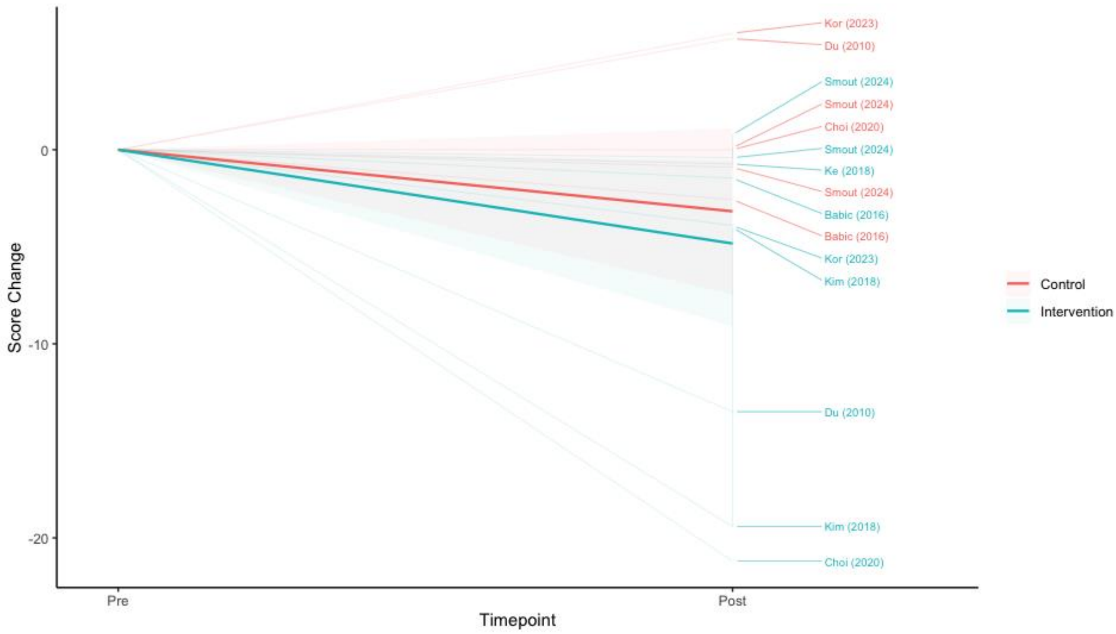
Note. Pooled change (starts at 0) using SE = 0.5. Faint lines = individual studies; bold lines = pooled trajectories; light fill = 95% CI for pooled change.

Figure 4.3 Percentage change in problematic use from pre- to post- intervention: control vs. intervention



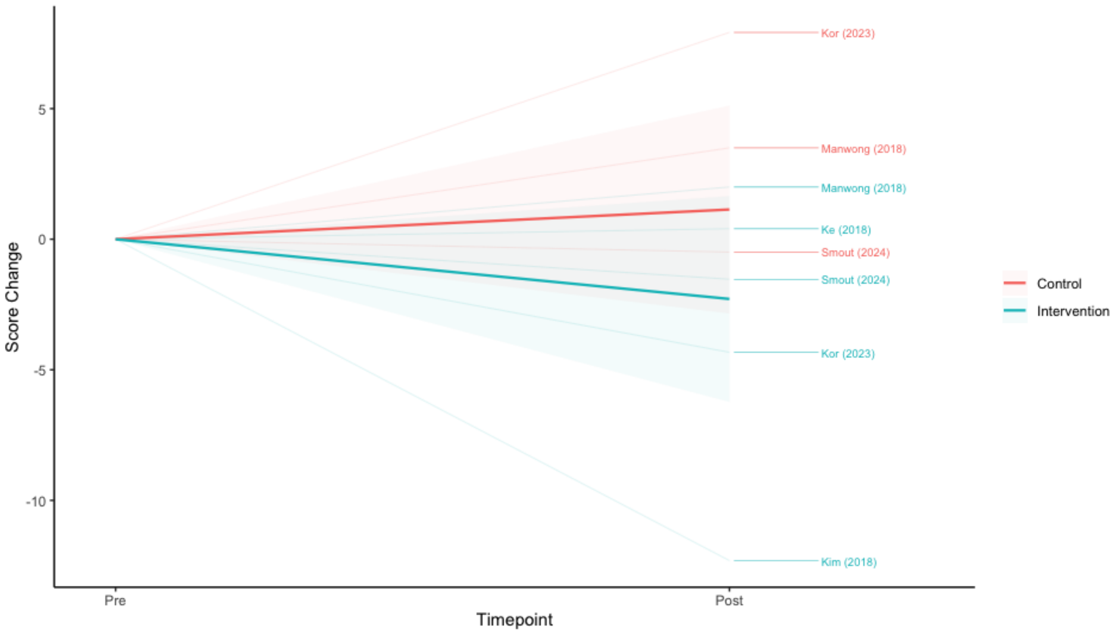
Note. Pooled change (starts at 0) using SE = 0.5. Faint lines = individual studies; bold lines = pooled trajectories; light fill = 95% CI for pooled change.

Figure 4.4 Percentage change in anxiety from pre- to post- intervention: control vs. intervention



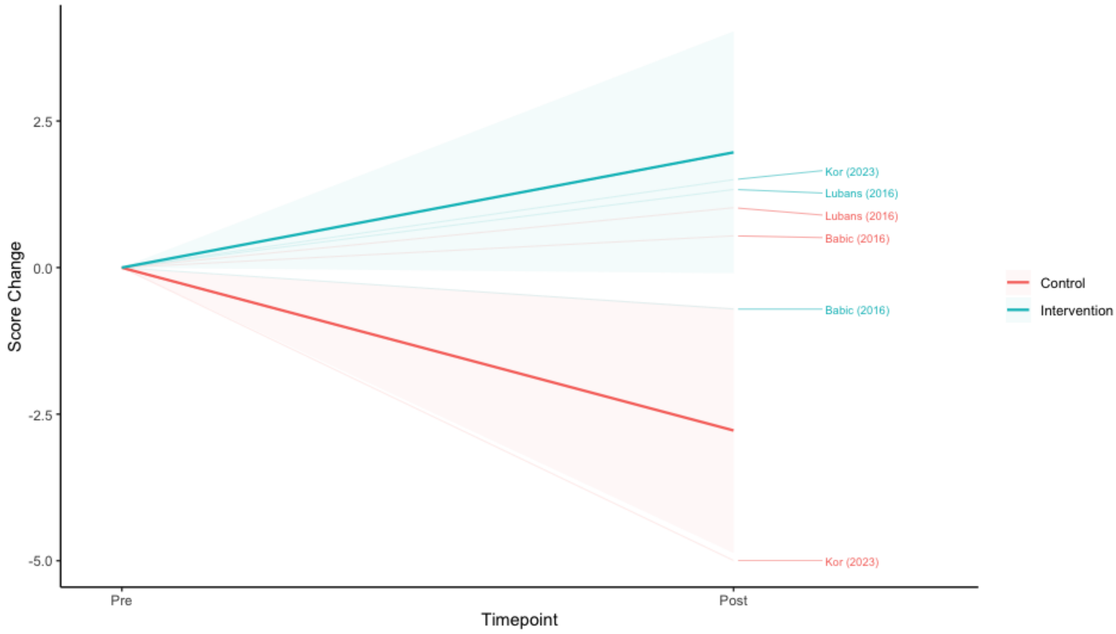
Note. Pooled change (starts at 0) using SE = 0.5. Faint lines = individual studies; bold lines = pooled trajectories; light fill = 95% CI for pooled change.

Figure 4.5 Percentage change in depression from pre- to post- intervention: control vs. intervention



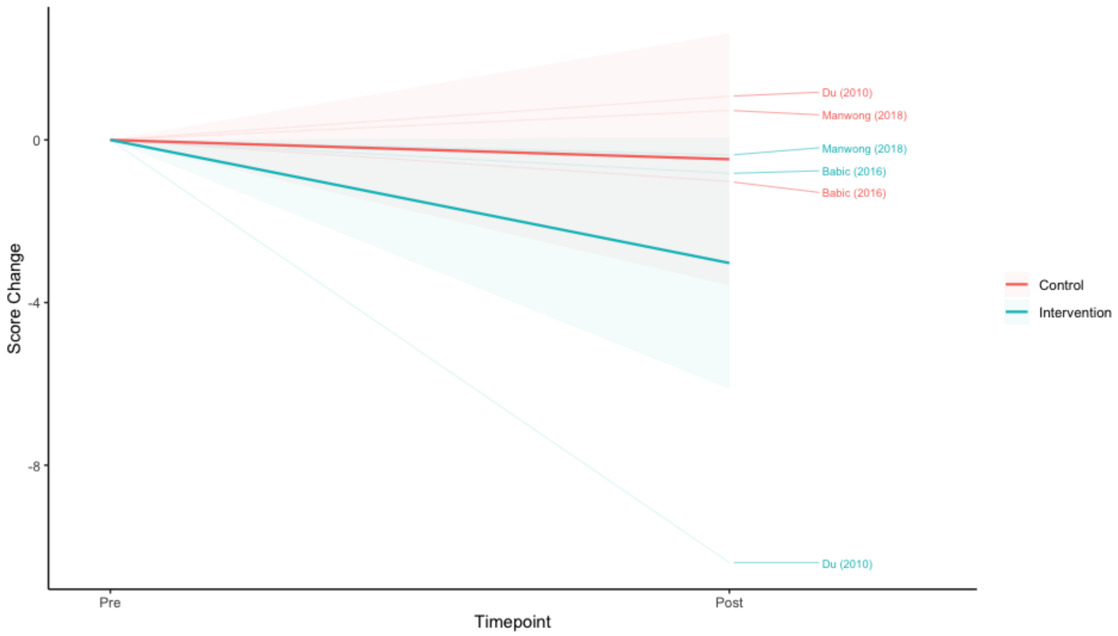
Note. Pooled change (starts at 0) using SE = 0.5. Faint lines = individual studies; bold lines = pooled trajectories; light fill = 95% CI for pooled change.

Figure 4.6 Percentage change in life satisfaction and flourishing from pre- to post-intervention: control vs. intervention.



Note. Pooled change (starts at 0) using SE = 0.5. Faint lines = individual studies; bold lines = pooled trajectories; light fill = 95% CI for pooled change.

Figure 4.7 Percentage change in Strengths and Difficulties Questionnaire - Psychological difficulties from pre- to post- intervention: control vs. intervention



Note. Pooled change (starts at 0) using SE = 0.5. Faint lines = individual studies; bold lines = pooled trajectories; light fill = 95% CI for pooled change.

4.7 Appendix

Table A4.1 Systematic search keywords and database searching details

	PubMed	
Search	**Keywords**	**Results**
#1	(((((((Adolescen*) OR (Youth)) OR (Teen*)) OR (juvenil*)) OR (student*)) OR (pupil*) OR ("Adolescent"[Mesh]) OR ("Students"[Mesh])))	2,891,986
#2	((((((((((((Smartphone) OR (ICT)) OR ("Information and communication technologies")) OR (Digital technolog*)) OR (phone)) OR (tablet*)) OR (social media)) OR (social network*)) OR (social networking site*)) OR (sns)) OR (digital media)) OR (Internet)) OR (screentime) OR (screen time) OR ("Smartphone"[Mesh]) OR ("Social Media"[Mesh]) OR ("Social Networking"[Mesh]) OR ("Internet Use"[Mesh]))	570,661
#3	((((trial*) OR (experiment*)) OR (intervention*)))	6,195,748
#4	(((((((((mental health) OR (depression)) OR (anxiety)) OR (quality of life)) OR (life satisfaction)) OR (affect*)) OR (mood)) OR (loneliness)) OR ("Mental wellbeing") OR ("Mental well-being") OR ("Psychological wellbeing") OR ("psychological well-being") OR ("Mental Health"[Mesh] OR ("Depression"[Mesh]) OR ("Anxiety"[Mesh])) OR ("Psychological Well-Being"[Mesh]) OR ("Affect"[Mesh]))	3,836,895
#5	(((school-based) OR (classroom-based)))	18,972
#6	#1 AND #2 AND #3 AND #4 AND #5	258

	PsycINFO	
Search	**Keywords**	**Results**
#1	(((Adolescen*) OR (Youth)) OR (Teen*)) OR (juvenil*)) OR (student*)) OR (pupil*) OR (DE "Youth Mental Health")))	1.331.911
#2	((Smartphone) OR (ICT) OR ("Information and communication technologies") OR (Digital technolog*) OR (phone) OR (tablet*) OR (social media) OR (social network*) OR (social networking site*) OR (sns) OR (digital media) OR (Internet) OR (DE "Smartphone Use") OR (screen time) OR (screentime) OR (DE "Screen Time") OR (DE "Information and Communication Technology") OR (DE "Digital Technology") OR (DE "Social Media") OR (DE "Digital Media") OR (DE "Social Networks"))	179,009
#3	(((trial*) OR (experiment*)) OR (intervention*)))	1,385,188
#4	((mental health) OR (depression)) OR (anxiety)) OR (quality of life)) OR (life satisfaction)) OR (affect*)) OR (mood)) OR (loneliness) OR ("Mental wellbeing") OR ("Mental well-being") OR ("Psychological wellbeing") OR OR ("psychological well-being") OR (DE "Mental Health") OR (DE "Depression (Emotion)") OR (DE "Anxiety") OR (DE "Quality of Life") OR (DE "Life Satisfaction") OR (DE "Loneliness"))	1,751,911
#5	((school-based) OR (classroom-based))	39,196
#6	#1 AND #2 AND #3 AND #4 AND #5	336

	CINAHL	
Search	**Keywords**	**Results**
#1	(((Adolescen*) OR (Youth)) OR (Teen*)) OR (juvenil*)) OR (student*)) OR (pupil*) OR (DE "Youth Mental Health")))	909,770
#2	((Smartphone) OR (ICT) OR ("Information and communication technologies") OR (Digital technolog*) OR (phone) OR (tablet*) OR (social	182,709

	media) OR (social network*) OR (social networking site*) OR (sns) OR (digital media) OR (Internet) OR (DE "Smartphone Use") OR (screen time) OR (screentime) OR (DE "Screen Time") OR (DE "Information and Communication Technology") OR (DE "Digital Technology") OR (DE "Social Media") OR (DE "Digital Media") OR (DE "Social Networks"))	
#3	(((trial*) OR (experiment*)) OR (intervention*)))	1,182,644
#4	((mental health) OR (depression)) OR (anxiety)) OR (quality of life)) OR (life satisfaction)) OR (affect*)) OR (mood)) OR (loneliness) OR ("Mental wellbeing") OR ("Mental well-being") OR ("Psychological wellbeing") OR OR ("psychological well-being") OR (DE "Mental Health") OR (DE "Depression (Emotion)") OR (DE "Anxiety") OR (DE "Quality of Life") OR (DE "Life Satisfaction") OR (DE "Loneliness"))	1,015,425
#5	((school-based) OR (classroom-based))	12,627
#6	#1 AND #2 AND #3 AND #4 AND #5	91

ERIC

Search	Keywords	Results
#1	(Adolescen*) OR (Youth) OR (Teen*) OR (juvenil*) OR (student*) OR (pupil*) OR (MJMAINSUBJECT.EXACT.EXPLODE("Youth"))	1,029,827
#2	(Smartphone) OR (ICT) OR ("Information and communication technologies") OR (Digital technolog*) OR (phone) OR (tablet*) OR (social media) OR (social network*) OR (social networking site*) OR (sns) OR (digital media) OR (Internet) OR (screen time) OR (screentime) OR (MJMAINSUBJECT.EXACT.EXPLODE("Social Media")) OR (MJMAINSUBJECT.EXACT.EXPLODE("Social Networks")) OR (MJMAINSUBJECT.EXACT.EXPLODE("Internet"))	92,419
#3	(trial*) OR (experiment*) OR (intervention*)	218,810
#4	(mental health) OR (depression) OR (anxiety) OR (quality of life) OR (life satisfaction) OR (affect*) OR (mood) OR (loneliness) OR ("Mental wellbeing") OR ("Mental well-being") OR ("Psychological wellbeing") OR ("Psychological well-being") OR (MJMAINSUBJECT.EXACT.EXPLODE("Mental Health")) OR (MJMAINSUBJECT.EXACT.EXPLODE("Depression (Psychology)")) OR (MJMAINSUBJECT.EXACT.EXPLODE("Anxiety")) OR (MJMAINSUBJECT.EXACT.EXPLODE("Quality of Life")) OR (MJMAINSUBJECT.EXACT.EXPLODE("Life Satisfaction"))	191,452
#5	((school-based) OR (classroom-based))	17,943
#6	#1 AND #2 AND #3 AND #4 AND #5	50

EMBASE

Search	Keywords	Results
#1	(Adolescen*) OR (Youth) OR (Teen*) OR (juvenil*) OR (student*) OR (pupil*) OR ('adolescent'/syn) OR ('juvenile'/syn) OR ('student'/syn) OR ('pupil'/syn)	5,265,053
#2	(Smartphone) OR (ICT) OR ("Information and communication technologies") OR (Digital technolog*) OR (phone) OR (tablet*) OR (social media) OR (social network*) OR (social networking site*) OR (sns) OR (digital media) OR (Internet) OR (screen time) OR (screentime) OR ('smartphone'/syn) OR ('digital technology'/syn) OR ('tablet'/syn) OR ('social media'/syn) OR ('social network'/syn) OR ('internet'/syn)	755,470
#3	(((trial*) OR (experiment*)) OR (intervention*)))	11,211,792
#4	(mental health) OR (depression) OR (anxiet) OR (quality of life) OR (life satisfaction) OR (affect*) OR (mood) OR (loneliness) OR ("Mental wellbeing") OR ("Mental well-being") OR ("Psychological wellbeing") OR ("psychological well-being") OR ('mental health'/syn) OR ('depression'/syn) OR ('anxiety'/syn) OR ('quality of life'/syn) OR ('life satisfaction'/syn) OR	5,360,997

	('affect'/syn) OR ('mood'/syn) OR ('loneliness'/syn) OR ('psychological well-being'/syn)	
#5	((school-based) OR (classroom-based))	21,748
#6	#1 AND #2 AND #3 AND #4 AND #5	406

Web Of Science

Search	Keywords	Results
#1	(((Adolescen*) OR (Youth)) OR (Teen*)) OR (juvenil*)) OR (student*)) OR (pupil*)	2,754,010
#2	((Smartphone) OR (ICT) OR ("Information and communication technologies") OR (Digital technolog*) OR (phone) OR (tablet*) OR (social media) OR (social network*) OR (social networking site*) OR (sns) OR (digital media) OR (Internet) OR (screen time) OR (screentime)	1,315,889
#3	(((trial*) OR (experiment*)) OR (intervention*)))	11,487,394
#4	((mental health) OR (depression)) OR (anxiety)) OR (quality of life)) OR (life satisfaction)) OR (affect*)) OR (mood)) OR (loneliness) OR ("Mental wellbeing") OR ("Mental well-being") OR ("Psychological wellbeing") OR ("psychological well-being")	5,801,044
#5	((school based) OR (classroom based))	28,409
#6	#1 AND #2 AND #3 AND #4 AND #5	123

Table A4.2 Thresholds for interpreting the meta-analysis results

Interpretation	Negative	Positive
Screen time (hours/day)		
Trivial	> -17.4	< 17.4
Small	-17.5 to -38.8	17.5 to 38.8
Moderate	-38.9 to -56.5	38.9 to 56.5
Large	-56.6 to -76.0	56.7 to 76.0
Very Large	< -76.0	> 76.0
Problematic use		
Trivial	> -4.0	< 4.0
Small	-4.1 to -10.0	4.1 to 10.0
Moderate	-10.1 to -16.0	10.1 to 16.0
Large	-16.1 to -23.9	16.1 to 23.9
Very Large	< -23.9	> 23.9
Anxiety		
Trivial	> -3.9	< 3.9
Small	-4.0 to -9.8	4.0 to 9.8
Moderate	-9.9 to -15.7	9.9 to 15.7
Large	-15.8 to -23.5	15.8 to 23.5
Very Large	< -23.5	> 23.5
Depression		
Trivial	> -3.3	< 3.3
Small	-3.4 to -8.3	3.4 to 8.3
Moderate	-8.4 to -13.3	8.4 to 13.3
Large	-13.4 to -20.0	13.4 to 20.0
Very Large	< -20.0	> 20.0
Life satisfaction and Flourishing		
Trivial	> -4.5	< 4.5
Small	-4.6 to -11.2	4.6 to 11.2
Moderate	-11.3 to -17.9	11.3 to 17.9
Large	-18.0 to -26.8	18.0 to 26.8
Very Large	< -26.8	> 26.8
SDQ - Psychological difficulties		
Trivial	> -2.7	< 2.7
Small	-2.8 to -6.7	2.8 to 6.7
Moderate	-6.8 to -10.7	6.8 to 10.7
Large	-10.8 to -16.0	10.8 to 16.0
Very Large	< -16.0	> 16.0

Note. SDQ: Strengths and Difficulties Questionnaire. The extent of overlap was estimated as the areas of the sampling distribution falling in substantial and trivial magnitudes. These areas represent the probabilities that the true effect has those positive magnitudes.

Justification of magnitude of thresholds: The extent of overlap of the 95% CI with trivial or substantial (i.e., small, moderate, and large) values was used to assess sampling uncertainty. The extent of overlap was estimated as the areas of the sampling distribution falling in substantial (i.e., small, moderate, and large) and trivial magnitudes. These areas represent the probabilities that the true effect (i.e., very large sample effect) has those positive magnitudes. Thresholds for interpreting the probabilities for a given magnitude are provided in the table below. We interpreted the area of the sampling uncertainty below the normal distribution curve ***on the right side of zero (positive magnitude)***.

Table A4.3 Interpretations of sampling uncertainty in the 95% CI limits

Probability	Interpretation of sampling uncertainty	Conclusion[a]
≤ 0.005	Most likely substantial effect	Strong conclusive evidence for effect
0.005 – 0.05	Very likely substantial effect	Very good conclusive evidence for effect
0.05 – 0.25	Likely substantial effect	Weak conclusive evidence for effect
0.25 – 0.75	Possible substantial effect	Some conclusive evidence for effect
0.75 – 0.95	Unlikely substantial effect	Good conclusive evidence against effect
0.95 – 0.995	Very unlikely substantial effect	Very good conclusive evidence against effect
≥ 0.995	Most unlikely substantial effect	Strong conclusive evidence against effect

Note. [a]In cases where there was some conclusive evidence (i.e., a probability of 0.25 to 0.75) for both a substantial negative and substantial positive magnitude, the effect in question was deemed to be inconclusive. The probability represents the area of the sampling distribution falling between trivial or substantial (i.e., small, moderate, and large) values on the right side of zero.

Table A4.4 Meta-analyses of percentage changes in outcome variables from baseline to post intervention, using a correlation coefficient of 0.5

Group	Estimate	SE	Lower 95% CI	Upper 95% CI	p value	Interpretation
Model: Screen time (hrs/day)						
Control	9.071	3.287	2.629	15.512	0.006	Strong conclusive evidence against intervention effect
Intervention	-3.673	3.250	-10.043	2.698	0.259	Weak conclusive evidence for intervention effect
Contrast						
Intervention - Control	-12.743	1.754	-16.180	-9.306	<.0001	Strong conclusive evidence for intervention effect
Intervention - Control[a]	-11.964					
Model: Problematic use						
Control	-4.688	5.475	-15.419	6.044	0.392	Inconclusive evidence
Intervention	-6.156	5.320	-16.582	4.270	0.247	Inconclusive evidence
Contrast						
Intervention - Control	-1.468	2.023	-5.433	2.496	0.468	Weak conclusive evidence for effect
Model: Anxiety						
Control	-3.174	2.180	-7.447	1.099	0.145	Weak conclusive evidence for intervention effect
Intervention	-4.832	2.171	-9.088	-0.577	0.026	Very good conclusive evidence for intervention effect
Contrast						
Intervention - Control	-1.658	0.344	-2.333	-0.983	<.0001	Strong conclusive evidence for intervention effect
Model: Depression						
Control	1.138	2.030	-2.841	5.116	0.575	Some conclusive evidence for intervention effect
Intervention	-2.287	2.011	-6.228	1.653	0.255	Weak conclusive evidence for intervention effect
Contrast						
Intervention - Control	-3.425	0.476	-4.358	-2.492	<0.0001	Strong conclusive evidence for intervention effect
Model: Life satisfaction and Flourishing						
Control	-2.779	1.065	-4.866	-0.691	0.009	Strong conclusive evidence against intervention effect
Intervention	1.967	1.052	-0.094	4.029	0.061	Very good conclusive evidence for intervention effect
Contrast						
Intervention - Control	4.746	0.751	3.274	6.218	<.0001	Strong conclusive evidence for intervention effect
Model: SDQ - Psychological difficulties						
Control	-0.475	1.580	-3.570	2.621	0.764	Some conclusive evidence for intervention effect
Intervention	-3.028	1.578	-6.120	0.065	0.055	Very good conclusive evidence for intervention effect
Contrast						
Intervention - Control	-2.553	1.132	-4.772	-0.335	0.024	Very good conclusive evidence for intervention effect

Note. SDQ: Strengths and Difficulties Questionnaire. [a]: Back-transformed contrast. ***: $p < 0.001$.

Table A4.5 Sensitivity analyses using correlation coefficients of 0.2, 0.5, and 0.8.

Corr Coeff	Group	Estimate	Lower 95% CI	Upper 95% CI
Model: Screen time (hrs/day)				
0.2	Control	9.292	2.767	15.816
	Intervention	-3.452	-9.874	2.969
0.5	Control	9.070	2.629	15.512
	Intervention	-3.673	-10.043	2.698
0.8	Control	8.213	1.130	15.296
	Intervention	-4.541	-11.595	2.513
Model: Problematic use				
0.2	Control	-4.635	-15.627	6.357
	Intervention	-6.066	-16.573	4.442
0.5	Control	-4.688	-15.419	6.044
	Intervention	-6.156	-16.582	4.270
0.8	Control	-4.706	-14.991	5.579
	Intervention	-6.083	-16.249	4.082
Model: Anxiety				
0.2	Control	-3.012	-7.319	1.294
	Intervention	-4.690	-8.971	-0.410
0.5	Control	-3.174	-7.447	1.099
	Intervention	-4.832	-9.088	-0.576
0.8	Control	-3.316	-7.464	0.832
	Intervention	-4.917	-9.058	-0.776
Model: Depression				
0.2	Control	1.323	-2.392	5.038
	Intervention	-2.157	-5.816	1.503
0.5	Control	1.138	-2.841	5.116
	Intervention	-2.287	-6.228	1.653
0.8	Control	0.907	-3.264	5.078
	Intervention	-2.384	-6.538	1.770
Model: Life satisfaction and Flourishing				
0.2	Control	-2.831	-5.090	-0.572
	Intervention	1.899	-0.319	4.118
0.5	Control	-2.778	-4.866	-0.691
	Intervention	1.967	-0.094	4.029
0.8	Control	-2.734	-4.577	-0.890
	Intervention	2.078	0.246	3.910
Model: SDQ - Psychological difficulties				
0.2	Control	-0.371	-3.502	2.759
	Intervention	-2.949	-6.077	0.179
0.5	Control	-0.474	-3.570	2.621
	Intervention	-3.028	-6.120	0.065
0.8	Control	-0.588	-3.647	2.471
	Intervention	-3.093	-6.150	-0.036

Note. SDQ: Strengths and Difficulties Questionnaire.

Table A4.6 Egger test results for the meta-analyses

Group	*k*	I^2 percent	*z* score	*p* value	limit *b*	95% CI
Model: Screen time (hrs/day)						
Control	5	83.75	-0.744	0.457	13.94	-0.630, 28.502
Intervention	5	61.69	-0.533	0.594	-1.796	-10.94, 7.34
Model: Problematic use						
Control	3	81.53	-1.867	0.062	8.45	-5.86, 22.75
Intervention	5	96.43	-4.109	<0.001	23.23	8.31, 38.15
Model: Anxiety						
Control	6	95.63	0.0838	0.933	1.0506	-3.46, 5.56
Intervention	9	98.97	-2.4600	0.014	1.2058	-6.15, 8.56
Model: Depression						
Control	3	96.87	0.4433	0.658	0.4171	-15.04, 15.87
Intervention	5	95.78	-0.7502	0.453	-0.2939	-8.50, 7.91
Model: Life satisfaction and Flourishing						
Control	3	88.61	0.8416	0.4000	4.51	-12.85, 3.83
Intervention	3	0.00	-0.7886	0.4304	2.16	-0.04, 4.36
Model: SDQ- Psychological difficulties						
Control	3	0.00	0.2798	0.780	-1.07	-9.76, 7.63
Intervention	3	93.44	-4.8371	< .0001	21.74	11.79, 31.70

Note. SDQ: Strengths and Difficulties Questionnaire.

Table A4.7 GRADE assessment

	Design	Risk of Bias	Inconsistency	Indirectness	Imprecision	Publication Bias	Certainty
Outcome: Screen Time (h/day)							
5 studies, 9,238 participants	RCT	Non-serious	Serious	Non-serious	Non-serious	Non-serious	**Moderate**
Inconsistency was downgraded because the model reported substantial unexplained I^2 and significant QE test. The overall certainty was downgraded from High to Moderate.							
Outcome: Problematic Use							
5 studies, 412 participants	RCT, non-RCT, and pre-post	Non-serious	Serious	Serious	Serious	Serious	**Very Low**
Inconsistency was downgraded because the model reported substantial unexplained I^2 and significant QE test. Indirectness was downgraded due to the different designs included in the meta-analytic model. Imprecision was downgraded due to the 95% CI range of the contrast, which includes substantial positive and negative magnitudes. The overall certainty was downgraded from High to Moderate, from Moderate to Low, and from Low to Very Low.							
Outcome: Anxiety							
7 studies, 8,799 participants	RCT, non-RCT, and pre-post	Non-serious	Serious	Serious	Non-serious	Serious	**Very Low**
Inconsistency was downgraded because the model reported substantial unexplained I^2 and significant QE test. Indirectness was downgraded due to the different designs included in the meta-analytic model. Publication bias was downgraded due to the potential publication bias in the intervention arms. The overall certainty was downgraded from High to Moderate, from Moderate to Low, and from Low to Very Low.							
Outcome: Depression							
5 studies, 8,617 participants	RCT, and pre-post	Non-serious	Serious	Serious	Non-serious	Non-serious	**Low**

Inconsistency was downgraded because the model reported substantial unexplained I^2 and significant QE test.
Indirectness was downgraded due to the different designs included in the meta-analytic model.
The overall certainty was downgraded from High to Moderate, and from Moderate to Low.

Outcome: **Life Satisfaction**

3 studies, 2,353 participants	RCT	Non-serious	Non-serious	Non-serious	Serious	Non-serious	**Moderate**

Imprecision was downgraded due to the 95% CI range of the contrast, which includes substantial positive and negative magnitudes.
The overall certainty was downgraded from High to Moderate.

Outcome: **Strengths and Difficulties Questionnaire**

3 studies, 623 participants	RCT	Non-serious	Non-serious	Non-serious	Serious	Serious	**Low**

Imprecision was downgraded due to the 95% CI range of the contrast, which includes substantial positive and negative magnitudes.
Publication bias was downgraded due to the potential publication bias in the intervention arms.
The overall certainty was downgraded from High to Moderate, and from Moderate to Low.

Figure A4.1 Traffic-light plot of Risk of Bias for each included study (RoB2)

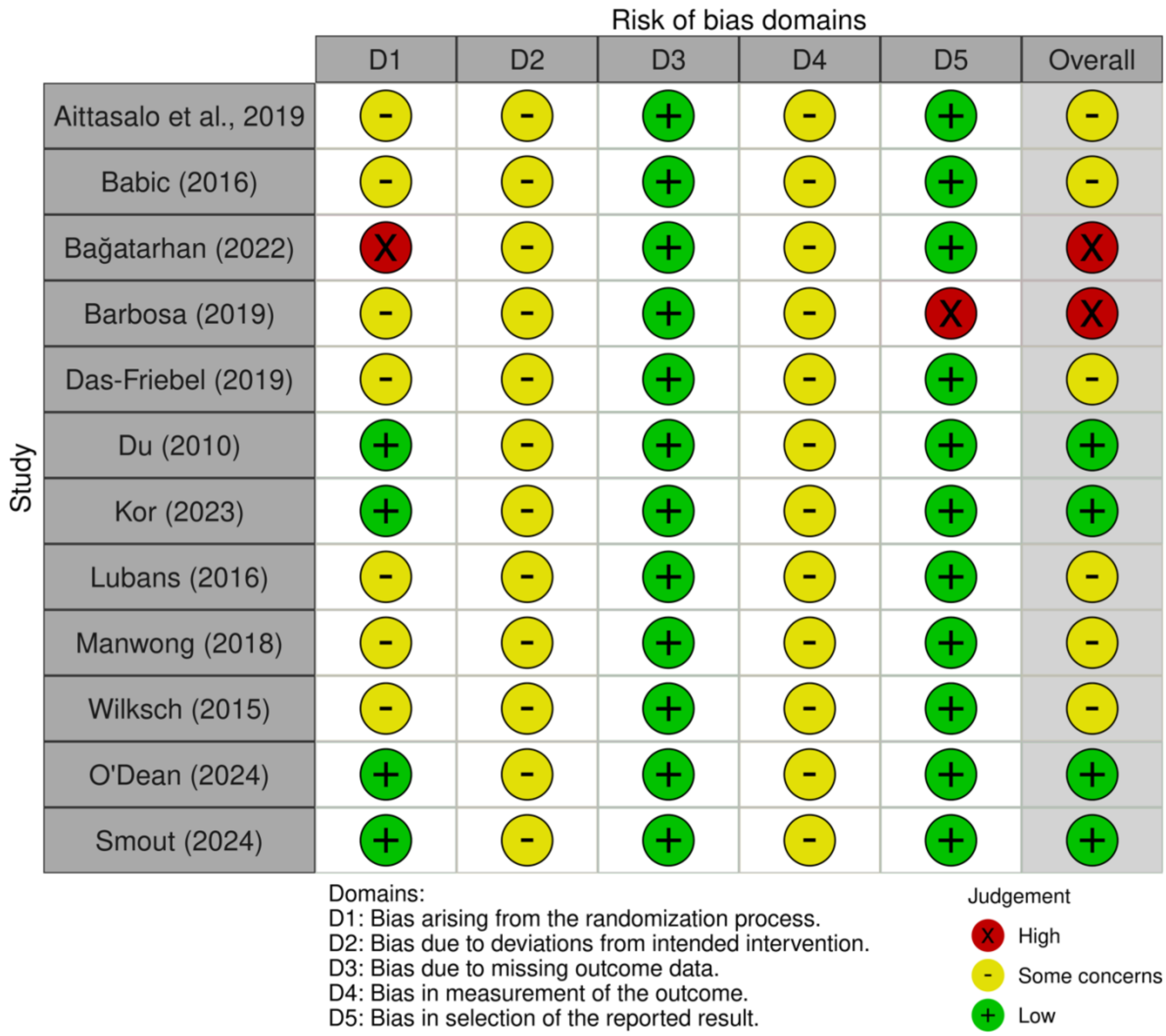


Figure A4.2 Summary plot of Risk of Bias for each RoB2 domain

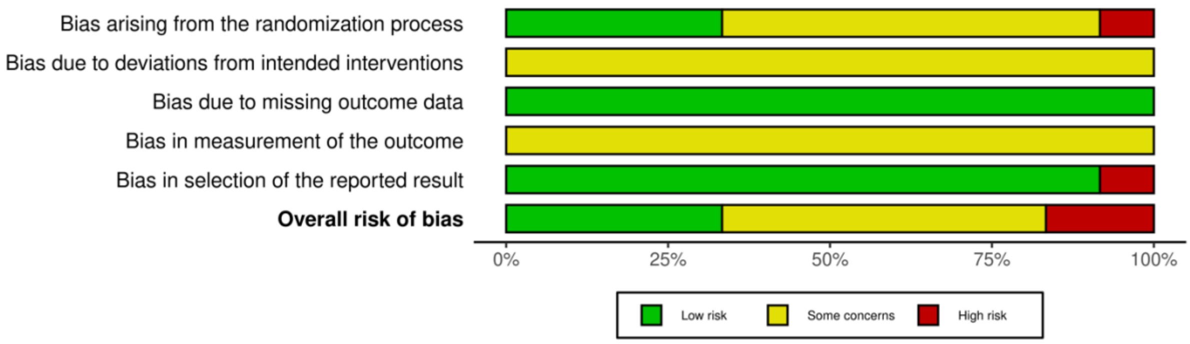


Figure A4.3 Traffic-light plot of Risk of Bias for each included study (ROBINS-I)

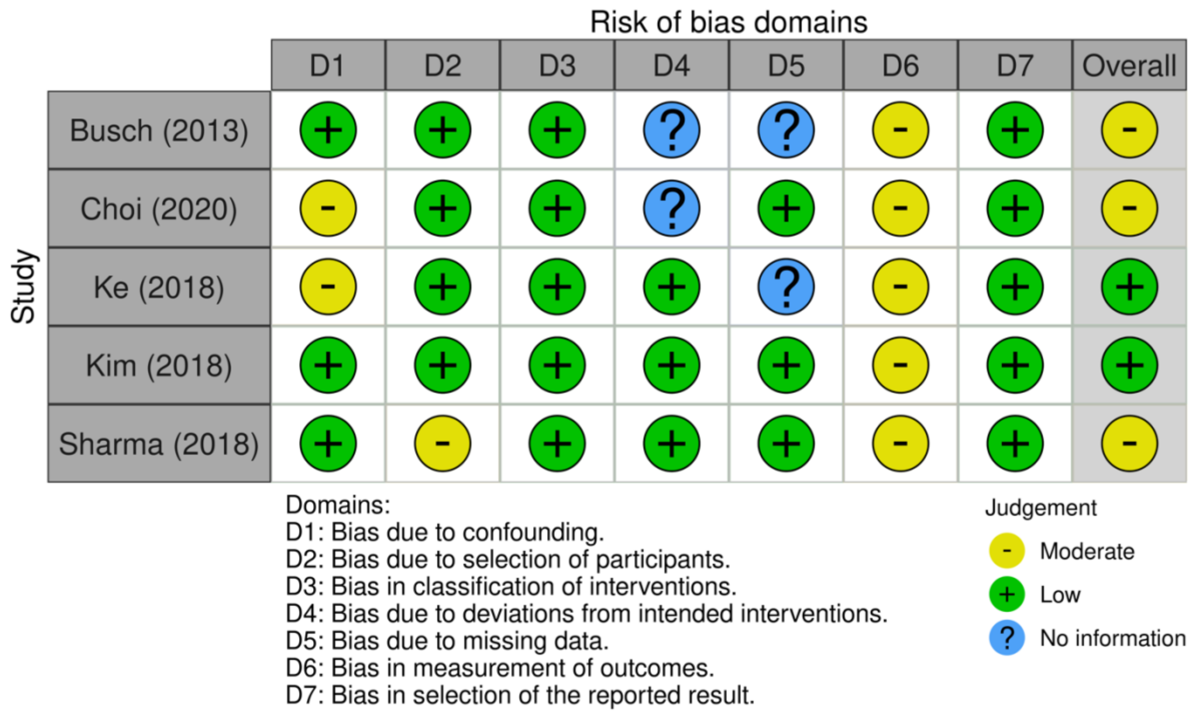


Figure A4.4 Summary Plot of the Risk of Bias for Each ROBINS-I Domain.

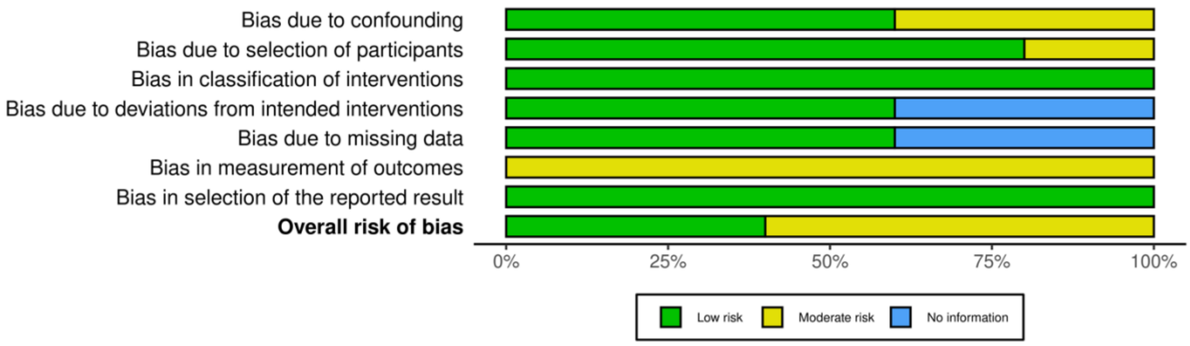


Figure A4.5 Funnel plots of the meta-analysis of the screen time (hours/day)

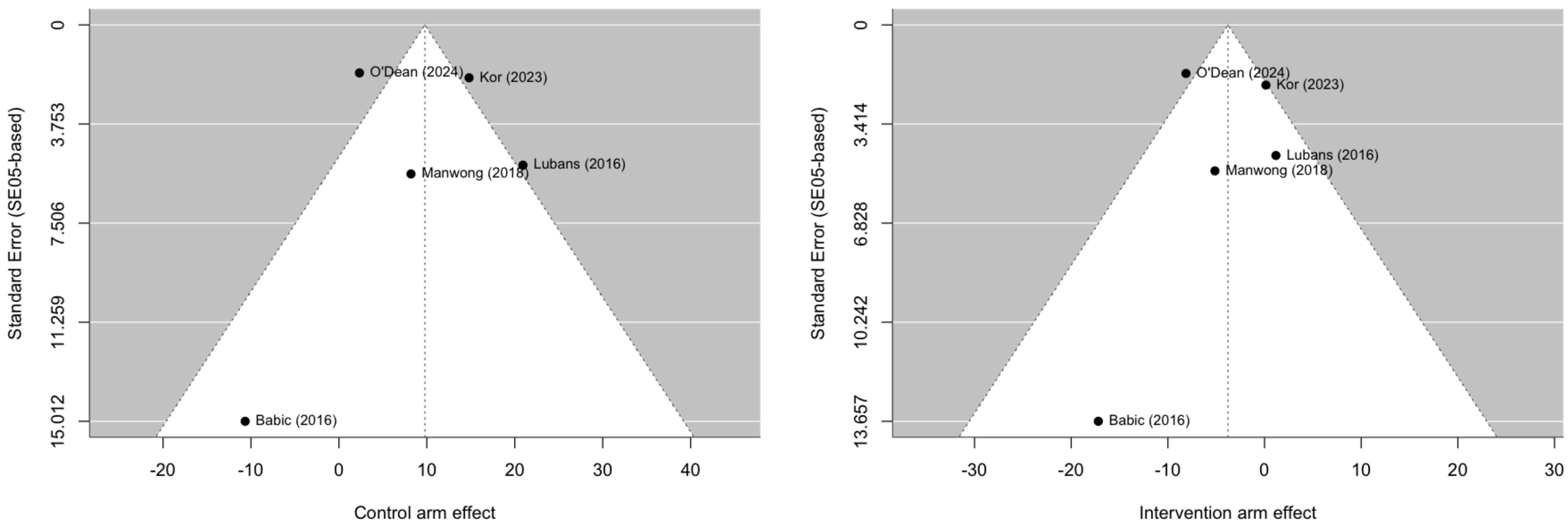


Figure A4.6 Funnel plots of the meta-analysis of the problematic use

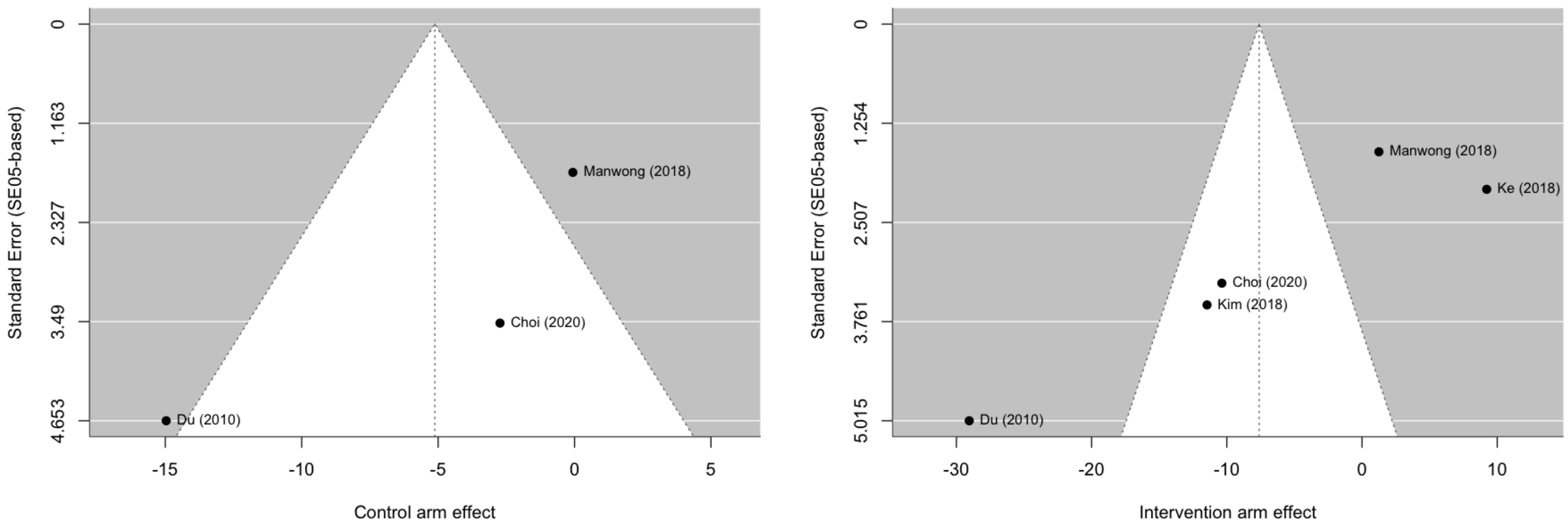


Figure A4.7 Funnel plots of the meta-analysis of the anxiety scores

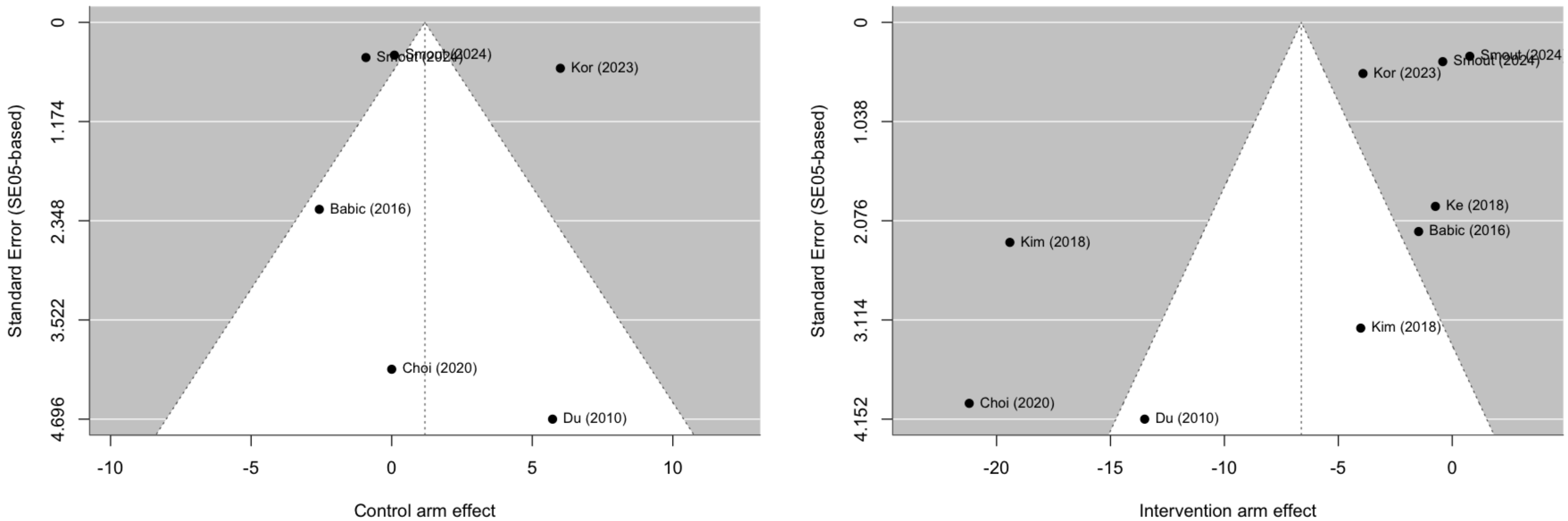


Figure A4.8 Funnel plots of the meta-analysis of the depression scores

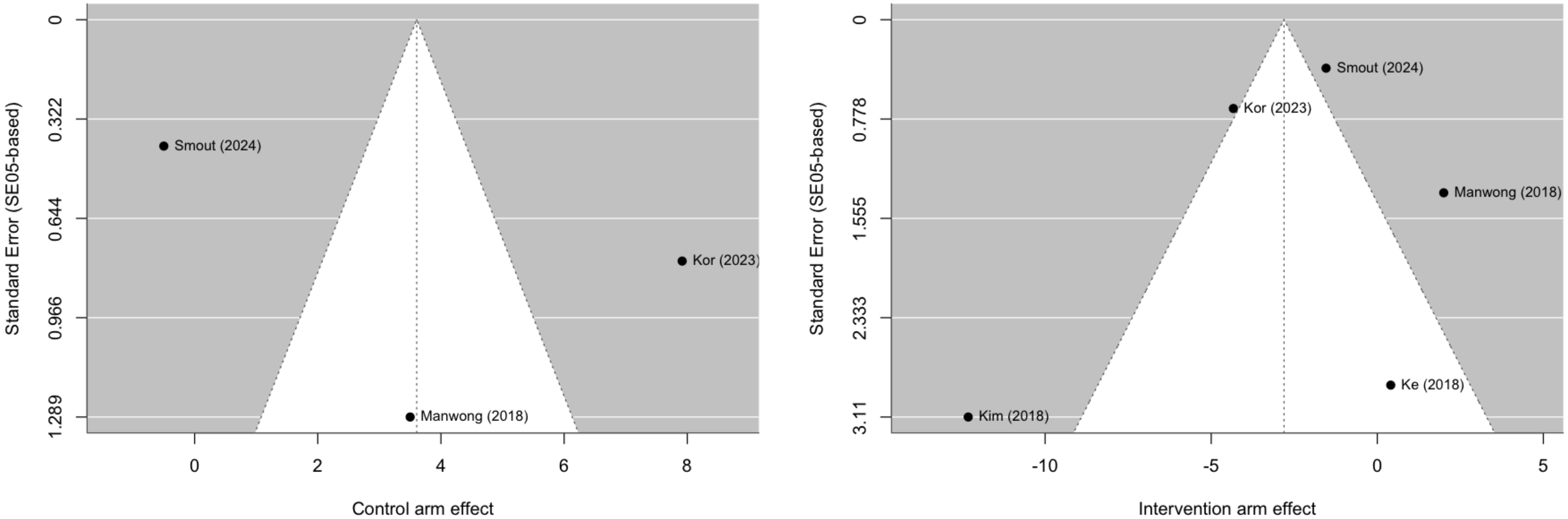


Figure A4.9 Funnel plots of the meta-analysis of the life satisfaction and Flourishing scale scores

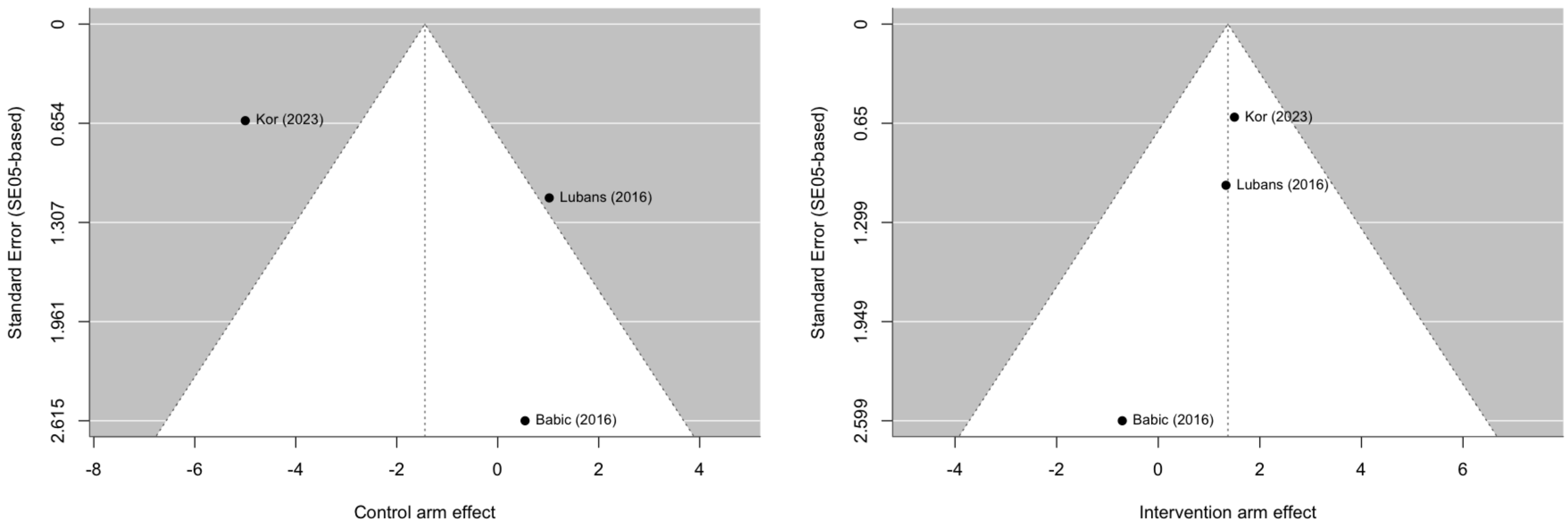
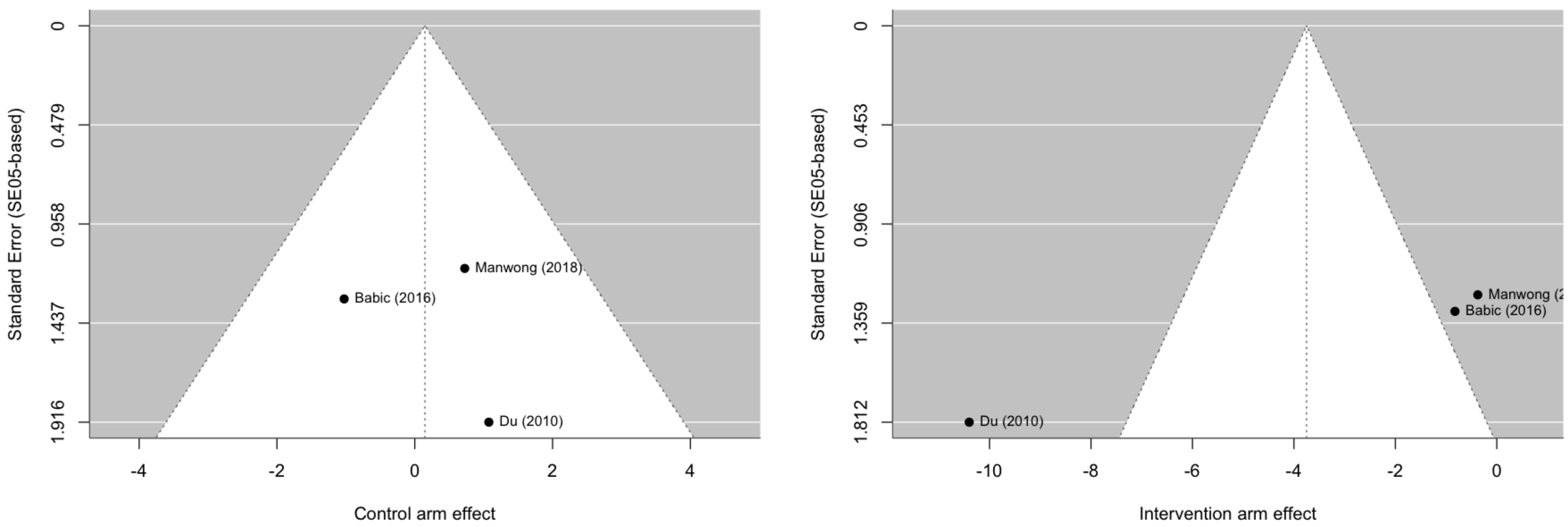


Figure A4.10 Funnel plots of the meta-analysis of the Strengths and Difficulties Questionnaire – Psychological difficulties scores



Chapter 5: Study 4 - Does digital detox reduce adolescents' problematic phone use and improve affective well-being? A controlled field experiment with experience sampling method

This chapter is being prepared for submission to ***Journal of Adolescence*** *as of October 2025.*

Abstract

The excessive and problematic smartphone use and its negative impact on well-being, have been a main concern for several years. However, research on digital detox programmes provided inconclusive findings and was largely concentrated on adults. We investigated whether having a week of digital detox (i.e., setting a daily time off from phones) could reduce adolescents' (problematic) phone use and improve their affective well-being in the short term, and whether individuals' adherence to the protocol and subjective experience of the digital detox intervention impacts the effectiveness intervention. Adolescents from five schools were assigned to either control or digital detox groups ($N = 269$; $M_{age} = 15.3$ (SD = 1.47); 59.8% girls). Outcome variables (phone use indicators, momentary affect) were measured using experience sampling method, and participants reported their completed sessions, duration and perceived easiness of the sessions during the intervention week. Results showed no effect of the intervention on any of the outcomes. The digital detox group was able to cope with their momentary withdrawal better. Additionally, participants with shorter digital detox sessions lowered phone use after the digital detox week, yet the ones with longer sessions remained the same levels. The study implications and recommendations for future research are discussed.

Keywords: Adolescents, Digital detox, Problematic phone use, Momentary affect, Experience sampling method; Intervention

5.1 Introduction

Smartphones are an essential part of the daily life of adolescents. Despite the benefits that smartphones, internet, and social media may carry to adolescents' mental and social well-being (Livingstone & Helsper, 2010), excessive usage of mobile devices and feelings of phone "addiction" are important concerns of contemporary societies (Boyd, 2014; Davis, 2001; van Rooij et al., 2010; Kurniasanti et al., 2019). As a result, policies and guidelines such as recommendations for a maximum screen time for children and teens, family protection software programs, and programmes that promote offline activities were created to combat the potential harmful effects of risky digital use (O'Neill, 2013; Oh et al., 2022). In this context, theories on identity development have suggested that a successful intervention strategy should put adolescents themselves at the centre, while fostering their sense of agency over their behaviours (Granic et al., 2020; Maniccia; 2011).

There have been various approaches to intervene on problems related to adolescents' digital use. While multi-component health interventions can reduce excessive screen time (Oh et al., 2022), interventions addressing adolescents' problematic use need further research (Ayub et al., 2023; Zhang et al., 2023). Although common interventions include family- or school-based digital literacy education programmes (e.g. Babic et al., 2016), group-based trainings, or therapy sessions, scholars have increasingly paid attention to the potential success of practicing self-regulation, i.e., various forms of digital detox and called out a need for more empirical evidence (e.g., Nassen et al., 2023; Radtke et al., 2022; Schmuck, 2020).

The present study focuses on the role of digital detox practices in shaping adolescents' phone use and affective well-being. Using experience sampling method (ESM; Csikszentmihalyi & Larson, 1983), we test the effectiveness of digital detox practice on reducing smartphone use indicators, and improving mental health outcomes. In doing so our study makes three key contributions: first, it provides experimental evidence on the short-term effects of digital detox on adolescents; second, it introduces an adolescent-centred design that seeks to balance the potential harms and benefits of smartphone use; and third, it employs high-frequency ESM data to capture momentary changes in affect and phone use indicators, thus allowing us to test whether a flexible, self-directed form of digital detox can realistically improve adolescents' digital practices and mental health.

5.1.1 Interventions for Adolescent Phone Use and Mental Well-being

The relationship between adolescents' phone use and their mental well-being has been examined extensively with positive, negative, and null results (e.g., Girela-Serrano et al., 2024; Thomée, 2018; Jensen et al., 2019; Karsay et al., 2023), suggesting that screen time itself is not a comprehensive concept to capture the extent of digital use. To explore the potential harms of digital use, researchers increasingly focused on the addictive natures of smartphones, internet, and social media (Busch & McCarthy, 2021; Kurniasanti et al., 2019; Pellegrino et al., 2022). For example, studies show that adolescents who excessively use their smartphones may show signs of problematic phone use, i.e., feelings of dependency and compulsion (Panova & Carbonell, 2018). Some of the indicators of problematic phone use are identified as losing sense of control when using smartphones, exceeding the intended usage duration, or being mentally preoccupied with the phone when being out of range (Foerstel et al., 2015). These negative experiences disrupt adolescents' daily lives, leading to not only long-term consequences mental well-being (Elhai et al., 2017; Sohn et al., 2019), but also impairing their momentary emotions, sleep, and mood (Burnell et al., 2024; Kross et al., 2013; Mei et al., 2018). Although some scholars are apprehensive about defining smartphone addiction as a stand-alone mental health disorder (Busch & McCarthy, 2021; Elhai et al., 2017; Panova & Carbonell, 2018), there is growing consensus that problematic use patterns can undermine both adolescents' daily functioning and their mental well-being. Our study aims to provide a potential strategy that could help adolescents to address their (problematic) phone use habits and improve their momentary affective well-being.

Most research addressing the impact of digital interventions on behavioural change and well-being have drawn on self-determination theory (SDT; Ryan & Deci, 2000; Deci & Ryan, 2000). According to SDT, adolescents are more inclined to be successful at forming new habits if they have intrinsic motivations, as opposed to extrinsic motivations. While extrinsic motivations could be strengthened by short-term goals such as having an external assessment for the target behaviour, to achieve intrinsic motivations, three psychological needs should be supported: autonomy (i.e., a sense of agency in the choice of forming the new habit) competence (i.e., a sense of capability of achieving the new habit) and relatedness (i.e., a sense of connectedness with others having similar experiences) (Ryan & Deci, 2017). Designated phone apps assisting to the target behaviour could satisfy these needs through effective nudging mechanisms such as personalised goal setting, virtual rewards for achievements, and leader boards, which could help individuals to boost intrinsic motivations to stay consistent (Villalobos-Zúñiga & Cherubini, 2020).

Previous empirical studies suggest that interventions targeting the three psychological needs included in SDT might help adolescents to reduce their time using digital technologies. For instance, one study illustrated that having participants to reflect on their overconsumption of social media, followed by a brief abstinence period, could help them to regain their sense of agency and regulate their social media use (Turel, 2021). One other study assessed effectiveness of a group-based phone use limiting app and found that limiting phone use simultaneously as a group of friends helped to feel connected and less isolated throughout the intervention (Ko et al., 2016). Finally, a recent study found that young people's active planning to reduce their phone use led them to have higher self-efficacy in behavioural change, which resulted in lower usage (Brockmeier et al., 2025). This study particularly highlights the importance of centring individuals' own goal preferences and perceived competence in the intervention design could be a successful strategy. Our study contributes to the little evidence on the effectiveness of digital programmes targeting adolescents by designing a digital detox practice that seeks to foster adolescents' intrinsic motivation to attempt for a behavioural change in their phone use habits.

5.1.2 Digital Detox Programmes

The notion of practicing "digital detox" as a solution to excessive digital use has become highly popular both in pop culture as well as among researchers (Nassen et al., 2023; Radtke et al., 2021; Schmuck, 2020; Ugur & Koc; 2015; Syvertsen & Enli, 2019). The perspectives on what digital detox should entail varies; the general definition is refraining from using electronic devices (e.g., smartphones) in pre-defined ways (e.g., cutting smartphone use during mealtimes, reducing total phone use, reduce social media consumption) and for a specific time period (one day, several hours, weeks) (Radke et al., 2022). The digital detox practice can be in the form of a luxurious retreat from the busy and tech-heavy world (Collier, 2009; Dickinson et al., 2016). Alternatively, there are several commercially available apps on the market that helps individuals to track and manage their total or app-specific screen time such as *Moment, Forest*, or *Offtime,* with each of them offering different incentives, mechanisms, and monetary payment systems (Nassen et al., 2023). Some researchers created and tested their own versions of digital detox apps and found promising preliminary results for adult populations, suggesting that these apps useful to regulate their phone use (Ko et al., 2015; Ko et al., 2016; Purohit et al., 2022), and also show reduction in their problematic phone use (Hiniker et al., 2016; Keller et al., 2021).

One central common goal of digital detox interventions is to reduce mental well-being problems such as anxiety, stress, and addiction-like feelings, and improve on offline socialising by balancing digital time use (Nassen et al., 2023; Radtke et al., 2021). Particularly, digital detox practice can act as a habit disruption and re-forming mechanism by helping individuals to be more aware of their digital use, self-monitor their screen time and digital activities, and avoiding habitual behaviours such as frequent phone-checking. In line with the SDT framework, these intentional changes in the daily interactions with mobile devices could contribute to long-term mental well-being through improved self-efficacy, autonomy in digital behaviours, as well as connectedness if digital detox is practiced as a collective effort (e.g., as a friend group or within classrooms) (Kolhe & Naik et al., 2025; Marciano et al., 2024; Ryan & Deci, 2017).

Although research in this area has boomed in recent years, the main focus of the digital detox research was on adults, or young adult population, with a notable lack of evidence on adolescent age groups (Ansari et al., 2024; Liu et al., 2025). Phones and social media are an essential part of adolescents' educational, leisure, and social routines (Holmarsdottir et al., 2024), and digital engagements could induce a positive state of flow that can have positive impacts on adolescent daily mood (Csikszentmihalyi, 2013; Leung, 2020). Thus, scholars have suggested that aiming to limiting, and not banning, digital use might have more substantial benefits for younger age groups (Marciano et al., 2024) since such drastic measures on phone use may not be sustainable in the long-term and could have unintended negative consequences (Haddon and Livingstone, 2017). A digital detox practice that allows for *some* phone use but promotes active decision-making to diversify the contexts joyful experiences such as physical or creative activities that can elicit positive state of flow) could lead to a more sustainable habit shift. This strategy is supported by the evidence on young adults. One study found that university students who limit their social media use to 30 minutes a day for three weeks had lower depressive complaints, and loneliness (Hunt et al., 2018), whereas another study on mainly young adults found that total abstinence is not leading to greater improvement in mental well-being outcomes, compared to reduced smartphone use (Brailovskaia et al., 2023). Finally, a recent study on medical students found that participants who were instructed to supplement digital detox with alternative activities such as physical activities or social interactions showed greater mental well-being compared to participants who only committed to screen time reduction (Farrukh et al., 2025). Therefore, this study adopts a more realistic approach to digital detox with a blended strategy, where adolescents are allowed to have access to their phones and be encouraged to be mindful about their usage by (i) allocating a time period to limit their phone use and (ii) picking an alternative activity that they can do instead.

An important gap of the literature is that the few studies evaluating the impact of digital detox on adolescent outcomes typically rely on retrospective self-report measurements of digital use and mental well-being outcomes from past days. Given that individuals, and adolescents particularly, tend to falsely evaluate their screen time based on their retroactive memory (Verbeij et al., 2021), it is crucial to use a more appropriate methodology to capture the potential impacts of digital detox. To address this memory bias, one study on young adults asked participants to fill out end of the day dairies and report their digital use either based on their memory for the day (Hall et al., 2021). While daily diaries are informative, the design of the data collection relies on individuals' memories to report their time with mobile devices as well as mood and emotions throughout the day retroactively, which makes it challenging to match the fluctuations in digital use and momentary mood. This calls for new evidence using a nuanced approach to overcome the operational challenges. For example, with the ESM methodology, scholars can fill in these gaps by prompting participants multiple times throughout the day and assess context-sensitive digital use and emotional states. Our study seeks to meet this important gap in the literature by using an ESM approach.

5.1.3 The Present Study

The present study investigates whether a school-based digital detox intervention can reduce adolescents' problematic phone use and improve their momentary mental well-being. Building on prior research that has shown inconsistent effects of digital detox, particularly among adults and university students, we adapt the intervention to the daily routines and developmental needs of adolescents.

Using the SDT framework, we incorporate agency, competence, and connectedness elements to our design. To support the adolescents' agency and competence, we offer options for digital detox practice duration each day that they can choose the time period they can succeed. We also encourage participants to choose how they would spend their time during digital detox period to further encourage their agency in their time use. To support adolescents' relatedness, we deliver the digital detox instructions in classroom context to highlight that the students are participating in our experiment as a group. To assess the effectiveness of this intervention, we implement a cluster randomised controlled trial across five Irish secondary schools, combining ESM methods with daily app-based tracking of digital detox practices. We investigate the following research questions:

1. Does digital detox reduce adolescents' daily (problematic) phone use?
2. Does digital detox help to improve adolescent affective well-being?

3. Does digital detox moderate the association between digital use (i.e., daily phone use, problematic phone use) and affective well-being?

4. Do individual differences in adherence to the protocol and their subjective experience of the digital detox practice impact on their phone use and mental well-being outcomes?

5.2 Methods

5.2.1 Study Design and Participants

This study employed a clustered nonrandomised controlled trial (cNRCT). Ethical approval for this study was previously obtained by the Ethics Committee of the Faculty of Humanities, Arts and Social Sciences from Trinity College Dublin. The sampling strategy combined convenience and purposive sampling. First, all secondary schools in counties Dublin, Meath, Kildare, and Wicklow were invited to participate in this study in December 2022. Five schools representing different socioeconomic and geographical areas agreed to participate (four in Dublin County, one in Wicklow). Based on Pobal HP Deprivation Index (Haase, 2016), two of the participating schools were located in socioeconomically disadvantaged areas, two were from an average socioeconomic level area, and one from and affluent area. prior to data collection phase, although the school staff and students of the intervention group were informed only when the intervention week started.

First, schools were allocated into two groups with the considerations of the demographic areas and sample sizes within schools. The completely random allocation was not possible due constraints regarding sample size variations across schools and uneven school number with an imbalance of socioeconomic backgrounds. Then, the two groups were assigned to each treatment condition with the group with larger sample size to be the intervention group to achieve a higher statistical power. The control group included one school from disadvantaged area and one average area. The intervention group included one school from disadvantaged area, one from average area, and one from affluent area. One class was randomly selected from each of the 6 school grades (students from 12 to 18 years old), which were then invited to participate in our study. A total of 252 students provided parental consent and participated in the study. All participant schools and families received an educational voucher as an acknowledgement of participation from the research team.

5.2.2 Procedure

The schools were visited four times throughout the data collection process in May 2023. First, prior to baseline assessments, two researchers met each class, explained the purpose of the study to the students, and invited students to retrieve parental consent. At second visit, researchers instructed students who provided parental consent to fill out daily ESM questionnaires for the following week. Because to design and schedule of ESM questionnaires can be overwhelming at first (Rintala et al., 2021), a detailed briefing session was carried out in smaller groups. At the end of the briefing session, students downloaded the ESM questionnaires app *m-Path*, filled out an initial questionnaire to become familiar with the interface of the app, and ask any questions they might have had.

After the pre-assessment week, the researchers delivered the digital detox programme to those schools that were allocated in the experimental group, asking the students to engage in digital detox activity for the following week. The digital detox briefing also carried out in smaller groups to make sure every participant was able to understand the instructions clearly. The briefing started with encouraging students to keep participating the study and resolve any issues they may have had regarding the questionnaires. The participants then watched a video prepared by the research team that explains the importance of participating in digital detox practice. Finally, researchers presented the instructions for how to practice digital detox for the following week. In the control group schools, the researchers only repeated the first section of the debriefing session and encouraged the participants to keep filling out the daily ESM questionnaires. At the end of the digital detox week, the researchers went to the school for the last time to make sure students were still motivated to participate in the study for the final week of data collection.

5.2.3 Experience Sampling Method

ESM, also referred to as ecological momentary assessment, is an ecologically validated, a more detailed version of dairy data collection technique that assesses individuals' momentary experiences multiple times a day (Csikszentmihalyi & Larson, 1987; Myin-Germeys, & Kuppens, 2021; van Roekel et al., 2019). In this study, ESM assessments (beeps) were sent at semi-random way. The random questionnaires were scheduled to be sent any time between 4pm to 10pm, with one beep to be sent within two hours of time blocks. The schedule was meant to prevent overlapping with the school hours and sleep hours at night. To make sure the responses were truly measured at random times, and to prevent accumulation of unanswered questionnaires on participants' phones, the beeps were set to expire after 10 minutes. Additionally, a morning button was added to the main screen of the *m-Path* app, so that participants could manually log their recent and problematic phone use (before bedtime in this case), and momentary affect. This led to a total of 55 beeps per participant, 27 beeps before the digital detox week (one morning beep was missed in the first day), and 28 beeps after the digital detox week. This schedule was explained in detailed at each school visits to ensure the participants understood what is expected of them

5.2.4 Intervention

Throughout the detox week, a daily notification was scheduled after school to participants' *m-Path* accounts (8 days in total). The notification included a 1-minute motivational video that aimed to encourage participants for practicing their daily digital detox. There were unique videos for each day to keep participants engaged in the study.

To help participants to carry out their digital detox sessions, we created a simple digital detox applet within *m-Path*. Sample screen captures from the applet are presented in Figure A5.1. The applet had two buttons on the main page: "start digital detox" button, and "need help" button. The need help button included key information and the instructions for digital detox. The start digital detox button included a pre-detox questionnaire followed by "plan digital detox" page that had "duration" and "offline activity" sections. Participants were able to customise their digital detox practice duration from 30 to 60 minutes in 5-minute increments. This customisation was designed to be flexible for each participant's daily routine, to encourage participants' competence in their practice, and to make sure participants perceive digital detox as a manageable challenge rather than a chore or an impossible task. Participants then reported what activities they had planned (e.g., reading, doing hobbies) to do during digital detox practice. The participants had the autonomy to choose what kind of activities they wanted to do, although they were encouraged to stay offline from other digital devices as well. The last page had a final message instructing participants to put their phones away and enjoy their digital detox.

After the pre-planned duration expired, an automated "end digital detox" notification, with a relative in-app button, was sent to the participants at the end of the detox. After the participants ended the digital detox by clicking on the button, post-detox questions were asked.

5.2.5 ESM Measures

Positive and negative momentary affect. Similar to previous ESM studies (e.g., Espinoza et al., 2022; Palmier-Claus et al., 2011), a modified and shortened version of the Positive and Negative Affect Scale (PANAS; Watson et al., 1988) for momentary affect. At each measurement point, participants were asked to rate how much they feel each affect item from 0 (not at all) to 100 (extremely). The items for positive affect were: energetic, calm, and cheerful. The items for negative affect were tired, low, nervous, irritated, lonely, and stressed. The mean scores for positive and negative momentary affect were computed separately.

Phone use indicators. For recent phone use, participants were asked how much they used their phones in the last 30 minutes. The answers were: 0 (not at all) to 4 (the whole time). For problematic phone use, two items of the withdrawal and loss of control subscales from the Mobile Phone Problem Use Scale - 10 (MPPUS-10; Foerster et al., 2015) were adapted to capture momentary experience. For momentary withdrawal, participants were asked to rate how much they found it difficult to stay away from their phone from 0 (not at all) to 100 (extremely) if they reported that they haven't used their phones. For momentary perceived loss of control, participants were asked to rate how much they agreed that they used their phone longer than they intended from 0 (not at all) to 100 (extremely) if they reported that they have used their phones.

Digital Detox week measures for experiment condition. During digital detox week, participants reported the duration of their digital detox sessions from 30 to 60 minutes, planned activities (studying, domestic chores, offline activities, etc.), and how easy they found their digital detox session from 0 (not easy at all) to 100 (extremely easy).

Control variables. We controlled for age, gender, and immigration background. These variables were self-reported measures from participants collected at initial assessment survey at schools.

5.2.6 Statistical Analysis

Linear mixed effect modelling was employed to assess the effectiveness of the experiment with measurement points (beeps) nested within individuals to account for the potential variations in within and between individuals. A two-level model approach was opted over a three-level model approach (with addition of individuals nested schools) due to concerns of low number of groups at the highest level could lead to imprecise results (McNeish & Wentzel, 2016). All analyses were conducted with constraining errors in adjacent beeps by an autocorrelation structure (AR1) using package *lme4* (Bates et al., 2022) at R Studio. Gender, age, and ethnic background were controlled for at each model. Separate models were used for each outcome measures. The first set of analyses aimed to test the cross-level interaction of experiment group and time with random intercept for group and random slope for time. Five outcomes were examined: momentary positive affect, momentary negative affect, recent phone use, momentary withdrawal, momentary loss of control. The second set of analyses aimed to test the effect of the treatment on the relationships between momentary affect and group-mean centred phone use variables (recent phone use, momentary withdrawal, momentary loss of control), with slopes for time and phone use variables were randomised at each model. Because these analyses required three-way interactions with group and time, we examined each phone use variable in separate models. Two outcomes were examined: momentary positive affect, momentary negative affect. The third set of analyses focused on the digital detox group subsample to explore the effects of compliance to digital detox practice indicators (number of days digital detox session was completed, average digital session practice minutes, and average digital detox easiness). As these variables are aggregated at the individual level, they were grand mean centred for the analyses. Five outcomes were examined: momentary positive affect, momentary negative affect, recent phone use, momentary withdrawal, momentary loss of control.

5.3 Results

5.3.1 Participants

Twenty-one participants were excluded due to missing demographic indicators. Missingness were random at age ($t(244) = 1.190, p = 0.235$), school ($\chi^2(4) = 3.540, p = 0.472$), immigration background ($\chi^2(1) = 0.031, p = 0.860$), and experiment group ($\chi^2(1) = 0.742, p = 0.389$). Figure 1 demonstrates the modified CONSORT 2010 Flow diagram of participation at each of the assessment phase. Out of the remaining 231 participants, 169 finished the ESM protocol (i.e., completed the pre- and post-detox week assessments). Older students ($t(229) = 1.919, p = 0.028$), girls ($\chi^2(1) = 5.824, p = 0.016$), and students from affluent school areas ($\chi^2(4) = 17.226, p = 0.002$) were more likely to finish the ESM protocol. Table 5.1 shows the final sample characteristics. On average, the participants in the control group were younger, reported higher phone use at pre-week and lower withdrawal at post-week. Table 5.2 reports the correlations at the beep level. Table 5.3 reports the correlations at the individual level with the aggregated variables. Overall, almost all the variables had small to moderate correlations both before and after the digital detox week as well as at the individual level.

The mean response rate was 34.3% (SD = 15.5); although it is marginally above the recommended lowest threshold of 30% for ESM studies (Delespaul, 1995), lower compliance is not uncommon for adolescent age group (März et al., 2025). We tested the intra-class correlations (ICC) using the empty models with only random intercept for each outcome. ICC represents the portion of variability at the level 2 (between-person) in the outcome, and lower ICCs indicate higher fluctuations at level 1 (within-person). Model results showed ICCs of $r = 0.33$ for positive affect, $r = 0.56$ for negative affect, $r = 0.19$ for recent phone use, $r = 0.44$ for momentary withdrawal, and $r = 0.34$ for momentary loss of control. These results indicate that broadly, at least half of the variation was at the beep level, and a two-level model is justified to account for the variations at both levels.

5.3.2 Digital Detox Week Assessments

Out of 114 participants in the experimental group, 57 participants completed a daily digital detox session for at least half of the digital detox week. 17 participants did not complete any session throughout the digital detox week. The preference for digital detox duration was either towards the shortest or the longest options, with 24% of the participants aimed between 30-35 minutes on average, and 26% of the participants aimed between 55-60 minutes on average. The most common planned activity was educational activities (46.3%), followed by socialising offline (43.83%). The detailed overview of activities is reported at Table A5.1. Overall, participants found digital detox practice easy ($M = 72.97$; SD = 21.04).

5.3.3 Effects of the Digital Detox Week

The results of the linear mixed effects model results for the outcome measures are presented at Table 5.4 and more detailed fluctuations of the outcome measures across beeps for each measurement weeks were illustrated at Figure 5.2. For positive affect, the control group showed a negligible decrease, and the digital detox group showed a slight increase after the digital detox week, difference was not statistically significant between the two groups. For negative affect, both groups had an increase after the digital detox week. Although the digital detox group showed less increase, the group difference in this was not statistically significant.

For recent phone use, the digital detox group already showed lower use, and the difference was marginally significant (B = -0.259, SE = (0.077), $p = 0.075$, 95% CI = [-0.409, -0.109]). Both groups lowered recent phone use after the digital detox week, although the digital detox group showed less decrease, and the group difference was not statistically significant. For momentary withdrawal, both groups showed increases after the digital detox week, and although the digital detox week showed higher increase, the group difference was not statistically significant. For momentary loss of control, the control group showed a slight decrease and the intervention group showed an increase, although the difference was not statistically significant.

5.3.4 The Relationship Between Phone Use and Affective Well-being

The interactions of group, time, and phone use indicators (recent phone use, momentary withdrawal, and momentary loss of control) are illustrated at Figure 5.3. The results for each of the predictors on positive and negative affect are reported below.

Recent phone use. For positive affect, the higher phone use was associated with lower positive affect for both the control group and the digital detox group before the digital detox week, although the difference was not statistically significant. After the digital detox week, the group difference increased, but the three-way interaction of time, group, and recent phone use was not statistically, indicating that the effect of phone use on the positive affect was consistent across groups and time. For negative affect, higher recent phone use was associated with slightly higher negative affect for the control group before the intervention week, although the effect was not statistically significant. The association was slightly stronger for the treatment group before the intervention week, but this difference was not statistically significant. After the intervention week, the group difference increased slightly with a more slope for the control group, but the three-way interaction of time, group, and recent phone use was not statistically significant, indicating that the effect of phone use on negative affect was largely consistent across groups and weeks. The full results for both outcomes are depicted at Table A5.2.

Momentary withdrawal. For positive affect, higher withdrawal was associated with slightly higher positive affect for the control group before the digital detox week, although the effect was not statistically significant. The association was negative and statistically significant for the digital detox group before the digital detox week (B = -0.395, SE = 0.103, $p < 0.001$, 95% CI = [-0.597, -0.193]). After the digital detox week, the group difference slightly decreased; the slope for withdrawal was more steep and much smaller for the digital detox group, but the three-way interaction of time, group, and withdrawal was not statistically significant, indicating that the effect of withdrawal on positive affect was largely consistent across groups and time. For negative affect, higher withdrawal was associated with lower negative affect for the control group before the intervention week, although the effect was not statistically significant. The association was significantly more positive for the digital detox group before the digital detox week (B = 0.311, SE = 0.093, $p = 0.001$, 95% CI = [0.129, 0.493]). After the digital detox week, withdrawal was associated with slightly higher negative affect overall (B = 0.276, SE = 0.099, $p = 0.005$, 95% CI = [0.081, 0.471]) as the slope of the association changed direction (from negative to positive) after the digital detox week for the control group. The three-way interaction of time, group, and withdrawal was significant and negative (B = -0.432, SE = 0.116, $p < 0.001$, 95% CI = [-0.660, -0.204]), indicating that after the digital detox week, the association between withdrawal and negative affect was less pronounced in the digital detox group compared to the control group**.** The full results for both outcomes are depicted at Table A5.3.

Momentary loss of control. For positive affect, higher perceived loss of control was associated with slightly higher positive affect for the control group before the digital detox week, although the effect was not statistically significant. The association was significantly more negative for the digital detox group before the digital detox week, as indicated by the loss of control × group interaction (B = -0.132, SE = 0.048, p = 0.005, 95% CI = [-0.226, -0.038]). After the digital detox week, the group difference slightly decreased as the slopes of the association was negative for both groups, but the three-way interaction of time, group, and loss of control was not statistically, indicating that the effect of perceived loss of control on positive affect was largely consistent across groups and time. For negative affect, higher perceived loss of control was associated with slightly higher negative affect for the control group and the digital detox group before the digital detox week, and the difference was not statistically significant. After the digital detox week, the slopes of this association were stronger for both groups, but the three-way interaction of time, group, and loss of control was not statistically significant, indicating that the effect of loss of control on negative affect was largely consistent across groups and time. The full results for both outcomes are depicted at Table A5.4.

5.3.5 The Roles of the Variables from Digital Detox Week

The interactions of time with digital detox adherence variables (days which digital detox sessions completed, digital detox session minutes, and perceived easiness of digital detox practice) are presented at Figure 5.4 and Table A5.5. For positive affect outcome, none of the three interactions significant. For negative affect, the interactions were not significant. By contrast, for the recent phone use outcome, the interaction with digital detox session minutes was statistically significant (B = 0.112, SE = 0.006, p = 0.048, 95% CI: [0.000, 0.024]) suggesting that participants who practiced shorter sessions reduced their phone use after the digital detox week, but participants who practiced longer sessions remained similar phone use levels. The other two interactions did not produce statistically significant results. For momentary withdrawal, the interactions were not statistically significant. Finally, for momentary loss of control, the interactions were again not statistically significant.

Overall, the results presented in Figure 5.4 indicate that the outcomes of the digital detox week were rather consistent across participants regardless of the number of sessions completed, session duration, or perceived easiness. This finding suggests that individual differences in adherence or subjective experience of the digital detox did not meaningfully influence changes in the outcomes, with the exception of session duration for recent phone use.

5.4 Discussion

The goal of this study was to examine whether a daily digital detox practice could help adolescents to regulate their phone use and improve momentary affect. Using an ESM approach, we assessed the changes in participants' recent phone use, momentary problematic phone use (feelings of withdrawal and loss of control), and affective well-being. We also examined the changes in the relationship between phone use indicators and affect outcomes. Finally, we explored whether participants in the experimental group could benefit differently from their digital detox dependent on their adherence and subjective experiences. By using an ESM approach, we were able to capture a more nuanced understanding of the impact, or lack thereof, of the digital detox intervention than previous research. Overall, this study offers a novel field experiment design and contributes to the ever-growing digital detox literature by focusing on an underrepresented age group in the literature: adolescents.

Our study has a number of relevant findings to the literature. First, we overall found that a week of digital detox did not change adolescents' phone use outcomes and affective well-being. This is not an uncommon finding in the young adult literature where social media detox, for example, does not have conclusive evidence on improving mental well-being (e.g., Hall et al., 2019). The lack of effects in this study could be explained by different reasons. It is possible that the design of the digital detox was simply not severe enough. We intentionally refrained from a strict abstaining design and aimed a more realistic and sustainable approach, considering that the former option does not necessarily yield stronger results (Brailovskaia et al., 2023). However, it is possible that a period of eight days of digital detox in total may not be enough to alter phone use habits, or to have an impact on the affective well-being. While some previous studies on older participants demonstrated positive changes after a one-week intervention (e.g., Brailovskaia et al., 2023; Brown & Kuss, 2020; Turel et al., 2018), adolescents may need more time to adjust to a new routine.

Second, our analyses revealed that the digital detox intervention did not improve the existing relationships between phone use and affective well-being. This indicate that the week of digital detox did not help to buffer the negative outcomes of excessive and problematic phone use on momentary affect. There was, however, an interesting finding to discuss in relation to momentary sense of withdrawal. For the adolescents in the control group, higher momentary withdrawal predicted higher negative affect after the digital detox week compared to before. On the contrary, for the adolescents in the digital detox group, this association became weaker after the digital detox week compared to before, suggesting that adolescents in the digital detox group were able to cope with the negative outcome of their withdrawal feelings after a week of digital detox. This could be due to the informative nature of the interventions; participants in the digital detox group were given an educational session which explained the potential benefits of digital detox. These sessions, supplemented with video reminders, might have helped adolescents' to recontextualise their momentary sense of withdrawal when they were away from their phones, as research on behavioural change indicates that reminders help to keep intrinsic motivation by supporting autonomy (Villalobos-Zúñiga & Cherubini, 2020; Wicaksono et al., 2009). This may highlight the potential benefits of strengthening the psychoeducational elements of the digital well-being initiatives in which helping young people to understand their problematic use tendencies could protect them from harmful effects on their mental well-being (Das-Friebel et al., 2019).

Third, our final set of analyses showed that the number of days in which the digital detox was practiced, as well as the subjective experience of perceived easiness of the sessions, did not make a difference in changing the phone use and affective well-being outcomes. Interestingly, although the average duration of participants' digital detox sessions did not alter participants' problematic phone use indicators and affective well-being outcomes, adolescents who had shorter sessions on average reported lower phone use after the digital detox week. This could be explained by the fact that adolescents who did longer sessions were already reporting lower phone use, while participants who did shorter sessions reported higher phone use prior to the digital detox week. Thus, the brief achievable durations of abstinence might have supported their autonomy and competence enough to activate their intrinsic motivation to reduce their phone use after the digital detox week (Turel, 2021). This result supports the idea that, rather than focusing solely on abstinence, educational programs should emphasize strategies that allow for short and manageable breaks from phones that could also help to motivate young people to manage their phone use habits in their own pace.

This study is not without limitations. First, in our study we cannot rule out the possibility that unidentified school level confounding factors that might have impacted our results. Further research with a robust RCT design and with a larger sample size at school-level is needed to test the effectiveness of digital detox interventions delivered at schools. Second, the challenging feature of testing digital detox through ESM needs to be acknowledged. While digital detox instructed adolescents to take an allocated time off from using their phones, the ESM questionnaires were sent at random times with an expiration limit to assess the true momentary experience (Myin-Germeys & Kuppens, 2021). This could have led participants to pay closer attention to their phones, and check their notifications more often throughout the study. To prevent participants to overly concerned about missing beeps, participants were explicitly instructed "not to worry too much about completing all the beeps, but try to do their best to answer when they see a notification". However, this could have resulted in missing participants who were truly off their phones for extended periods of time and missed the windows of the beep response time more frequently. Future ESM studies should further investigate the implications of these programme features. Third, our methodology did not allow for an objective measurement of adolescents' phone use. Previous studies attempted to solve this issue with alternative approaches. For instance, two studies (Hanley et al., 2019; Brockmeier et al., 2025) utilised a tracking app to objectively record participants' phone activities. While tracking apps offer promising solutions to measure real-time phone use, these studies using mobile-app tracking methods had to limit their sample to Android phone users only due to compatibility issues with the Apple's operating system IOS. This limitation may create bias in the socioeconomic and digital profiles of users. Future studies with a more suitable methods of measuring app-specific screen time in smartphones could expand our understanding of how young people engage with their phones in real time and advance the adolescents' digital use literature in the context of digital detox interventions.

5.5 Conclusion

This study adds to the inconclusive evidence on the effectiveness of digital detox interventions by focusing on adolescents. While we did not observe consistent improvements in phone use or affective well-being, our findings contribute to the growing literature on digital detox practices, and demonstrate the challenges in effectively forming a new digital habit involving smartphones. By employing an ESM approach, we were able to capture nuanced momentary associations that highlight both the limitations and the advantages of this particular methodology in the digital use research. Taken together, our results suggest that rather than prescribing strict abstinence, school-based digital well-being initiatives may be most effective when they combine realistic, autonomy-supportive strategies with educational components that help adolescents critically reflect on their digital use. Future research address methodological challenges and testing interventions at a more robust scale to expand our understanding of how to promote healthier digital habits to young people.

5.6 Tables and Figures

Table 5.1 Sample characteristics

Variable	Total	Experimental group	Control group	*p*
N	269	114	55	
Girls (%)	59.8%	61.4%	56.4%	0.646
Age (SD)	15.3 (1.47)	15.5 (1.57)	14.9 (1.19)	0.019
Native Irish (%)	86.4%	89.5%	80.0%	0.149
M. positive affect pre-week (SD)	49.4 (20.6)	49.1 (20.3)	50.1 (21.1)	0.330
M. positive affect post-week (SD)	50.0 (21.3)	49.9 (21.9)	50.2 (20.3)	0.759
M. negative affect pre-week (SD)	27.7 (19.4)	28.1 (19.0)	26.5 (20.3)	0.102
M. negative affect post-week (SD)	29.2 (22.7)	29.5 (22.1)	28.8 (23.8)	0.588
Recent phone use pre-week (SD)	0.96 (0.99)	0.91 (0.95)	1.08 (1.07)	<0.001
Recent phone use post-week (SD)	0.78 (0.99)	0.74 (0.96)	0.84 (1.02)	0.082
M. withdrawal pre-week (SD)	13.3 (21.3)	12.3 (19.0)	15.9 (26.5)	0.068
M. withdrawal post-week (SD)	17.8 (24.4)	19.4 (24.7)	15.1 (23.8)	0.029
M. loss of control pre-week (SD)	27.0 (27.8)	26.5 (27.0)	27.9 (29.5)	0.446
M. loss of control post-week (SD)	28.5 (28.3)	27.5 (28.2)	30.1 (28.4)	0.287

Note. M.: Momentary.

Table 5.2 Pairwise-correlations of continuous beep-level variables

	1	2	3	4	5
1. M. positive affect	-	-0.470***	-0.075**	-0.093*	-0.124**
2. M. negative affect	-0.489***	-	0.131***	0.360***	0.290***
3. Recent phone use	-0.085***	0.129***	-	-	0.290***
4. M. withdrawal	-0.196***	0.312***	-	-	-
5. M. loss of control	-0.048	0.220***	0.237***	-	-

Note. N_{beep} = 3,186. M.: Momentary. The correlations below the diagonal represent pre-week measurements and above the diagonal represent post-week measurements. Because M. withdrawal is only asked when recent phone use is 0 “not at all”, and M. withdrawal and M. loss of control variables are mutually exlusive due to the branching of the survey, their pair-wise correlations are not calculated. *: $p < 0.05$; **: $p < 0.01$ ***: $p < 0.001$.

Table 5.3 Pairwise-correlations of continuous variables aggregated at the individual level

	1	2	3	4	5	6	7	8
1. M. positive affect	-							
2. M. negative affect	-0.342***	-						
3. Recent phone use	-0.157*	0.133	-					
4. M. withdrawal	-0.164*	0.471***	0.026	-				
5. M. loss of control	-0.003	0.224**	0.107	0.134**	-			
6. Digital detox days[a]	-0.054	-0.107	-0.111	-0.165	0.065	-		
7. Digital detox minutes[a]	-0.008	-0.156	-0.200*	-0.266**	-0.011	0.316**	-	
8. Digitial detox perceived easiness[a]	0.139	-0.217*	-0.201*	-0.494***	-0.064	0.150	0.278**	-

Note. $N_{individual}$ = 169. M.: Momentary. [a]: Correlations for experimental group only (N = 97) since these variables are only measured during the digital detox week. *: $p < 0.05$; **: $p < 0.01$ ***: $p < 0.001$.

Table 5.4 Results of the linear mixed effect models: group x time interaction

Variable	Positive affect		Negative affect		Recent phone use		Withdrawal		Loss of control	
	B (SE)	**95% CI**	**B (SE)**	**95% CI**	**B (SE)**	**95% CI**	**B (SE)**	**95% CI**	**B (SE)**	**95% CI**
Fixed effects										
Intercept	68.433*** (10.267)	[48.302, 88.565]	34.954* (12.889)	[9.681, 60.227]	1.536*** (0.395)	[0.761, 2.310]	4.632 (13.673)	[-22.193, 31.457]	20.837 (15.235)	[-9.045, 50.719]
Exp. group										
Control (ref)										
Dig.Dtx	1.188 (2.224)	[-3.203, 5.790]	0.944 (2.661)	[-4.309, 6.198]	-0.138 (0.086)	[-0.308, 0.031]	-2.233 (2.983)	[-8.125, 3.660]	-2.443 (3.254)	[-8.868, 3.983]
Time										
Pre-week (ref)										
Post-week	-0.660 (1.863)	[-4.312, 2.993]	3.073 (1.708)	[-0.276, 6.423]	-0.259** (0.077)	[-0.409, -0.109]	0.476 (2.667)	[-4.755, 5.708]	-0.705 (3.042)	[-6.7672, 5.262]
Cross-level interaction										
Dig.Dtx x post-week	1.829 (2.287)	[-2.656, 6.314]	-1.306 (2.096)	[-5.415, 2.803]	0.122 (0.094)	[-0.063, 0.307]	4.303 (3.253)	[-2.079, 10.684]	2.813 (3.740)	[-4.523, 10.149]
Random effects										
Intercept SD (ind.)	11.408	[9.888, 13.162]	14.725	[12.975, 16.711]	0.416	[0.354, 0.488]	14.461	[12.439, 16.812]	16.182	[13.905, 18.833]
Slope SD (time)	9.129	[7.067, 11.792]	9.001	[7.251, 11.173]	0.332	[0.243, 0.452]	12.686	[9.939, 16.193]	13.249	[9.738, 18.026]
Residual	16.849	[16.351, 17.363]	13.627	[13.198, 14.070]	0.879	[0.857, 0.903]	15.938	[15.242, 16.666]	22.344	[21.513, 23.208]
ICC	0.34		0.58		0.21		0.49		0.38	
Marginal R^2 / Conditional R^2	0.026 / 0.361		0.009 / 0.588		0.022 / 0.226		0.011 / 0.500		0.011 / 0.382	
N individual	169		169		169		163		166	
N beep	3186		3186		3186		1428		1757	

Note. Exp.: Experiment, DigDtx: Digital detox. CI: Confidence interval. SD: Standard deviation. ICC: Intra-class correlations. Age, gender, and ethnic background were controlled for in all analyses. *: $p < 0.05$; **: $p < 0.01$ ***: $p < 0.001$

Figure 5.1 Modified CONSORT 2010 flow diagram of participants

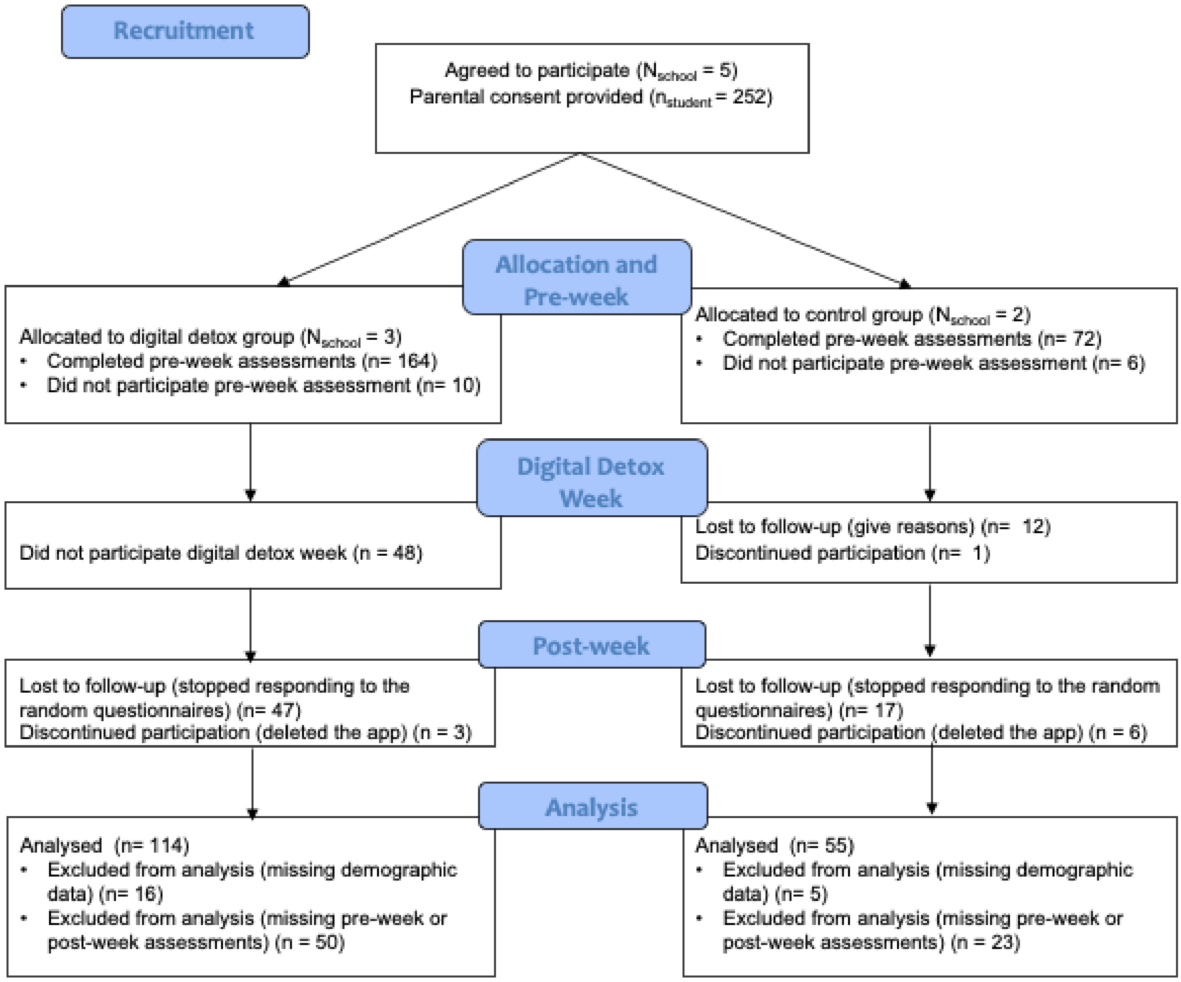
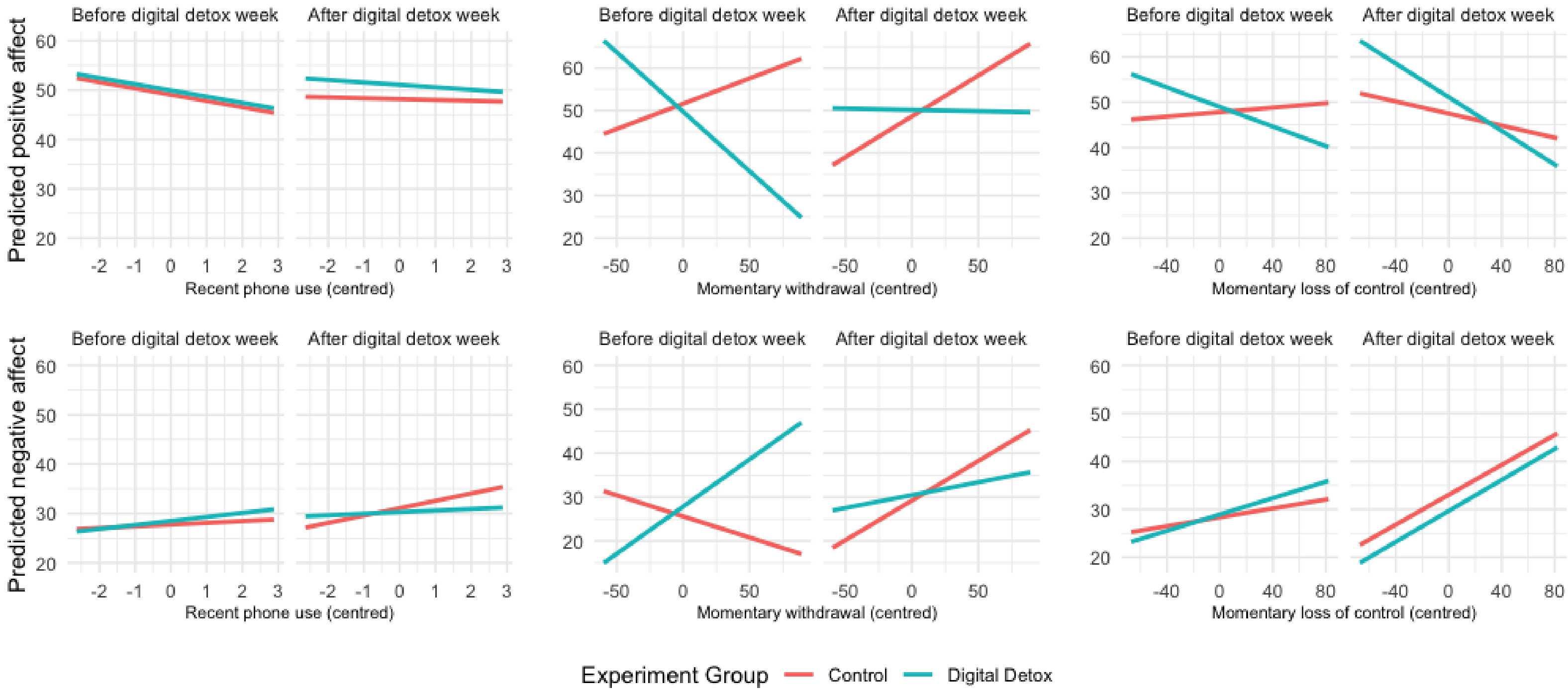


Figure 5.2 Trajectories of outcome variables across time

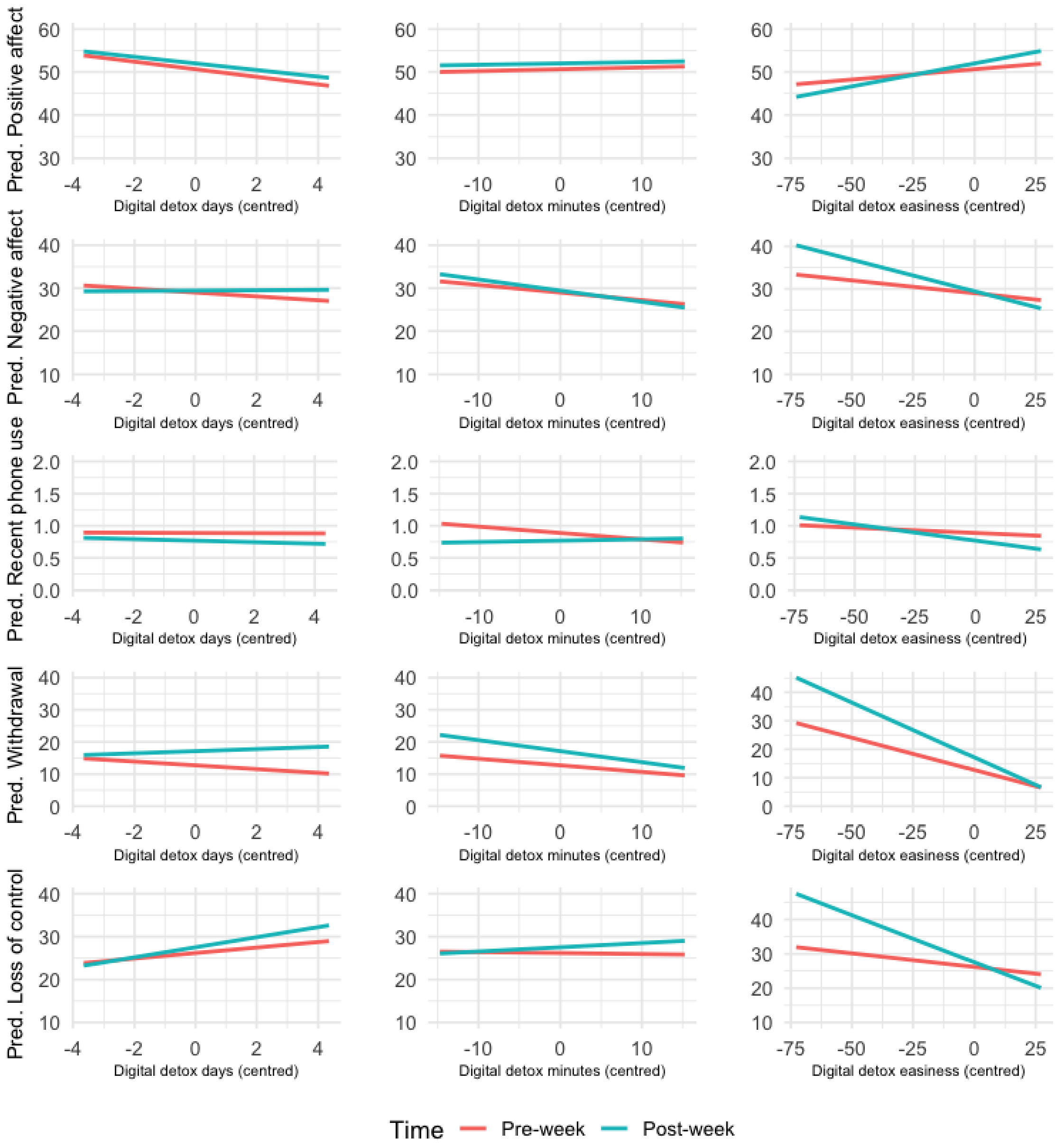
Note. Age, gender, and ethnic background were controlled for in all analyses.

Figure 5.3 Experiment condition differences in the relationship between digital use indicators and affect outcomes



Note. Age, gender, and ethnic background were controlled for in all analyses.

Figure 5.4 The associations between adherence to the digital detox variables and perceived easiness, and outcome variables before and after the digital detox week



Note. The analyses are conducted on the digital detox group only.

5.7 Appendix

Table A5.1 Reported activities during digital detox sessions

Activity category	**Planned at pre-detox**	**Reported at post-detox**
Socialising offline	43.83%	42.59%
Educational activities	46.30%	41.36%
Physical activities	31.48%	30.25%
Eating / sleeping / napping	27.78%	33.33%
Domestic chores	19.14%	17.28%
Using other mobile devices	11.73%	13.58%
Miscellaneous (e.g., commuting, bathing)	22.84%	22.22%

Note. Participants were allowed to choose multiple options.

Table A5.2 Results of the linear mixed effect models: group x time x recent phone use

Variable	**Model: Positive affect**		**Model: Negative affect**	
	B (SE)	**95% CI**	**B (SE)**	**95% CI**
Fixed effects				
Intercept	72.805*** (10.794)	[51.641, 93.969]	33.524* (13.532)	[6.992, 60.056]
Recent phone use	-1.298 (0.752)	[-2.773, 0.176]	0.353 (0.545)	[-0.714, 1.421]
Exp. condition				
Control (ref)				
Dig.Dtx	1.031 (2.229)	[-3.370, 5.433]	0.999 (2.662)	[-4.257, 6.255]
Time				
Pre-week (ref)				
Post-week	-0.845 (1.878)	[-4.527, 2.837]	3.314 (1.710)	[-0.038, 6.666]
Cross-level interactions				
Dig.Dtx x Recent phone use	0.037 (0.928)	[-1.782, 1.856]	0.454 (0.672)	[-0.863, 1.771]
Post-week x Recent phone use	1.148 (1.130)	[-1.068, 3.363]	1.154 (0.868)	[-0.548, 2.855]
Dig.Dtx x Post-week	1.971 (2.302)	[-2.542, 6.484]	-1.516 (2.095)	[-5.625, 2.592]
Dig.Dtx x Post-week x Recent phone use	-0.393 (1.438)	[-3.212, 2.426]	-1.648 (1.102)	[-3.808, 0.513]
Random effects				
Intercept SD (individual)	11.438		14.737	
Slope SD (time)	9.155		8.981	
Slope SD (recent phone use)	2.028		0.836	
Residual SD	16.741		13.579	
ICC	0.35		0.59	
Marginal R^2 / Conditional R^2	0.028 / 0.370		0.011 / 0.591	
N individual	169		169	
N beep	3186		3186	

Note. Exp.: Experiment, DigDtx: Digital detox. CI: Confidence interval. SD: Standard deviation. ICC: Intra-class correlations. Age, gender, and ethnic background were controlled for in all analyses. *: $p < 0.05$; **: $p < 0.01$ ***: $p < 0.001$.

Table A5.3 Results of the linear mixed effect models: group x time x momentary withdrawal

Variable	Model: Positive affect		Model: Negative affect	
	B (SE)	**95% CI**	**B (SE)**	**95% CI**
Fixed effects				
Intercept	62.965*** (12.797)	[37.859, 88.071]	37.382* (14.887)	[8.176, 66.589]
Momentary withdrawal	0.117 (0.088)	[-0.055, 0.289]	-0.096 (0.079)	[-0.250, 0.058]
Exp. condition				
Control (ref)				
Dig.Dtx	-2.024 (2.784)	[-7.523, 3.476]	2.620 (2.961)	[-3.228, 8.468]
Time				
Pre-week (ref)				
Post-week	-2.873 (2.314)	[-7.413, 1.666]	3.513 (2.198)	[-0.800, 7.826]
Cross-level interactions				
Dig.Dtx x Momentary withdrawal	-0.395*** (0.103)	[-0.597, -0.194]	0.311** (0.093)	[0.127, 0.494]
Post-week x Momentary withdrawal	0.072 (0.119)	[-0.161, 0.305]	0.276 (0.099)	[0.082, 0.471]
Dig.Dtx x Post-week	3.401 (2.809)	[-2.110, 8.911]	-0.946 (2.676)	[-6.197, 4.305]
Dig.Dtx x Post-week x Momentary withdrawal	0.199 (0.139)	[-0.074, 0.472]	-0.432*** (0.116)	[-0.660, -0.203]
Random effects				
Intercept SD (individual)	12.217		14.661	
Slope SD (time)	6.283		8.235	
Slope SD (momentary withdrawal)	0.119		0.205	
Residual SD	17.453		13.91	
ICC	0.34		0.59	
Marginal R^2 / Conditional R^2	0.046 / 0.374		0.024 / 0.604	
N individual	163		163	
N beep	1428		1428	

Note. Exp.: Experiment, DigDtx: Digital detox. CI: Confidence interval. SD: Standard deviation. ICC: Intra-class correlations. Age, gender, and ethnic background were controlled for in all analyses. *: $p < 0.05$; **: $p < 0.01$ ***: $p < 0.001$

Table A5.4 Results of the linear mixed effect models: group x time x momentary loss of control

Variable	Model: Positive affect		Model: Negative affect	
	B (SE)	**95% CI**	**B (SE)**	**95% CI**
Fixed effects				
Intercept	55.130*** (3.615)	[48.040, 62.220]	28.553* (13.406)	[2.257, 54.849]
Momentary loss of control	0.025 (0.039)	[-0.051, 0.101]	0.049 (0.030)	[-0.009, 0.108]
Exp. condition				
Control (ref)				
Dig.Dtx	0.874 (2.155)	[-3.381, 5.130]	0.755 (2.641)	[-4.460, 5.970]
Time				
Pre-week (ref)				
Post-week	-0.179 (2.123)	[-4.344, 3.986]	4.752* (1.842)	[1.139, 8.366]
Cross-level interactions				
Dig.Dtx x Momentary loss of control	-0.132** (0.048)	[-0.226, -0.039]	0.034 (0.037)	[-0.038, 0.105]
Post-week x Momentary loss of control	-0.089 (0.061)	[-0.209, 0.030]	0.114* (0.049)	[0.017, 0.211]
Dig.Dtx x Post-week	2.286 (2.612)	[-2.838, 7.410]	-4.016 (2.261)	[-8.451, 0.420]
Dig.Dtx x Post-week x Momentary loss of control	0.010 (0.078)	[-0.144, 0.164]	-0.038 (0.064)	[-0.163, 0.087]
Random effects				
Intercept SD (individual)	10.424		14.09	
Slope SD (time)	8.593		7.574	
Slope SD (momentary loss of control)	0.088		0.042	
Residual SD	15.681		12.972	
ICC	0.37		0.56	
Marginal R^2 / Conditional R^2	0.035 / 0.396		0.029 / 0.596	
N individual	166		166	
N beep	1757		1757	

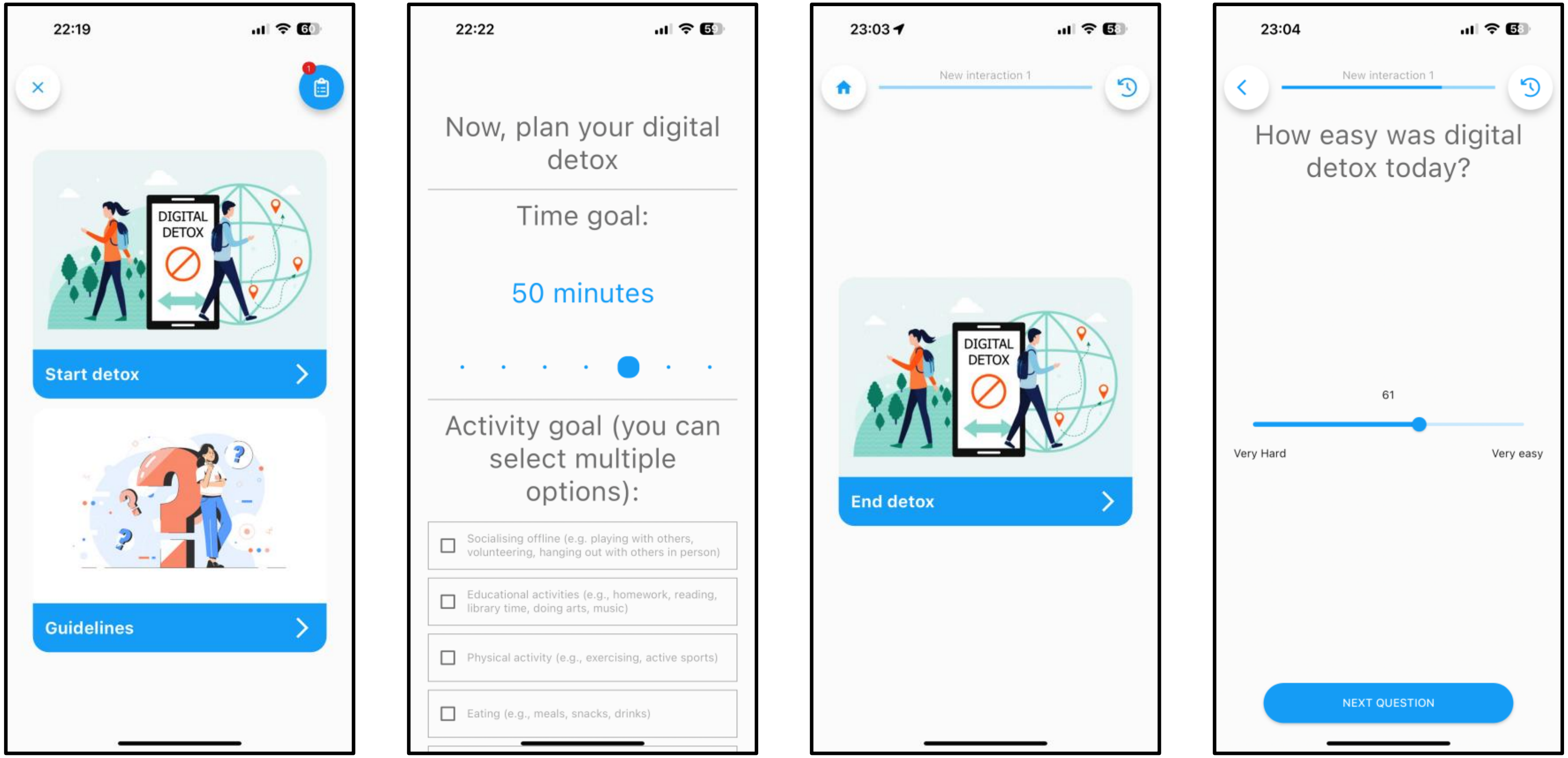
Note. Exp.: Experiment, DigDtx: Digital detox. CI: Confidence interval. SD: Standard deviation. ICC: Intra-class correlations. Age, gender, and ethnic background were controlled for in all analyses. *: $p < 0.05$; **: $p < 0.01$ ***: $p < 0.001$

Table A5.5. Results of the linear mixed effect models: the roles of adherence to digital detox and subjective perceived easiness

Variable	**Positive affect**		**Negative affect**		**Recent phone use**		**Withdrawal**		**Loss of control**	
	B (SE)	**95% CI**	**B (SE)**	**95% CI**	**B (SE)**	**95% CI**	**B (SE)**	**95% CI**	**B (SE)**	**95% CI**
Fixed effects										
Intercept	66.456*** (12.881)	[41.193, 91.719]	9.581 (15.854)	[-21.514, 40.676]	1.554** (0.509)	[0.556, 2.551]	-13.368 (12.817)	[-38.529, 11.792]	4.985 (19.546)	[-33.378, 43.348]
Dig.Dtx days	-0.884 (0.584)	[-2.043, 0.276]	-0.451 (0.715)	[-1.872, 0.969]	-0.002 (0.024)	[-0.049, 0.046]	-0.585 (0.600)	[-1.778, 0.607]	0.638 (0.898)	[-1.145, 2.422]
Dig.Dtx minutes	0.042 (0.133)	[-0.222, 0.306]	-0.177 (0.162)	[-0.499, 0.144]	-0.010 (0.005)	[-0.021, 0.001]	-0.205 (0.137)	[-0.477, 0.067]	-0.023 (0.204)	[-0.428, 0.383]
Dig.Dtx easiness	0.048 (0.063)	[-0.077, 0.173]	-0.060 (0.077)	[-0.214, 0.094]	-0.002 (0.003)	[-0.007, 0.003]	-0.227*** (0.062)	[-0.350, -0.104]	-0.079 (0.097)	[-0.272, 0.114]
Time										
Pre-week (ref)										
Post-week	1.361 (1.480)	[-1.543, 4.264]	0.447 (1.480)	[-2.456, 3.349]	-0.119* (0.061)	[-0.239, -0.000]	4.406* (2.144)	[0.197, 8.615]	1.343 (2.871)	[-4.292, 6.978]
Cross-level interactions										
Post-week x Dig.Dtx days	0.114 (0.647)	[-1.155, 1.383]	0.494 (0.651)	[-0.782, 1.770]	-0.010 (0.026)	[-0.062, 0.041]	0.913 (0.946)	[-0.945, 2.770]	0.533 (1.243)	[-1.907, 2.974]
Post-week x Dig.Dtx minutes	-0.011 (0.147)	[-0.299, 0.277]	-0.083 (0.147)	[-0.372, 0.206]	0.012* (0.006)	[0.000, 0.024]	-0.138 (0.213)	[-0.555, 0.280]	0.121 (0.289)	[-0.445, 0.687]
Post-week x Dig.Dtx easiness	0.059 (0.067)	[-0.072, 0.190]	-0.089 (0.068)	[-0.221, 0.044]	-0.003 (0.003)	[-0.009, 0.002]	-0.158 (0.093)	[-0.341, 0.024]	-0.195 (0.135)	[-0.459, 0.069]
Random effects										
Intercept SD (ind.)	9.945		13.49		0.407		8.398		15.299	
Slope SD (time)	6.634		8.605		0.238		10.844		15.793	
Residual	17.447		14.625		0.872		16.782		22.262	
ICC	0.28		0.48		0.18		0.3		0.37	
Marginal R^2 / Conditional R^2	0.029 / 0.300		0.046 / 0.505		0.035 / 0.213		0.158 / 0.415		0.037 / 0.391	
N individual	97		97		97		95		97	
N beep	1838		1838		1838		853		985	

Note. Analyses are conducted on digital detox group only. Exp.: Experiment, Dig.Dtx: Digital detox. CI: Confidence interval. SD: Standard deviation. ICC: Intra-class correlations. Age, gender, and ethnic background were controlled for in all analyses. *: $p < 0.05$; **: $p < 0.01$ ***: $p < 0.001$

Figure A5.1 Sample screen captures from the custom created digital detox applet



Chapter 6: Conclusion

6.1 Summary of this Doctoral Dissertation

This thesis has examined how digital use relates to adolescents' mental well-being using a variety of theoretical frameworks and empirical methodologies. Specifically, the present thesis has examined (1) whether the relationship between PSMU and adolescent mental well-being is driven by socioeconomic inequalities operating and intersecting at the micro (family) and macro (societal) level, (2) how different types of digital user profiles do in terms of their mental well-being outcomes and whether digital maturity explains such patterns, and (3) how school-level intervention studies, including a digital detox programme, can impact adolescent (problematic) digital use patterns, as well as their mental well-being.

Each empirical chapter has asked a distinct, yet complementary, research question. Chapter 2 (Study 1) aimed to investigated individual, school, and country level socioeconomic inequalities in the relationship between PSMU and mental well-being of adolescents using a multi-level modelling approach to a cross-national dataset. Chapter 3 (Study 2) aimed to identify distinct digital user profiles using a GLMA method, and examined whether the differences in digital maturity levels for each user profile groups identified could explain their differences in mental well-being outcomes with a mediation analysis. Chapter 4 (Study 3) conducted a systematic review and meta-analysis to explore effectiveness of school-based interventions targeting adolescents' digital use and mental well-being. Chapter 5 (Study 4) tested the effectives of a digital detox strategy combining a field experiment and ESM designs.

The goal of Chapter 6 is to (a) summarise the main finding of this thesis, going chapter by chapter, (b) discuss the implications of the thesis, both at the scientific and policy level, (c) discuss the thesis strengths and limitations, (d) present suggestions for future research, and (e) summarise the main concluding remarks of the thesis.

6.2 Summary of Key Findings and Contributions

Chapter 2 (Study 1) examined whether the harms associated with problematic social media use (PSMU) are evenly distributed or stratified by individual level resources and macro level contexts. Using a cross-national approach, the chapter showed that higher PSMU is associated with more psychological complaints and lower life satisfaction, and that these associations are consistently steeper for adolescents in low-SES families than for their high-SES peers. This pattern resonates with research on second- and third-level digital divides, in which skills, supports, and outcomes, and not merely access to social media, differentiate experiences (van Deursen & van Dijk, 2019; Livingstone et al., 2011). Families with more economic and cultural capital appear better positioned to buffer risk through digital parenting strategies, quality devices and connections, and access to formal and informal mental-health supports (Bohnert & Gracia, 2021; Livingstone et al., 2018).

At the macro level, interestingly, Chapter 2 uncovered a non-linear moderation by income inequality. The results show that mid-inequality countries concentrate the largest harms of PSMU, whereas low- and high-inequality contexts look surprisingly similar. This pattern suggests that social comparison pressures and limited safety nets may be most misaligned in intermediate contexts, consistent with work on diffusion and infrastructural unevenness (Fuchs, 2009; Zhang, 2013), and with research on status anxiety in adolescent online ecologies (Nesi & Prinstein, 2015). By contrast, higher national wealth appears protective, plausibly via better resourced schools and health systems and a wider base of digital literacy (Ma et al., 2019; Van Dijk, 2020). Taken together, Chapter 2 situates PSMU as a general risk whose consequences are sharpened by family disadvantage, and by national contexts to a much weaker extent.

Chapter 3 (Study 2) contributed to the literature by shifting the lens from "how much" adolescents use digital media to "what kind" of users they are, and whether digital maturity helps explain profile-specific risks linking digital users and different well-being outcomes. The analyses identified three classes or profiles of users: Light, Reserved, and Outgoing users. These profiles captured the variations in the intensity, purposes, and types of platforms that the adolescents used. Light users reported relatively low intensity and primarily communicative purposes; Reserved users combined medium intensity with more private, consumption-oriented patterns; Outgoing users were high-intensity, active, and public-facing. Results indicated that both Reserved and Outgoing adolescents reported lower well-being than Light users. Crucially, digital maturity fully mediated the disadvantage of Outgoing users, but not that of Reserved users. Because digital maturity is a concept reflecting individuals' autonomy, competence, and relatedness in digital contexts (Laaber et al., 2023), these finding sheds light into how having Outgoing use pattern might impair these psychological needs of young people that might inevitably lower mental well-being.

The findings of Chapter 3 of the thesis complement work showing that public-facing and validation-seeking engagement can heighten social comparison and conflict, thereby undermining well-being (Winstone et al., 2022; Verduyn et al., 2022), while also aligning with SDT-based accounts that link self-determined use to better psychological outcomes (Ryan & Deci, 2020; Vissenberg et al., 2022). The non-mediation for Reserved users points to alternative mechanisms, such as social anxiety, low offline support, or fear of missing out, which are less about competence and autonomy deficits and more about relational vulnerabilities (Burnell et al., 2019; O'Day & Heimberg, 2021). The analyses and results of Chapter 3 therefore deepen the field’s shift away from unitary “screen time” toward typologies of users by positioning digital maturity (Laaber et al., 2024; Koch et al., 2024) as a novel mediator in shaping why some digital users do worse than others in terms of mental well-being.

Chapter 4 (Study 3) synthesised school-based interventions targeting digital use and mental well-being during adolescence. The review and meta-analysis conducted in this chapter indicated that schools are credible platforms for some change in digital habits and well-being outcomes, at least when looking at some important outcomes investigated. Indeed, the school-level programs tended to reduce overall screen exposure to some degree and, more importantly, were associated with relevant reductions in depressive symptoms and anxiety. These benefits sit alongside mixed evidence for problematic/compulsive use, life satisfaction, and strengths-and-difficulties outcomes, in part because existing programs are often multi-component, short in duration, and variably implemented, which obscures the active ingredients (Busch et al., 2013; Oh et al., 2022; Cilar et al., 2020).

The review conducted in Chapter 4 implied that digital elements (apps, messages) layered onto education can help, but their effectiveness may hinge on students’ digital skills and the school’s capacity to deliver consistent routines, a finding that was discussed and raised in the literature on second-level divides and intervention equity (Livingstone & Helsper, 2010; Dekkers & Luman, 2023). By quantifying separate outcomes for digital behaviour and mental health, the chapter contributes with a sharper picture than prior sedentary-behaviour reviews, which were directly addressing physical health, rather than mental well-being, while it makes a substantive case for designing school programs that explicitly build digital maturity, emotion regulation online, and social-comparison literacy.

Finally, Chapter 5 (Study 4) built from the previous review and meta-analysis by implementing a study embedded into a one-week daily digital-detox routine into school life, using ESM to measure potential changes in smartphone use, problematic phone use indicators, and positive and negative affect. The observed mean effects on recent use, withdrawal, loss of control, and affect were null, an outcome somewhat consistent with mixed evidence in young adult detox studies where short abstinence can sometimes backfire or produce only transient changes (Przybylski et al., 2021; Vally & D'Souza, 2019). Yet, two process findings emerged to some extent in this study. First, the coupling between withdrawal feelings and negative affect weakened in the intervention group after the detox week. This finding suggested improved coping with cravings—possibly supported by psychoeducational framing and light reminders, which the behaviour-change literature identifies as helpful for scaffolding autonomy and competence (Das-Friebel et al., 2019; Turel, 2021). Second, interestingly, the findings revealed that shorter, more feasible detox sessions predicted lower subsequent phone use, consistent with SDT's emphasis on aligning goals with perceived competence to sustain adherence (Ryan & Deci, 2017).

Despite the mixed findings, Chapter 5 is an innovative empirical study in applying a digital detox practice with adolescents, which an important addition to a literature that has overwhelmingly targeted adult smartphone users (Ansari et al., 2024; Liu et al., 2025). The findings of this chapter suggest the limits of brief, low-dose routines for shifting digital habits. It shows the value of designing interventions around achievable practices in everyday digital life that protect adolescents' autonomy, and it informs an innovative and emerging field of research of the advantages, but also the challenges, of measuring and enabling behavioural change in the context of digital interventions.

Overall, bringing the empirical chapters into dialogue and putting them together, three integrative conclusions emerge from the findings of this thesis. First, socio-digital harms are structured by social inequality. Family-level resources, mediation and skills explain more than school- or country-level conditions (Livingstone et al., 2018). Second, beyond screen time, what adolescents do online matters in their digital maturity as well as in their mental well-being. Distinct user profiles carry different risks, and digital maturity is a modifiable explanatory mechanism that helps to explain why active, public-facing engagement is linked to poorer well-being (Ryan & Deci, 2020; Winstone et al., 2022; Verduyn et al., 2022). Third, school-based interventions seem to be important in reducing risky screen exposure and produce improvements in outcomes like depression and anxiety. However, digital-detox routines in the context of digital interventions are complex, and could produce limited average effects among adolescents, unless an equilibrium between intensity and duration is achieved.

6.3 Policy Implications

Beyond scientific implications, this study has important implications for policy and practice. First, based on our findings regarding the consistent socioeconomic inequalities in the relationship between PSMU and mental well-being across countries in Study 1 and the effectiveness of school-based interventions targeting adolescent digital use and mental well-being in Study 3, policies should prioritise targeted programs for disadvantaged youth, digital skills and literacy programs at school level to alleviate the disadvantages experienced by youth from low-SES families. Study 3 particularly demonstrated that screen time focused educational programmes work at the school level. Policies should aim to incorporate such programmes into the education system to ensure any relevant tools are available to every student by default at schools. This would help to close not only the second level divide in digital skills and engagement, but also the third level divide in relation to the inequalities in the mental health outcomes of digital use.

Second, although the thesis could not conclude on one effective intervention strategy that target young people's digital use and their mental well-being, the findings of the Study 3 in combination with the theoretical overview of Study 4 suggest that the interventions targeting excessive and problematic digital use should move beyond restrictive or abstinence-only models, which are rarely sustainable and not realistic to an average daily life of a young person. Study 4 argued that a more flexible approach to regulating adolescents' digital use that integrates school-level trainings. Future policies should also prioritize education-focused strategies, autonomy-supportive approaches, and aim to induce adolescents' intrinsic motivations. Moreover, the strategies should consider fostering the building block of digital maturity. The findings of Study 2 in addition to previous studies (Laaber et al., 2024; Koch et al., 2025) show that adolescents with higher digital maturity tend to have better well-being outcomes. Since this is a holistic concept, targeting the subdimensions of digital maturity would help many young people to obtain effective tools to use digital devices in beneficial ways.

6.4. Strengths and Limitations

This thesis has several strengths. First, each empirical study included in this thesis has distinct designs, which allows for addressing complex objectives in a nuanced way. For instance, Study 1 tackles cross-national inequalities and Study 2 explores individual level mechanisms in the relationship between digital use and mental well-being. Moreover, Studies 3 and 4 approach intervention research with diverse designs. By combining observational studies (Studies 1–2) with evidence synthesis (Study 3) and an original field experiment (Study 4), the thesis bridges gaps between identifying risks, theorizing mechanisms, and testing change strategies. Second, this thesis adopts strong theoretical frameworks to move beyond outdated conceptualising of digital use such as screen time literature. By incorporating person-centric approaches, Self-Determination Theory, and digital divides framework with a variety of methodologies deepens our understanding of how adolescents engage online, not just how much, and positions socioeconomic disadvantages, personal digital use habits, and digital maturity as mechanisms for well-being. Third, this thesis advances the field of intervention research, particularly emerging digital detox literature, with studies 3 and 4. The systematic review and meta-analysis in Study 3 expands the field's understanding of what school-based interventions currently achieve, while the digital detox experiment in Study 4 serves as a building block for adolescent-focused digital self-regulation research. The mixed findings contribute a nuanced understanding to current debates on digital detox, highlighting feasibility, dosage, and autonomy as key considerations for adolescent-focused interventions.

The main limitations of the thesis can be summarised into four key domains that should guide future research. First, the studies of this thesis have some limitations in addressing causality and robust designs. Studies 1 and 2 acknowledge that the cross-sectional data is not sufficient examine bidirectionality of the relationship between digital use and mental well-being. Secondary cross-national longitudinal datasets are too scarce to explore the objective of Study 1, and primary longitudinal data collection was not within the scope of this PhD project. Although these limitations prevent us to draw casual interpretations, the design of these studies and their findings serve as preliminary results to further longitudinal research. Study 3 had the limitation of relying of existing academic articles, and the quality of published intervention studies drove the robustness of the findings of the study. Consequently, the data synthesis in Study 3 was constrained by heterogeneous study designs and limited power in meta-analyses. Study 4 arguably had challenges in testing digital detox through ESM. Expecting random notifications throughout the day could have unintentionally led participants to check their phones more often than usual, which could have confounded the effect of the intervention week.

Second, the limitations in measurement and constructs need to be noted. Studies 1 and 2 omitted some of the potentially confounding factors that might be theoretically relevant, such as personality, parental support, and peer dynamics. Study 4 ultimately relied on self-report and lacked an objective, app-level use metrics on phone use. While more contemporary research projects aim to develop tracking methodologies to measure real-time phone use, the existing studies using mobile-app tracking methods had to face compatibility issues between Android and IOS (two of the most common operating systems) (e.g., Hanley et al., 2019; Brockmeier et al., 2025), and this may create bias in the socioeconomic, demographic and digital profile of users. Study 3 pooled studies with a diverse range of designs and measurements, which led to exclusion of some critical studies due to incompatible measurements with the rest of the studies, and blurred the contents of the interventions included in the study.

Third, this thesis had limitations in capturing the scope of mechanisms at each social level. Study 1 had to rely on general family affluence as a proxy of individual- and family-level digital resources due to contents of the available data. Although family affluence is a validated measure that allows for effective socioeconomic comparisons across cultures and countries (Torsheim et al., 2016), the interpretations of Study 1 could have yielded more precise results if there were more available information on family resources. Similarly, Study 2 had limited information on adolescents' parental resources, as the majority of the parents did not fill out the complementary parental survey provided after the parental consent form, whereas information on parents' digital mediation and skills was omitted. In Study 3, the low sample of existing articles for some outcomes prevented from conducting further mediation or moderation analyses to examine if changes in digital use mediated changes in mental well-being within the intervention context. Finally, Study 4 aimed to explore potential moderating interplays, but role of digital maturity, among other critical factors, was not considered for reasons of space.

Finally, there were some limitations throughout this thesis involving statistical power, heterogeneity, and follow-up. For example, the primary data used in Study 2 was cross-sectional, and lacked a follow-up measurement of participants in their developments of digital maturity. Study 3 suffered from small k of extracted results, and we were not able to separate short- and long-term effects of the outcomes, due to scarcity of the follow-up measurements in the included studies. Additionally, the limitation with follow-up measurements affected Study 4 as well, while its design could have benefitted from a larger and more diverse sample at the school level.

6.5. Avenues for Future Research

This thesis offers several insights for future research. First, longitudinal designs with comprehensive and even cross-nationally comparable measures remains to be a crucial need in the literature. The more detailed designs would also allow for exploring potential mechanism such as digital maturity in a more nuanced and causal approach. Future research should prioritize the development of cross-national longitudinal datasets that can better capture the bidirectional dynamics between digital use and well-being. Intervention studies, as in Study 3 and Study 4, would also benefit from stronger causal designs with more robust RCT methodologies with sufficient statistical power and appropriate follow-up periods to capture both immediate and sustained effects of interventions targeting digital use and mental well-being. However, scholars need to be mindful about assessing short term changes as well because digital devices have become deeply intertwined with the daily lives of young people. Although long-term consequences are crucial and need attention, researchers in the future should also acknowledge the daily disruptions and mood fluctuations that might be caused by digital use (Burnell et al., 2024; Kross et al., 2013; Mei et al., 2018).

Second, future research should advance the methodological strategies to capture adolescents' digital use more objectively. The direction of research in this vein moves towards screen tracking technologies, however, this option is yet to be perfected. Moreover, phone tracking is a challenging methodology with concerns regarding data privacy and ethical considerations. There are some screen tracking software and apps available for commercial use, yet data privacy can be challenging to protect with a third-party agent. Future studies should ensure to comply with the most current data management guidelines to protect young people's digital privacy and safety. For instance, some researchers avoided these limitations by creating their own apps (e.g., Grüning et al., 2023; Ko et al., 2015). Moreover, building a tracking tool from scratch can be costly and difficult to open to common use for researchers.

Finally, future intervention research should focus more deeply on improving the digital use, efficacy, and resources of adolescents. While the evidence on screen time in Study 3 is conclusive that school-based programs help to reduce excessive digital use, future studies need to explore more effective strategies to help students, particularly in low-SES families, to build resilience against problematic use tendencies.

6.6. Closing Remarks

In closing, the thesis demonstrates that adolescent digital risks are not uniform, but heterogeneous, in how digital use related to mental well-being. The empirical findings from this dissertation indicate that the way digital media related to adolescent mental well-being is strongly shaped by family socioeconomic resources across countries and by the ways in which young people engage with their devices and platforms. Additionally, the findings of this thesis imply that risk is highest when competence, autonomy, and connectedness online are weakest, when engagement is public-facing and validation-seeking, and when institutional supports are thin. Finally, the analyses on intervention designs point to credible levers for change: build digital maturity, support feasible and autonomy-preserving routines, and use schools as equitable delivery systems while paying close attention to who benefits, but it also shows the limitations that certain types of digital interventions have, at least in the short term, in changing digital habits and emotional well-being. Overall, this dissertation has demonstrated that the way digital use links to adolescent mental well-being is far from universal and depends on individual-, family- and school-level mechanisms that intersect to each other.

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